Vrije Universiteit Amsterdam

Optimal inventory levels at Etos

Writen by:
Christa Vendel
Studentnr: 2653742

External supervisor:
Tim Blijleven

First Supervisor:
Ger Koole

Second Reader:
Oliver Fabert

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Preface

This report was written for my thesis for the Master Business Analytics at the Vrije Universiteit. The research aimed to minimize the inventory at the warehouse and all the stores of the Etos. This research was performed at the Supply Chain Department of Etos and this report will describe the methodology and the results.

The reason behind this was to give more insight into the possibilities of reducing the inventory based on the parameters in the order calculations. These parameters were set manually, and I was asked if I could design a method that would give advice about the parameter settings. For this project, I did mapped the process, gathered the data, modeled the optimization problem, and analyzed the results.

I enjoyed my time at the Etos doing this research. Hopefully, the results could be used to decrease the inventory levels. During the project, there were a few difficult tasks. These tasks were centered around programming the high-dimensional problem efficiently. I would like to thank my colleagues at Etos for their help working through these difficulties. I also want to thank Tim Blijleven, Etos's supervisor, for his help during this project. Lastly, I want to thank my supervisor from school, Ger Koole, for his help and knowledge of the methodology and approach.

Christa Vendel
July 21, 2022
Bergen

Management summary

This report is about research into minimizing the inventory by optimizing the parameters in the order calculation. The considered locations were all Etos stores and its distribution center (DC). Etos did not have a clear insight into how the order calculations were performing and how the inventory at the locations could be decreased based on the parameters. The research aimed to provide these insights and advise which parameters would improve the inventory levels when changed.

During the complete research, the process was considered in 2 parts: the supplier-DC and the DC-stores process. The methodology for the supplier-DC process was only an analysis. The reasoning was that there was no complete documentation of this process. The analysis compared the sales term of the round level to the payment term of the supplier.

The methodology for the DC-stores process was a linear program and a K-means clustering. The linear program optimized the inventory at the stores. The program's decision variables were the order calculation parameters. The choice for a linear program was related to the literature. The literature either used this method or aimed to reach the same quality in the results. [8, 5] The K-means clustering made it easier to maintain the results because it reduced the number of parameter sets for maintenance. The choice for K-means clustering was related to the fact that this is a standard methodology in Python and clustering was not the research goal. However, it might be worthwhile to invest some more time into the clustering to add the possibility of unequal cluster sizes.

The analyses for the supplier-DC process showed that 74% of the products had a round level with a sales term smaller than the payment term. For the other 26%, it was determined if the round level could decrease while still satisfying the supplier agreement. In a lot of cases, this was possible.

The model for the DC-stores process provided realistic results based on the performed analyses. An important analysis result was that the model resulted in two decision variables taking over each other's functions. This was not desired and it was advised to alter the model so that this would not happen anymore. However, the model still resulted in realistic inventory levels. The analysis also showed that most product-store combinations had a maximum of 2 weeks of inventory, a maximum of 2 delivery periods at stock, and an order multiple of 1. Finally, the analysis showed that the model only orders if a shortage threatens to arise.

To give the main conclusion of the research: the used methodology gave realistic results. However, the method does require some adjustments before it could be used in practice. The requirements would mainly be that the goal of the decision variables would be more clearly taken into account in the model. For the supplier-DC process, the main advice would be to minimize the round level, as far as possible according to the supplier agreement, of the products which do not sell within the payment term.

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Definitions

Abbreviations

BE Order quantity in which the stores order at the DC; (Dutch: Besteleendheid).

DC Distribution Center; Warehouse.

EDA Exploratory Data Analysis; Analysis of the data to find patterns and missing values.

FSC Physical Shelf Capacity (Dutch: Fysieke Schap Capaciteit); The maximum amount that fits on the shelf.

KPI Key Performance Indicator; The most important performance measure.

MPV Minimum presentation inventory (Dutch: Minimale presentatie voorraad); The amount that fits on a single row of a shelf.

SCT Supply Chain Tactics; department of Etos.

WDF Warehouse Demand Forecast; The demand the DC has to be able to meet for the stores.

Glossary

Classification Indication of how important this product is for Etos. There are 7 classifications from most important to least important they are N, Z, A, E, B, C, and D.

Fill rate The amount of the demand that you can immediately meet with the inventory at hand.

FSC factor The maximum number of times you want to have the FSC in stock.

K-means clustering A clustering method that creates k evenly sized clusters around a cluster center. The cluster center contains the average value of all the samples in that cluster for the inputted parameters.

MPV factor The minimum number of times you want to have the MPV in stock.

Order profile Group of parameter settings for the order calculation from DC to stores. Each product-store combination gets an order profile assigned, based on the type of product, the store, the rotation speed, and the classification.

Payment term The number of days after which Etos has to pay the supplier.

Round level	The amount in which the DC orders by the supplier. This can indicate orders either per case (C), per pallet layer (L), or per pallet (P).
Safety factor	A factor that shows how much safety stock should be at the stores. The safety stock follows from multiple this factor with $\sqrt{ED_{pst}}$.
Shortage indication	An indication if an order should only be placed if the inventory is not sufficient for the expected demand. The indication is either 1/True, if the indication is used, or 0/False, if the indication is not used.

Sub- and Superscripts

i, j	delivery/order moments
p	product
r	rounded
s	store
t	time in order moments
ur	unrounded

Variables

BE_p	Order multiple (Dutch: Besteleenheid) for product p for all time units and all stores.
D_{ptij}	Expected deliveries of product p at time t between next order moment i and delivery moment j.
ED_{pst}	Expected demand of product p at store s and time t.
$ED16_{pt}$	Expected demand of product p at time t in the 16 days after the next delivery.
EDD_{ptij}	Expected demand of product p at time t between next delivery moments i and j $(i < j)$.
$EDOD_{ptij}$	Expected demand of product p at time t between following order moment i and following delivery moment j.
EPD_{pst}	Expected promotional demand of product p at store s and time t.
$EPDD_{ptij}$	Expected promotional demand of product p at time t between following delivery moments i and j $(i < j)$.
FRI_{pst}	Fill rate inventory; The inventory level necessary at time t to meet the fill rate required of product p at store s.
FSC_{ps}	Physical shelf capacity for product p at store s.
FSC_{ps}^{factor}	Maximum number of times you want to have the FSC in inventory for product p at store s.
ID_{ptsi}	Expected inventory of product p at time t and store s just before next delivery moment i.
IO_{pti}	Expected inventory of product p at time t and following order moment i.

LB_{pt}	Lower bound of the order process from supplier to DC for product p ate time t.
LB^{r}_{pst}	Rounded lower bound of ordering (between DC and stores) for product p at store s and time t.
LB^{ur}_{pst}	Unrounded lower bound of ordering (between DC and stores) for product p at store s and time t.
m^{LB}_{pst}	Number of times BE_p is required to round the LB^{ur}_{pst} up to complete BE's.
m^{UB}_{pst}	Number of times BE_p is required to round the UB^{ur}_{pst} up to complete BE's.
MPV_{ps}	Minimum presentation inventory of product p at store s.
MPV^{factor}_{ps}	Minimum number of times you want to have the MPV in inventory for product p at store s.
ND_{ptij}	Number of days between following delivery i and j at time t for product p.
O^{promo}_{pst}	Promotional unrounded order of product p at store s and time t.
O^{reg}_{pst}	Regular rounded order of product p at store s and time t.
OS_{pt}	Unrounded order size for product p at time t in the process from supplier to DC.
OO_{ptij}	Outstanding orders for product p at time t between next order moment i and delivery moment j.
Pal_p	Amount on one pallet of product p.
RL_p	Round level of product p.
S^{days}_p	Number of additional safety days used in the process from supplier to dc for product p.
S^{factor}_{ps}	Safety factor for ordering for product p at store s.
$Safe_{pt}$	Safety demand of product p at time t in process from supplier-DC
UB_{pt}	Upper bound of the order process from supplier to DC for product p ate time t.
UB^{r}_{pst}	Rounded upper bound of ordering for product p at store s and time t.
UB^{ur}_{pst}	Unrounded upper bound of ordering for product p at store s and time t.

Introduction

The paper research concerned minimizing the inventory by optimizing the order calculation parameters. The research reason was that there was no clear insight into which order calculation parameters should be altered to improve the inventory levels. This also leads to the research goal: optimize the order calculation parameters to minimize the inventory of all locations.

The entire project took place at the Supply Chain Tactics department of Etos. The department's work is all centered around the Etos supply chain. The work goal is to ensure that enough inventory is in the stores to supply the customer demand.

As mentioned, the research goal was to optimize the inventory at the different locations. This is a very well-researched subject in the literature. [6, 2] However, this project did have the restriction that the calculation method could not be changed. To keep the calculations in place the project went more towards parameter optimization. This type of optimization was also very well-represented in the literature. [9] However, it was necessary to alter the literature methodology so that it could handle all of the problem-specific restrictions.

This report describes the entire research process of the project. The report starts with an introduction of the company and department in Section 1 and the problem introduction in Section 2. What is followed by the first steps of the research, namely the mapping of the inventory process (Section 3) and the data collection and preprocessing (Section 4). Once the data was gathered, the methodology was defined. Section 5 describes these methods. The following section is the results in Section 6. The final section, Section 7, gives a conclusion and discussion of the research.

In the entire report, some Etos related terminology was used. The glossary section (above this introduction) contains all the definitions of these terms, abbreviations, and variables.

1 Business context

This section introduces the company and department where the research took place. Subsection 1.1 will introduce Etos, the company, and Subsection 1.2 the department Supply Chain Tactics.

1.1 Etos - a general description

Etos originates in 1919 as a part of Philips under the name “Philips Coöperatieve Verbruiksvereeniging”. The company was founded due to the decrease in sales related to the price increase. At the store, the employees could buy their supplies at a discount. In 1931, Etos become independent of Philips and took the name Etos, which stands for “Eendracht, Toewijding, Overleg en Samenwerking”. Currently, Etos is a part of Ahold Delhaize. This happened in 1973 when Albert Heijn overtook Etos. In 2000 was the next development, namely the possibility to buy their products online. The store also won the title of “Beste drogisterij” seven times, with the first win in 2008. After this, the company grew a lot with the stores at the NS train stations and the franchise stores. Currently, there are 550 stores in the Netherlands and an Etos webshop. The Etos products are also sold internationally, however, they are presented in other stores. [1]

Recent developments at Etos are the automation of the orders for the stores. This automation means that the store systems determine how many items of each product should be ordered. However, there is also a half-automation, in which it is still possible to adjust the order (as the store manager) if you disagree with the advice. Another development is the big growth of the webshop.

The mission of Etos is to be the number one well-being partner. To reach this goal, Etos inspires and helps people to live happier and healthier lives. They do this by supplying the customers with the best products and advice about health and beauty. In total, Etos gives health advice 20 million times per year, and 8 million people start and end each day with their products.

An organizational chart of only four layers can describe the organization of Etos. This organization chart is visible in Figure 1.1. The chart shows that Etos has six main departments, namely: Supply Chain, Retail Operations, Finance, Merchandise, Marketing & E-Commerce, and HR.

The main competitors of Etos are Kruidvat and DA. Recently, Etos became the most visible store of these three stores through the website of Etos with up-to-date information and the collaboration with “Gezondheidsplein”. However, Etos has a broad assortment of products, from their brand to the top brands like Nivea. Etos also tries to keep improving its products and stores to keep customer interest and to stay ahead of its competitors. [4]

1.2 Supply Chain Tactics

The department Supply Chain Tactics (SCT) is in the third layer (marked in yellow) of the organization chart in Figure 1.1. They are responsible for managing, optimizing, and innovating the Supply Chain of Etos, from supplier to the shelf in the store. The SCT department consists of Replenishment and Warehouse Consultants, Replenishment Coaches, Analysts, and Employee Analysts. All of these employees answer to the Manager of Supply Chain Tactics.

The department works on different subjects all about the Etos supply chain. A few examples are the placement of the items in the distribution center, the forecasting of the promotional sales, the transport from and to the distribution center, and the online webshop. The department is currently transitioning to a completely data-driven department. The consequence is the automation of the standard procedures and activities. Eventually, the department would have grown from a descriptive to a predictive analytics mindset and eventually even a prescriptive analytics mindset.

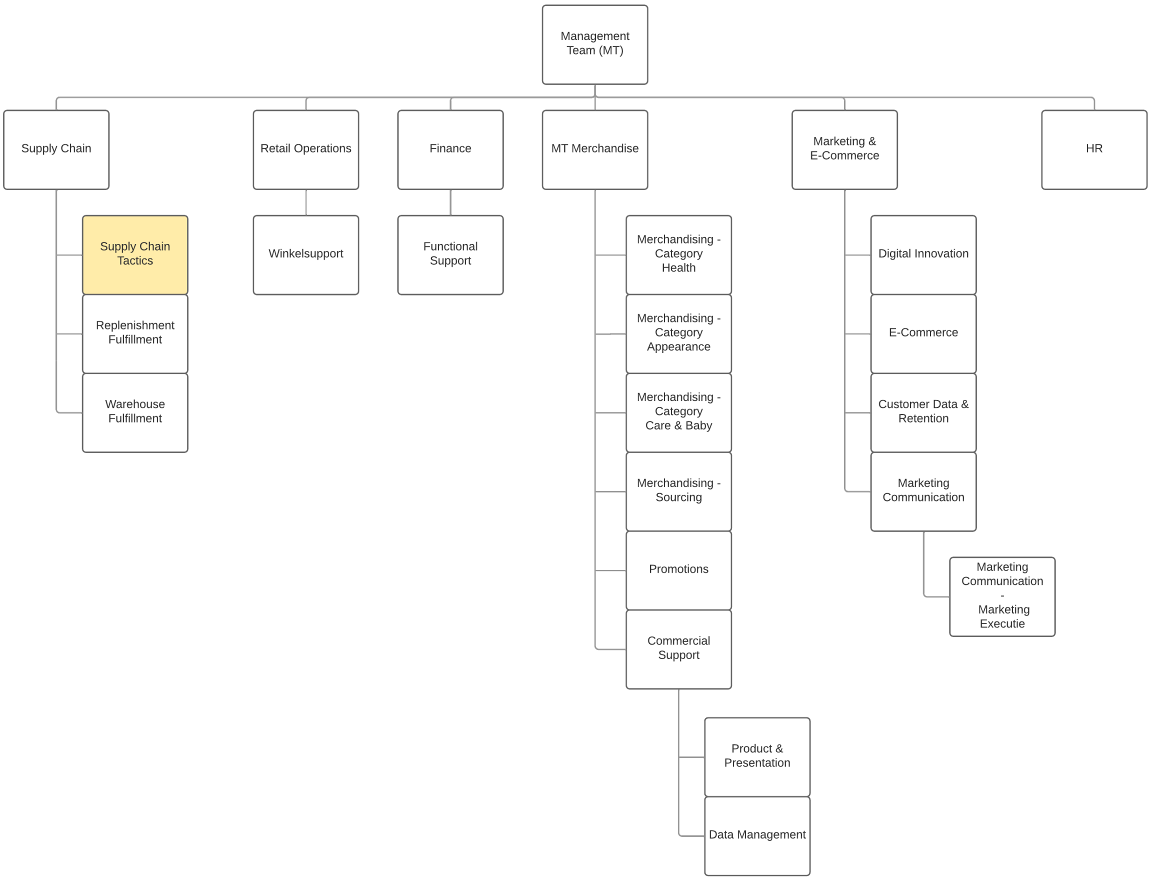


Figure 1.1: Organization chart of Etos

2 Problem description

This project researched the inventory management of Etos. Currently, multiple systems together make the orders and determine the order size. However, there is no clear insight into the reasons for the resulting inventory levels. For example, is the inventory so high because of the order quantity or due to the amount of safety stock taken into account? These questions were answered by the model and/or tool at the end of the project. The order and order calculation systems use a set of parameters. With these parameters, the previous questions were answered.

The research goal was to answer the questions "Which parameter should be changed to improve the inventory levels?" and "What should the value of these parameters be?". To answer the questions all the order parameters were identified and optimized. The identification happened during the mapping of the current inventory process. Section 3 describes these order processes.

When looking at the optimization of the parameters, it is important to know the key performance indicators (KPI) and the restrictions. The KPI for this project is the number of inventory days of a product at each location. The optimization should minimize this value. The model had two main restrictions, the calculations had to stay the same, and the fill rate should be met at each location. The distribution center had a required average fill rate of at least 98%, and the fill rate at the stores was related to which product it was. Every product has a classification. This classification shows the importance of having the product in stock at the stores. These classifications can change over the year. For example, sun products have a higher classification in the summer than in the winter. The fill rate differs from 95.9% to 98% and shows how much of the demand should be immediately met from stock.

After the optimization, the insights were put together. The analyses of the model results provided these insights. The model parameter values were saved into a data frame. The analyses also contained some summarizing insights, which are discussed in Section 6.

In conclusion, the main reason for this project was to create insights into the inventory levels of the products and to improve these levels.

2.1 Final product

As described in this section, the main goal is to deliver insights into what could improve the inventory levels. The results of the analysis into the order multiples, round level and BE, were represented in a tool. With this tool, it is possible to zoom in to a single supplier and see for which products the order multiple should be changed. For the other parameters that were tuned, a data frame was given as output. This data frame contains the parameter values for all the product-store combinations. A summary of these parameters will also be provided in the form of the results of an analysis.

3 Inventory process

This section describes the inventory process of Etos. The process consists of two parts, the supplier-DC process to control the inventory at the DC. And the DC-stores process to control the inventory at the stores. The following subsections describe these processes. These subsections use an expected demand. This research assumes that these expectation were already known and could be used as input.

3.1 From supplier to distribution center

The process between the supplier and the warehouse was controlled by the WDF (Warehouse Demand Forecast) process. This process was already under review, to make sure that it works as expected and as documented. The main idea of the process is to work from the expected demand for the stores (which the DC has to supply) towards an order quantity. The idea is to only order when the stock is lower than a lower bound. And if you order, you immediately order an upper bound. These bounds were based on sales without promotions. This means that the promotional sales still have to be added to the bounds when deciding to order or not. This main idea is also visualized in Figure 3.1

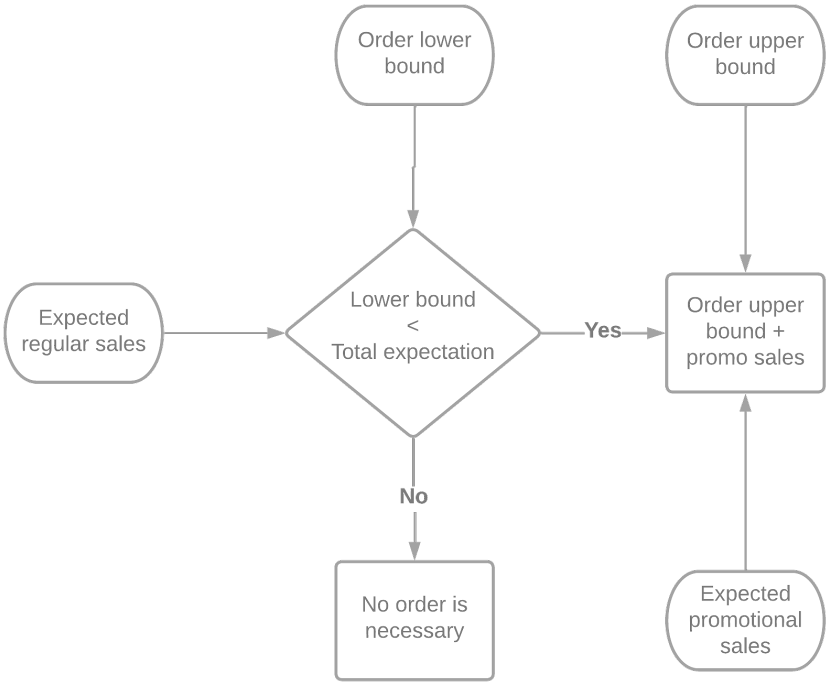


Figure 3.1: Main idea Supplier-DC ordering process

Both bounds were the minimum of two values with a safety component. The safety component ($Safe_pt$) of both bounds were the same and were calculated by Equation (3.1) with the expected demand between delivery 2 and 3 (EDD_{pt23}), some additional safety days (S_{pt}^{days}), and the number of days between delivery 2 and 3 (ND_{pt23}). The upper bound is calculated by Equation (3.2) where Pal_p is the amount that finds on one pallet and $ED16_{pt}$ the expected demand in the 16 days following the next delivery moment. And the lower bound with Equation (3.3) where $EDOD_{pt13}$ represents the expected demand between order moment 1 and delivery moment 3 and $EDOD_{pt12}$ is the same but ends at the second delivery moment. This lower bound contains another safety component, the term with the square root and the natural logarithm. This term was chosen for the shape of the square root and a quicker ascent due to the logarithm. Together they gave the desired shape for safety stock.

$$Safe_{pt} = EDD_{pt23} \cdot S_{pt}^{days} \cdot ND_{pt23} \tag{3.1}$$

$$UB_{pt} = \min(Pal_p, ED16_{pt}) \tag{3.2}$$

$$LB_{pt} = \min(EDOD_{pt13}, EDOD_{pt12} + \left(\sqrt{EDOD_{pt12}} \cdot \ln EDOD_{pt12}\right) \tag{3.3}$$

Once the bounds were known, the order decision was made. This decision was made with Equation (3.4). The variables in the equation stand for the expected inventory at order moment 1 (IO_{pt1}); the expected promotional demand before the next delivery moment ($EPDD_{pt01}$) and between delivery moments 1 and 2 ($EPDD_{pt12}$); the outstanding orders between order and delivery moment 1 (OO_{pt11}); the deliveries between order and delivery moment 1 (D_{pt11}), and; the lower bound (LB_{pt}).

$$IO_{pt1} + OO_{pt11} + D_{pt11} - EPDD_{pt01} < LB_{pt} + EPDD_{pt12} \tag{3.4}$$

If the statement in Equation (3.4) was true, an order was placed with the size calculated in Equation (3.5). This equation contains the order size (OS_{pt}), the upper bound (UB_{pt}), the expected promotional demand between delivery moments 1 and 2 ($EPDD_{pt12}$), and the expected inventory at delivery moment 1 (ID_{pt01}). The equation also rounds the bound up/down to the closest round level (RL_p) multiple. The round level shows if Etos ordered in cases, pallet layers, or pallets. The round level was determined by an automized calculation that took the supplier agreement into account. The supplier agreement showed if there was a minimum round level for the product.

$$\lceil OS_{pt} \rfloor_{RL_p} = \lceil UB_{pt} + EPDD_{pt12} - ID_{pt01} \rfloor_{RL_p} \tag{3.5}$$

This entire process is visualized in Figure 3.2.

When connecting this process to the project goal, five variables influence the inventory levels. The variables are:

- The minimum order quantity of the supplier agreement;
- The round level;
- The lower bound for ordering;
- The upper bound to order, and;
- The safety components for an order.

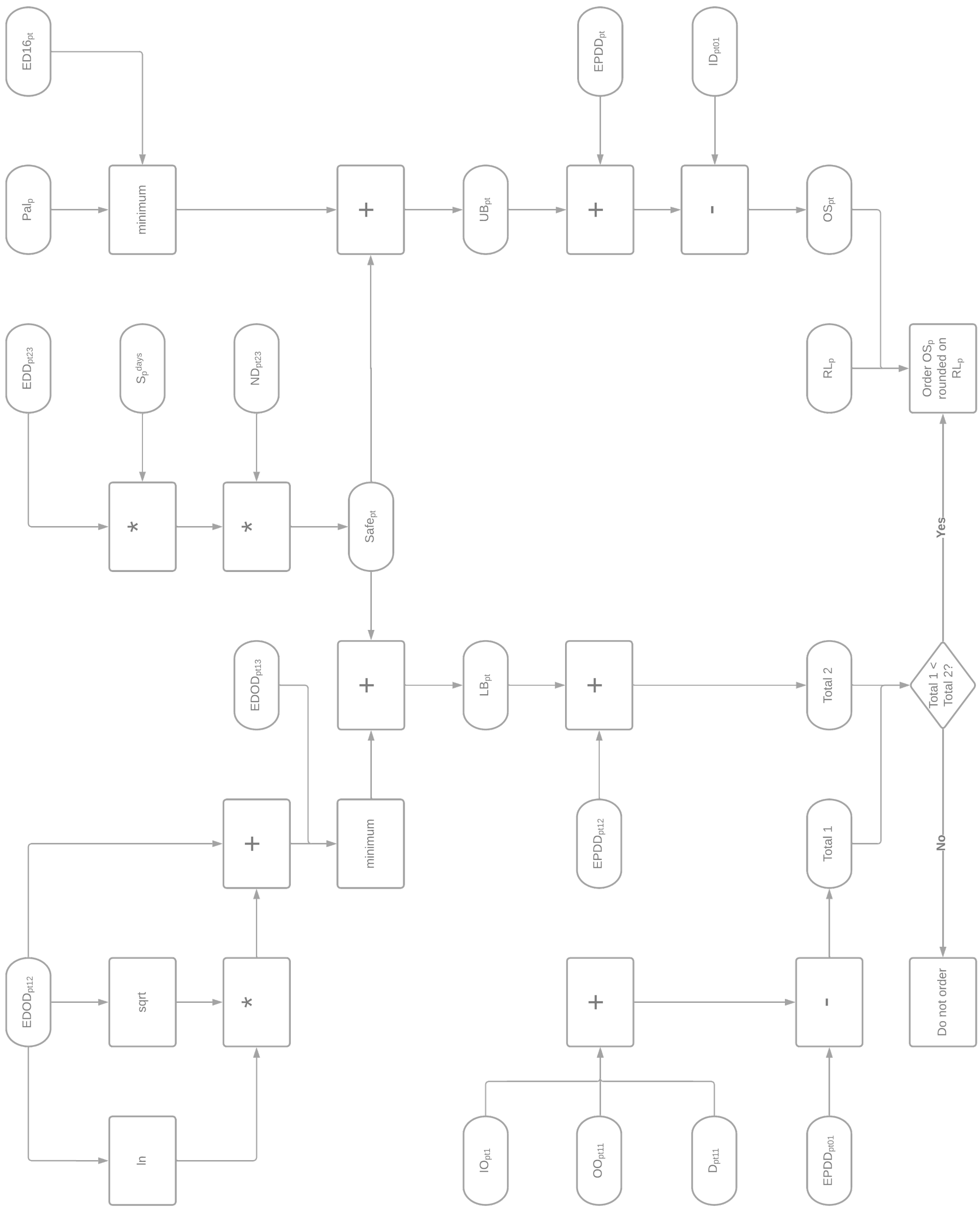


Figure 3.2: Detailed Supplier-DC calculation process

3.2 From distibution center to stores

The process from DC to the stores will be introduced in four parts. These parts are the product-specific variables, the order profiles, the order profile settings, and the actual order calculation.

Product-specific variables The product-specific variables say something about the order quantity (BE) of the products and the space in the stores for the products. The store space is a variable that can differ per store, so this is a product-store-specific variable. In total, three product(-store)-specific variables were used:

- **The order quantity (BE);**
  The order quantity of products.
- **The minimum presentation inventory (MPV), and;**
  The amount that fits in 1 row on the shelf in the store. For example, the MPV of Figure 3.3 is 8 because there are 8 bottles in a row.
- **The capacity of the shelf (FSC).**
  The maximum amount that fits on the shelf in the store. For example, the FSC of Figure 3.3 is 48 since there are 8 bottles on a row and 6 rows fit on the shelf.

Figure 3.3: Example MPV and FSC [3]
$MPV = width \cdot hight = 8 \cdot 1 = 8,\ FSC = MPV \cdot depth = 8 \cdot 6 = 48$

Order profiles For making the orders, the products and stores are assigned an order profile. These profiles say something about how much safety should be present and how much you want to have at least in the store for a good presentation and at most to limit your inventory. The following paragraph describes the settings of these profiles.

There are eight order profiles in total. The assignment of the products to the profiles happened on the classification, the store, and the type of product. The classification represents the importance of the products for Etos. In other words, it shows how high the fill rate target is. In total, there are six classifications. The order of these classifications from most important to least important are N, Z, A, E, B, C, and D. The products are assigned to these classes based on their rotation speed and the gross profit.

The following list describes the main idea and usage of the different order profiles. The values for the profile settings of seven profiles are described in Appendix A.

- **Standard**
  This profile is used in 90% of the cases and represents the most desirable inventory control.

- **Commercial**
  This is an option for the franchise stores. This profile will result in a higher inventory level for products to get a better commercial appearance on the shelf.

- **Minimum**
  This profile results in a lower inventory level for the products. It is used in the last week before a (temporary) store closure(e.g. due to renovations). The franchise stores are also able to choose this profile.

- **Min-max**
  This profile will only order when a lower bound is hit and immediately places a big order (of the upper bound).

- **Scarcity**
  When scarcity was expected, this profile will be used. The profile then only orders the absolute necessities.

- **Wheel clamp**
  This profile works in the same way as the scarcity profile, but in this case, the reason is that the stores have a hard to meet the payments. When this profile is used, it is often seen that the store closes a little while later.

- **Webshop**
  The profile has some sub-profiles based on the type of products, however, the main idea behind the profile is to have a good availability but no unnecessary inventory.

- **Various**
  This profile, represents multiple exception profiles. An example of an exception is the sun products in the (beginning of the) summer. In this case, other profile settings were used than in the other seasons.

Order profile settings The last paragraph introduced the different profiles. This paragraph continues with the profile settings. Each of the profiles has six settings, namely:

- **A safety factor (S_{ps}^{factor} - per product and store);**
  The amount of safety you want to take into account. The filled in *value* is used to calculate the safety as follows $value \cdot \sqrt{\text{needed demand}}$.

- **FSC factor (FSC_{ps}^{factor} - per product and store);**
  The maximum number of times you want to have the FSC in stock.

- **MPV factor (MPV_{ps}^{factor} - per product and store);**
  The minimum number of times you want to have the MPV in stock.

- **Maximum inventory weeks;**
  The number of weeks to limit the inventory at the store at.

- **Threshold expensive product, and;**
  If the price of a product in the profile is higher than this threshold, the MPV factor value will be manipulated to be 1. This is done to control the total inventory value at the stores.

- **Shortage indication.**
  If this variable is marked to use, orders only took place if a shortage was expected.

Order calculations The order calculation considered for this project, is divided into 2 parts, namely the regular order and the promotion order. Besides these two order flows, Etos uses some more order types, that were not related to the expected sales in the stores.

The first part of the order calculation was the regular (non-promotional) order. The regular sales were calculated, per product and store, with a lower and upper bound. The lower bound (LB^{ur}_{pst}) can be calculated with Equation (3.6). This equation is build from the (always present) minimum presentation inventory, the expected demand (ED_{pst}) of product p at store s and time t, an safety component, and the expected inventory (ID_{pst1}) at delivery moment 1 of product p at store s and time t. The process then rounds the lower bound up based on the order BE, to avoid a shortage. For the upper bound there were two options. Equation (3.7a) was the first upper bound and consists of the shelf capacity (FSC_{ps}) and the expected inventory (ID_{pst1}) at delivery moment 1 of product p at store s at time t. The second upper bound, Equation (3.7b), consists of the demand of the next few weeks and the expected inventory (ID_{pst1}) at delivery moment 1 of product p at store s at time t. Both of these bounds were rounded down based on the BE. The final order size for store s and product p at time t was calculated with Equation (3.8). In the case that the shortage indication was used, the order only took place if all the bounds (LB^{ur}_{pst}, $UB1^{ur}_{pst}$, and $UB2^{ur}_{pst}$) were greater than 0.

$$LB^{ur}_{pst} = (MPV_{ps} \cdot MPV^{factor}_{ps}) + ED_{pst} + (S^{factor}_{ps} * \sqrt{ED_{pst}}) - ID_{pst1} \qquad \forall p, s, t \quad (3.6)$$

$$UB1^{ur}_{pst} = (FSC_{ps} \cdot FSC^{factor}_{ps}) - ID_{pst1} \qquad \forall p, s, t \quad (3.7a)$$

$$UB2^{ur}_{pst} = \text{expected demand for next x weeks}_{pst} - ID_{pst1} \qquad \forall p, s, t \quad (3.7b)$$

$$O^{reg}_{pst} = \max(\lceil LB^{ur}_{pst} \rceil_{BE_p}, \lfloor \min(UB1^{ur}_{pst}, UB2^{ur}_{pst}) \rfloor_{BE_p}) \qquad \forall p, s, t \quad (3.8)$$

The second part of the order calculation is for the products in the promotions. This calculation was quite a bit easier and is described by Equation (3.9) where PD_{is} represents the expected promotional demand of product i at store s.

$$O^{promo}_{pst} = 0.75 \cdot EPD_{pst} - ID_{pst1} \quad (3.9)$$

Translation to the project When looking at the project goal, the variables were identified that influence the inventories. The found variables were all the variables described in the paragraphs “Product-specific variables” and “Order profile settings”. To minimize the inventory, these variables were optimized by the methodology.

4 Data

This section will describe how the necessary data was gathered in Subsection 4.1 and the exploratory data analysis in Subsection 4.2. The data gathering is split into three parts: the store, product, order and shelf information, the required fill rate, and the demand information.

4.1 Data gathering

As mentioned, this project used three data frames, the demand, the fill rates, and the general information about the stores and products. This subsection discusses all the made decisions made during the data gathering.

General store and product information For the project it was important to know which products and stores were inside the scope. A data frame was created to determine these products and stores. The data frame consists of all the current product-store combinations. This means that if a closed store and products that were no longer sold were left out of the project's scope. The next filter was on the stores so only stores were included for which the described order processes were used. This meant that only the stores with a store number below 8900 and not equal to 7857 were in the project's scope. The last filter was that only the products sold at the stores were taken into account. The DC also delivers non-sellable products to the stores because they need them to have a functioning store. An example of a non-sellable product is the cleaning supplies that the store uses.

With these filters, a data frame with all the information about the stores, products, shelf sizes, and ordering profiles was made. The gathered information about the stores, was the store number, the franchise indication, the number of deliveries per week, and the number of weekdays the store is open. For the products, the data contained the type of product, the price, the order multiple for the stores and DC, the possible reference product, and the supplier. The shelf size was added per product-store combination. The shelf size consisted of the width, height, and depth in the number of items. It also contains the maximum amount that fits onto the shelf (FSC) and the amount that fills one row on the shelf (MPV). Finally, the order profile information was added. Each order profile had there own set of parameter values (shown in Appendix A).

Required fill rates The second data frame is significantly smaller than the first. Etos has different fill rate requirements for products in the stores based on their classification. There are seven classifications, namely N, Z, A, E, B, C, and D. Each has there own fill rate. Table 4.1 shows the found fill rates for each classification.

Classification	Fill rate requirement
N	98%
Z	97.5%
A	97.2%
E	96.4%
B	96.4%
C	95.9%
D	95.9%

Table 4.1: Fill rate for every classification

Demand data The last data needed for the research were the sales per product and store. Since the project's scope only contained the regular order process, the data was filtered on this criteria. The final data frame contained the sales, a promo indication, and a moving average of the last five days. The data was collected for every day of the last year, every store, and every product.

4.2 Data analysis

This section discusses the exploratory data analysis (EDA) results. The analyses looked into the missing values and dimensionality reduction.

4.2.1 Missing Values

The collected data contained some missing values. This subsection will discuss these missing values. The missing values either represent missing information on the stores, the products, the combination of store and product, order profiles, or the supplier.

Store level The data on store level showed if the store was a franchise store, a part of a store group, the number of deliveries in the week, and the number of days in the week a store was open. In total, 528 stores were a part of the project. The missing values about these stores were the store groups of 443 of them, which is 83.9% of the stores. However, it is correct that this value was often missing. The store group value was only used to make the order profile connections easier. For example, in Subsection 3.2 the order profile Wheel Clamp was discussed. This profile was only assigned to stores that have a hard time meeting the payments. The profile can then be linked to a certain store group number. Then it would only be necessary to add the store to the store group if it gets into trouble.

Product level The product level information showed the product type (sunblock, shampoo, conditioner, etc.), the order multiple for the stores, the classification, the price, and a possible reference product. In total 14048 products are taken into account for this research. For 7 of these products, the price was missing for some of the stores. However, the price is the same in every store. In case of a missing value, the median of the other stores' prices was used. The only other column with missing values was the reference products. This is logical since the column was only filled if it was a new product. Most of the products were not new anymore at the time of the research. This meant that the references were not always present.

Product-store level This project is about 15,366,896 product-store combinations. The data contained the shelf size and order profile for each combination. Only for eight combinations was the shelf size missing. In this case, another store's information could not be used due to differing shelf sizes. Eventually, it was decided to leave these eight products outside the project scope since the data was needed for the model.

Order profile level There were 32 order profiles under consideration for the project. These profiles had no missing values, even though the column "threshold expensive product" contains empty cells. When this value was missing, it meant that the profile did not have a threshold and that all the products were treated the same.

Supplier-product level When analyzing the missing values at the supplier-product level it was important to exclude products not directly delivered from supplier to store. That left 10536 of the 14048 products to analyze. For 450 products there were still some missing values. However, non of the missing values were crucial for the model.

4.2.2 Dimensionality reduction

As mentioned in Subsection 4.1, the project had a scope of more than 15 million product-store combinations. For each combination, the correct order parameters were determined for supplier-DC and the DC-stores process. This is a huge dimensionality for any model and would lead to long computation times. To make the data easier to handle for the models, the data was reduced into segments. One run of the model then handled one segment of the data.

Model per process The project's scope was to optimize the order process parameters to reduce the inventory levels. To reduce the number of parameters for the model, it was a good idea to handle the supplier-DC and DC-stores process separately. Eventually, this resulted in different methods for each process. The DC-stores model still had to handle all 15 million product-store combinations.

Segments in DC-Store process To reduce the 15 million combinations to a reasonable size, the combinations were segmented on the product classification. This segmentation was used since it resulted in groups with the same fill rate which made the model easier to check. However, it would still leave a large group of products to go through the model at once. To reduce the group sizes even more, the groups were segmented on product type. The product type was expressed in the department, the class, and the subclass. After these segmentations, the group sizes were reasonable for a model to handle. Figure 4.1 shows a histogram of the sizes of the groups. In this figure, it is visible that most groups have not more than 25 products which leads to a dimensionality of 13200 (25 products at 528 stores). For this project this was reasonable. The found groups were also logical since the second segmentation grouped the products so that similar products go through the model together. For example, one run for sunscreen, one for body lotions, and so on.

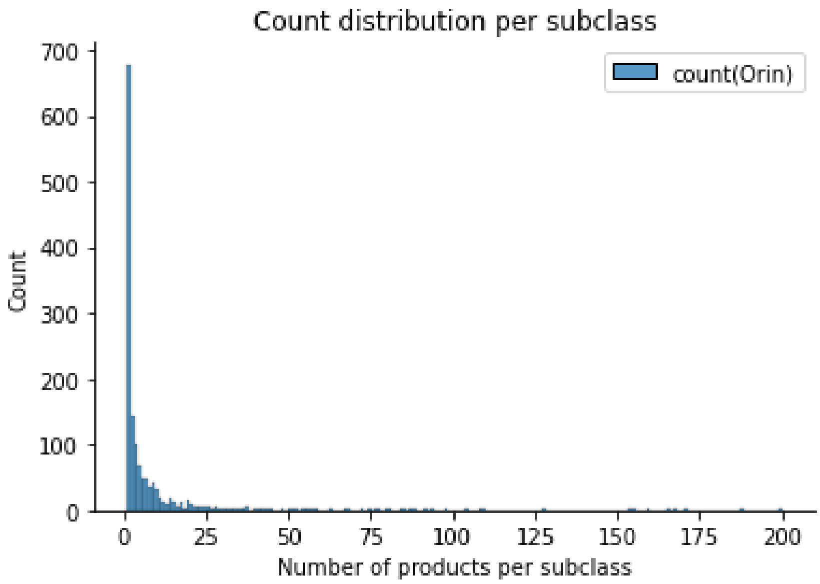


Figure 4.1: Groupsize distribution of segmentation for DC-Store process

5 Methodology

This section will describe the methods to find the optimal parameter values for the processes from supplier to DC and from DC to the stores. For the process from supplier to DC analyses were performed and a tool was made. The parameters for the DC-stores process were optimized with a linear program. The following subsections describe the methods in detail.

5.1 Methodology: Supplier - DC

The introduction mentions that analysis and tooling were used for the supplier-DC process. The reason for analyzing instead of optimizing was due to the uncertainties in the documentation of the process. Subsection 3.1 describes the process as far as it is documented. However, the subsection also showed that there was safety stock was added at multiple places. However, it is not known if this happens. To not be limited by the uncertainties in the process, this research only analyzed the round levels (order multiple from supplier to DC).

The main idea of the analysis was to determine if the sales period of the round level was smaller than the payment term. The round level had three possible values, namely: case (C), layer (L), or pallet (P). For each of the possibilities, the sales period in days was determined. With this knowledge, it could be seen if the sales period was smaller than the payment term. This was determined for every product and then summarized per supplier and product. To make the results easy to access a dashboard was built. This dashboard gave an overview per supplier and it was possible to zoom into a supplier and see the products.

Subsection 6.1 gives a summary of these results.

5.2 Methodology: DC - Store

This subsection will describe the methodology used for the inventory process from DC to stores. Subsection 3.2 describes how this process worked and introduces a lot of the terminology. The method used to optimize the inventory at all the stores was a linear program. Due to the high dimensionality of the problem, this is not the obvious choice. However, many articles do use this model as a baseline or aim to match the quality of the results. With this in mind, it was decided to still use a linear program but reduce the dimensionality that the model has to handle at once. [8, 5] How the dimensionality was reduced can be found in Sub-subsection 4.2.2.

5.2.1 The LP model

The order calculation described in Subsection 3.2 was the basis for the LP model. The calculations for regular orders in the subsection were imputed into the model since the research aimed to find the correct parameter values but not change the calculations. The model was given more freedom to find a solution by relaxing some of the constraints. For this problem, this meant that some parameters were determined based on an analysis of the model output instead of making them decision variables of the model.

Decision variables, Supporting Variables, and Parameters The used model had three decision variables, seven sets of constraints, and a minimization objective. The decision variables of the model were the parameters of the order calculation. The variables were defined as:

FSC_{ps}^{factor}	Maximum number of times you want to have the FSC in inventory for product p at store s
MPV_{ps}^{factor}	Minimum number of times you want to have the MPV in inventory for product p at store s
S_{ps}^{factor}	Safety factor for ordering for product p at store s

To be able to formulate the entire model, there were some parameters necessary. These parameters are described below together with some supporting variables of the LP model. These supporting variables were determined by the model but it was not the goal to determine them. It was necessary to know them to determine the decision variables' value.

<u>*Parameters*</u>

BE_p	Order multiple (Dutch: Besteleenheid) for product p for all time units and all stores
ED_{pst}	Expected demand of product p at store s and time t
FRI_{pst}	Fill rate inventory; The inventory level necessary at time t to meet the fill rate required of product p at store s
FSC_{ps}	Physical shelf capacity for product p at store s
MPV_{ps}	Minimum presentation inventory of product p at store s

<u>*Supporting variables*</u>

ID_{ptsi}	Expected inventory of product p at time t and store s just before next delivery moment i
LB^{r}_{pst}	Rounded lower bound of ordering for product p at store s and time t
LB^{ur}_{pst}	Unrounded lower bound of ordering for product p at store s and time t
m^{LB}_{pst}	Number of times BE_p is required to round the LB^{ur}_{pst} up to complete BE's
m^{UB}_{pst}	Number of times BE_p is required to round the UB^{ur}_{pst} up to complete BE's
O^{reg}_{pst}	Regular rounded order of product p at store s and time t
UB^{r}_{pst}	Rounded upper bound of ordering for product p at store s and time t
UB^{ur}_{pst}	Unrounded upper bound of ordering for product p at store s and time t

Constraints The second step in making the model was to formulize the constraints. The first two constraints are that the upper and lower bound for ordering are determined according to Equations (3.6) and (3.7a) of Subsection 3.2. These equations immediately represented the first constraints which calculated the lower and upper bound. Equations (5.1b) and (5.1a) show these constraints once more.

$$FSC_{ps} \cdot FSC^{factor}_{ps} - ID_{pst1} = UB^{ur}_{pst} \qquad \forall p, s, t \tag{5.1a}$$

$$MPV_{ps} \cdot MPV^{factor}_{ps} + ED_{pst} + S^{factor}_{ps} \cdot \sqrt{ED_{pst}} - ID_{pst1} = LB^{ur}_{pst} \qquad \forall p, s, t \tag{5.1b}$$

With these definitions of the ordering bounds, the order could be calculated with Equation (3.8) of the order process. The equation first rounded the bound. The lower bound was rounded up and the upper bounds were rounded down based on the BE. This was done to translate the bound into an amount that could be ordered. The rounding was added to the LP model in the for of Constraints (5.2a) and (5.2b) for the lower bound and Constraints (5.3a) and (5.3b) for the upper bound. For these constraints to work properly, the supporting variables m^{LB}_{pst} and m^{UB}_{pst} should be added to the objective. With as reasoning that these variables should have the smallest integer value for which the constraints were satisfied.

$$m^{LB}_{pst} \cdot BE_p \geq LB^{ur}_{pst} \qquad \forall p, s, t \tag{5.2a}$$

$$m^{LB}_{pst} \cdot BE_p = LB^{r}_{pst} \qquad \forall p, s, t \tag{5.2b}$$

$$m^{UB}_{pst} \cdot BE_p \geq UB^{ur}_{pst} \qquad \forall p, s, t \tag{5.3a}$$

$$(m^{UB}_{pst} - 1) \cdot BE_p = UB^{r}_{pst} \qquad \forall p, s, t \tag{5.3b}$$

The next step to determine the actual order was to take the maximum of the rounded bounds. Which is done by adding supporting variable O^{reg}_{pst} to the objective and adding Constraints (5.4a) and (5.4b) to the model. O^{reg}_{pst} was added to the objective to ensure that it would get the smallest value that satisfied the constraints.

$$O_{pst}^{reg} \geq LB_{pst}^{r} \qquad \forall p, s, t \tag{5.4a}$$

$$O_{pst}^{reg} \geq UB_{pst}^{r} \qquad \forall p, s, t \tag{5.4b}$$

With this last set of constraints, the order process was covered. However, it was also necessary to know the inventory at each store for the order calculations. The inventory for each store, product, and time was calculated with Equation (5.5). This equation was also added to the model so that the model could keep track of the changes in the inventory.

$$ID_{ps(t-1)1} + O_{ps(t-1)}^{reg} - ED_{ps(t-1)} = ID_{pst1} \qquad \forall p, s, t \tag{5.5}$$

The last constraint for the model, given by Equation (5.6), was that the required fill rate should always be met. The fill rate is already taken into account in the parameter FRI_{pst}. This parameter shows which inventory level meets the fill rate for that product-store-time combination. To find this value the Poisson distribution was used with a moving average retrieved from the historical sales. The Poisson distribution was used because demand in stores often occurs according to this distribution. The choice for a moving average was based on the fact that Etos uses this method to estimate the expected sales. And finally, the used fill rate was between 95.9% and 98%, and the classification of a product-store combination determines which fill rate it was exactly.

$$ID_{pst1} + O_{pst}^{reg} \geq FRI_{pst} \tag{5.6}$$

Objective As mentioned before, this LP model had a minimization objective. The model aimed to determine the values of the decision variables while minimizing the inventory at each store. The inventory at the store just before delivery is represented by supporting variable ID_{pst1}. This would mean that the objective would be to minimize the sum over all p, s, t of this variable. However, the variables m_{pst}^{LB}, m_{pst}^{UB}, and O_{pst}^{reg} should also be added to the objective to make sure that all the constraints work properly. The exact reasoning behind this was described in the previous paragraph. All of this together results in the following objective:

$$\min \sum_{p} \sum_{s} \sum_{t} ID_{pst1} + m_{pst}^{LB} + m_{pst}^{UB} + O_{pst}^{reg}$$

Complete model The previous paragraphs introduced all the components of the LP model. With all of these constraints and the objective, the final model was as follows:

$$
\begin{array}{llcll}
\min & \sum_p \sum_s \sum_t ID_{pst1} + m^{LB}_{pst} + m^{UB}_{pst} + O^{reg}_{pst} & & & \\
s.t. & MPV_{ps} \cdot MPV^{factor}_{ps} + ED_{pst} + S^{factor}_{ps} \cdot \sqrt{ED_{pst}} - ID_{pst1} & = & LB^{ur}_{pst} & \forall p,s,t \\
& FSC_{ps} \cdot FSC^{factor}_{ps} - ID_{pst} & = & UB^{ur}_{pst} & \forall p,s,t \\
& m^{LB}_{pst} \cdot BE_p & \geq & LB^{ur}_{pst} & \forall p,s,t \\
& m^{LB}_{pst} \cdot BE_p & = & LB^{r}_{pst} & \forall p,s,t \\
& m^{UB}_{pst} \cdot BE_p & \geq & UB^{ur}_{pst} & \forall p,s,t \\
& (m^{UB}_{pst} - 1) \cdot BE_p & = & UB^{r}_{pst} & \forall p,s,t \\
& O^{reg}_{pst} & \geq & LB^{r}_{pst} & \forall p,s,t \\
& O^{reg}_{pst} & \geq & UB^{r}_{pst} & \forall p,s,t \\
& ID_{ps(t-1)1} + O^{reg}_{ps(t-1)} - ED_{ps(t-1)} & = & ID_{pst1} & \forall p,s,t \\
& ID_{pst1} + O^{reg}_{pst} & \geq & FRI_{pst} & \forall p,s,t
\end{array}
$$

5.2.2 Analysis on model results

The previous sub-subsections mentioned that there were some relaxations in the model. These relaxations were order calculation parameters that could be determined based on the model output analyses. This sub-subsection describes these analyses.

In total, four analyses were performed, namely:

- Group the product-store combinations for easy maintenance;
- Analyse the maximum number of weeks where you want to limit your inventory.
- Analyse if the product-store combinations use a shortage indication, and;
- Analyse which BE would be best for each product-store combination.

After these analyses, the only order calculation parameter not discussed was the "threshold expensive products". In Appendix A it is visible that was not used. For this reason, it was decided that it was not necessary to include this parameter in either the model or the analyses.

The first analysis was a clustering of all the combinations. For easy maintenance, it was decided that there should not be more than 20 sets of parameters to maintain. This directly translated into a maximum of 20 clusters. The clustering was performed with the standard K-means clustering of the *scikit-learn package* of Python. This method creates 20 cluster center points and gives each cluster center the product-store combinations closest to that center. Then several iterations were performed to determine the best centers and the best clusters. This led to 20 centers with the same amount of combinations assigned to them. [7]

The second analysis was into the maximum amount of weeks you want to have in stock. The goal of this analysis was to see if the model results were realistic. The method for this analysis was to translate the resulting inventory levels to the number of inventory weeks based on the historic sales. The final result came from maximizing these values per product-store combination.

The third analysis was into the shortage indication. For the calculation method of Etos, it was important to know if the shortage indication was 0 (False) or 1 (True). This was determined by an analysis of the lower and upper bound outputted by the model. If it ever happened that an order was placed, but one of the bound was 0, then the indicator was 0. Otherwise, it could be set to 1. However, in that case, it does not matter too much which value the indication had, since the calculation automatically handles it as if there was a 1.

The final analysis was into the BE (order multiple) of the product-store combinations. To determine this, the greatest common divider (GCD) was taken for the order size that came out of the model. In this case, the GCD would also be the best BE for that combination, since you would never order more than needed. The goal of the analysis was to find out which BE occurred and which were the most common ones.

Subsection 6.2 discusses the results of all of these analyses.

6 Results

In Section 5 introduced the methods. This section continues on these methods, by presenting the results coming from the analysis and models described in the previous section. Subsection 6.1 shows the results of the analysis performed for the supplier-dc process and Subsection 6.2 for the dc-stores process.

6.1 Supplier-DC

Subsection 5.1 described the performed analyses for the supplier-DC process. This subsection will continue with the results of these analyses.

The first important result is that 77.4% of the products already have a round level that sold within the payment term. Figure 6.1 shows which round levels were used and if they were sold within their respective payment terms. The figure shows that the round level Case (C) was the most common and that the majority of this round level was sold within the term. When looking at the bigger round levels, Layer (L) and Pallet (P), it is visible that the difference between the number sold within and outside of the payment term decreases. However, for all the round levels most products were sold within the payment term.

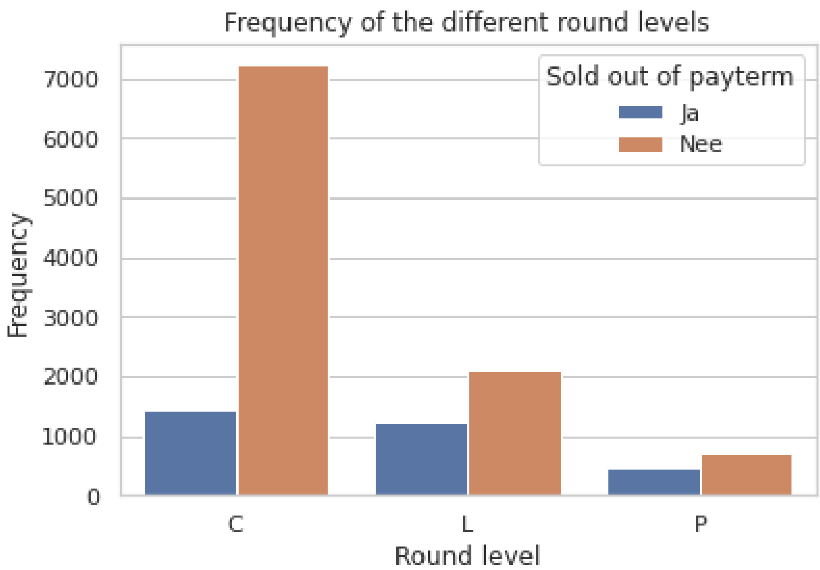


Figure 6.1: Distribution of the different round level

The following sub-subsections give a more in-depth analysis of each group of products. Sub-subsection 6.1.1 shows the results of an in-depth analysis of the products with a round level sold within the payment term and Sub-subsection 6.1.2 sold outside of the payment term.

6.1.1 Round levels sold in pay term

This sub-subsection discusses the products with a round level sold within the payment term. For this group, it was determined if the used round level was also the biggest round level that sold within the payment term. The results of this analysis is presented in Figure 6.2. The first thing to notice in this figure is that the pallet round level is always the same as the maximum round level sold in the payment term. This is logical since Etos never orders more than one pallet at a time. The figure also shows that at least 500 products with a layer round level could have a pallet round level. This is visualized by the blue bar (round level below max) by round level L. Lastly, it is visible that several of the products with round level case could have had a larger round level.

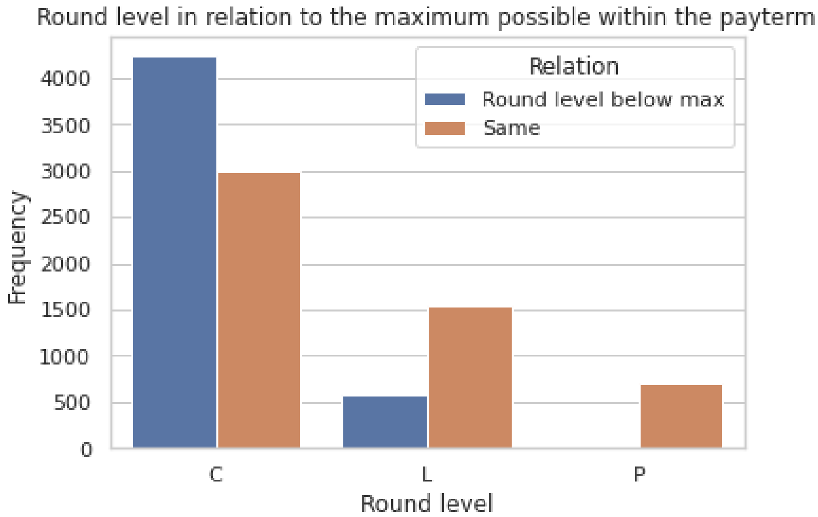


Figure 6.2: Round level versus the round level that just fits in the payment term

To conclude this sub-subsection, a lot of products (approximately 50%) have a round level which could be increased, when looking at the amount sold within the payment term. An advantage of ordering in bigger quantities would be that the order frequency decreases. This could lead to lower transport- and fixed ordering costs. However, a disadvantage is that you need more space in the inventory and the inventory costs will increase due to the bigger amount that will be stored.

6.1.2 Round levels sold outside of pay term

This sub-subsection discusses the products with a round level not sold within the payment term. For this group, three analyses were performed, namely: the type of suppliers; the number of suppliers, and; the number of products that could have a lower round level.

The first two analyses were into the number and type of suppliers with round levels not sold within the payment term. Table 6.1 shows the number of suppliers where the percentage of products sold within the payment term is given by a range. This table shows that 41.8% (112 out of 268 suppliers) had round levels not sold within the payment term. During a closer look at these suppliers, it was noticeable that the suppliers with a low percentage were either very large suppliers or suppliers where Etos only orders a few products. Etos is one of the smaller clients for the large suppliers. This has as consequence that they have less influence on the round level. The suppliers namely create these round levels based on their best clients. For the suppliers with only a few products, it might be possible to discuss the round level and decrease it by at least one step.

Percentage products sold in pay term	**Number of suppliers**	**Percentage of all suppliers**
Below 10%	10	3.7%
Between 10% en 20%	1	0.4%
Between 20% en 30%	3	1.1%
Between 30% en 40%	5	1.9%
Between 40% en 50%	10	3.7%
Between 50% en 60%	6	2.2%
Between 60% en 70%	11	4.1%
Between 70% en 80%	10	3.7%
Between 80% en 90%	27	10.1%
Between 90% en 100%	29	10.8%
Exactly 100%	156	58.2%

Table 6.1: Frequency amount of products sold within the payment term

The last analysis was into the relationship between the used round level and the minimum round level required by the supplier (noted as the supplier agreement). Figure 6.3 shows the results of this analysis. In this figure, it is visible that the round level Case is never below the supplier agreement. That makes sense since a case is the smallest round level possible. When looking at the products with round level layer (L) or pallet (P) it is visible that the majority could have a lower round level based on the supplier agreement. This does not mean that all products are sold within the payment term if they are lowered to the supplier agreement. However, it does improve the amount of inventory at the DC, since you have inventory for a shorter period than you had before.

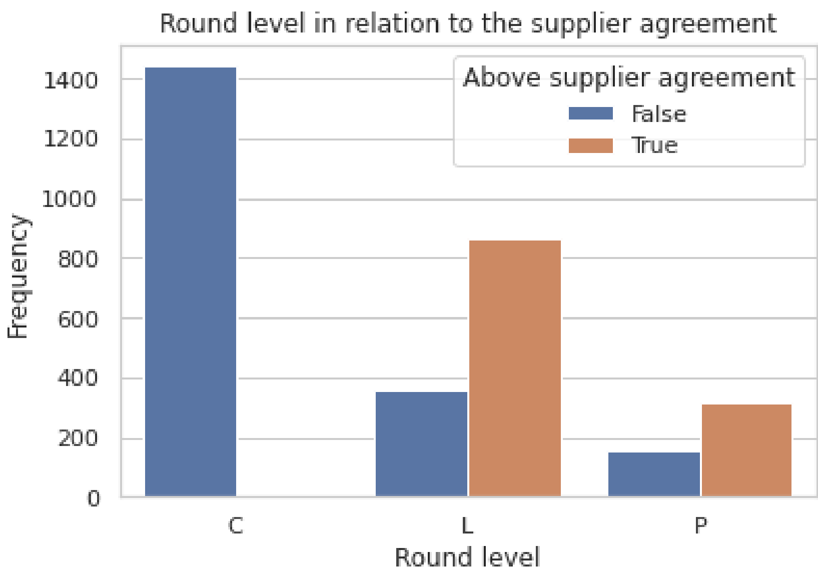


Figure 6.3: Indication if the round levels were above the supplier agreement

In conclusion, the round level of a lot of products in this group could be lowered.

The recommendation from this analysis is to decrease the round level if possible based on the supplier agreement. This can be done by adding the payment term as a factor to the model which determines the used round level. A final recommendation is to look if the case sizes can be decreased by the suppliers with the round level case but which can't be sold within the payment term.

6.2 DC-stores

In Sub-subsection 5.2.2 there were four analyses described based on the results of the LP model. In this subsection, the results of these analyses will be discussed.

6.2.1 Clusters

The first analysis was into the clustering of all the product-store combinations. As mentioned, the clustering happened with a K-means clustering method and resulted in the 20 clusters described in Table 6.2. When looking at these clusters, it is visible that some of the clusters are very similar. For example, clusters 5 and 6 could be joined together with a maximum of two weeks of stock and a shortage indication of 0. The shortage indication would be 0 because the calculation would automatically use a shortage indication if it is necessary for the combinations of cluster 6.

When looking at the values of the safety factor it is noticeable that most of these values are smaller than 0.1, which results in only a very smaller added value in the calculation of the lower bound. The MPV factor has the exact opposite pattern from the safety factor. This factor is on the larger side if the safety factor is small and the other way around. From these results, it could be concluded that the MPV factor has taken over some of the functions of the safety factor. This results in the MPV factor making sure that there is enough safety stock, which was supposed to be the function of the safety factor.

In the column of the maximum number of inventory weeks, it is noticeable that cluster 19 has a very large value in comparison to the other clusters. The reasoning for this is that this cluster mostly contains product-store combinations with a low rotation. For example, a combination where only 1 item was sold every week.

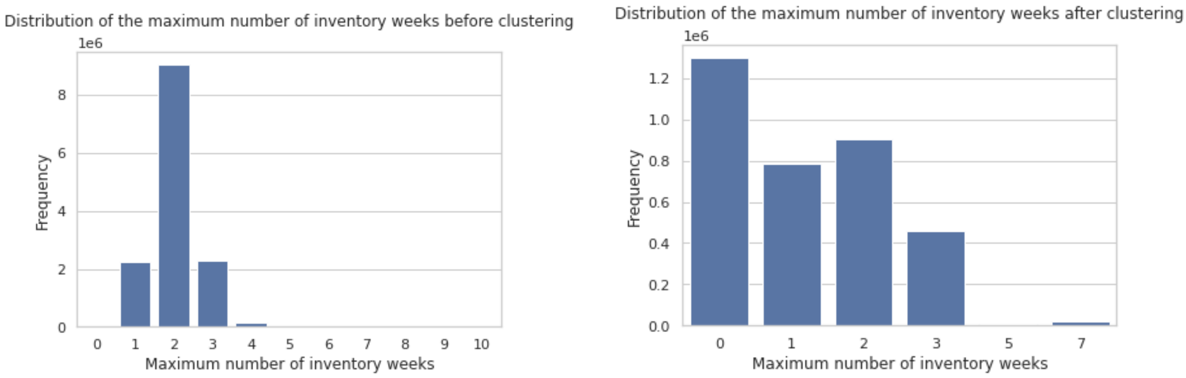
Finally, when looking at the shortage indication, there were 11 clusters with indication 1 and 9 with indication 0. So almost the same amount of products have a shortage indication as that do not have that indication. Currently, the indication was used to lower the stock for the stores that were about the (temporarily) close, so that fewer products had to be returned to the DC. This means that in the current situation there are a lot more combinations without the indication than with the indication. However, it is logical that the model would use the indication more often since it aims to minimize the stock at the stores. This follows in the order process, where you then would only order if you truly need anything.

Cluster	Safety factor	FSC factor	MPV factor	Max. stock weeks	Shortage indicator
1	0.011	1.986	1.059	1	1
2	0.012	0.394	0.950	1	1
3	0.000	18.584	9.628	2	1
4	0.007	0.516	1.958	3	1
5	0.006	0.268	0.977	1	0
6	0.006	0.330	0.929	2	1
7	0.004	0.393	1.382	2	0
8	0.001	0.456	2.144	2	0
9	0.010	1.884	1.392	2	0
10	0.000	0.728	3.387	3	1
11	0.001	0.478	1.589	2	1
12	1.271	0.391	0.042	2	0
13	0.000	8.270	3.637	1	1
14	0.004	1.155	1.023	1	0
15	1.303	2.331	0.067	2	0
16	1.616	0.435	0.107	3	0
17	0.026	0.258	0.821	2	0
18	0.000	0.582	2.196	2	1
19	0.013	2.996	7.005	7	1
20	0.003	3.180	2.040	2	1

Table 6.2: Found profile settings

6.2.2 Maximum number of inventory weeks

The second analysis was into the maximum number of inventory weeks. The analysis was started by looking at the frequency of each number of weeks before and after clustering. Figure 6.4 shows the results from this analysis. As visible in Figure 6.4a the number of inventory weeks before clustering had a left-skewed distribution with the peek by two weeks. However, this shifts further to the left during the clustering. In Figure 6.4b it is visible that some combinations have 0 inventory weeks. This is a possible result because some combinations have more than one delivery per week and only cover enough for a single delivery period. When comparing the before and after clustering situations, it is also visible that after clustering there are no combinations anymore with more than seven weeks of inventory. From the comparison, it was concluded that the clustering had a big influence on the maximum number of inventory weeks the product-store combinations.



(a) Before clustering

(b) After clustering

Figure 6.4: Frequency of maximum number of inventory weeks

Besides looking at the maximum number of inventory weeks, the analysis also looked at how many delivery periods were on stock. This analysis was based on the average sales of the past year for the product-store combinations. Figure 6.5 shows the results of this analysis. This figure shows that most combinations had either 1 or 2 delivery periods at stock. The frequencies of more than two delivery periods decrease very quickly and are not visible anymore in the figure from 4 periods.

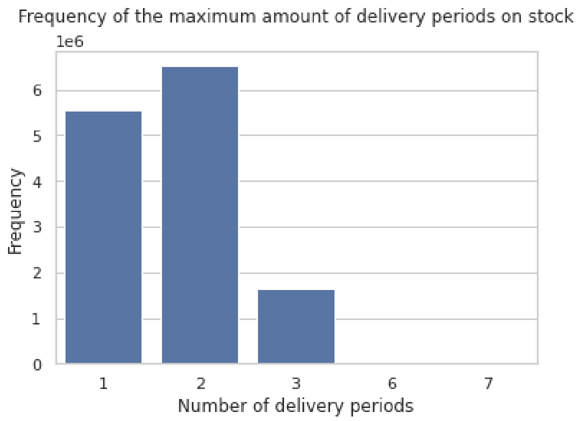


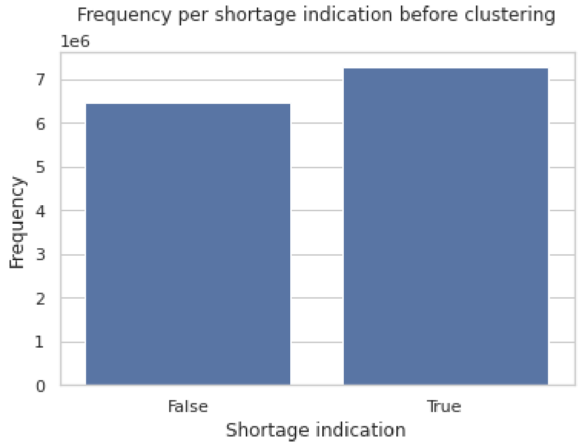
Figure 6.5: Number of delivery periods on stock

To conclude this analysis, most combinations at most two weeks of inventory and two delivery periods at the stores. These results are realistic because most combinations had either 1 or 2 delivery periods per week, which corresponds with the found results. A question of the analysis was if the model results were realistic. The answer to this question was, that the results were realistic based on the maximum number of inventory weeks. This can be concluded since the results correspond to the number of deliveries per week and are just below the 4-week maximum which is currently used.

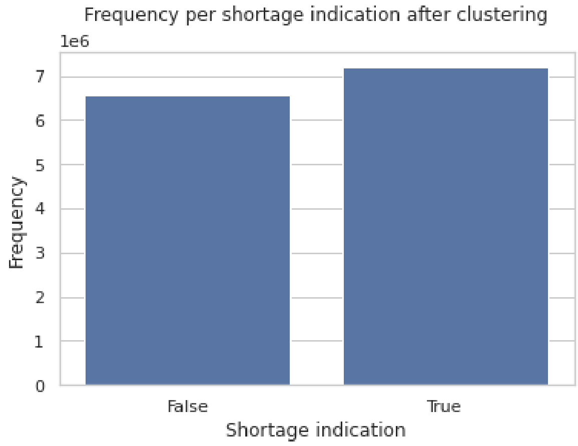
6.2.3 Shortage indication

The third analysis of Sub-subsection 5.2.2 was into the shortage indication. This subject was already shortly touched upon in Sub-subsection 6.2.1 which concludes that the model results in more combinations with a shortage indication than currently used. The sub-subsection also mentioned that this is logical since the model minimizes the inventory at the stores, which results in the fact that the model would only have an order greater than zero if you could not satisfy the fill rate otherwise. This sub-subsection gives some more results on this subject.

Figure 6.6 shows the number of combinations with a shortage combination before and after clustering. Both situations result in approximately the same figure, where most combinations have a shortage indication. However, there is only a small difference between the amount with shortage indication and the amount without. This could also be concluded from the cluster presented in Table 6.2, which shows that the difference is the size of the two more clusters with the indication.



(a) Before clustering



(b) After clustering

Figure 6.6: Frequency for each shortage indication

The analysis also included looking into the number of changes compared to the current situation. The results of this analysis are represented in Figure 6.7. In this figure, it is visible that most of the combinations that the model gives a shortage indication of 1 currently have a value of 0. However, the model only changes a few of the ones that currently have an indication of 1 to the group with the indication at 0.

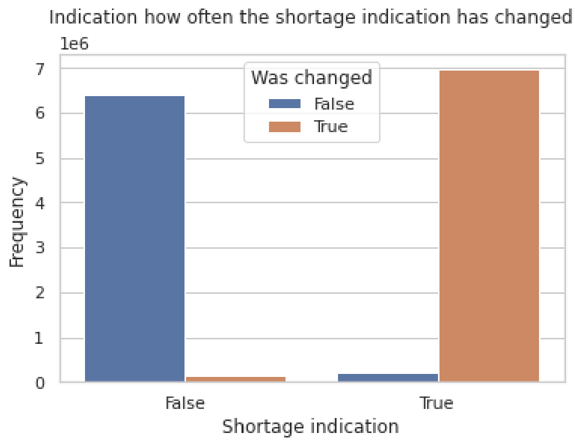


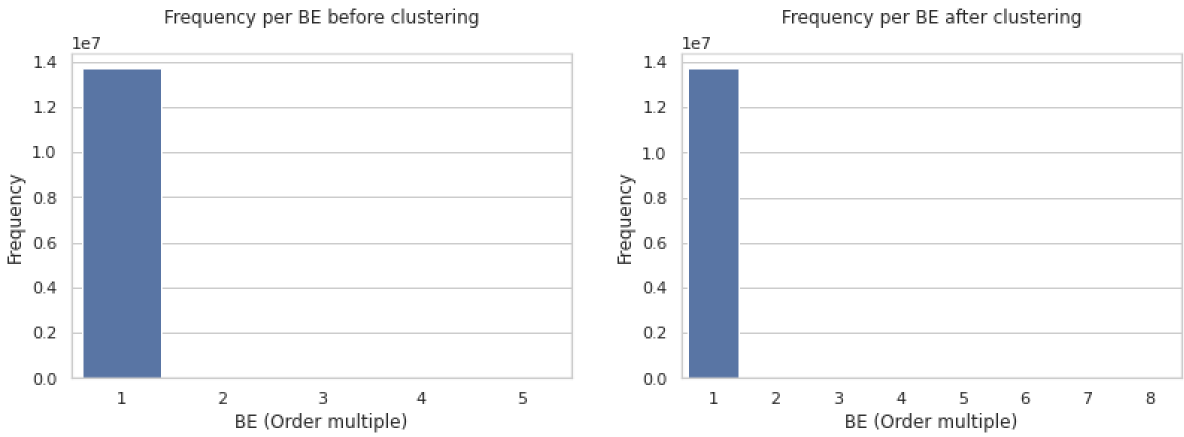
Figure 6.7: Shortage distribution with change indication

To conclude this analysis the model changes a lot of the shortage indication. Most of these changes are from indication 0 to indication 1. This means that the model gives more combinations a shortage indication than what is currently used. This result is logical since the goal of the model was to minimize the inventory at the stores, which leads to the fact that an order would only be placed if the fill rate was not met otherwise.

6.2.4 BE

This sub-subsection is about the results from the last analysis described in Sub-subsection 5.2.2. The analysis goal was to determine which BE and how often each BE was used.

In Figure 6.8 the results of these analyses are shown. There are two situations represented, namely before and after clustering. As visible in these figures, the clustering does not change the results much. However, the clustering does change the maximum BE from five to eight. In both Figure 6.8a and 6.8b it is visible that most product-store combinations should have a BE of 1. However, the other BEs mentioned in the graph also occur, but only for a very small set of combinations compared to the set for BE 1.



(a) Before grouping (b) After grouping

Figure 6.8: Frequency of how often each BE was used

The analysis also included an analysis of the changes in the BEs from the current situation. Figure 6.9 shows the result of this analysis. In this figure the same information is visible as in Figure 6.8b, so this figure also shows that BE 1 is mostly used. However, the figure also shows that several of these combinations currently do not have a BE of 1. Approximately 8 million combinations should have a BE of 1 based on the analysis after clustering that currently have a different BE.

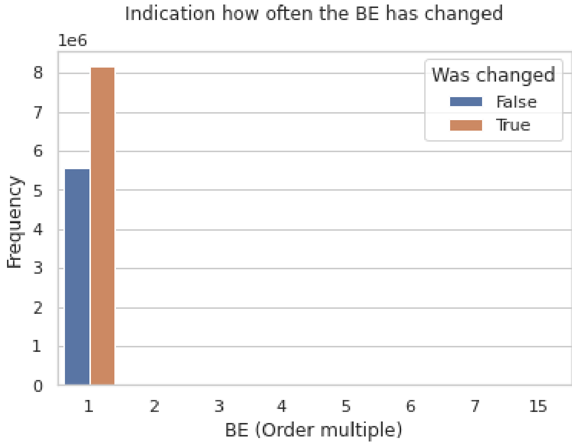


Figure 6.9: Final BE distribution with change indication

To conclude this analysis, most product-store combinations should have a BE of 1. Currently, more than half of these combinations do not have a BE of 1. This means that a lot of BE should be changed according to the model.

7 Conclusion and discussion

This paper's research aimed to find the parameter values for the order process from supplier to DC and from DC to the stores. The optimized parameter for the supplier-DC process was the order multiple (round level). For the DC-stores process, there were six parameters to optimize. The parameters were:

- The MPV factor (factor to make sure that you have enough in the store for a nice presentation);
- The FSC factor (factor to make sure that you do not have more than fits on the shelf);
- The safety factor (to make sure you have enough safety stock);
- The BE (order multiple);
- The shortage indication (indication if you should only order if you can not cover the expected demand), and;
- The maximum number of inventory weeks you want to have at the store.

Supplier-DC process For the supplier-DC process, only an analysis was performed. The analysis compared the used round level and the payment term Etos has by the supplier. There were three possible round levels, a case, a layer, or a pallet. The analysis shows that the case was used the most and the pallet the least. It also showed that 74% of the products had a round level that was sold within the payment term. For this group of products, there were some products for which the round level could be increased without having the sales period exceed the payment term. For the group with a round level that was not sold within the payment term, there were several products for which the round level could be decreased based on the supplier agreement. For example, some products with a layer round level could be moved to the group with a case round level.

It would be advised to decrease the round level where necessary and possible. For the other products with a round level exceeding the payment term, it would be advised to start a conversation with the suppliers to see if there is anything possible. For the products which sold within the payment term, it might be worth will to increase the round level if possible. But to give good advice about this situation analyses including costs would be necessary.

DC-stores process For the DC-stores process a LP-model was used. To the results of this model, a K-means clustering was applied to make it easier to maintain. During the analysis of the results after clustering, it was found that the resulting inventory levels were realistic and that these results could be used. However, the MPV factor seemed to take over the function of the safety factor. Further, it was found that compared to the current situation more product-store combinations should have a shortage indication of 1 according to the model. This is logical since the model minimizes the stock at the stores and only places an order if the fill rate would not met in the coming delivery period. When looking at the BE (order multiple) it was found that a BE of 1 is the most common. In comparison, only a few combinations should have a BE of 2 or higher.

Lastly, the analyses showed that most combinations have at most two inventory weeks and two delivery periods at stock.

From all of these results, it was recommended, to alter the model to prevent the MPV factor from taking over the function of the safety factor. It would also be wise to take a second look at the clustering. The method currently used, makes clusters of the same size. For this problem, it might be more realistic if unequal cluster sizes were applied. The final advise was to use the shortage indication more often and to decrease the BE if the model suggests this.

Final remark To conclude the research, the chosen methods gave good results in general. However, to make sure the results could immediately be used some alterations are necessary to the model and clustering methods.

References

[1] Etos is 100 jaar! https://www.etos.nl/over-etos/geschiedenis/, accessed: 2022-1-10

[2] Diks, E., de Kok, A., Lagodimos, A.: Multi-echelon systems: A service measure perspective. European Journal of Operational Research **95**(2), 241–263 (1996). https://doi.org/https://doi.org/10.1016/S0377-2217(96)00120-8, https://www.sciencedirect.com/science/article/pii/S0377221796001208

[3] Iris: Nieuw: Etos test me store aan de lijnbaan in rotterdam. http://www.irispraat.nl/2017/09/nieuw-etos-test-me-store-aan-de.html, accessed: 2022-7-21

[4] Le Clercq, P.: Etos concurreert met kruidvat én body shop (2017), accessed: 2022-1-10

[5] Mousavi, S.M., Hajipour, V., Niaki, S., Alikar, N.: A multi-product multi-period inventory control problem under inflation and discount: A parameter-tuned particle swarm optimization algorithm. International Journal of Advanced Manufacturing Technology **70**, 1739–1756 (02 2014). https://doi.org/10.1007/s00170-013-5378-y

[6] Nunes, D., Vieira, A.: An inventory model for optimization of a two-echelon periodic-review system. Brazilian Journal of Operations Production Management **1**, 2 (03 2016). https://doi.org/10.14488/BJOPM.2016.v13.n1.a1

[7] Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., Duchesnay, E.: Scikit-learn: Machine learning in Python. Journal of Machine Learning Research **12**, 2825–2830 (2011)

[8] Perakathu, P.: Heuristic based inventory optimization in three-stage divergent supply chain (04 2011). https://doi.org/10.13140/2.1.1848.4480

[9] Yu, T., Zhu, H.: Hyper-parameter optimization: A review of algorithms and applications. CoRR **abs/2003.05689** (2020), https://arxiv.org/abs/2003.05689

Appendices

Appendix A Inventory Process: Profile settings

This appendix shows the order profile settings that were used when the research of this problem started. In Table A.1 all of the profiles with there settings were used.

Profile	Classification	Safety factor	FSC factor	MPV factor	Max. stock weeks	Threshold expensive	Shortage indicator
Standard	Z	1.25	1.10	2.00	4		0
	A	0.5	1	1.75	4		0
	E	0	1	2	4		0
	B	0.1	1	1.2	4		0
	C	0	1	0.95	4		0
Commercial	Z, A	1.25	1.25	2.5	6		0
	B, E	0	1	2	6		0
	C - FR	0	1	1.1	6		0
	C - WWM	0	1	2	6		0
Minimum	Z	0.75	1	2	1		1
	A, E	0.1	1	1.25	1		1
	B	0	1	1	1		1
	C	0	1	0.75	1		1
Min-max	Z	1.25	1.1	2	6		1
	A	0.5	1	1.75	6		1
	E	0	1	2	5		1
	B	0.1	1	1	5		1
	C	0	1	0.8	6		1
Scarcity		0	0	0.25	1		1
Wheel clamp	Z	0	1	0.5	1		1
	A	0	1	0	1		1
	E, B, C	0	1	0	1		1
Webshop	Deco	0	100	1	4		1
	Fast rotation	1.5	100	1	3		1
	Slow rotation	0.5	100	1	3		1

Table A.1: Profile settings per classification and profile
WWM = Etos' own stores; FR = Franchise stores