Optimizing the dynamic safety stock levels of Grolsch

A simulation-based evaluation of the dynamic safety stock levels

Bart Snoeijink

Grolsch

Asahi
ASAHI BEER

UNIVERSITY OF TWENTE.

This is a public version of the original thesis report delivered to Grolsch. We have sometimes removed data, graphs, and axis values of the graphs, and we have sometimes used percentages instead of absolute numbers in order to preserve the confidentiality of the used data.

Colophon

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Preface

This thesis report marks the end of my Master's in Industrial Engineering and Management (IEM) at the University of Twente. I look back on a great student time, where I was offered the full resources to develop myself on both a personal and a professional level. I was fortunate enough to be able to develop myself by doing a minor in Mexico, doing a lot of committee work, doing a board year at Integrand Twente, gaining professional work experience, and doing a graduate internship at one of the best brands from the region of Twente.

I would like to thank Grolsch for the opportunity to perform my graduation internship within the Supply Chain (Planning) department. In particular, I would like to thank Evi Dubbink and Kristian Kamp for their help during my graduation assignment. Even though both of them left the Supply Chain Planning department for the packaging department during the conduct of my research, they both kept showing an interest in helping me finish my thesis. Whenever I needed help I could always ask them despite their busy schedules, which is much appreciated! The sharp feedback and advice, keeping in mind both the interests of Grolsch and the academic constraints, helped me a lot to finish my thesis with, hopefully, useful results and insights for Grolsch.

From the University of Twente I would especially like to thank Dennis Prak for being my first supervisor. Whenever I had a question he was always there to give me a quick and proper response so that I could continue my research. The thorough academic knowledge of Dennis helped me to bring my thesis to a higher (academic) level with, hopefully, useful applications in practice for Grolsch and for the academic body of knowledge. Moreover, I would like to thank Matthieu van der Heijden for being my second supervisor. Due to his experience in the academic field and his extensive knowledge in the field of inventory management, Matthieu was always able to provide critical feedback on the (academic) methods that I used, which helped me a great deal to improve the quality of my research.

I also want to thank my family for always supporting me during my studies to continuously keep me motivated and I want to thank all my friends that I have met during my studies, with whom I was lucky enough to be able to study together and also make fun a lot. I look forward to making some more good memories after our studies and I am looking forward to keep continuing myself on a professional and a personal level!

Bart Snoeijink
Denekamp, 24$^{\text{th}}$ of August 2023

Management Summary

Grolsch is currently not able to reach its target service levels for its SKUs. Grolsch measures its service level using a Stock Availability percentage, equal to the ready rate in the literature, indicating how much percent of the active product portfolio is in stock over the entire year. The target Stock Availability percentage for SKUs that are made to forecast and sold domestically is 98.5%. Therefore, we researched how Grolsch can achieve an average of 98.5% Stock Availability against minimal inventory-related operational costs. In our research, we focus on SKUs that are sold domestically and made to forecast. Moreover, of these domestic MTF SKUs we only focus on the SKUs that are filled on Filling Line 2. SKUs of Filling Line 2 are sold in Returnable Bottles with a volume capacity of 300 ml or 330 ml.

Grolsch was not able to reach 98.5% Stock Availability because the forecast uncertainties and production lead time uncertainties are not (or at least minimally) taken into account when determining the safety stocks. As Grolsch has a lot of seasonal SKUs in its portfolio it uses a dynamic safety stock for all its SKUs. Grolsch uses a minimum Days of Cover for all their SKUs. Thus Grolsch expresses its inventory level for each SKU in the number of days for which it can satisfy the SKU demand with the inventory in stock. Just like with a safety stock level in absolute units, the Days of Cover (DoC) should never be lower than the minimum Days of Cover (minDoC). The only difference is that now the safety stock in absolute units moves along with the forecast of the SKU.

We observed that the current inventory control policy of Grolsch is the most similar to an (R,S,Q) inventory control policy and we have used the calculations of this control policy to take along the standard deviation of the forecast error and the standard deviation of the production lead time to calculate a new minimum Days of Cover for each SKU. However, before we calculated a new minimum Days of Cover we first updated the ABC classification using the most recent data and we introduced an additional classification called the XYZ classification. The XYZ classification indicates the degree of forecast reliability. Using a combination of the ABC and the XYZ classification we got 9 different classifications in total. Each SKU can have a different classification per quarter as the differences in classification between the quarters is rather big for some SKUs. Next, we calculate the minimum Days of Cover per SKU per week and with this minimum Days of Cover per SKU per week we use 3 methods to calculate a new minimum Days of Cover allocation for Grolsch. The new minimum Days of Cover are calculated as follows:

1. The first method is called the VMQ-method (Variable Minimum Days of Cover per Quarter). We classify every SKU per quarter based on the combination of the ABC and the XYZ classification. The XYZ classification indicates the degree of forecast reliability. We can calculate an average minimum Days of Cover per quarter per SKU based on the weekly minimum Days of Cover per SKU. As every SKU has a different classification per quarter we can then calculate an average minimum Days of Cover per classification and we can then assign this aggregated minimum Days of Cover per classification to the corresponding combination of the SKU and the quarter.

2. The second method is called the AA-method (Average Aggregated) and uses the (aggregated) minimum Days of Cover of the first method that we calculated per quarter per SKU. Based on the minimum Days of Cover per quarter we calculate an average minimum Days of Cover for the entire year for each SKU.

3. The third method is called the ANA-method (Average Non-Aggregated) and uses the minimum Days of Cover per week per SKU and then calculates the average minimum Days of Cover per SKU over all 52 weeks, such that every SKU has its separate fixed minimum Days of Cover for the entire year. In this method, we do not aggregate the minimum Days of Cover based on the classification, which we did using the AA-method.

The new minimum Days of Cover allocations that we found show much higher values than the old minimum Days of Cover. Especially the ANA-method shows widely varying minimum Days of Cover for each SKU. The VMQ-method shows that the XYZ classification has only little effect on the minimum Days of Cover

The new minimum Days of Cover allocations are used to adjust the one-year ahead production plan of Grolsch, which we used as input for our simulation. It is important to note that the results that we show are thus based on a simulation where the production plans are used as input instead of using the new minimum Days of Cover directly as input within our simulation. Moreover, within the simulation, we assume that the forecast errors are normally distributed with an average forecast error equal to 0 such that the forecast is unbiased. In the simulation, we estimate the inventory-related operational costs by means of obsolescence costs, holding costs, and commuting costs. The commuting costs are the costs that Grolsch pays when they need to transfer stock to their warehousing location in the harbour because their warehouse at the brewery does not have sufficient space available to store all pallets.

Using our simulation, to simulate both the old production plan and our new production plan using the VMQ-method we found a higher Stock Availability percentage (97.6% for old versus 98.3% for new). Moreover, we also found that the total costs have risen by 20.2%. The total cost increase is for 80% caused by the higher obsolescence costs, and we see that especially for SKUs with a short shelf life and seasonal demand patterns the obsoletes are increasing. A fixed minimum Days of Cover leads to a higher Stock Availability percentage than when using a varying minimum Days of Cover per quarter (98.3% for varying the minimum DoC versus 99.0% for the AA-method), but it also leads to 58.5% higher total costs compared to the costs of the old production plan. The higher Stock Availability percentage is most probably caused by the larger absolute fluctuations of the stock level, as during the low season of an SKU the absolute safety stock level is now even lower than it was. The cost increase is quite hefty and is mostly caused by additional obsolescence costs. Moreover, the ANA-method performs even better than the AA-method in terms of Stock Availability (99.0% for the AA-method versus 99.3% for the ANA-method). The increase in Stock Availability does lead to additional costs (63.9% higher total costs than the total costs of the old production plan). Taking into account production delays we estimate that Grolsch would have sufficient storage space available to apply all methods for all SKUs. However, the AA- and the ANA-method both are rather close to the current available warehousing capacity of Grolsch.

Using the 4 production plans we performed sensitivity analyses to see which method performs best in case the current situation is subject to changes. The initial simulation did take into account the forecast errors, but it did not take into account the production delays. Moreover, in the initial simulation, we assumed that once a product has passed 1/3 of its expiration time it can still be used to satisfy customer demand. We have done tests for both by running simulations for all 4 production plans and the simulations showed that when taking into account production delays the Stock Availability percentage for each method would drop about 30% compared to the original SA percentages that we found per method and the total costs decreased with about 50% for each method. Taking into account that products that have passed 1/3 of their expiration date cannot be sold anymore leads to a decrease of about 6 to 7% compared to the original SA percentages that we found per method. Another sensitivity analysis that we have done for all 4 production plans strengthens the conclusion that the ANA-method performs the best in terms of Stock Availability percentage for every standard deviation of the forecast error and we see that the absolute difference in Stock Availability percentage between the production plans using different methods increases in proportion to the increase of the standard deviation of the forecast error. However, for the ANA-method we also pay the most euros per SA percentage so relatively seen the method is more expensive than all of the other methods regardless of the standard deviation of the forecast error.

For all 3 new methods we see a big increase in the number of products that pass 1/3 of their expiration time compared to the original production plan, especially for SKUs with a rather short shelf life and a seasonal demand pattern. For all seasonal SKUs with a shelf life shorter than x days, we observed that the obsolescence costs are quite high whilst the Stock Availability target was more than reached. Therefore we lowered the minimum Days of Cover of these seasonal SKUs to 67% of the regular minimum Days of Cover. Moreover, we found that for seasonal SKUs with a shelf life of x days or longer it would be worth it to increase the minimum Days of Cover given the number of additional obsoletes compared to the Stock Availability percentage that is gained. For all SKUs not following a seasonal demand pattern, we would recommend Grolsch to leave these minimum Days of Cover as they are given the achieved Stock Availability percentages that are rather high already. Following this recommendation we made a production plan for the Filling Line 2 SKUs where we applied the ANA-method only to the SKUs with a seasonal demand pattern (more than 25% difference between the worst quarter and the best quarter in terms of sales volume in hectoliters) and a shelf life of x days or longer, with a maximum of 167% of the regular minimum Days of Cover as the ANA-method showed some really high minimum Days of Cover for some SKUs. For the seasonal SKUs with a seasonal demand pattern and a shelf life lower than x days, we changed the minimum Days of Cover by 67% of the regular minimum Days of Cover and for the other SKUs we did not change the production plan. Applying the method just specified would lead to a Stock Availability of 98.6% and a total cost that is 10% higher than the total costs of the old production plan. Taking into account the additional sales that we would have missed when using the old production plan, Grolsch would have to pay an additional 1.35% of the total costs of the old production plan for the new method.

The goal of the research was to reach 98.5% Stock Availability against minimum operational costs. The average Stock Availability percentage achieved is 98.6% which is higher than the desired 98.5% Stock Availability. Despite the higher operational inventory-related costs that come with the higher Stock Availability percentage we would advise Grolsch to follow our advice by implementing the method that we just elaborated on in the last paragraph. In the competitive beer market, the availability of the SKUs plays a vital role in maintaining or increasing market share, especially within retail. Moreover, during our research, we found that the current minimum Days of Cover for the SKUs that have a (very) seasonal demand pattern are rather hard to forecast due to their strong weather dependency, which makes the fact that the current minimum Days of Cover are not high enough to reach the desired Stock Availability percentage. We advise Grolsch to start implementing this new method for the Filling Line 2 SKUs which are sold in the domestic market and made to forecast and which are not product X or product Y. Moreover, we advise the tactical planning of Grolsch to keep an eye on the next important KPIs when implementing this method: the schedule stability, the Stock Availability percentage, the obsolescence costs, the commuting costs, and the warehouse utilization. If implementation on Filling Line 2 appears to be a success we would advise Grolsch to look into implementation of this method on Filling Line 8 SKUs and after that maybe Filling Line 1 SKUs. When implementing this method on another filling line the tactical planning should carefully analyse what the seasonal SKUs are and what SKUs have a long shelf life. It might be the fact that the thresholds that we calculated for the Filling Line 2 SKUs are not the same for the SKUs of other filling lines as Filling Line 2.

In our simulation we have initially taken into account that obsolete SKUs can still be sold to every customer, whilst this is not always the case in reality. The obsolete products have an effect on the achieved Stock Availability percentage (about 6 to 7% in our case), whilst this is not taken into account within the safety stock calculations. For future research, it would be recommended to find out how the perishability of the SKU can be taken into account when determining the safety stock level. It would be interesting here to find out to what extent the (target) service level and the shelf life of the SKU have an effect on the obsolescence costs. Furthermore, we assume in our simulation that the forecast errors are always normally distributed and that the average forecast error is equal to 0. However, in reality, we found that the forecast errors do not always follow a Normal distribution, and the demand is over-forecasted for most SKUs. Therefore, for future research, it would be worth finding out what the change in the forecast error distribution does for the optimality of the minimum Days of Cover.

We simulated the production plans for which the minimum Days of Cover were used as input. The 1-year ahead production plan is used as input, but the production plan is not changed based on the realized sales and the production delays. Moreover, we only incorporated the production delays within the simulation using the sensitivity analysis. The fact is that it is rather hard to build a simulation where all of the planning decisions and the production delays are realistically simulated. It would be good to extend this research by looking into how we can best simulate the effects of production delays and how this affects the optimality of the safety stocks exactly. In addition, we would advise Grolsch to look further into what the effect of the batch sizes is on the optimality of the Stock Availability percentage and the total costs, especially if production delays are encountered.

Contents

Glossary

AA-method = The Average Aggregated method. This approach calculates a minimum Days of Cover per SKU for the entire year that is based on the classification of the SKU per quarter.
ANA-method = The Average Non-Aggregated method. This approach calculates a minimum Days of Cover per SKU for the entire year where we do not aggregate the minimum Days of Cover across classification.
Asahi = The Asahi Group Holdings is a Japanese beverage concern, and is also the parent company of Grolsch.
CSL = Cycle Service Level. The Cycle Service Level is equal to the probability of not having a stockout during a replenishment cycle.
DES = Discrete-Event Simulation. This is a simulation method that models the operation of a system in a discrete sequence of events forward in time. Every event changes the state of the system.
DoC = Days of Cover. The Days of Cover is a number that indicates the number of days that the forecasted demand for the coming days can be satisfied from stock.
FL = Filling Line.
FR = Fill Rate. The Fill Rate equals the probability that a product demand is directly delivered from stock.
HL = Hectoliter. 1 Hectoliter is equal to 100 liter.
MAD = Mean Absolute Deviation. A measure that indicates how much all of the data points deviate from the average. By taking the absolute difference between each data point and the average we prevent having negative values.
MinDoC = Minimum Days of Cover. The minimum Days of Cover is a number that represents the number of days that Grolsch would always want on stock. the minimum number of days that Grolsch wants to be able to satisfy the incoming demand from stock.
MOQ = Minimum Order Quantity.
MSE = Mean Squared Error. A measure that indicates how much all of the data points deviate from the average. By squaring the difference between each data point and the average we prevent having negative values.
MTF = Make-To-Forecast. A Make-To-Forecast product is a product for which the inventory level is controlled based on the demand that is expected. The inventory can then be produced already before an order is placed by the customer.
MTO = Make-To-Order. A Make-To-Order product is a product that is only produced when it is ordered by the customer.
NRB = Non-Returnable Bottle.
Off-trade = When referring to the off-trade market, we refer to the target market that is operating in the retail sector, such as supermarkets, and liquor stores.
On-trade = When referring to the on-trade market, we refer to the target market that is operating in the catering and events sector.
OOS = Out Of Stock. This indicates that a product is not in inventory anymore.
OTIF = On Time In Full. The On Time In Full is expressed in a percentage, and indicates how much percent of the active sales orders have been satisfied fully and on time.
Overstocking = In case we have a product in stock that surpasses 1/3 of its expiration time such that it cannot be sold via the regular way anymore the product is considered to be obsolete, and we call it an overstocking.
RB = Returnable Bottle.
RR = Ready Rate. Indicates the fraction of time that a product is in stock during a certain time period.
SA = Stock Availability. The stock availability is expressed in a percentage, and indicates how much percent of the active product portfolio is on stock.
SKU = Stock Keeping Unit. A Stock Keeping Unit represents one unique product that is kept in stock.
Ss = Safety stock. A number of units of a product that is additionally kept in stock to accommodate for uncertainties in the supply chain to prevent stockouts from occurring.
Undershoot = The number of units that we drop below our reorder point before the next reorder moment.
Understocking = In case we have demand occurring for a product, that cannot (immediately) be satisfied from stock such that we cannot deliver the product(s) both on time, we call it an understocking.
VMQ-method = The Variable MinDoC per quarter method, where MinDoC equals minimum Days of Cover. This approach calculates a minimum Days of Cover per SKU per quarter which is based on the classification of the SKU in the specific quarter. This way we (can) get a varying minimum Days of Cover per quarter for each SKU.

Mathematical glossary

δ = The maximum relative error.
ϵ = The degrees of freedom.
ζ = The demand in hectoliters.
θ = The (desired) Cycle Service Level.
$\Lambda_{OS,\gamma}$ = The overstocking costs in case of outcome γ.
μ_D = The average demand during lead time.
μ_F = The average forecast error during lead time.
$\mu_L = E(L)$ = The expected duration of the lead time.
$\mu_R = E(D_R)$ = The expected demand during the review period.
$\mu_{t,j}$ = The average weekly forecasted demand in week t for SKU j.
π = The production quantity in hectoliters.
ρ = The sales in hectoliters.
σ_D = The standard deviation of the demand during lead time.
$\sigma_D^{'}$ = The standard deviation of the demand during lead time and review period.
σ_F = The standard deviation of the forecast error of the demand during lead time.
$\sigma_F^{'}$ = The standard deviation of the forecast error of the demand during lead time and review period.
σ_L = The standard deviation of the duration of the lead time.
σ_R = The standard deviation of the demand during the review period.
σ_Z = The standard deviation of the undershoot.
υ = The number of observations in a data set (to determine the number of bins needed in order to establish the distribution).
$\Phi(\cdot)$ = The standard normal cumulative distribution function, with between the brackets the desired Cycle Service Level.
$\psi_{j,t}$ = A binary variable that equals 1 when SKU j has more than 1 day worth of demand on stock in time t, and 0 otherwise.
ω = The opening stock in hectoliters.
A = The costs of one drive back and forth to an external storage location of Grolsch.
B = the average amount of pallets that fits in one truck.
C = The cost price of a pallet.
$E[Z]$ = The expected undershoot, which is the amount that we expect to go below the reorder point due to a periodic review inventory policy.
G_t = The forecast error in period t, which is the difference between the forecasted sales in period t and the actual sales in period t.
$HarbourStock_j$ = The number of pallets that Grolsch has in stock on its harbour location on day j.
I = The inventory position at the end of the period.
j = the SKU number, where $j \in 1, 2, ..., J$, where J equals the last SKU number of Grolsch.
k = the quartile of the year, where $k \in 1, 2, 3, 4$.
L = The lead time in general.
M = The profit margin of the SKU.
m = the day of the year, where $m \in 1, 2, ..., 365$.
$MinBatch$ = The minimum batch size for the SKU, which equals the maximum of the packaging batch size ($MinBatchPackaging$) and the brewing batch size ($MinBatchBrewing$).
$MinBatchBrewing$ = The minimum brewing batch size for the SKU.
$MinBatchPackaging$ = The minimum packaging batch size for the SKU.
$MinDoC$ = The minimum Days of Cover for the SKU.
n = the day of the week, where $n \in 1, 2, 3, 4, 5, 6, 7$.
O = The reorder point.
$OS_{j,m}$ = The amount of HL of SKU j that passed 1/3 of its expiration time on day m.
$p_{\alpha,\beta}$ = The probability that decision α will result in outcome β.
$PalletsCommuted_j$ = The number of pallets that Grolsch has commuted from its warehouse at the brewery to its warehouse location(s) in the harbour on day j.
$ProductionDay_{j,m,pos}$ = The day on which the production is scheduled of SKU j in week m when the batch is

scheduled on position number pos in that week.
Q = The (ordered) batch size.
R = The review period in days.
S = The number of pallets of the product that are over 1/3 of the expiration time.
$SKUVolume_{j,m,u}$ = The total amount of HL that is scheduled of SKU j in week m when the batch is scheduled in position number u in that week.
SS = The safety stock in Hectoliters.
T = The last time unit when the unit of time is unknown.
t = The weeknumber, where $t \in 1, 2, ..., 52$.
u = The position of the production batch in the weekly schedule of the Filling Line.
$U_{j,m}$ = The demand in hectoliters of SKU j on day m that cannot be sold due to stock unavailability.
$x_{t,j}$ = A binary variable that should equal 1 if a batch should be ordered in week t for SKU j, and 0 otherwise.
Z = The undershoot.
z_j = The shelf life of SKU j in days. If an SKU is longer on the shelves than this number of days, it is considered obsolete.

1 Introduction

1.1 Grolsch

Koninklijke Grolsch B.V., further in this report referred to as Grolsch, is a beverage producer located in Enschede. Grolsch was founded in 1615 in the village of Grolle, currently called Groenlo. In 1922 Grolsch merged with the brewery in Enschede, and it is only since 2004 that Grolsch is located in its current location in Enschede, close to Boekelo. Since 2016 Grolsch is part of an international Japanese beverage concern called Asahi Group Holdings, better abbreviated as Asahi. Asahi has multiple locations spread out over the entire world. They have offices in for example Australia, the Czech Republic, Italy, the USA, and Canada. Although Grolsch is mostly known for its own beer brand, it also produces many other beers like De Klok, Peroni, and Grimbergen. Besides producing for the domestic market in The Netherlands Grolsch also produces to export its product portfolio to other countries, like the countries we just mentioned. For the products sold in the domestic market, Grolsch makes the products to forecast and they promise a lead time of 1 day. A Make-To-Forecast product is a product of which the inventory level is controlled based on the demand that is expected. Based on the expected demand the inventory allocation that is considered to be optimal is applied. The forecast is normally based on past data, trends, and upcoming events. For the international market, Grolsch makes most of the products on order, and it promises a lead time of multiple weeks. Within the domestic market, Grolsch has divided its customers into 2 categories, namely the on-trade and the off-trade. The off-trade category includes supermarkets and retailers, whereas the on-trade category includes the catering and events sector.

Grolsch wants to fulfill the incoming demand as much as possible, but it has limited storage space in both its own warehouse and two rented warehouses in the Enschede harbour. Moreover, Grolsch also needs to deal with the production capacity of the production processes. For the production capacity, the most important and constraining factor is the capacity of the Filling Lines, and in particular Filling Line 2, but later in this report in Section 1.3.2 this is elaborated more. Next to both the capacity constraints, inventory also involves a lot of costs. Especially in the case of Grolsch where the obsolescence costs of the Finished Goods and the raw materials have to be taken into account. The Supply Chain Planning Department within Grolsch is responsible for the trade-off between fulfilling the demand as much as possible and keeping the inventory costs as low as possible, given the capacity constraints that have to be dealt with. Later in this thesis in Section 2.1 we give a more elaborate introduction to the organization of Grolsch but first, we dive deeper into the problem.

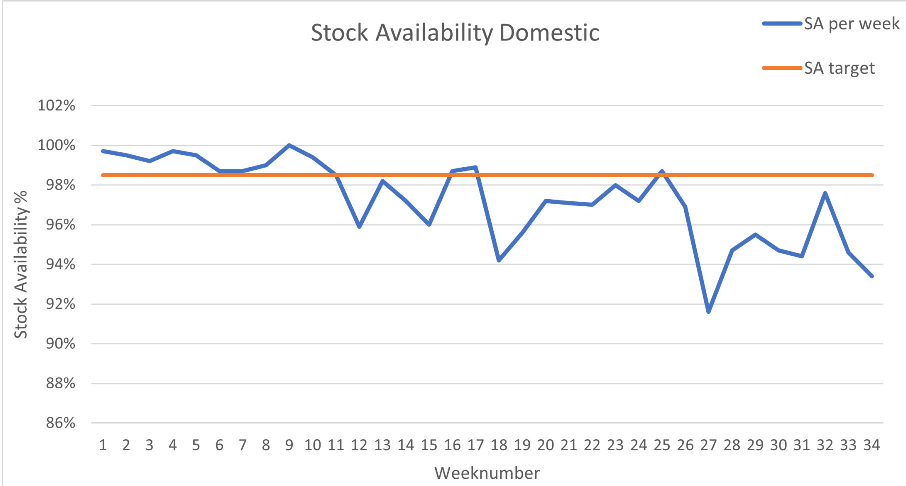
1.2 Problem Identification

1.2.1 Action problem

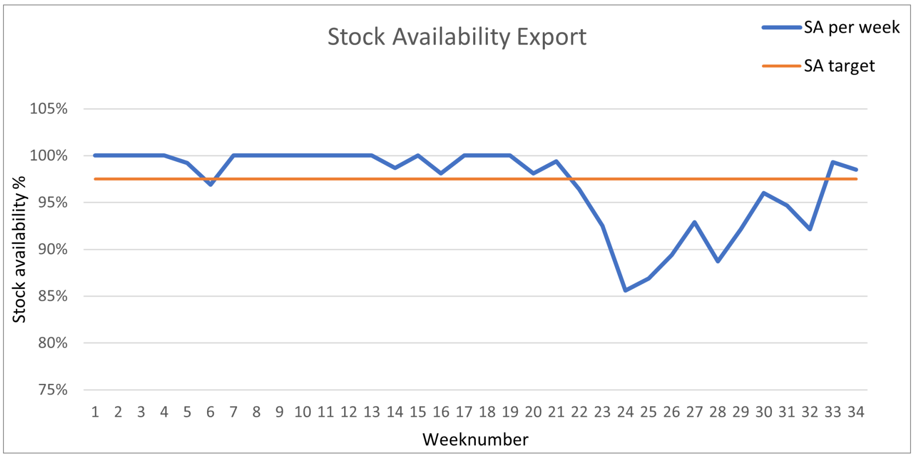
Currently, Grolsch is facing a problem concerning its Stock Availability (SA). Whereas their targets are 98.5% Stock Availability for the domestic market and 97.5% Stock Availability for the export market Grolsch is currently not always able to reach these percentages within the given capacity constraints. The SA is defined by the fraction of the products of the product portfolio that can currently be delivered directly from stock. It is good to mention that within this thesis sales is defined as the demand that Grolsch is actually receiving, whereas demand refers explicitly to the forecasted demand that Grolsch is expecting to sell during a specific period. The SA is often expressed in percentages and is calculated as is shown in Equation 1.

$$\frac{\text{number of SKUs on stock}}{\text{total number SKUs}} \cdot 100\% \tag{1}$$

Below in Figure 1 are the SA percentages that Grolsch reported over the year 2022 up until the month of August. The SA is calculated every day at Grolsch, and the graph takes the average SA of each week to calculate the SA per week. As is visible in the graphs, especially in the graph with the Domestic SA, the realized SA percentages are in a lot of cases not reaching the targets. Especially, for the domestic products the Stock Availability is showing a downward trend moving further into the summer because Grolsch experiences a high peak in demand during spring and summer. The underlying cause of this is discussed later in the next section (Section 1.2.2). In general, Grolsch is known in the market for its excellent Stock Availability. However, the current SA performance of Grolsch in 2022 is not representative of this reputation anymore.



(a) SA for domestic products.



(b) SA for export products.

Figure 1: The Stock Availability percentages per week for domestic and export products, from the beginning of 2022 up until August 2022.

1.2.2 Problem description

Grolsch is reporting a lower SA in The Netherlands when moving further into the summer as visible in Figure 1. The lower SA in the summer is mainly due to two reasons. The first reason is that Grolsch has a lot of seasonal products that are very dependent on the weather, and as the weather forecast is not always accurate the actual demand can deviate a lot from the forecast. Although Grolsch also has seasonal products that are sold during autumn and winter, they have more seasonal products that are sold during spring and summer, and the products sold during spring and summer are much more sensitive to changes in weather. The second reason is that Grolsch has higher sales than average during spring and summer, whereas it is the experience of Grolsch that the production has more delays during this period. The increase in delays during this season is for example due to the fact that a lot of employees are on vacation including the employees of the technical services department. When a lot of employees of the technical services department are on holiday the department has to deal with a lower capacity, and they miss a lot of knowledge. When a lot of employees of the technical services department are on holiday the department has to deal with a lower capacity, and they miss a lot of knowledge.

The seasonal sales surplus and the capacity limitations of the production facilities of Grolsch are two exemplary reasons that cause the SA to drop below the target, which is found by means of observations and interviews.

However, the customer service team of Grolsch keeps track of all of the products that could not be delivered both On Time and In Full (OTIF). If Grolsch cannot deliver a product OTIF, then it often means a stockout has occurred. If a product could not be delivered OTIF, then the customer service team puts in a reason in an Excel file. We have gathered the data from this Excel file and we have made a graph of this data with the most frequent causes that are put in. As is visible in the graph in Figure 2 the most frequent cause that is put in is production. We explain in the next paragraphs what the causes entail in more detail. The graph is made based only on the domestic sales, as we are focusing only on the products in this area, which is explained later in Section 1.3.2. The causes that are put in here are still rather broad and vague, so to know more about all of these causes we have made graphs of the comments that are made after each cause is filled in. The comments given per cause type are given below in the next section.

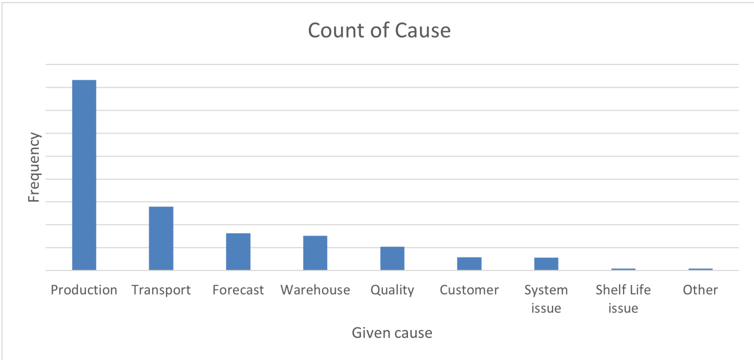
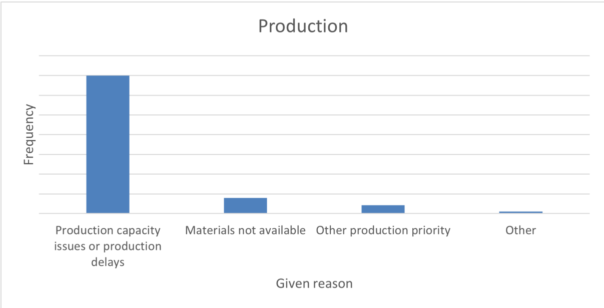


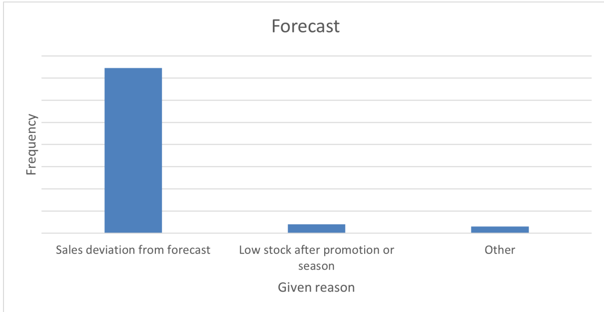
Figure 2: The reasons that the products could not be delivered both On Time and In Full to the customers in 2022.

1.2.3 Root Cause Analysis

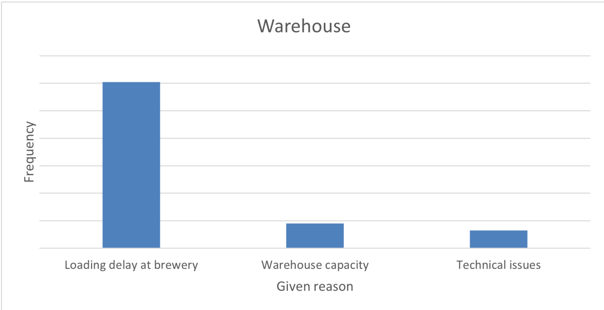
As is visible in Figure 2 the categories that are most frequently reported as reasons for the products not being delivered On Time and In Full are thus production, transportation, forecasting, warehousing, and quality. We focus only on these 5 categories as these are by far the most frequent causes. For each of these categories, we analyze the most frequent reasons that are given, except for the categories quality, and transportation. The quality category is left out, as we are not aiming to solve quality-related issues of the product within this research, given our educational background. The transportation category is also left out as transportation does not have an influence on Stock Availability. In Figure 3 the frequency of each reason is given per category. The comments that were given were often the same but stated in other words. Therefore, we have filtered the data and summarized the most important reasons given. The frequency of each reason is visible in the graphs.



(a)



(b)



(c)

Figure 3: The frequency of each comment that is placed when an order is not delivered On Time and In Full per category.

Production

When a product cannot be delivered in time due to production it is often the case that the available production capacity is not sufficient or that the production has suffered delays. These reasons we consider more or less to be the same, as both reasons implicate the fact that the production line cannot produce the demanded capacity. We expect that a big part of the production lead time uncertainty can be taken away by increasing the Filling Line 2 capacity, as the capacity of Filling Line 2 is the reason that is mentioned most frequently for a product not being delivered OTIF. However, we also observe large deviations between the planned efficiencies and the actual efficiencies of the production lines. These large deviations occur almost every week, and these deviations make it very hard to predict if there is enough stock available on time. We found out that the tactical planning at Grolsch does not take into account production lead time variation for calculating the safety stock levels. This has an effect on both the Stock Availability and the inventory costs.

The raw material availability can be identified as the second most frequent reason for a product not to be delivered OTIF. There are several reasons that underlie raw material unavailability. We notice the cans and bottles take up a lot of space, which makes the fact that Grolsch cannot keep a lot in stock of these raw materials, hence a stockout can easily occur. In addition, for the other packaging materials of the beer, there are a lot of different raw materials used for all SKUs, which means Grolsch needs to keep a safety stock for all of these different raw materials. A lot of SKUs use the same packaging materials with a small detail change, like the caps of the bottle where extra detail is added to the print for another SKU. The fact that these raw materials for each SKU slightly differ prevents Grolsch from being able to apply risk pooling.

The last reason that is given is that another SKU is given priority over the availability of another SKU. The availability of the most important SKU is often prioritized over the availability of the other SKUs. Grolsch does not want to stock out on the most important product of its product portfolio. Grolsch is keeping a rather low safety stock level for this SKU in terms of Days of Cover, therefore if the stock level of this SKU becomes critical the planning chooses to first produce this SKU, which means that the production of many other scheduled products will be delayed.

Forecasting
When forecasting is given as cause, it is often the case that the forecast differs a lot from the actual sales. When the forecast deviates a lot from the actual sales the stock levels can be too low to cover the actual sales. It would be obvious to improve the forecast of Grolsch however, Grolsch indicated that they have already two FTEs working on improving the forecasts and they have made serious improvements on this over the last years. We also found out that the Supply Chain Planning is currently using forecasts to make the tactical plan but the uncertainty of this forecast is not taken into account. The current minimum Days of Cover did use a standard deviation of the forecast error, but this is based on historic forecast errors that were registered in 2019 and since then a lot has changed. This has the effect that the (safety) stock levels cannot always cover the actual sales. Grolsch is using the forecast a lot for controlling their inventory levels, therefore the current method is highly dependent on the forecast accuracy and uncertainty. Currently, the forecast uncertainty is not taken into account when determining the safety stock levels, which makes the current inventory control method vulnerable. The low stock that is kept at the end of the season is caused by the fact that Grolsch is very careful at that time because the risks on obsoletes are very high at that time.

Warehouse
When the warehouse is given as cause then it is often the case that the loading at the brewery has been delayed. However, a loading delay at the brewery still means that there is stock available. Therefore, the loading delay does not have an effect on the Stock Availability. The second most frequent cause is the warehouse capacity. When the warehouse does not have space enough to store all Finished Goods, the planners will have to cut back on production quantities. A cutback on production leads to higher out-of-stock risks. Technical issues are the last reasons for a product not being delivered OTIF. Technical issues are for example when the automatic transport from the Filling Lines to the warehouse breaks down.

1.2.4 Root Cause

The lower Stock Availability can thus be traced back to several different root causes. We choose to solve the following root causes: the production lead time uncertainty that is not taken into account when determining the safety stock levels of the SKUs and the forecast uncertainty that is not always well taken into account when determining the safety stock levels of the SKUs. We choose to address 2 root causes because we think that it benefits the outcomes of this research. When taking both uncertainties into account the safety stock levels are better allocated, because both uncertainties have a big impact on the optimality of the allocation. We have chosen these root causes because the safety stock levels are an important factor that determines the Stock Availability percentage. With proper safety stock allocation, stockouts can be prevented, whilst the operational costs can be kept to a minimum. A proper allocation of the safety stocks is thus needed and Grolsch also indicated that this is desirable.

Normally, the safety stock level equals a fixed number of units. However, Grolsch expresses their safety stocks in Days of Cover (DoC). Grolsch forecasts the demand for their products. The tactical planners make the planning based on the forecast. As the forecast volumes per SKU are available per day Grolsch can calculate how many days they can cover the demand with their current inventory level for each SKU. For each product, Grolsch currently takes into account a minimum DoC, which is the same throughout the entire year. Besides a fixed minimum DoC for each SKU, there is no standard method that determines the minimum DoC that Grolsch must keep in order to reach a certain service level. The minimum DoC indicates how many days' worth of demand should be kept in inventory at least before another batch should be 'ordered' to produce. The minimum DoC is therefore not directly equal to the safety stock level, as the expected demand during the production lead time still needs to be taken into account here. Later in Section 2.2.1 we discuss more on the minimum DoC and the inventory control policy that Grolsch is currently using.

1.3 Research questions and scope

With the root causes known that we address in this research, we can define the main research question and the scope. To be able to answer the main research question we pose multiple research questions and we elaborate on how we are planning to solve these in this section. Finally, we describe the further outline of this thesis in the last part of this section.

1.3.1 Main research question

The question for Grolsch is how they can improve the safety stock allocation for their Finished Goods (FG), taking into account the capacity limitations of the production facilities, such that the service level target is reached. This brings us to the next main research question of the thesis:

How can Grolsch improve its safety stock allocation for its Finished Goods such that the service level targets are reached against minimum operational costs?

Instead of taking the current capacity of the warehouses as a limitation we have chosen to optimize for the minimum operational costs. We consider the needed storage capacity for the optimal (safety) stock levels to be an output of the research. The operational costs depend on the total stock that is stored. A higher stock means higher operational costs, hence we implicitly optimize for the minimum storage capacity needed. In Section 2.2.2 we explain more about what we consider to be operational costs in this research.

1.3.2 Scope

As mentioned in Section 1.2.4 Grolsch is currently using a fixed minimum DoC throughout the entire year. However, Grolsch is looking for ways to make the minimum DoC level dynamic. In this case, dynamic means that the minimum DoC levels for each SKU can differ per time unit. Therefore, the focus is especially on methods that are able to dynamically allocate the safety stock levels of the SKUs. Moreover, Grolsch sells a lot of SKUs. Due to time constraints, we focus on all of the products that are produced on Filling Line 2. All of the Filling Line 2 products are produced in a Returnable Bottle that has a smaller volume capacity than 0.4 liters. In Section 2.1.6 we explain more about what Filling Line 2 products are. We focus on Filling Line 2 products because the Supply Chain Department of Grolsch notices that they are struggling the most with keeping these products available, as the output on this production line is unreliable and most of the hectoliters that could not be delivered in time are from SKUs that are produced on Filling Line 2. Moreover, we can see that the share of Filling Line 2 products in the OTIF cases is rising throughout the year 2022.

As mentioned in Section 1.2.3 we decided together with the tactical planners of Grolsch to take the forecast as a given input for the safety stocks. The tactical planners of Grolsch prefer a focus on improving the safety stock allocation with a given forecast. Therefore, forecasting improvement methods are out of the scope of this research. What we focus on in this research are methods to improve the safety stock allocation based on the given forecast errors and uncertainties. In addition, we focus on methods that are able to incorporate both the forecasting uncertainty and the lead time uncertainty caused by delays in production into the safety stock calculations as we want to incorporate both uncertainties within the safety stocks.

Grolsch promises a lead time of at least 2 weeks to the customer for products that are exported and/or made to order. For the products that are sold according to a Make-To-Forecast (MTF) inventory control policy within the domestic market, Grolsch promises to deliver the products the next day. Therefore the availability of the MTF products sold within the domestic market is more dependent on the forecast accuracy, and the lead time uncertainty. For this reason, we focus on the SKUs that are made to forecast and sold within the domestic market.

Grolsch has 1 separate warehouse available at Twente Airport where they keep product X in stock. That is because product X has to stay in storage for a while in the bottle before it can be delivered. This also means that the lead time of this SKU differs from the lead time of the other SKUs. Both the significantly longer lead time and the fact that this SKU needs to be stored in another warehouse make the fact that we leave this SKU out of the scope when determining the optimal safety stock level.

Product Y is also produced on another Filling Line. Besides production on Filling Line 2, the product is produced on Filling Line 3. As this SKU is produced on 2 Filling Lines we leave this SKU out of the scope of this research.

Conclusion
In this research we focus on reaching the Stock Availability target against minimum operational costs by optimizing the dynamic safety stock level for the products. The safety stock calculation needs to be able to incorporate the forecast and lead time uncertainties. We focus only on the Filling Line 2 products that are sold in the domestic market based on an MTF inventory control policy, and we leave product X and product Y out of the scope. The needed warehouse capacity is considered an output of the research on which we can advise Grolsch.

1.3.3 Research questions

To find out how Grolsch should allocate its safety inventories to improve the service level we first need to find out some more about the current situation. Therefore, the next research questions are answered:

1a. What capacity restrictions does Grolsch need to deal with when allocating the safety stocks?
1b. How is Grolsch currently allocating its safety stocks?
1c. How is Grolsch currently evaluating its operational costs?

The restrictions within this research mainly include capacity restrictions of the production capacity available. To know the capacity restrictions when allocating the safety stocks we asked the tactical planning of the Supply Chain Department. We asked the tactical planners for the production capacity that Grolsch has available in terms of production hours that might form a constraint for the production capacity. Moreover, we consider the warehouse capacity as an output of our research but in order to give Grolsch proper advice on the needed warehouse capacity it is nice to know how much storage capacity Grolsch currently has available and how much Grolsch has been using over the last year(s). A warehousing manager has answered our questions concerning the available storage capacity. For the current allocation of the safety stocks, we needed input from the tactical planners of the Supply Chain department. We asked the tactical planners for the relevant factors for determining the safety stock level and we asked them how they are currently planning. For the operational costs, we used a report from a study that was performed earlier at Grolsch and we asked Customer Service, the tactical planners, and the warehouse manager for information about the specific inventory-related costs that Grolsch needs to deal with and how these costs could be estimated. In Chapter 2 all three (1a, 1b, and 1c) research questions are answered. In Section 2.1 we answered question 1a and in Section 2.2 we answered question 1b and 1c.

With the current situation of Grolsch more clear we need to find out how we can improve the safety stock allocation of Grolsch. First, we do this by looking for techniques available in the literature to dynamically improve the safety stock levels. That brings us to the next research question:

2. What techniques are available in the literature to dynamically improve the safety stock allocation, taking into account production lead time and forecasting uncertainties?

Grolsch has a safety stock that they want to keep for each SKU, which is expressed in a minimum number of days that Grolsch wants to be able to cover the forecasted demand. However, if we want to be able to improve the performance of the service level whilst taking into account the capacity restrictions, then we need to research alternative methods within the scientific literature to allocate the safety stocks in a dynamic way. Research question 2 is answered in the literature review in Chapter 3.

With the techniques found in the literature we need to determine which method would be the most suitable to apply within Grolsch and we need to determine how we apply this method. Therefore we have the following research questions:

3a. What would be the most suitable method to determine the new dynamic safety stocks at Grolsch?
3b. How should the new dynamic safety stock method be adjusted for application within Grolsch?

We answered question 3a by elaborating on the current inventory control policy that Grolsch is using, and the methods that suit this specific inventory control policy. In addition, we described here how we needed to adjust the method from the literature to be able to use the method within Grolsch. The answers to research questions 3a and 3b are given in Chapter 4.

Once we have chosen a method and we have adjusted the method to the situation of Grolsch we can calculate new safety stock levels per SKU. Therefore we have asked ourselves the next question:

4. What would be the new safety stock level per SKU for Grolsch in case (one of our) new safety stock allocation methods is used?

With the new safety stock allocation methods we have different allocations. In total, we use 3 different methods to calculate new safety stock allocations. For all methods, we use a static safety stock calculation and we use this static safety stock calculation to calculate a minimum Days of Cover. In Section 2.2.3 we explain why we want to express the new safety stock level in terms of Days of Cover. Of the 3 methods, 1 method has a different minimum Days of Cover per quarter per SKU, and the other 2 methods have a fixed minimum Days of Cover for each SKU, where each of these 2 methods calculates the fixed minimum Days of Cover per SKU in a different way. In Chapter 5 we elaborate more on the new safety stock allocation method used. Moreover, the new minimum Days of Cover for each method are also given in Chapter 5.

Once we have different allocations of the minimum Days of Cover for the SKUs we need to validate and evaluate the methods to see if the techniques are leading to better results than the current safety stock allocation method of Grolsch. Therefore we have posed the next question:

5. What would be the impact of implementing the dynamic safety stock allocation techniques on the service level measures and the operational costs compared to the current situation?

Evaluating the performance of the new dynamic safety stock allocation techniques is rather difficult. We cannot simply take historical production data and initial stock data to tell if the new safety stock allocation techniques perform better than the old one. Due to different safety stock levels, different choices would probably be made in the production schedule. Therefore, we have chosen to evaluate the performance of the new safety stock allocation technique by means of a simulation. We simulate the stock levels of Grolsch for an entire year for both the new and the old safety stock allocation methods, such that we can measure the impact of the new safety stock allocation method on Grolsch. In the second part of Chapter 5 we describe in more detail how we plan to simulate the effects of both the new and the old safety stock allocation methods on the situation of Grolsch and in Section 6.2 we answer research question 5.

With new safety stock allocation methods and the simulation results based on these new safety stock allocation methods we would like to know what the effect is if the situation of Grolsch changes. Therefore, we change some parameters of the current system of Grolsch and evaluate the outcomes of these simulations. That brings us to the next research question:

6. To what extent do different parameters or settings of the simulation change the outcomes of the evaluation of the (new) safety stock allocation techniques?

In the simulation and in our calculations we assume a certain standard deviation of the forecast error per quarter. However, these could be easily subject to change. Therefore, we run additional sensitivity analyses to simulate the effect that a change in these standard deviations has on the optimality of our new methods. Moreover, normally the Supply Chain Planning team schedules a batch of a certain amount of hectoliters of each SKU on the production line. However, it often happens that the scheduled batch sizes do not match the actual filled volumes due to different reasons (e.g. material availability, availability of the beer, production delays, or advances). Therefore, we would like to change the actual filled volumes based on the scheduled volumes, such that we can measure the effects of the schedule changes on the Stock Availability and the total inventory-related costs of Grolsch. Moreover, we assume in our initial simulation that all products that have passed 1/3 of the expiration time can still be sold to customers, whereas in fact, this is not always the case at Grolsch. Therefore, we change this assumption and we perform a simulation where we remove the products from stock that have passed 1/3 of the expiration time to see what the effect is on the achieved service level measures. The answer to research question 6 is given in Section 6.3.

When we know if (one of) the new safety stock allocation techniques are better evaluated by means of the simulation, we need to know how we can implement the new technique within Grolsch. To find out how the safety stock allocation technique can be best applied we need to ask ourselves the following research question:

7. How can the dynamic safety stock allocation technique, which is best suitable to the situation of Grolsch, be implemented?

To find out the best implementation strategy within Grolsch we use the knowledge that we gained during the execution of the research and the limitations of the execution method. We describe which KPIs the tactical planning should keep an eye on and how the tactical planning should act in case the KPIs show a deviation compared to the desired results. We report on the best implementation and evaluation method for Grolsch, and we report on how this method could also be used for the SKUs that are filled on other lines than Filling Line 2.

1.3.4 Action plan

The goal of this research is to optimize the dynamic safety stock level for the Filling Line 2 products that are sold domestically according to an MTF inventory policy by minimizing the operational costs for a given target service level. To achieve the research goal we need to know more background information about the Supply Chain department, and the production processes that are needed to produce the end products of Grolsch. In Chapter 2 the background information is given in Section 2.1. Next, we need to know more about the current inventory control policy that Grolsch is using, the capacity restrictions that we need to deal with (except for the storage capacity), and the way Grolsch is currently evaluating the operational costs, so in short the current situation. The current situation is described in Section 2.2. After the current situation is described we dive into the literature to find methods with which we can calculate a dynamic safety stock level using lead time and forecast uncertainties. The literature review can be found in Chapter 3. In Chapter 4 we discuss which (adjusted) safety stock allocation methods we have used and the rough approach we have chosen to execute the research. The new safety stock allocations and a more detailed description of the method we applied follow up the approach in Chapter 5. In Chapter 5 we continue to describe in more detail how the simulation works before we dive into the results of the simulation in Chapter 6. Chapter 6 also contains the results of the sensitivity analysis, which shows to what extent the safety stock allocation method is optimal when different parameters, assumptions, or settings are subject to change, and the chapter contains the recommended implementation. Finally, we conclude our research in Chapter 7.

2 Context Analysis

With a clear core problem, and research approach we first need some more background information on the Supply Chain department within Grolsch, the planning process, and the process that is between receiving the raw materials and finishing a beer that is ready to be marketed. The background information on the Supply Chain department, on the planning and production processes, and on the available production capacity and warehouse utilization is described below in Section 2.1. Thereafter we will answer the first research questions regarding the current situation of Grolsch in Section 2.2.

2.1 Introduction to Supply Chain and available capacity

The Supply Chain Planning department is responsible for the safety stock allocation. Therefore, we first need to know some more background information on the organizational structure (of the Supply Chain department) of Grolsch, the planning process at Grolsch, the division of roles, and the production process of making beer. After we have given some background information we dive into the available production capacity that Grolsch has available. Finally, we describe what capacity we have available within the warehouses at Grolsch and how much of it is currently used. Although we consider the needed warehouse capacity to be an output of our research, it is good to know how much Grolsch is currently using to advise them on the (additional) capacity needed for storage.

2.1.1 Grolsch organization & the Supply Chain Department

Grolsch employs about 600 people in total and those 600 employees are led by a Management Team (MT). In total, there are 9 directors residing within the Management Team of Grolsch. One of these 9 directors is the Managing Director of Grolsch who presides over the Management Team. The Technical & Supply Chain Director is a member of the Management Team, and this function presides over the Integrated Supply department within Grolsch. The Supply Chain Manager is part of the management team of the Integrated Supply department that is presided over by the Technical & Supply Chain Director. Finally, the Supply Chain Manager presides over the Supply Chain Department, where the Team Lead Supply Chain Planning presides over the Supply Chain Planning department again. The organizational chart of the Supply Chain department is given below in Figure 4.

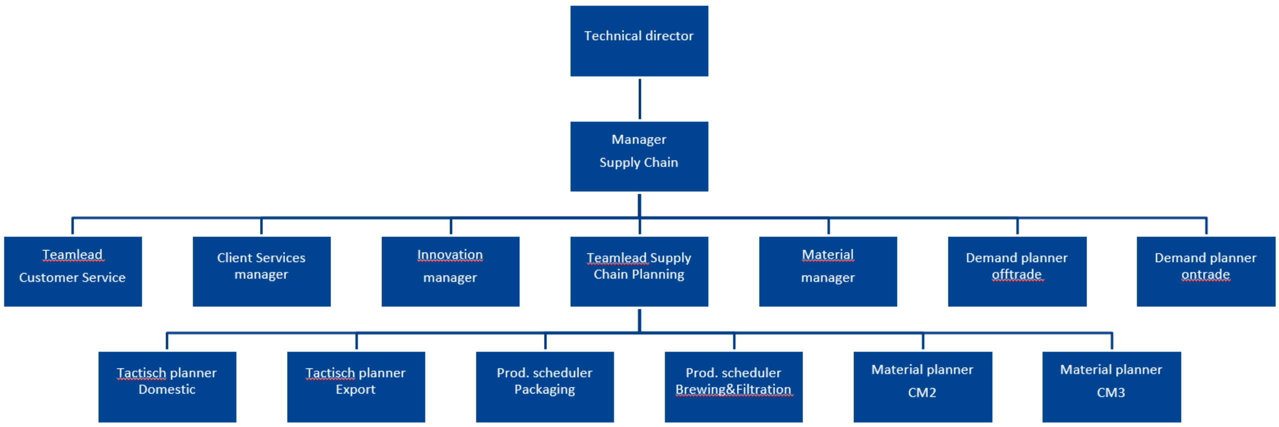


Figure 4: The organizational chart of the Supply Chain Department and the Supply Chain Planning Department within Grolsch.

Before we dive into how Grolsch is currently controlling its inventories we should know some more details about the relevant functions that come with controlling the inventories and how the tasks are divided within Grolsch. A rough sketch of the process is as follows. First, the demand planning will make a forecast. With the forecast, the tactical planners make a plan at the weekly level. One of the schedulers turns the plan at the weekly level into a concrete plan on the daily level. With the concretized plan, the other scheduler and the material planners will check for the availability of the needed brews and materials. Below we discuss the functions of demand planning, tactical planning, scheduling, and material planning in more detail. Thereafter we elaborate on the production process at Grolsch.

2.1.2 Demand planning

The forecasting team keeps in close contact with the Sales Department. Both employees in demand planning forecast a different branch. One employee focuses on forecasting the off-trade demand. The off-trade demand is the demand that comes from retailers, like supermarkets and liquor stores. The other employee focuses on the on-trade market. The on-trade market includes all products that are sold to cafes and events. Both demands are forecasted in different ways, which is why the tasks are divided this way.

Off-trade

The off-trade is forecasted by using a baseline demand, which is based on historical sales data. Using the historical sales data per week, an average of sales per retail store in which the product is available is obtained. Next, the average sales per retail store in that week is multiplied by the number of retail stores in which the product is to be sold in the period that is to be forecasted. Next, the demand planning calculates a seasonal factor per week which is different for each SKU. This seasonal factor is mainly based on historic demand. The last factor taken into account with the demand planning is the promotions. The uplift in terms of percentage per promotion is calculated, and then the additional promotional volume is multiplied (1 + the additional volume percentage) with the baseline demand to come to a weekly forecast per SKU. As the forecast is now expressed in the number of products of each SKU sold per week, it is assumed that the sales are spread out equally over the weekdays. The forecast per day is therefore calculated by dividing the total expected demand per week by 5.

On-trade

To forecast the demand of an SKU that will be sold to the cafes and the events 2 variables are very important. The rate of sale, and the acquisition rate. The rate of sale indicates how fast a product is selling i.e., how many of each SKU are sold in the specific week in the previous years. The acquisition rate indicates the number of cafes and outlets to which the SKU is sold. The rate of sale that is used automatically incorporates a seasonal pattern, as the rate of sale differs very much per week as it is based on historical data. Using the rate of sale and the rate of acquisition a baseline demand is created per week. It is also assumed that this demand is spread out equally over the week, so every day of the week the same demand is forecasted. Based on the baseline demand per day an additional volume percentage based on the sales of previous years during holidays is used to update the forecast during the holidays of the following period. In addition, the dates of the events to which Grolsch is selling are also added to this forecast. The volume of these events is forecasted based on the demand of previous years, or if the event is new then it is based on an estimation of the number of visitors.

2.1.3 Tactical planning

The 2 tactical planners are scheduling the coming 2-78 weeks. The first 13 weeks are planned in more detail and for the following months, the plan is very much subject to change. As the forecast is updated every week, the tactical plan is also updated every week based on the updated forecast. Based on a lot of different factors, such as the forecast, the current stock on hand, and the warehousing capacity the tactical planning makes a plan for how many hectoliters to produce of each SKU in each week. Tactical planning is mainly keeping an eye on the Stock Availability. The maximum Days of Cover of an SKU on stock is expressed by 1/3 of the expiration time of the product. For example assume a termination date of the product of 1 year, then the maximum DoC is equal to 4 months. The minimum DoC differs very much per SKU. We will describe this in more detail later in Section 2.2.

2.1.4 Scheduling

The production process can be divided into two steps, namely the filtration process, and the filling process. Both schedulers have therefore divided their tasks in this way. One scheduler is responsible for the filtration process planning, whilst the other one is responsible for the planning of the filling lines. The filling process is seen as the bottleneck within the production, so the focus is on planning the filling lines. Based on the number of hectoliters to produce per week per SKU, which is the input delivered by the tactical planning, the filling line scheduler plans in which order the SKUs should be produced over the week. To make the filling line schedules as efficient as possible this scheduler will try to minimize the change-over times, whilst taking into account other operational aspects such as maintenance, and tests on the production lines. The filtration scheduler will then make sure that the brews are available on time for the filling line schedules.

2.1.5 Material planning

The material planning is responsible for having all raw packaging materials available for the production schedule. Based on the tactical production plan, and the operational production plan they make sure that all materials are available in time to start the production. If the forecast, and therefore tactical plan changes a lot the material planners might not always be able to have all materials available in time for production, as they have to deal with a lead time at the suppliers and the material planners have limited storage space for their materials. However, material planners can rather easily cancel deliveries or schedule additional deliveries. Therefore, we consider the capacity of these raw material warehouses and the availability of the materials out of the scope of this research.

2.1.6 The production process

The current production process of beer is robustly divided into two parts, namely the brewing process and the filling process. In the brewing process, the liquids are brewed in one large tank. In the filling process, the liquids are filled into the desired packaging. As mentioned already in Section 2.1.4 the filling process is the bottleneck at Grolsch, and therefore the focus is on planning the filling lines instead of planning the brewing department. That is the reason why we consider the capacity of the brewing department to be out of the scope of this research. The focus of this research is on the filling lines, and to be precise on the Filling Line 2 products. Therefore we have described the process of the filling lines below in more detail.

The filling process

When the beer is filtered and is residing in a bright beer tank the liquid is poured into its desired packaging on the filling lines. Grolsch has multiple filling lines available. Line numbers: 1, 2, 3, 4, 7, and 8. Each filling line can handle different packages. Lines 2, 3, and 4 can all produce Returnable Bottles (RB). The difference is that line 4 is filling the 450 ml bottles. Moreover, line 3 is only making 2 specific SKUs. In Figure 5 an example is visible of the products that are produced on Filling Lines 2, 3, and 4 to indicate the difference.

(a) Line 2 & 3.

(b) Line 4.

Figure 5: Examples of products that are produced at filling lines 2, 3, and 4.

Filling Line 2 capacity restrictions

The available capacity on Filling Line 2 to be scheduled depends mainly on the number of shifts that Grolsch is able to schedule. In total Grolsch has about 168 so-called processing hours available for production on Filling Line 2 per week when working in 5 shifts and 120 processing hours available for production on Filling Line 2 per week when working in 3 shifts. The processing hours are not all available for production, as some weeks are reserved (partly) for maintenance and public holidays. Based on the processing hours a production schedule can be made, so Grolsch knows how much they can schedule in that week to produce. This is relevant for the reorder point because when a lot of SKUs will stock out in a certain week, the products will need to be produced earlier (or sometimes later) to fit the production schedule for the week. Grolsch has a document available in which the number of available production hours is noted per week per Filling Line.

Warehousing capacity
The total warehousing capacity that is available at Grolsch is a subject of discussion within the company. The total capacity for Finished Goods depends on the space that is used by other materials or objects, which are needed for production or for events. Warehousing assumes 23,000 pallet locations available for Finished Goods, whereas Supply Chain Planning argues to have a higher total capacity of pallet locations available for storage of Finished Goods. We assume in this further research that the total (theoretical) capacity is 23,000 pallet locations. Grolsch has a warehouse at the brewery, 2 additional warehousing locations in the harbour, and 1 additional warehousing location at Airport Twente. The warehousing location at Airport Twente is not taken into account in this research as this location is only used to store 1 specific SKU (product X). The 2 additional warehouses located in the harbour are very close to each other, but to prevent confusion one warehouse is mentioned as the warehouse in the harbour, whereas the other one is called BOA (named after the former company that was located there). The warehouse in the harbour has a total practical limit of 3,000 pallet locations, and the BOA warehouse has a total practical limit of 2,000 pallet locations. The warehouse of Grolsch located at the brewery has, in theory, a limit of 21,500 pallets. In practice, the warehouse is only capable of handling about 18,000 pallets. The practical capacity limit of the warehouse is lower due to various factors. For example, when Grolsch produces larger batches they can pile more pallets on top of each other so less space is taken in the warehouse. Different products cannot be stacked in most cases. That brings us to a total of 23,000 practical pallet locations available.

2.2 The current situation

In this section, we answer research questions 1b and 1c. We take a look at the current situation of Grolsch by first looking at the current inventory policy that Grolsch is using, the safety stock allocation that comes with this inventory control policy, and the SKU classification on which the safety stocks are partly determined in Section 2.2.1. In Section 2.2.2 the current way of evaluating the operational costs is discussed before concluding this chapter in Section 2.2.3.

2.2.1 The current inventory control policy, safety stock allocation & SKU classification

Grolsch is using a value for the minimum Days of Cover to control their inventory levels. When making the tactical production plan Grolsch makes sure that the stock level is sufficient to cover the forecasted demand for the minimum Days of Cover until the next batch is 'ordered' to produce. That means that the reorder point of Grolsch is dynamic, especially since we are dealing with non-stationary demand. Stationary demand assumes the same demand pattern in every time frame, hence non-stationary demand implies that the demand pattern can be subject to seasonal factors, trends, and other factors.

Review period
The review period (R) is in theory equal to 1 week, which equals 5 working days. The tactical planning of Grolsch is updating the tactical plan once per week and that is also the time that they are checking the inventory levels of each SKU. In practice, tactical planning does check the inventory level of some SKUs every day per week when they are running a tool to check the Stock Availability. However, Grolsch has a fixed moment in the week when they fix the production schedule for the next week. That moment is Friday afternoon. When Grolsch observes on Monday that they will run out of stock this week they can in theory schedule another batch within this same week so an out-of-stock occasion is prevented. However, this is very undesirable in practice as these last-minute changes have a big impact on other parts of the organization. Moreover, in a lot of cases, last-minute changes are also not possible anymore as for example the raw materials cannot be delivered on time anymore. Therefore, we assume that Grolsch will run out of stock when they observe on Monday or later that they will run out of stock in the same week. We do make an assumption here that if Grolsch needs to schedule a batch the next week it has enough capacity available to produce the batch. The assumption that Grolsch can run out of stock in the same week if they observe it on Monday or later during the same week means that we need

to take into account a review period for the inventory policy of Grolsch and that we can run out of stock during this review period. We should thus take into account undershooting in case the batch size of Grolsch is fixed.

Lead time
When Grolsch plans a new production batch on Friday afternoon the production can be scheduled randomly in the next week, that is the production can take place from Monday to Sunday (or Friday when working in 3 shifts). For almost every SKU the probability of being scheduled on a certain day of the week is equal to $\frac{1}{7}$ ($\frac{1}{5}$ in case of working in 3 shifts). Therefore, if we would calculate the average production lead time in case we would not take into account a production delay and we would consider working in 3 shifts it would be calculated as follows:

$$E(L) = \frac{1}{5} \cdot \sum_{i=1}^{5} i = 3 \tag{2}$$

However, on Filling Line 2 Grolsch is working in 5 shifts most of the time. When working in 5 shifts it is not relevant if the products are produced on Saturday or Sunday. If a product is produced on Saturday or Sunday then it is available on Monday, which is day 6, as nothing is sold by Grolsch during the weekends. Therefore the calculation will change as follows:

$$E(L) = \frac{1}{7} \cdot \sum_{i=1}^{7} \min(i, 6) = 3\frac{6}{7} \tag{3}$$

Finally, we need to take into account the production delay for the average lead time. Over 2021 the production delay on Filling Line 2 per week is almost x hours, which means that in theory Filling Line 2 would have needed an average of x additional hours per week to finish the schedule. We have to make the assumption here that the plan remains the same and products are not scheduled in other weeks due to production delays, which would increase the expected lead time. Moreover, we assume the average delay per day builds up over the week linearly. That means the expected delay on day 1 would be (in hours): $\frac{x}{7}$ when working in 5 shifts. The last assumption that we have to make here is that we assume that when the SKU is scheduled in a certain week we know already when it is scheduled in the week, such that the standard deviation of the lead time duration only depends on the production delays. Then we can calculate the average production lead time as follows:

$$E(L) = \frac{1}{7} \cdot \sum_{i=1}^{7} \min(i, 6) + \frac{\frac{x}{7}}{24} \cdot i = y \tag{4}$$

The expected lead time at Grolsch when working in 5 shifts thus equals y days. In addition, the review period R equals 5 days, as the tactical planning 'orders' every week on Friday afternoon.

Besides the expected lead time duration we can also calculate the standard deviation of the lead time duration. The standard deviation of the lead time duration is relevant for our research as it tells us a lot about the uncertainty of the lead time duration. The standard deviation of the lead time over the week equals z hours. These z hours are calculated by using the production delay on Filling Line 2 in hours over 2021. The schedulers at Grolsch note per day how many hours every production line is running ahead or behind on the plan. By summing the hours of every week separately we get a 'delay' per week for Filling Line 2 that can be both positive or negative. The cumulative delay per week in hours is used to calculate the standard deviation over the entire year of 2021 (as all of the data for 2022 was not readily available yet).

Reorder point
When the tactical planning observes the inventory position on Friday afternoon they will reorder if the inventory position at that moment is lower than the inventory needed to equal the minimum Days of Cover and the review period, assuming all of the demand of that Friday has been fulfilled already. Thus in theory the reorder point of SKU j (O_j) is always between the minimum Days of Cover of SKU j and the minimum Days of Cover of SKU j plus the review period. When the reorder point needs to be expressed in units, then the formula below in Equation 5 represents the decision of whether or not to order. In this formula, $x_{t,j}$ is a binary variable

that equals 1 if a batch will be ordered in week t of SKU j and 0 if nothing is ordered. Let $I_{t,j}$ equal the inventory position at the end of week t for SKU j, and let $MinDoC_j$ equal the Minimum Days of Cover for SKU j. $\frac{MinDoC_j}{5}$ results in a real number that represents the weeks that we can cover the demand for SKU j. R represents the review period in days. The formula assumes that the demand for each week is evenly distributed over the weekdays. In addition, to keep the formula simple we have chosen to assume that the average weekly demand is equal for every week falling within the minimum Days of Cover and the review period, which equals $\mu_{t,j}$. $\mu_{t,j}$ therefore equals the average forecasted weekly demand in week t of SKU j.

$$x_{t,j} = \begin{cases} 1, & \text{if } I_{t,j} \leq (\frac{MinDoC_j + R}{5}) \cdot \mu_{t,j} \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

Safety Stocks

If Grolsch will order the products when their inventory level is lower than the demand expected during the minimum Days of Cover and the review period, then the safety stock level of Grolsch is equal to the reorder point minus the (expected) demand during the lead time without the review period. As the average lead time (without the review period) equals y days we will need to subtract the demand during this lead time from the reorder point to arrive at the safety stock level. As we have just mentioned the reorder point should in theory always be between the minimum Days of Cover and the sum of the minimum Days of Cover and the review period. We assume that the reorder point is uniformly distributed between both, which means that the reorder point should on average equal the sum of the minimum Days of Cover and half of the review period. Therefore, the safety stock level in terms of Days of Cover equals the reorder point minus y days (the lead time), and minus $2\frac{1}{2}$ days (half of the review period). To express the safety stock level in units we need to subtract the demand of the first y days from the reorder point to arrive at the safety stock level in units. That means that the safety stock level of Grolsch in units is calculated as shown in Equation 6 below. In this equation, $\mu_{t,j}$ represents the average forecasted weekly demand.

$$SS_{t,j} = \frac{MinDoC_j + \frac{1}{2} \cdot R - y}{5} \cdot \mu_{t,j} \tag{6}$$

Batch sizes

The batch size that is ordered in week t for SKU j, which equals $Q_{t,j}$, depends on a lot of different factors. The minimum batch size for SKU j, the number of hours that Grolsch has available on the production line in that week, the shelf life, the current inventory position, and the forecasted demand in the next weeks are all factors that play a role in determining the batch size. The forecasted demand in the next weeks is rather important as it will determine the Days of Cover for the SKU after production, and the tactical planning looks at the Days of Cover such that it is not too high, and that the Days of Cover at the end of the cycle time is equal to the minimum Days of Cover set for the SKU. In summary, the tactical planner mainly keeps the following things in mind when planning the batch sizes of an SKU:

- The inventory position of SKU j in week t and the ordered batch size of SKU j in week t should not be greater than the demand that is forecasted for the next z_j days. Where z_j is equal to one-third of the expiration time of SKU j.
- The ordered batch size of SKU j in week t together with the inventory position of SKU j in week t should be equal to or greater than the sum of the forecasted demand during the weeks between this week and the week the next production is scheduled of SKU j, and the number of units needed to cover the demand during the minimum Days of Cover of SKU j.
- The ordered batch size should be equal to or higher than the minimum batch size for SKU j, which equals $MinBatch_j$. The minimum batch size is set, because the tactical planning has agreed that the change-over times should not be longer than the actual production time needed for the batch size. However, Grolsch also has minimum brewing quantities due to the change-over times within the brewing department. When we mention 'the minimum batch size' in our research we take the maximum of both the minimum brewing batch size and the minimum packaging batch size, as follows: $MinBatch_j = \max\{MinBatchPackaging_j, MinBatchBrewing_j\}$

Current minimum Days of Cover allocation
Grolsch is using a minimum Days of Cover to determine the reorder point. Grolsch is currently using a fixed minimum DoC throughout the entire year for every SKU that they have. The minimum Days of Cover that Grolsch is using is determined based on a combination of experience, shelf life, production lead time, minimum batch size, and the season. Products with a long shelf life, high production lead time, and high minimum batch sizes typically have a high minimum Days of Cover. The lowest minimum DoC is 53% of the regular minimum Days of Cover, which is for product Y. All of the other SKUs have a minimum DoC of 67%, 80%, 100%, or 133% of the regular minimum Days of Cover. Grolsch is currently basing the minimum DoC levels on a combination of calculations that have been done back in 2018 and has sometimes adjusted these minimum DoC levels in between when for example they notice a lot of stockouts or when the number of obsoletes is very high. However, Grolsch is not basing their minimum DoC levels on up-to-date calculations to determine the minimum DoC of their SKUs, which means that it could be the fact that the minimum DoCs are not allocated optimally. Besides not using up-to-date calculations, the production lead time uncertainties are not taken into account with the previous calculations for the minimum DoC level and the calculations take into account a target Cycle Service Level whereas Grolsch is aiming for a Stock Availability percentage. Also, Grolsch bases the minimum DoC levels partly on the SKU classification and on the forecast uncertainty distribution of 5 years ago, which are both not up-to-date anymore.

The current SKU classification of Grolsch
Grolsch has classified its SKUs by using an extended version of the ABC classification method. The current classification of Grolsch is still based on data from the year 2018, therefore the current classification could use an update. Besides the classic ABC classification, Grolsch uses three additional categories, which are D, E, and "no classification". The products classified as D products are the SKUs that are made to order, the products that are classified as E are the SKUs that are exported, and the SKUs classified as "no classification" are the products that are not (yet) classified. The products are labeled "no classification" if they have been introduced recently such that they do not have enough historical sales data available to classify these products. Once new products are introduced and they are more than 1 year in the portfolio then Grolsch chooses a classification. When the Supply Chain Department makes this decision it is often based on the classification of an SKU that has more or less similar product characteristics. To illustrate an example, when a new SKU has more than enough data available the Supply Chain Department checks the demand pattern and then checks which of the SKUs that already have a classification has the most similar demand pattern. Based on this comparison the new SKU gets the same classification. The classification is done per quarter due to the seasonal character of some products.

We have made an analysis of the average minimum Days of Cover that Grolsch is currently using for each classification, based only on the Filling Line 2 SKUs that are made to forecast and sold domestically. None of the FL2 SKUs made to forecast and sold domestically were introduced less than 1 year ago, so we can discard the products that are not classified as they were recently introduced. The average minimum Days of Cover per classification in percentage given the regular minimum Days of Cover is shown below in Figure 6. We see that the average minimum Days of Cover per classification is not really consistent. Normally, we would expect to see either higher Days of Cover for the A products, as these products are often the most important products with which we would not like to run out of stock, or a lower minimum Days of Cover for the A products as these products have a more stable demand pattern and a shorter lead time. It could have also been the fact that the C products are higher in Days of Cover due to the relatively low combination of price and volume and the potentially unpredictable volumes, which would be legitimate reasons to keep a higher Days of Cover for the C products. However, we see a higher Days of Cover for B products, which we do not consider to be the most rational choice. We were not able to find other methods that would rationalise the choice for the difference in the minimum Days of Cover.

Classification	Avg MinDoC
A	95%
B	105%
C	100%

Figure 6: The average minimum Days of Cover per classification that Grolsch is currently using as a percentage of the regular minimum Days of Cover.

2.2.2 Operational costs

In case we want to evaluate the optimality of the safety stock level using the (variable) operational costs we should first specify what the relevant operational costs are within our research. Kamp (2018) already established that the operational inventory-related costs are the holding costs, the stockout costs, and the obsolescence costs. The other inventory-related costs that Kamp (2018) found in the literature (setup costs and production costs) mainly depend on the batch size that is scheduled. In our research we are not trying to optimize the batch sizes, thus we leave the setup and production costs out of the scope of our research. Moreover, as we are aiming for a Stock Availability percentage already we should discard the stockout costs. Therefore, we should know what it costs for Grolsch to hold 1 unit in stock for one time unit, and we have to know what it costs for Grolsch if a product becomes obsolete. In the next paragraphs, we describe how Grolsch evaluates the costs that are relevant to our research.

Overstocking costs

When a product is on the shelves at Grolsch for at least $\frac{1}{3}$ of the total shelf life the product can in some cases not be sold to a lot of regular customers like the big supermarkets. In case $\frac{1}{3}$ of the expiration date is reached the product can sometimes still be sold to one of the smaller customers of Grolsch. In case the product is sold after $\frac{1}{3}$ of the expiration date it can both be sold for the regular price or for a discount price, which often equals the cost price and an additional 50% of the regular profit margin. Moreover, in some cases, the products are still not sold after the product reaches $\frac{2}{3}$ of its total shelf life. At that point, the product is often sold for its cost price. However, if it cannot be sold before the product expires it has to be destroyed and additional costs will need to be charged for the destruction. Kamp (2018) has also used a decision tree in his research in case a product has passed $\frac{1}{3}$ of its expiration date, just like the paper did for the stockout costs. Below in Figure 7 the decision tree is visible with the corresponding probabilities and payoffs that Kamp (2018) established. In the decision tree, $p_{\alpha,\beta}$ equals the probability that decision α will result in outcome β. Moreover, $\Lambda_{OS,\gamma}$ equals the overstocking costs in case of outcome γ. M equals the profit margin of the product, S equals the number of pallets of the product that are over 1/3 of the expiration time, and C equals the cost price of 1 pallet of the SKU. Based on the decision tree an expected cost for an obsolete product (a product is considered obsolete in case it reaches $\frac{1}{3}$ of its expiration date) was calculated. Using the decision tree visualized below Kamp (2018) discovered that an obsolete product costs Grolsch about 29% as a percentage of the gross profit margin of the SKU.

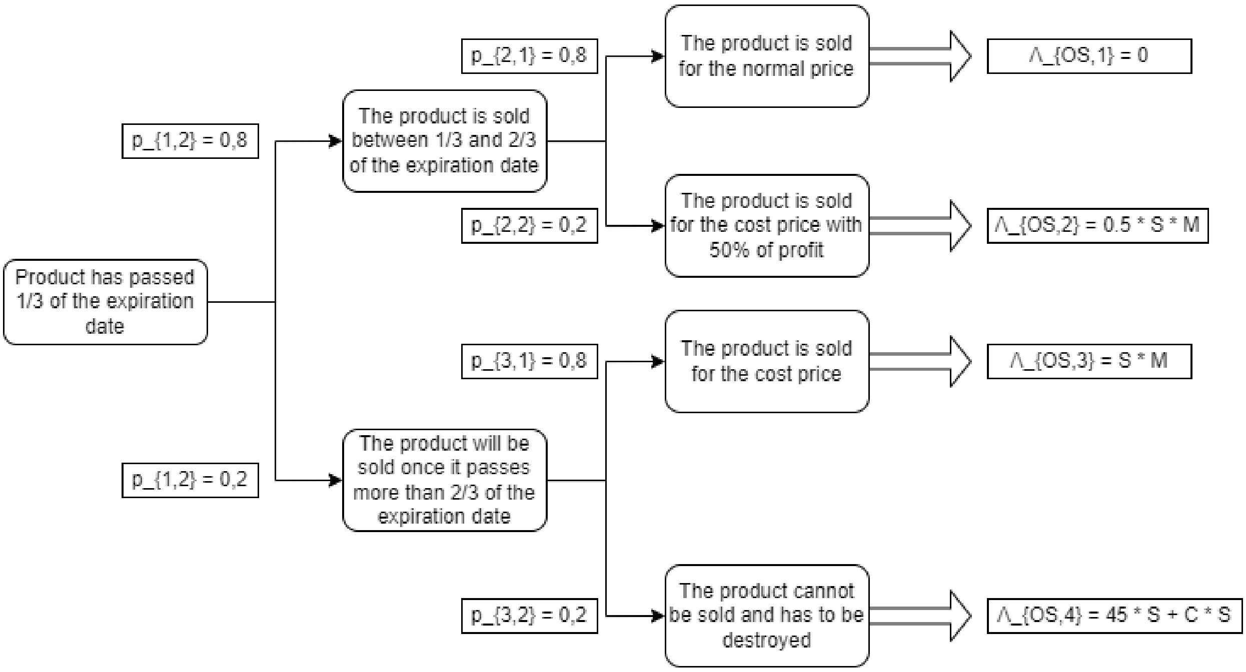


Figure 7: The decision tree in case a product becomes obsolete at Grolsch with its corresponding probabilities and payoffs.

Holding costs

To determine the holding costs per SKU on stock we need to know the operational costs that come with moving the inventory and storing them. In his thesis Kamp (2018) found already that the holding costs are strongly correlated to the stock level. In addition, Kamp (2018) introduced a formula to determine the holding costs based on a different number of parameters. However, the used formula can be adjusted and simplified. We also use the Weighted Average Costs of Capital (WACC) and multiply this WACC by the number of pallets in stock of SKU j on day m and the value of SKU j per pallet. Although we do not have information on the specific WACC at Grolsch we found from a recent study done by KPMG in Germany (Schöniger, Snellen, and Tschöper, 2022) that the WACC for consumer companies was around 6.7% in 2022. In addition to the WACC, we know that the warehouse of Grolsch at the brewery has a practical limit of 18,000 pallets. If Grolsch has more than 18,000 pallets in stock it starts to commute pallets from its own warehouse location to one of its external storage locations on the harbour. Normally if Grolsch is storing more pallets than its practical limit it has to relocate pallets in its own warehouse internally as well. However, we assume in our research that the capacity of the (number of) forklift drivers working is fixed and that the forklift drivers would be working regardless of the number of internal relocations that have to be done of the finished goods. That brings us to the next equation for the total inventory holding costs for day m ($h_{m,Total}$) as shown below in Equation 7.

$$h_{m,Total} = \sum_{j=1}^{J} WACC \cdot I_{m,j} \cdot C_j + \max\{A \cdot \left\lceil \frac{(I_{m,Total} - 18,000)}{B} \right\rceil, 0\} \tag{7}$$

Below all parameters of Equation 7 are described:
$I_{m,j}$ = the inventory level of SKU j on day m in pallets.
C_j = the cost price of 1 pallet of SKU j.
A = the costs of one drive back and forth to an external storage location of Grolsch.
B = the average amount of pallets that fit in one truck, which is equal to 26 pallets.
$I_{m,Total}$ = the inventory level on day m of all SKUs together

2.2.3 Conclusion

The plan changes weekly based on the Days of Cover, and a product can be stocked at Grolsch until it reaches 1/3 of its expiration time after which it is considered obsolete. The scheduling department attempts to make a plan as efficient as possible for the filling lines out of the weekly plan because the filling lines are the bottleneck. The filtration capacity is not assumed to be an issue as are the capacity of the raw material warehouses and the availability of the raw materials. The focus of this research is on Filling Line 2, thus we only focus on the products that are sold in a Returnable Bottle that can contain less than 0.4 liters. Finally, all three storage locations of Grolsch have a practical limit of 23,000 pallet locations.

Grolsch uses a minimum Days of Cover per SKU that is fixed throughout the entire year to control the inventory of the MTF SKUs. The current inventory control method gives Grolsch a dynamic reorder point, which is appropriate to be used for seasonal demand patterns that Grolsch experiences on a lot of its SKUs. Grolsch 'orders' a new batch of products every Friday afternoon, so the review period R is equal to 1 week (or 5 workdays), and the average production lead time, when taking into account delays on Filling Line 2, is equal to y days. The standard deviation of the duration of the lead time equals z hours per week. The tactical planning of Grolsch uses a periodic review method, places an 'order' when the stock is below a certain level, and orders a batch size that is more or less fixed, so we can establish that Grolsch is using an (R,s,Q)-method for its inventory control policy. In Section 3.1 we explain more about the inventory control policies. Based on the (R,S,Q)-policy that the tactical planning of Grolsch uses for controlling its inventory we look in the literature for dynamic safety stock allocation methods in the next chapter. We know that Grolsch is currently using a Stock Availability percentage as a service level measure and the tactical planning indicated that they want to keep this service level measure. Therefore, we also look into the literature for possible service level measures and safety stock allocation methods that we can use with each of these alternative service level measures.

As already mentioned the tactical planning of Grolsch is currently using a minimum Days of Cover to control its inventory. Due to the fact that Grolsch is currently working with this dynamic safety stock method and due to the fact that they are working with forecasted demand, they would want to keep using this method. Therefore, we need to find a method in the literature such that we express the safety stock level in terms of Days of Cover. Also, the ABC classification of Grolsch needs an update as we cannot see a clear connection between the classification of the SKU and the minimum Days of Cover that is set for the SKU. Therefore, we also look into the literature for SKU classification methods, which we might be able to use within our research.

The batch sizes will not be optimized in this research, therefore the inventory-related operational costs of Grolsch that are relevant for our research are the overstocking costs, and the holding costs. The overstocking costs can be approximated by multiplying the margin of the SKU by 29%. The holding costs are calculated based on a formula (shown in Equation 7) that takes into account the stock level, as it was found that the holding costs are strongly correlated with the inventory level. As we currently know how we can approximate the inventory-related operational costs of Grolsch for the safety stocks we do not need to search the literature for possible methods to approximate the inventory-related operational costs.

3 Literature review

The literature review will first start in Section 3.1 with some information on the inventory control policies that are identified within the literature, so we know in what direction within the literature we need to search for safety stock allocation methods. Next, we shortly describe in Section 3.2 a limitation within the literature search to describe the general safety stock allocation methods available in the literature for the Cycle Service Level in Section 3.3. After the basic safety stock calculations are known we elaborate on the different service level measures that are available in the literature in Section 3.4, and we then describe in Section 3.5 how we can adjust the safety stock calculations such that we can use the Stock Availability percentage as a service level measure. Finally, we discuss the different SKU classification methods available within the literature in Section 3.6 before we conclude this chapter in Section 3.7.

3.1 Inventory control policies

The most well-known inventory control policies are: (s,S), (s,Q), (R,S), (R,s,S), and (R,s,Q). These policies can be distinguished based on two characteristics, namely the policies are either periodic or continuous and the policies are using either a fixed or a variable lot size. Below in Table 1 the policies based on each combination of characteristics are given (Silver, Pyke, and Thomas, 2016).

	Periodic review	**Continuous review**
Fixed lot size	(R,s,Q)	(s,Q)
Variable lot size	(R,s,S) or (R,S)	(s,S)

Table 1: Different inventory control policies based on the policy characteristics.

In Section 2.2.1 we established already that Grolsch is using an (R,s,Q)-policy. That means that Grolsch is using a periodic review method with a fixed lot size. Based on the (R,s,Q)-policy we should look for methods to optimize the safety stock level, as the inventory control policy is relevant if we are searching for safety stock allocation methods to use.

3.2 Dynamic versus static inventory planning

In the literature there is little to find on the usage of dynamic safety stock allocation within (R,S,Q)-systems, therefore we have chosen to look for static safety stock methods. The static safety stock methods can be used to calculate a dynamic safety stock level for Grolsch. In Chapter 4 we discuss more about how we will go from a static safety stock level to a dynamic safety stock level.

3.3 Safety stocks

3.3.1 Basic safety stock calculation

Within the current literature, the basic optimal safety stock level in units is calculated with the formula given below in Equation 8 (Chopra and Meindl, 2018).

$$SS = \Phi^{-1}(\theta) \cdot \sigma_D \tag{8}$$

In this basic safety stock level formula we take μ_D to be the average demand during lead time, σ_D to be the standard deviation of the demand during lead time, and L to be the lead time. The formula assumes the demand for each period is independent and normally distributed with mean D and standard deviation σ, therefore the formula assumes that the demand during lead time is normally distributed with the mean being $\mu_D = D \cdot L$, and the standard deviation being $\sigma_D = \sigma \cdot \sqrt{L}$ (Gonçalves, Sameiro Carvalho, and Cortez, 2020). $\Phi(\cdot)$ represents the standard normal cumulative distribution function, and θ indicates the desired Cycle Service Level. The Cycle Service Level equals the probability that no stockout will occur during a replenishment cycle, where a replenishment cycle equals the time between receiving two consecutive replenishment batches. More about the CSL and other service levels will be discussed in Section 3.4 (Gonçalves, Sameiro Carvalho, and Cortez, 2020).

3.3.2 Incorporating forecasting and lead time uncertainty

When the forecasted demand is used to determine a time-varying safety stock level, and the true standard deviation of the demand distribution is uncertain, then the calculated safety stock level is dependent on both the variability of the demand and the demand uncertainty. The variability of the demand and the demand uncertainty are two different things. Demand variability refers to the realized demand deviating from its mean demand, whereas demand uncertainty refers to the unpredictability that arises in forecasting future demand. The demand uncertainty is modeled by means of the distribution of the forecast errors, and the safety stock calculation is thus based on the variance of the distribution of the forecast errors.

To incorporate the variance of the distribution of the forecast errors in the safety stock models it is often proposed in the literature to use the demand forecast errors per period, which can be estimated using the Mean Squared Error (MSE) or the Mean Absolute Deviation (MAD) (Prak, Teunter, and Syntetos, 2017). The MSE and the MAD are calculated by the formulas shown in Equations 9, and 10, respectively (Chopra and Meindl, 2018). In the calculations of the variance measures t represents the period number, T represents the last period over which the measure is calculated, G_t represents the difference between the forecasted demand and the realized demand in period t, and G_t represents the absolute difference between the forecasted demand and the realized demand in period t.

$$MSE_T = \frac{1}{T} \cdot \sum_{t=1}^{T} G_t^2 \tag{9}$$

$$MAD_T = \frac{1}{T} \cdot \sum_{t=1}^{T} G_t \tag{10}$$

By choosing T to be equal to $T + L$ we can calculate the forecast error over the lead time. Moreover, when performing this calculation for multiple past lead time periods we can construct a distribution of the forecast errors over the lead times of the past periods. Using this distribution we can calculate the standard deviation of the forecast error over the past lead time periods, denoted by σ_F. Using the standard deviation of the forecast error over the past lead time periods we can calculate the safety stocks as follows (Barros, Cortez, and Carvalho, 2021):

$$ss = \Phi^{-1}(CSL) \cdot \sigma_F \cdot \sqrt{L} \tag{11}$$

The calculation shown in Equation 11 only considers the forecast deviation during an average lead time, where the lead time is assumed to be fixed. Ideally, the safety stock calculation should also incorporate the lead time uncertainty as well. Taking into account again the basic safety stock calculation in Equation 8 with the demand during the lead time normally distributed, we can calculate the optimal safety stock level considering uncertain lead times using Equation 12 below. The equation is only valid if the lead time and the demand per unit of time are assumed to be independent random variables (Barros, Cortez, and Carvalho, 2021).

$$ss = \Phi^{-1}(CSL) \cdot \sqrt{L \cdot \sigma_D^2 + (\sigma_L \cdot \mu_D)^2} \tag{12}$$

In case the forecast error over the lead time follows a normal distribution with standard deviation σ_F, and mean μ_F we can substitute the σ_D for σ_F in Equation 12, such that we incorporate both the forecast uncertainty and the lead time uncertainty in the safety stock calculation. Then we will arrive at the next formula (Axsäter, 2006):

$$ss = \Phi^{-1}(CSL) \cdot \sqrt{L \cdot \sigma_F^2 + (\sigma_L \cdot \mu_D)^2} \tag{13}$$

3.3.3 Undershoot

In the case of an (R,S,Q) inventory control policy we have to take into account undershooting. In case of a continuous review period, we can immediately order once we are below the reorder point. However, in case we only periodically review the stock level we have to take into account that the stock level can be far below the reorder point already by the time we review the stock level. The difference in time between checking the stock level and the moment we are going below the reorder point can cause undershoot. Therefore, when determining safety stocks this should be taken into account. In case we take into account undershoot for an (R,S,Q)-policy we should simply add the undershoot to the safety stock. The (expected) undershoot is represented by $E[Z]$ and the safety stock level with undershoot is calculated, in case demand is forecasted, as shown in Equation 14. To calculate (an approximation of) the undershoot under the (R,S,Q) inventory control policy we use the formula of the (S,Q) inventory control policy where R=1 (Silver, Pyke, and Thomas, 2016).

$$ss \approx E[Z] + \Phi^{-1}(CSL) \cdot \sqrt{L \cdot \sigma_F^2 + \sigma_Z^2} \tag{14}$$

The equation as given above by Silver, Pyke, and Thomas (2016) only does not take into account the uncertainty of the lead time. Therefore to incorporate both we can simply add $(\sigma_L \cdot \mu_D)^2$ within the square root to add both the uncertainty of the lead time and the undershoot. Then we get the formula as shown in Equation 15.

$$ss \approx E[Z] + \Phi^{-1}(CSL) \cdot \sqrt{L \cdot \sigma_F^2 + \sigma_Z^2 + (\sigma_L \cdot \mu_D)^2} \tag{15}$$

In the equation of the safety stock level we still have to calculate $E[Z]$ and σ_Z^2. These are both calculated as shown in Equation 16 and 17 (Silver, Pyke, and Thomas, 2016):

$$E[Z] \approx \frac{\sigma_R^2 + (E[D_R])^2}{2 \cdot E[D_R]} \tag{16}$$

$$var[z] \approx \frac{E[D_R^3]}{3 \cdot E[D_R]} + \frac{1}{4} \cdot (\frac{E[D_R^2]}{E[D_R]})^2 \tag{17}$$

In the equations $E[D_R]$ represents the expected demand during the review period, σ_R represents the standard deviation of the demand during the review period, and $E[D_R^2]$ and $E[D_R^3]$ represent the second, and third order moment of the demand during the review period (Silver, Pyke, and Thomas, 2016). The second and the third order moment can both be calculated using a more simplified formula in case the demand follows a normal distribution, and both $E[D_R]$ and σ_R are known. The second order moment ($E[D_R^2]$) can be calculated as shown in Equation 18, and the third order moment ($E[D_R^3]$) can be calculated as shown in Equation 19 (Wikipedia, 2023).

$$E[D_R^2] = E[D_R]^2 + \sigma_R^2 \tag{18}$$

$$E[D_R^3] = E[D_R]^3 + 3 \cdot E[D_R] \cdot \sigma_R^2 \tag{19}$$

3.4 Service Level measures

Going back to the basic safety stock calculation in Equation 8 in Section 3.3 we indicated that θ represents the Cycle Service Level. However, we can also use three other service level measures. The other measures for the service level are the Order Fill Rate, the (Product) Fill Rate, and the Ready Rate. All three definitions of the different service levels are defined as follows (Chopra and Meindl, 2018; Axsäter, 2006):

- The Cycle Service Level (CSL) is equal to the probability of not having a stockout during a replenishment cycle.
- The (Product) Fill Rate (FR) equals the probability that a product demand is directly delivered from stock.
- The Order Fill Rate (OFR) equals the probability that the order is delivered from the available inventory.
- The Ready Rate (RR) equals the fraction of time that the stock on hand is positive.

The Ready Rate is the same as the Stock Availability measures that Grolsch is currently using to evaluate its performance of Supply Chain Planning. Below in Equations 20, and 21 the formulas for both the average Ready Rate, and the average Stock Availability are given, where $\psi_{j,t}$ is a binary variable that equals 1 when SKU j has more than 1 day worth of demand on stock in time t, and 0 otherwise. As can be seen from the formulas the average Ready Rate first loops over time and then over the products, and the formula for the average Stock Availability first loops over the products and then over time (Kamp, 2018). This means that the average Ready Rate is exactly the same as the average Stock Availability. We will further in this report use the term Stock Availability for the sake of clarity.

$$RR_{Average} = \frac{1}{J}\sum_{j=1}^{J}\frac{1}{T}\sum_{t=1}^{T}\psi_{j,t} \tag{20}$$

$$SA_{Average} = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{J}\sum_{j=1}^{J}\psi_{j,t} \tag{21}$$

To calculate the Ready Rate for a specific reorder point O' under Normally-distributed lead time demand with mean μ_D, standard deviation σ_D, and lot size Q we find the following formula, which is almost equal to the Fill Rate (Axsäter, 2006):

$$RR \approx 1 - \frac{\sigma_D}{Q} \cdot G(\frac{O' - \mu_D}{\sigma_D}) \tag{22}$$

3.5 Approximating the optimal safety stock level with a Stock Availability as service level measure

Until now we have discussed how we can calculate a static optimal safety stock level in case we use a CSL as a service measure. However, as we just established Grolsch uses a Stock Availability percentage as a service measure, which is equal to the Ready Rate. Therefore, if we want to calculate the optimal safety stock level with a Stock Availability percentage and we assume an uncertain lead time we have to adjust the calculations. Axsäter (2006) proposed a formula to take into account uncertain lead times within the safety stock calculation using the Stock Availability percentage. To approximate the safety stock in case of uncertain lead times we can keep the expected demand during lead time (μ_D) the same, as the expected lead time does not change. However, the standard deviation of the demand during lead time (σ_D) is subject to change. The standard deviation of the demand during lead time and review period in case of uncertain lead time (represented by σ'_D) is calculated as shown below in Equation 23 (Axsäter, 2006).

$$\sigma'_D = \sqrt{\sigma_D^2 \cdot E(L) + \mu_D^2 \cdot \sigma_L^2} \tag{23}$$

In our case the demand is forecasted, which means the equation will change a bit as follows:

$$\sigma'_D = \sqrt{\sigma_F^2 \cdot E(L) + \mu_D^2 \cdot \sigma_L^2} \tag{24}$$

Next, if we want to incorporate the undershoot as we did for the safety stock calculation using the Cycle Service Level we have to do two things. First, we need to adjust Equation 22 by subtracting the expected undershoot ($E[Z]$) from the safety stock, and we should add σ_Z^2 within the square root of the formula that calculates σ'_F in Equation 26. This brings us to the next formulas that we can use to calculate the optimal safety stock level in case we want to use the Stock Availability as a service measure, incorporate the forecast and lead time uncertainty, and incorporate the undershoot (Silver, Pyke, and Thomas, 2016; Axsäter, 2006).

$$RR \approx 1 - \frac{\sigma'_F}{Q} \cdot G(\frac{O' - \mu_D - E[Z]}{\sigma'_F}) \tag{25}$$

Within formula 25 we should calculate σ'_F as follows:

$$\sigma_F^{'} = \sqrt{\sigma_F^2 \cdot E(L) + \sigma_Z^2 + (\sigma_L \cdot \mu_D)^2} \tag{26}$$

$E[Z]$ and σ_Z^2 are calculated as shown in Equations 16, and 17.

3.6 SKU classification

As stated by Bacchetti et al. (2013): "The categorization of SKUs helps to determine service requirements for different classes and facilitates the allocation of the most appropriate forecasting method and stock control policy in each category". Therefore, classifying the SKUs can help to set the appropriate service levels. A rather popular method used for classification that has been discussed already in Section 2.2.1 is the ABC analysis. The ABC method is described in the literature as a method to classify the SKUs according to their added value to the turnover of the company. It is based on the Pareto principle that 80% of the turnover is generated by 20% of the product portfolio. Therefore, when sorting the SKUs according to the turnover from largest to smallest, the first SKUs that make up 80% of the turnover of the company are labeled as A products. The next SKUs that make up 15% of the turnover are labeled as B products and the leftover products that make up the last 5% of the turnover are considered to be C products (Balaji and Senthil Kumar, 2014).

The ABC method is widely used, but also much criticized as the method is not developed to optimize inventory performance (Yang et al., 2017). Besides using a combination of the demand and the unit price there also exist other methods that can classify inventory. Another single SKU classification method is the VED method. The VED method classifies SKUs based on criticality. VED stands for Vital, Essential, and Desirable, respectively (Nareshchandra and Desai, 2019). Although the VED method can be used for regular inventory management we think it is better suitable for spare parts management.

Besides single criterion classification methods we also have classification methods that take into account multiple criteria (Yang et al., 2017). Models that use 2 criteria are called bi-criteria inventory classification methods, whereas methods that use 3 or more criteria are called Multi-Criteria Inventory Classification and Control (MCIC) (Yang et al., 2017; Nareshchandra and Desai, 2019). An often-used bi-criteria inventory classification method in a company where demand is forecasted is the ABC-XYZ method, where the products are classified according to the consumption value using the ABC method and the forecast/demand variation using the XYZ method.

3.7 Conclusion

We can calculate the optimal safety stock levels of Grolsch by using static formulas that are valid for an (R,S,Q) inventory control policy. By using the Mean Squared Error and the standard deviation of the production delays we can incorporate the forecast and lead time uncertainties in the calculations. Moreover, the undershoot calculations provide us with the benefit of incorporating the forecast errors during the review period. We can use the approximation shown in Equation 25 that uses the Stock Availability percentage as a service measure to calculate the optimal safety stock level for each SKU. With this static optimal safety stock level we have to go to a dynamic safety stock level, which is the minimum Days of Cover. In Chapter 4 we describe in more detail what data we use for the calculations and how we go from a static to a dynamic safety stock level.

There are many SKU classification methods available in the literature. Grolsch indicated that they would like to keep the current ABC classification method. We think that it would benefit Grolsch if the XYZ classification method is added to the ABC classification method, as this method is often used in case the inventory is controlled based on forecasts. The XYZ classification gives the tactical planning of Grolsch an indication of the volatility of the forecast error of the SKU. Moreover, we currently do not see a clear connection between the classification of an SKU and the minimum Days of Cover that is assigned to it. If both the turnover and the volatility of the forecast errors are taken along in the classification we expect to be able to see a clearer connection between the classification of the SKU and the minimum Days of Cover that is assigned to it. In Chapter 4 we elaborate on what data we use for the classification of the SKUs.

4 Methodology

In this chapter, we describe how we go from a static safety stock (calculation) to a minimum Days of Cover and how we evaluate the new minimum Days of Cover calculation. In Section 4.1 we first describe how we classify the SKUs and how we determine the service measure targets for all of the SKUs. Next, we describe in Section 4.2 how we calculate the static safety stock level and we describe how we go from a static safety stock level to a minimum Days of Cover. In Section 4.3 we describe the method we use to evaluate the minimum Days of Cover allocations and in Section 4.4 we describe how we evaluate the robustness of the minimum Days of Cover allocations in case parameters, settings, or assumptions of the simulation change to see what happens if the situation of Grolsch changes. The chapter is concluded in Section 4.5.

4.1 Service levels and SKU classification

As mentioned already in Section 3.7 we introduce a combination of the XYZ and the ABC classification within Grolsch, which means that every SKU that we research gets either one of the next classifications: AX, AY, AZ, BX, BY, BZ, CX, CY, or CZ. Grolsch sells a lot of seasonal SKUs of which the demand and the reliability of the forecast depend very much on the season. Therefore, every SKU is classified per quarter.

The ABC classification is based on the turnover of each SKU. The turnover of each SKU is calculated by multiplying the total number of SKUs that were sold in the last quarter that we have data on (for most quarters this is 2022, however for the fourth quarter this is 2021 as the year of 2022 is not finished yet) by the gross margin, which is calculated by averaging the gross margin of 2022 and 2023.

For the XYZ classification we look at the coefficient of variation. The coefficient of variation is calculated by dividing the standard deviation of the absolute forecast errors by the Mean Absolute Deviation, hence the value indicates how much the absolute forecast error fluctuates from the mean absolute forecast error. Based on the coefficient of variation we classify the products as either X, Y, or Z. The SKUs that show the lowest coefficient of variation of the forecast error are given an X classification, the SKUs that show the highest coefficient of variation are given a Z classification, and the leftovers in between are given a Y classification. By taking the absolute difference between the actual demand per week and the forecast per week we can calculate the mean per quarter and the standard deviation per quarter of the absolute differences, such that we can calculate a coefficient of variation for each SKU for each quarter. We use the data from the forecast and the actual sales from the previous 3 years, which means that we will use the data from 2020 up until the third quarter of 2022.

For each classification we set a target Stock Availability percentage. The tactical planning of Grolsch is currently working with a target Stock Availability percentage based on the ABC classification. Although we wanted to differ the target Stock Availability percentage for the combination of the XYZ and the ABC classification the tactical planning of Grolsch indicated that it would like to keep the current target service levels that are established based on the ABC classification intact. That means that we use a target Stock Availability percentage of 99.5%, 98.5%, and 97.5% for the SKUs classified as A, B, and C, respectively. The overall target Stock Availability percentage of Grolsch is 98.5%. Despite the fact that we only use the ABC classification for the target Stock Availability percentage we do use the XYZ classification later in this research. We assign different minimum Days of Cover to each combination of the ABC and the XYZ classification in Section 5.3.3 and we use this minimum Days of Cover per classification for at least 2 of the 3 methods that we use in our research.

4.2 Determining the minimum DoC

Based on the target Stock Availability percentage we use Equation 27 to calculate the optimal Safety Stock level in hectoliters. We thus assume that the forecast error for SKU j in quarter k follows a normal distribution with mean $\mu_{F_{j,k}}$ and standard deviation $\sigma_{F_{j,k}}$. We calculate the optimal safety stock level in hectoliters for every SKU for every week. $\sigma_{F_{j,k}}$ thus differs per quarter k for each SKU j and is calculated based on the variance of the forecast errors over the previous year, using the Mean Squared Error method, of SKU j in quarter k. Therefore, $\sigma'_{F_{j,k,t}}$ also differs per quarter k and per SKU j and it differs per week t, as $\mu_{D_{j,t}}$ is used to calculate

$\sigma_F^{'}$. $\mu_{D_{j,t}}$ is the demand during lead time for SKU j for week t, where the lead time starts in the beginning of week t. We calculate the expected lead time demand for week t by summing the forecasted demand of SKU j for week t, week $t+1$, week $t+2$, until week $t+\mu_L+R$, where μ_L equals the expected duration of the lead time, and R equals the duration of the review period. In case the expected duration of the lead time and review period in weeks is not an integer number we assume that the demand is spread out linearly over the week. To illustrate this let us take the following example. Let us take an expected lead time and review period duration of 2.5 weeks, and the demand for the next three weeks is 2, 3, and 5 hectoliters respectively. In this example, the lead time demand is equal to $(2+3+\frac{1}{2}\cdot 5=)$ 7.5 hectoliters. We want to determine the minimum Days of Cover that Grolsch should keep in 2023, so to calculate the expected lead time demand we use the most recent weekly forecast of Grolsch for 2023. The standard deviation of the lead time duration (σ_L) is calculated by calculating the standard deviation of the production delays in hours per week of Filling Line 2 of Grolsch.

In practice Grolsch does not always have a fixed batch size, so to calculate the safety stock we need a good estimation of the (average) batch size (Q_j) of SKU j that the tactical planning of Grolsch is 'ordering'. To have a good estimation of the average batch size we calculate the average batch size that the tactical planning has planned to 'order' in the year 2023 according to its budget plans. Therefore, in this case, the lot size does not change per quarter k.

$$SA_{j,k} \approx 1 - \frac{\sigma_{F_{j,k}}^{'}}{Q_j} \cdot G(\frac{O_{j,t,k}^{'} - \mu_{D_{j,t}} - E[Z_{j,k,t}]}{\sigma_{F_{j,k,t}}^{'}}) \tag{27}$$

$$\sigma_{F_{j,k,t}}^{'} = \sqrt{\sigma_{F_{j,k}}^2 \cdot E(L) + \sigma_{Z_{j,k,t}}^2 + (\sigma_L \cdot \mu_{D_{j,t}})}^2 \tag{28}$$

To take along the undershoot within the safety stock calculations for SKU j in quarter k and week t we calculate $E[Z_{j,k,t}]$ and $\sigma_{Z_{j,k,t}}$ with Equations 29 and 30. To calculate both we first calculate the expected demand during the review period of SKU j in week t ($E[D_{R_{j,t}}]$), and the standard deviation of the expected forecast error during the review period of SKU j in quarter k ($\sigma_{R_{j,k}}$). In our research, we assume that the demand during the review period is normally distributed with mean $E[D_{R_{j,t}}]$, and standard deviation $\sigma_{R_{j,k,t}}$ for every SKU, week, and quarter. The expected demand during the review period is easily calculated for SKU j in week t based on the duration of the review period and the expected demand of SKU j in week t. The expected demand is calculated for every week t for every SKU j based on the demand in week t for SKU j during the expected duration of the lead time and the review period. Just as for the expected lead time demand we assume here that the demand is equally spread out over the week in case the review period in weeks ($\frac{R}{5}$) is not an integer number. The standard deviation of the demand during the review period for SKU j in week t and in quarter k is calculated by multiplying the standard deviation of the forecast error ($\sigma_{F_{j,k}}$) with the square root of the review period in weeks ($\sqrt{\frac{R}{5}}$).

$$E[Z_{j,k,t}] \approx \frac{\sigma_{R_{j,k}}^2 + (E[D_{R_{j,t}}])^2}{2 \cdot E[D_{R_{j,t}}]} \tag{29}$$

$$\sigma_{Z_{j,k,t}}^2 \approx \frac{E[D_{R_{j,t}}^3]}{3 \cdot E[D_{R_{j,t}}]} + \frac{1}{4} \cdot (\frac{E[D_{R_{j,t}}^2]}{E[D_{R_{j,t}}]})^2 \tag{30}$$

To calculate the second ($E[D_{R_{j,t}}^2]$) and the third order ($E[D_{R_{j,t}}^3]$) moments of the expected demand during the review period for SKU j in week t we use Equations 31 and 32, respectively.

$$E[D_{R_{j,t}}^2] = E[D_{R_{j,t}}]^2 + \sigma_{R_{j,k,t}}^2 \tag{31}$$

$$E[D_{R_{j,t}}^3] = E[D_{R_{j,t}}]^3 + 3 \cdot E[D_{R_{j,t}}] \cdot \sigma_{R_{j,k,t}}^2 \tag{32}$$

Using all the calculated variables we can use the Excel solver to calculate the safety stock level in hectoliters for each SKU for each week by solving Equation 33 by changing the reorder point $O_{j,k,t}$ until the Stock Availability percentage is reached. Equation 33 is rewritten from Equation 27 that we have given earlier in Section 4.2. The safety stock is then calculated by subtracting the expected lead time demand ($\mu_{D_{j,t}}$) from the reorder point ($O_{j,k,t}$), and adding the expected undershoot ($E[Z_{j,k,t}]$) to the result of the subtraction.

$$\frac{Q_j \cdot (1 - SA_{j,k})}{\sigma'_{F_{j,k,t}}} \approx G(\frac{O'_{j,t,k} - \mu_{D_{j,t}} + E[Z_{j,k,t}]}{\sigma'_{F_{j,k,t}}}) \tag{33}$$

When we have calculated the safety stock level in hectoliters for each SKU for each week we use the average demand during the lead time that we have calculated separately for every week for every SKU and we divide the average demand during the lead time by the expected duration of the lead time (in weeks) to get the average demand per week. By dividing the safety stock level in hectoliters by the average demand per week we get a real number that represents the weeks of cover for every SKU for every week. To go from weeks of cover to Days of Cover we can multiply the weeks of cover by 5, such that we have a minimum Days of Cover per week per SKU available. Based on this Days of Cover per week per SKU we can calculate a new Days of Cover in separate ways. In our research, we use the following methods:

1. Our first method is to calculate an average minimum Days of Cover per SKU per quarter. Every SKU also has a different classification per quarter, thus we can calculate an average minimum Days of Cover per classification (aggregation). As every SKU has a different classification per quarter we can then assign the (aggregated) minimum Days of Cover per classification to the corresponding combination of the SKU and the quarter. Using this method the tactical planning department can easily base the minimum Days of Cover for its SKUs on the classification of the SKU. Further in this report, we refer to this method as the Variable MinDoC per Quarter method (the VMQ-method).

2. The second method uses the aggregated minimum Days of Cover of the first method that we calculated per quarter per SKU. Based on the minimum Days of Cover per quarter we calculate an average minimum Days of Cover for the entire year for each SKU. This way we can test if a variable minimum Days of Cover per quarter per SKU works better than a fixed minimum Days of Cover. Further in this report, we refer to this method as the Average Aggregated method (the AA-method).

3. The third method uses the minimum Days of Cover per week per SKU and then calculates the average minimum Days of Cover per SKU over all 52 weeks, such that every SKU has its separate fixed minimum Days of Cover for the entire year. In this method, we do not aggregate the minimum Days of Cover based on the classification, which we did using the AA-method. Using this method we can see if aggregation by using the SKU classification works better or not. Further in this report, we refer to this method as the Average Non-Aggregated method (the ANA-method).

4.3 Evaluating the new minimum DoCs

To know if the new minimum Days of Cover are performing better than the current minimum Days of Cover per SKU that Grolsch is using we evaluate the effect both minimum Days of Cover allocations have on the operational costs of Grolsch. By simulating the production and the sales of Grolsch for the year 2023 we can mimic the stock levels of Grolsch. We simulate 52 weeks within our simulation which is equal to 364 days. The 52 weeks of 2023 are simulated, whilst the forecast error data of the year 2022 is used as input data. We have chosen to simulate the year 2023 instead of the year 2022 because for us the biggest advantage of simulating the production plan of 2022 would be to compare the results with the actual results that Grolsch performed over 2022. However, since the production plan for 2022 was made before the year started a lot has changed during the course of the year like warehousing capacity, additional SKUs that have been added to the portfolio of Grolsch, SKUs that have been removed from the portfolio of Grolsch, etcetera. This makes the results from the simulation hard to compare with the actual results in 2022. Moreover, for Grolsch, it would add more value to see how well the current production plan is performing in 2023 even though the forecast error distribution is based on the year 2022. To simulate the stock levels of Grolsch we use a Discrete Event Simulation (DES) in Siemens PlantSim version 14.0.0.

Simulating the production plan
Creating a feasible 1-year ahead production plan with a new minimum Days of Cover is rather complicated, as a lot of aspects need to be taken into account for such a plan. Currently, Grolsch has an Excel document readily available with the budget plan for 2023. In this document, a production plan is made based on different input data. The input data includes among other things the forecasted demand for next year per week, the maintenance schedule, and the production capacity available per week. Besides this input data, also the minimum DoC level is used as input. The tactical planning of Grolsch currently uses a rough step-wise approach to make a production plan using all the inputs. However, in this step-wise approach, there is still a lot of room for slack, and the steps were never formalized yet. We made a formalized step-wise approach to create a 1-year ahead production plan based on a number of inputs, which leaves less room for slack, but this method did not give us a realistic production plan. Therefore, we have asked the team lead of the Supply Chain Planning department to make the new production plans based on the new minimum Days of Cover. For the sake of simplicity, the team lead of Supply Chain Planning has increased the opening stock for the SKUs until the actual minimum Days of Cover is always higher than the new minimum Days of Cover and in case it was needed the production quantities are slightly adjusted on the condition that all other constraints are still satisfied (production capacity available, minimum batch quantity, etc.). In particular for the VMQ-method with varying minimum Days of Cover per quarter, the Supply Chain Planning team lead has to adjust the production quantities. The production quantities are adjusted in such a way that the total produced volume remains the same as the forecasted volume.

Simulating the realized sales
As an input for the simulation we use the forecast of 2023 per week, which can also be found in the Excel document with the budget plan for 2023. In addition, we have the standard deviation of the forecast error per week from last year per quarter per SKU. Using both the simulated forecast error per week and the forecast per week we can calculate the realized sales per week in 2023. The forecast error is generated by using a normal distribution with a mean of 0 and a standard deviation equal to the standard deviation of the forecast error per week. We assume the mean is 0, as we expect the demand planning will adjust the forecast for 2023, such that it is not biased.

As we want to simulate the stock levels of Grolsch on a daily level we go from sales per week to sales per day by using a uniform distribution, such that the sales are more or less equally divided over the weekdays.

Simulating the production day
The new production plans determine how many hectoliters of which SKU should be produced in which week. However, we also want to determine the production day of the SKU in order to simulate the stock level on a daily level. In the simulation, we randomize the position of the SKU within the weekly schedule of the production line. Based on the position in the schedule we determine on which day the new production batch of the SKU is in stock.

Holding costs
Based on the number of pallets that we physically have on stock per day we calculate the holding costs with the formula as given in Equation 7. However, we have to adjust this formula a bit, as we do not take into account here if the stock was commuted to the harbour already, and we assume in this formula that all of the commuted stock to the harbour is sold immediately the next day from the harbour as well. We have adjusted Equation 7 below in Equation 34 by changing the calculation of the number of pallets that need to be commuted. We change variable $I_{m,j}$ by adding an extra index w which represents the location of the stock. $I_{m,j,w}$ then represents the stock level of SKU j on the beginning of day m in warehouse w, where w can take on values 0 (when the stock is stored in the warehouse at the brewery) and 1 (when the stock is stored in the warehouse at the harbour).

$$h_{m,Total} = \sum_{j=1}^{J} \sum_{w=0}^{W} WACC \cdot I_{m,j,w} \cdot C_j + A \cdot \left\lceil \frac{I_{m,Total,0} - 18,000,0}{26} \right\rceil \tag{34}$$

For the formula above we can calculate the stock level at the brewery ($I_{m,Total,0}$) on day m by taking the total stock level of yesterday ($m-1$) over both storage locations and subtracting the pallets that Grolsch commuted to the harbour yesterday and adding the pallets that Grolsch has sold from the harbour directly yesterday.

The stock is mostly sold directly from the brewery location of Grolsch, but when it is commuted to the harbour it will also be sold directly from the harbour location to the customers. The harbour is often used for longer-term stock build and we think, based on experience within the planning team of Grolsch, that it would be realistic to assume that the stock in the harbour would be completely sold after being 4 weeks in stock in the harbour. We assume here that the demand for the SKUs commuted to the harbour is uniformly distributed over the 4 weeks and that at the end of every week, Grolsch sells one-fourth of these commuted pallets directly from the harbour such that 4 weeks after commuting all of the pallets are sold directly from the harbour.

Overstocking
We assume that the products are sold according to the FIFO (First In First Out) principle. The production batch that was produced first is sold first. Once a batch is in stock more than 1/3 of the total expiration time without being sold we consider it to be an overstocking. A cost figure is assigned to the overstocking by multiplying the profit margin of the SKU by 29% and by multiplying this again with the number of SKUs in the batch.

If a batch surpasses 1/3 of its expiration time we do not subtract it from the stock on hand, but we assume that all products that surpass 1/3 of their expiration time can still be sold to regular customers. The tactical planning of Grolsch has a preference for this way of simulation as the production plans are made such that we produce exactly the same amount as we would sell. In the production plan, the tactical planning does not plan on Days of Cover that are higher than 1/3 of the expiration time but when sales are lower than forecast this situation can occur in our simulation. The latter makes it less realistic in the eyes of tactical planning and if we do not produce exactly the same as the forecasted demand whilst our simulation does not provide the option to change the production plans based on the occurring sales and production delays, the simulation will show much higher product unavailability and obsolescence of SKUs than in practice. Moreover, in practice, a lot of the products (96%) that pass 1/3 of their expiration time can in fact be sold even though they are sold against a discount price and not all customers want to receive these products (Kamp (2018)).

Out of stock & Stock Availability
In our simulation we assume that sales occur first in the morning, and after that, we receive the produced batches that are scheduled for production on that day. Therefore, in case sales occur and we do not have enough in stock at the beginning of that day we consider it to be an out-of-stock. Based on the stockouts we calculate the Stock Availability percentage per day and per SKU.

If (some) sales cannot be delivered in time and we have an out-of-stock we consider it to be back ordered, hence the theoretical stock level goes below 0 but the physical stock level will remain 0. In case we have back orders we first fulfill the demand of the back orders, before we fulfill the new demand arising. Therefore, if we do not have enough in stock to satisfy the back orders and the new sales orders we still have an out-of-stock on that day for that SKU. We model this in our simulation because the tactical planning of Grolsch has a preference for this way of simulation as well, as it would also better reflect reality.

Simulation results & outputs
Based on the original production plan (based on the current minimum Days of Cover), and on the 3 new production plans we run 4 different simulations. We evaluate the outcomes of the different simulations based on the Stock Availability percentages and the corresponding inventory-related operational costs. Moreover, we evaluate the effects that the new minimum Days of Cover allocations have on the warehouse capacity. The simulation results can be found in Section 6.2.

4.4 Sensitivity analysis

To check if the optimality of the outcomes would change in case the situation of Grolsch changes we perform a sensitivity analysis in Section 6.3. For the first results, we do not take along the production delays within our simulation even though we have incorporated the production delays in the calculation of the safety stock level. Grolsch has a KPI, called the production tracker, with which they measure the deviation between the planned quantity of a batch of an SKU and the actual finished quantity in that week. This is expressed in an average percentage per week. To illustrate an example if we plan 2 batches in week 1 of which 100 hectoliters of SKU X and 50 hectoliters of SKU Y for production and we find out in week 2 that we have produced a total of 80 hectoliters of SKU X and a total of 55 hectoliters of SKU Y in week 1, then the production tracker of week 1 equals ($\frac{\frac{80}{100}+\frac{55}{50}}{2}$ =) 95%. In case a lot of delays on the filling line take place batches are often shortened and/or moved to another week. Therefore, assuming a normal distribution, we can use the average and the standard deviation of this percentage to randomize the realized production batch size in order to simulate the effect that the production delay has on the optimality of the minimum Days of Cover allocation methods. The planning department schedules a number of hectoliters based on the operational standards. The operational standards change every year, so a disadvantage of using the production tracker of a different year is that the operational standards have been adjusted to these numbers already. However, this would be the best and easiest way to take along production delays.

Other than the production delays, we assume for our first results that an obsolete product can still be sold to the customers, which is not always realistic in the actual situation of Grolsch. Therefore, we perform a test where we subtract the obsolete SKUs from stock so we can measure what the effect of this is on the Stock Availability percentages of all 4 methods.

The last sensitivity analysis relates to the standard deviation of the forecast error of each SKU. We initially assume a fixed standard deviation of the forecast error per quarter per SKU. In reality, this standard deviation is often subject to change. Therefore we increase and decrease the standard deviations in terms of percentages such that we can see what it does to the results of all 4 methods.

4.5 Conclusion

We perform an ABC and an XYZ classification on the SKUs that we focus on within our research. The target Stock Availability percentage is based on the ABC classification solely. By using a static safety stock calculation for each week we get a safety stock level in hectoliters and convert this static safety stock level into a minimum Days of Cover by using the lead time demand for that week. This way we can calculate an average minimum Days of Cover for every classification or for every SKU, which we use as input to make the 3 new production plans. The 3 new production plans are made using the VMQ-method, the AA-method, and the ANA-method. The VMQ-method uses the classification per quarter of the SKU to vary the minimum Days of Cover per quarter per SKU (as each classification has a different minimum Days of Cover). The AA-method uses the minimum Days of Cover per classification to calculate an average minimum Days of Cover for each SKU that is fixed for the entire year. Finally, the ANA-method calculates an average minimum Days of Cover per SKU based on the minimum Days of Cover per week that we calculated for each SKU. Once we have the minimum Days of Cover for each method we can make the new production plans, which are made by the team lead of the Supply Chain Planning by increasing the opening stock and changing the production volumes only if needed to make a realistic production plan.

The production plan(s) together with the forecast of 2023 and the standard deviation of the forecast error of 2022 are used as input to simulate the effects of the inventory control method of Grolsch. The simulation registers overstockings but realized sales can still be fulfilled using expired SKUs. Moreover, if sales occur in the simulation when we do not have enough inventory to fulfill these sales we register the understockings but all these orders remain registered as back orders until we have enough stock available again. We evaluate the inventory control methods based on the realized Stock Availability percentage, the inventory-related operational costs, and the warehouse capacity utilization. To evaluate the robustness of the performance of the inventory control methods we perform different sensitivity analyses. First, we introduce production delays within our simulation by using the production tracker to randomize the percentage of the actual produced batch size versus the planned batch size. Second, we assume that none of the obsolete products can be sold anymore to the customers such that we can measure the effect it has on the Stock Availability percentage. Third, we change the standard deviations of the forecast error to assess the effect on the total costs and the Stock Availability percentage of each method.

5 New safety stock allocation and evaluation method

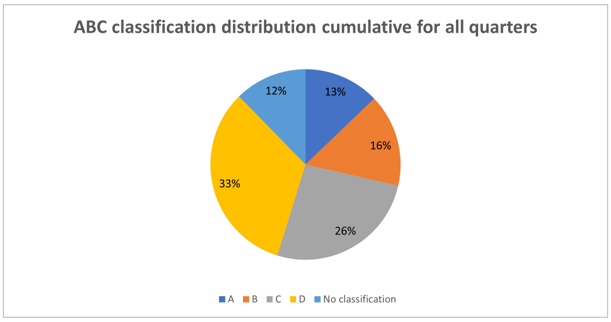
As we know the research method we first start to come to new safety stock allocations for each method in this chapter. We start in Section 5.1 by classifying all of the SKUs on which we focus in this research according to the combination of the ABC and the XYZ classification. Next, we calculate the safety stock levels in hectoliters for each SKU for each week in Section 5.2 using the formula that we found in the literature research. In Section 5.3 we calculate the minimum Days of Cover per week per SKU using the safety stock levels of each SKU of each week in hectoliters. With the minimum Days of Cover per SKU per week we calculate the minimum Days of Cover either per classification in Section 5.3.3 or per SKU in Section 5.3.4. Based on the new minimum Days of Cover, we first need to make new production plans. In Section 5.4 we describe in more detail how we create these new production plans. Next, in Section 5.5 we elaborate on the tests that we have done to find out the distribution of the forecast errors and we explain which distribution we use to simulate the forecast errors and why. In Section 5.6 we describe how we generate the forecast error and thus the demand per day in the simulation, after which we describe in Section 5.7 how we generate the day the production takes place in the simulation. In Section 5.8 we describe how we calculate the stock levels within the simulation and how we arrive at the operational costs and a Stock Availability percentage based on the input. Finally, in Section 5.9 we conclude this chapter.

5.1 SKU classification

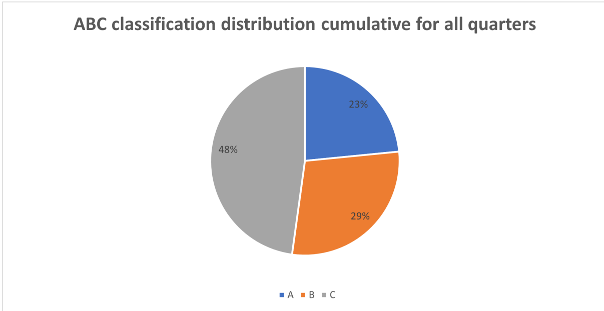
To get to a new safety stock allocation we first need to arrive at an SKU classification to base the target Stock Availability percentage on for the SKUs. The SKU classification consists of 2 parts, namely the ABC classification (described in Section 5.1.1), and the XYZ classification (described in Section 5.1.2). In the last part of this section (Section 5.1.3) we describe how every Filling Line 2 SKU is classified using the combination of the ABC and the XYZ classification.

5.1.1 ABC classification

The ABC classification is based on the percentage of sales volume of the SKU compared to the total sales volume of all SKUs. Therefore, we need to use the sales volume of all active SKUs that Grolsch is currently selling. However, we will leave the MTO products, the recently developed products (with less than 1 year of sales data), and the export products out of these calculations. That is because these products all receive another classification within Grolsch as described earlier in Section 2.2.1. To get the ABC classification of all SKUs we take the weighted average of the Net Producer Revenue (NPR) over 2022, and 2023. The NPR equals the gross margin on each SKU at Grolsch per Hectoliter. The NPR is weighted by means of the volume in hectoliters in which it is sold. The weighted average NPR over 2022, and 2023 is multiplied by averaging the actual sales volume of 2022 of the specific quarter, and the forecasted demand volume of 2023 of the specific quarter. This way we have an average sales volume of each SKU for each quarter of the year based on expectations and historical data. The average sales volume of the SKU is divided by the total sales volume of all other MTF SKUs that receive either an A, B, or C classification. That leaves us with a percentage of the total sales volume. By sorting the percentages from high to low, and calculating the cumulative percentage of sales volume from high to low, we give every SKU with a cumulative percentage lower than or equal to 80% an A classification, all SKUs with a cumulative percentage lower than or equal to 95% receive a B classification, and all of the SKUs that account for the last 5% are given a C classification. That leaves us with an ABC classification for every SKU for every quarter. About 33% of the SKUs that are currently actively sold on the domestic market by Grolsch are Made-To-Order. In addition, we have about 12% of the total number of SKUs that are actively sold on the domestic market that have been recently introduced to the market (less than 1 year of sales data available). That means we have about 55% of the active SKUs left to classify as either A, B, or C. Of this 55% about 23% of these SKUs account for 80% of the sales, and about (23%+29%=) 52% account for 95% of the sales. The remaining 48% of the SKUs account for the last 5% of the total sales volume. Below in Figure 8a, and 8b the percentages of the ABC division are visualized in circle diagrams. In addition, to show how the new classification compares to the old classification we made a graph in Figure 9. The graph shows what the previous classification was of each current classification. To illustrate an example, 44% of the SKUs that are now classified as A was previously classified as B.



(a) The division of the ABC classification of all of the active SKUs of Grolsch.



(b) The division of the ABC classification of all of the active SKUs of Grolsch that are sold in the domestic market, and produced to forecast.

Figure 8: The division of the ABC classification of all of the active SKUs of Grolsch. Every SKU can have another classification per quarter.

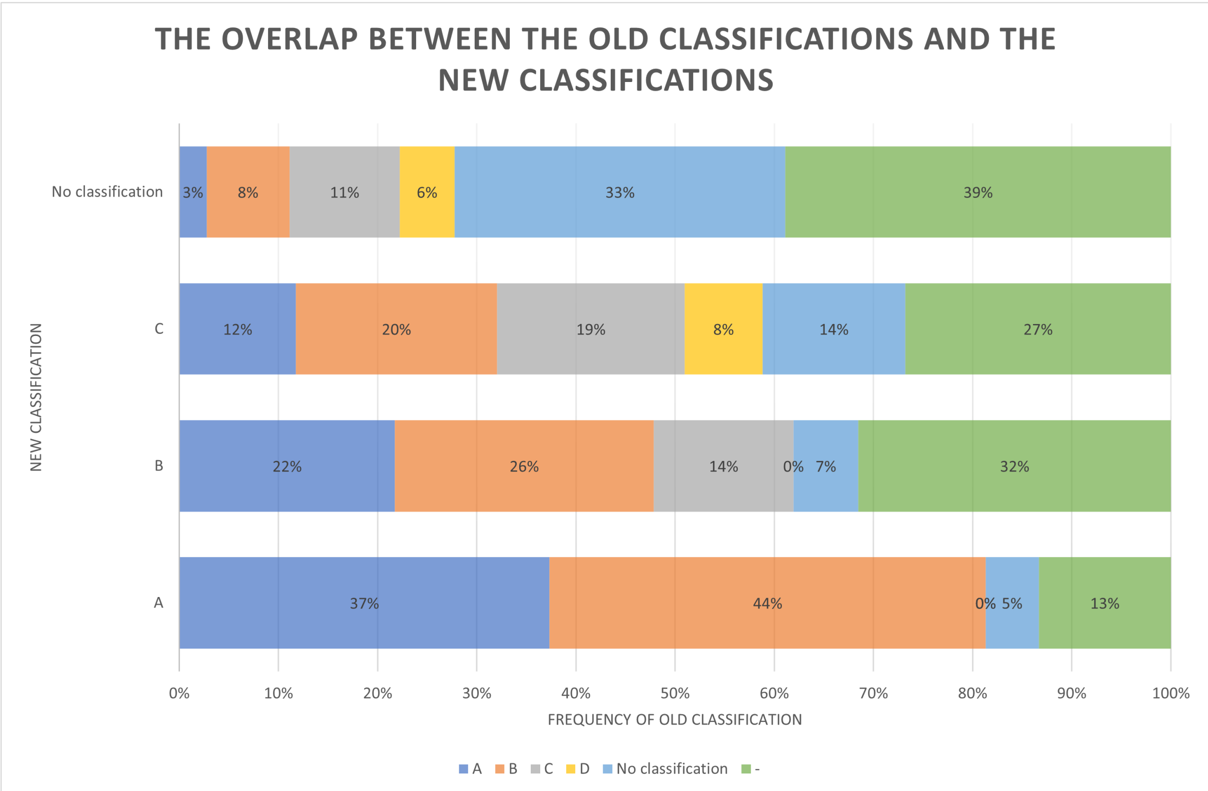
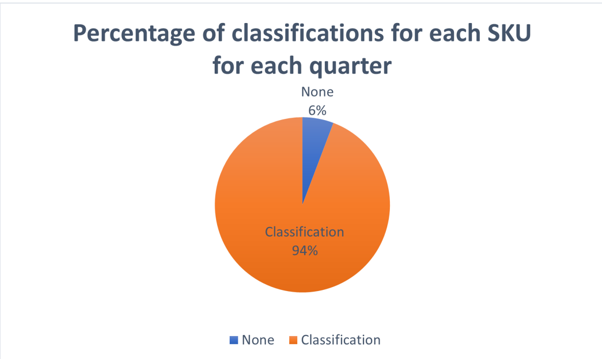


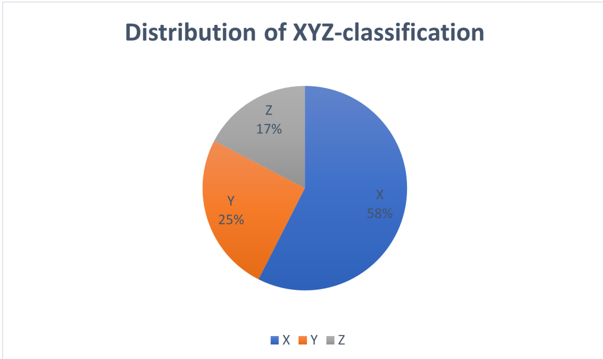
Figure 9: The graph shows what the previous classification was of each current classification. For example, 44% of all new MTF-A classifications were classified as MTF-B in the old classification. Take in mind here that every SKU has 4 classifications, namely 1 for each quarter.

5.1.2 XYZ classification

The XYZ classification serves to classify the SKUs according to the predictability of the demand volumes. Therefore, to measure the predictability we take the absolute differences between the forecasted demand, and the actual sales volume per week for the last 2 years (from the first week of 2020 until the last week that we have actual demand data available in 2022, which is week 42). We have chosen to take the coefficient of variation of the absolute forecast error of the year 2022 to give an indication of the predictability of the SKU. We use the absolute forecast error because in case the forecast is unbiased the average forecast error would be 0, which means we cannot calculate a coefficient of variation as we would have to divide by 0 in that case. The coefficient of variation is calculated by dividing the standard deviation of the absolute forecast errors by the mean absolute deviation over 2022, hence the value indicates how much the absolute forecast error fluctuates from the mean absolute forecast error. For a normal distribution, the coefficient of variation should then be 1.25. However, only for this XYZ classification do we discard the assumption that the forecast errors are normally distributed. Normally, when the XYZ classification is determined based on the coefficient of variation of the actual sales it is a regular practice to give an X classification to SKUs that have a coefficient of variation that is less than or equal to 0.25, a Y classification to SKUs that have a coefficient of variation that is less than or equal to 0.5, and the remaining SKUs are given a Z classification (t2informatik GmbH, 2023). However, as the XYZ classification should indicate how difficult it is to forecast the demand for a certain SKU instead of determining how the demand fluctuates we might need to set different thresholds for the coefficient of variation to classify the SKUs. Therefore, to check how we should classify these SKUs we try some values and see what the distribution of the classification looks like. Using the trial and error method we found thresholds of P, and Q. These thresholds implicate that SKUs with a coefficient of variation of the absolute forecast errors lower than P have an X classification, SKUs with a coefficient of variation lower than Q have a Y classification, and the left-over SKUs have a Z classification. The classification is again done per quarter per SKU and we need to take into account that some SKUs do not have a classification in every quarter because they are not (actively) sold in every quarter. For the analysis of the XYZ distribution, we have only looked at the SKUs that are sold in the domestic market exclusively for longer than 1 year, and produced to forecast. In Figure 10a it is visible how many quarters of all active SKUs that are produced to forecast have received a classification. From the 94% that received a classification, we have given the division between X, Y, and Z with the given thresholds of the coefficient of variation (P, and Q) in Figure 10b.



(a) The division of the number of SKUs that have a classification versus the non-classified SKUs.



(b) The division of the XYZ classification of all SKUs that have received an XYZ classification.

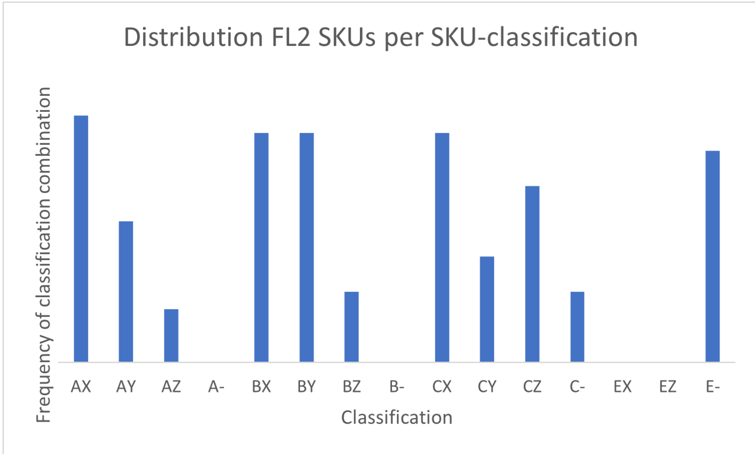
Figure 10: The division of the XYZ classification of all of the SKUs of Grolsch. Every SKU can have another classification per quarter.

5.1.3 Classification Filling Line 2 products

With the ABC and XYZ classifications done, we can evaluate the SKU classification of all Filling Line 2 SKUs based on the combination of both classifications. Remember that every SKU receives 4 classifications (one classification every quarter). Below in the table in Figure 11a the frequency in percentages of each classification is visible. 12% of the SKUs are exported, hence these receive a classification of "E-". The other 88% of the SKUs receive another classification per quarter, and the frequencies of these are given in Figure 11b.

	X	Y	Z	-	Total
A	14%	8%	3%	0%	25%
B	13%	13%	4%	0%	30%
C	13%	6%	10%	4%	33%
D	0%	0%	0%	0%	0%
E	0%	0%	0%	12%	12%
Total	40%	27%	17%	16%	100%

(a) The frequency of each classification combination in percentages.



(b) The frequency of each classification, without the export SKUs.

Figure 11: The frequency of the ABC-XYZ classification of all of the active SKUs that are filled on Filling Line 2.

Service Level targets

Based on the SKU classification we can determine a desired Service Level per classification. We now know that about 12% of the Filling Line 2 SKUs are exported, which should be kept out of the scope of this research as discussed in Section 1.3.2. All other SKUs will receive a service level target. The service level targets should be given by means of a Stock Availability percentage and the target percentage should be based solely on the ABC classification as already discussed in Section 4.1. SKUs classified in categories A, B, and C have a target of 99.5%, 98.5%, and 97.5%, respectively.

5.2 Safety stock level calculations

To calculate the safety stock levels we use the formula of Equation 27. To solve Equation 27 for every SKU j for every week t we need (to calculate) several variables and parameters. In this section, we elaborate in more detail on how we calculate the static safety stock level for every week and how we calculate a minimum Days of Cover per classification using the static safety stock level per week.

5.2.1 Parameter values

We know from the current situation that: the expected lead time is equal to y days, the standard deviation of the lead time duration is equal to $\frac{z}{24}$ days, the review period is equal to 5 working days, and the target Stock Availability percentage for each SKU classified as A, B, or C is 99.5%, 98.5%, and 97.5%, respectively. That means that we do not use the XYZ classification to determine the target Stock Availability percentage, but we do use the XYZ classification later in Section 5.3.1 to determine a minimum Days of Cover per classification for the VMQ-method and the AA-method. Moreover, we have done the ABC classification, so we know the target Stock Availability percentage for each SKU per quarter.

5.2.2 The average demand per week

To calculate the average demand per week for SKU j in week t we take the sum of the expected lead time and the review period $(R + E(L))$ and we calculate how many hectoliters we sell according to the forecast of 2023 from week t up until week number T. Assuming the lead time starts at the beginning of the week $t + R + E(L)$, which is rounded up to the nearest integer. We assume here that the demand of the week is equally divided over the days. Based on the demand during the lead time and the review period we calculate the average demand per week by dividing the forecasted demand of 2023 during the lead time and the review period by the expected duration of the lead time and the duration of the review period. Due to a changing demand per week t for every SKU j we get a different μ every week for every SKU. Using this average demand per week we calculate the expected demand during the review period $E[D_{R_{j,t}}]$ and the average demand during lead time $\mu_{D_{j,t}}$ by multiplying this weekly demand with the review period (R) and the expected lead time duration ($E(L)$), respectively.

5.2.3 The standard deviation of the demand per week

The standard deviation of the demand per week for SKU j in quarter k is equal to the standard deviation of the forecast error per week. The standard deviation of the forecast error per week is calculated over 2022 by using the Mean Squared Error method. The Mean Squared Error is calculated using Equation 9 in Section 3.3.2. The MSE is calculated separately for every SKU j per quarter k, so by taking the square root of the MSE we have an approximation of the standard deviation of the forecast error for each SKU j in each quarter k. The standard deviation of the demand during the review period $\sigma_{R_{j,k,t}}$ and the standard deviation of the demand during lead time is calculated using this standard deviation of the demand per week by multiplying the standard deviation of the weekly demand with the square root of the review period (R) and the square root of the expected lead time duration ($E(L)$), respectively.

5.2.4 Calculation of the undershoot

With the average demand during the review period and the standard deviation of the demand during the review period known, we can calculate the expected undershoot with Equation 29 and the variance of the undershoot with Equation 30, for which we use Equation 31 and Equation 32 to calculate the second and third order moments of the expected demand during the review period.

5.2.5 Calculation of standard deviation of forecast error under lead time uncertainty, forecast uncertainty, and undershoot

To calculate the standard deviation of the forecast error during the lead time ($\sigma'_{F_{j,k,t}}$) in case we forecasted the demand, we have an uncertain lead time duration, and we have to deal with a periodic review inventory control method we use Equation 28.

5.2.6 The batch size

As mentioned in Section 4.2 we use the average batch size that Grolsch has planned for the SKU j in 2023 to determine lot size Q_j.

5.3 Calculating a minimum Days of Cover

The safety stock in hectoliters still needs to be translated into a safety stock in Days of Cover, as Grolsch is using the minimum Days of Cover method. In this Section, we describe how we arrive at the new minimum Days of Cover per classification for Grolsch.

5.3.1 From HL to DoC

We solved the safety stock equation every week for every SKU, and we divided that safety stock level by the average demand per week (which was calculated separately for every week based on the demand during the lead time and the review period). Then we have the Weeks of Cover, and to transform it into a Days of Cover we multiply the Weeks of Cover by 5. With the Days of Cover per week per SKU we can calculate an average Days of Cover per quarter per SKU and we can calculate an average Days of Cover for the entire year per SKU. For the VMQ-method and the AA-method, we calculate the Days of Cover per category, based on the classification that we have given each SKU per quarter. For the ANA-method we do not use the classification and we calculate one minimum Days of Cover for the entire year per SKU.

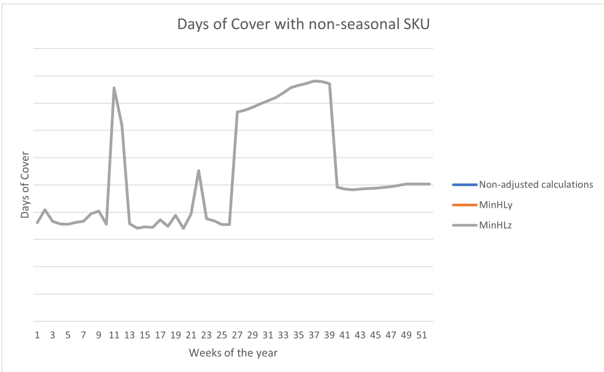
5.3.2 Analysing the Days of Cover

Causes of high and low Days of Cover

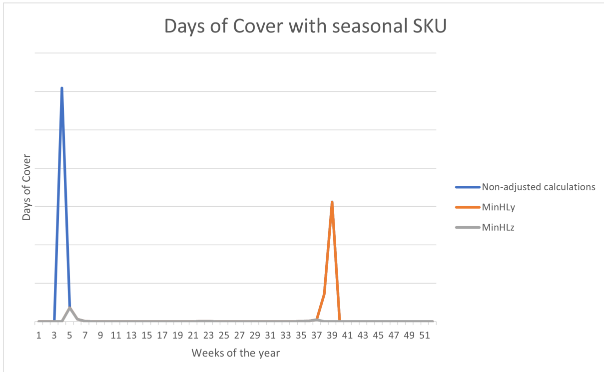
The method that we have described to calculate the Days of Cover does have some flaws. The method leads to widely varying results, as for some weeks and SKUs this leads to very high Days of Cover, whilst for other combinations it leads to very low Days of Cover. After a quick analysis, we noticed that a very low Days of Cover is often caused by a very high batch size in combination with a very low standard deviation of the lead time demand. The high Days of Cover are often caused by very low forecasts in some weeks. For example, some SKUs have a forecast of x hectoliters in one or more weeks.

High Days of Cover

To prevent having very high Days of Cover we have done a few tests. By setting a minimum threshold for the lead time demand for every week for every SKU that we need to take along in our calculations we want to prevent having very high Days of Cover. If the lead time demand is below a certain amount of hectoliters we discard the Days of Cover calculated for that week for that SKU. Below in Figure 12 the results of the tests for both a seasonal SKU and a non-seasonal SKU are visible. In the figure, we show the Days of Cover for a seasonal and a non-seasonal SKU per week that we have calculated. The figure shows the results for when we do not set a minimum threshold for the lead time demand (”Non-adjusted calculations”) when we set a minimum threshold of y hectoliters (”MinHLy”), and when we set a minimum threshold of z hectoliters (”MinHLz”).



(a) The ss calculated in DoC for a non-seasonal SKU with the different minimum thresholds for the lead time demand. We can see that all series follow the same line.



(b) The ss calculated in DoC for a seasonal SKU with the different minimum thresholds for the lead time demand.

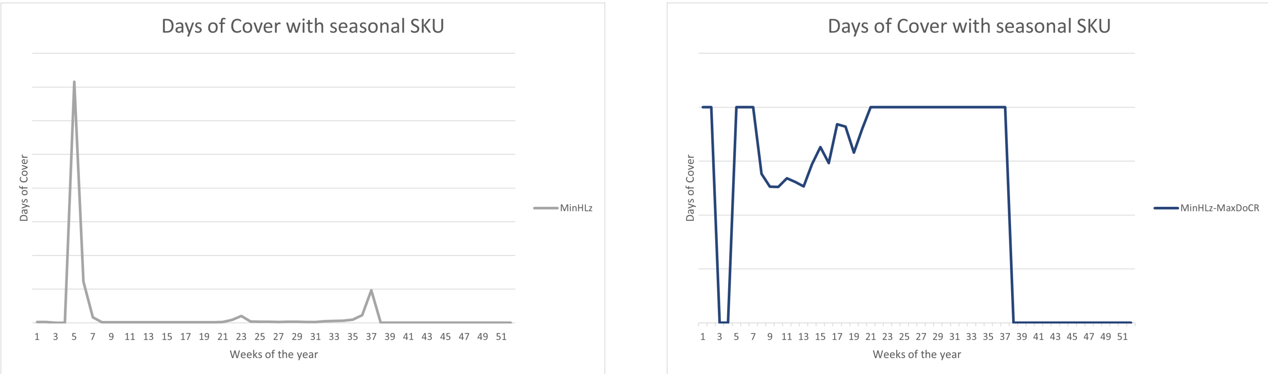
Figure 12: The safety stocks in Days of Cover per week of the year over 2023 for both a non-seasonal and a seasonal SKU.

In Figure 12 we can see that the seasonal SKU has multiple weeks for which we calculated very high Days of Cover as the lead time demand is below the threshold quite sometimes, whilst for the non-seasonal SKU the lead time demand is always above the threshold. If we set a minimum lead time demand and discard the Days of Cover that we calculated if the lead time demand for that SKU in that week is below the threshold we can filter out most of the outliers and get more realistic results for the average minimum Days of Cover. When removing the series in the graph for the seasonal SKU where we do not set a minimum threshold for the lead time demand (”non-adjusted calculations”), and where we set a minimum threshold for the lead time demand of y hectoliters (”minHLy”), we are left with a very different graph already, as shown in Figure 13a. In this graph, it is visible that we are still dealing with extremely high values for the Days of Cover for the seasonal SKU. These very high Days of Cover are caused by a combination of multiple factors. We only have these very high Days in case all of the criteria below are satisfied:

- The SKU is only sold actively during 3 seasons or less (thus the SKU has a very seasonal demand pattern).
- In the specific week for which we calculate the Days of Cover the SKU has a very low lead time demand forecasted compared to the total forecast during that quarter.

- The standard deviation of the forecast error of the SKU is high during the specific quarter.
- The average batch size of the SKU over the entire year is rather low.

We want to filter out the (extreme) outliers, but we do not want to remove too many observations. For some SKUs Γ HL of demand may not be as much, whereas for others it might be regularly seen. Therefore, we set a maximum Days of Cover in case the Days of Cover are still very high whereas the lead time demand is higher than the threshold that we have set. In our opinion, a maximum Days of Cover of R, would be more than reasonable. This way we can filter out all extreme outliers. In Figure 13b the Days of Cover over the weeks of the year are shown for the seasonal SKU when setting a minimum lead time demand of z hectoliters and a maximum Days of Cover of R.



(a) The ss calculated in DoC for a seasonal SKU with the threshold for the minimum lead time demand set at y HL.

(b) The ss calculated in DoC for a seasonal SKU in case we use a threshold for the minimum lead time demand of y HL and we use a maximum Days of Cover of R.

Figure 13: The safety stocks in Days of Cover per week of the year over 2023 for a seasonal SKU when setting a threshold for the minimum lead time demand and a threshold for the maximum Days of Cover (or not).

Low Days of Cover

Besides a very high Days of Cover we also have a very low Days of Cover in some cases. To filter out the outliers that have very low Days of Cover we do not differ the standard deviation of the forecast error, because the standard deviation of the forecast error has been calculated based on historical data. Moreover, we do not change the production batch size to filter out the outliers with very low Days of Cover, because we based this production batch size on the average production batch size that is planned for 2023. Therefore, the easiest way to filter out the outliers is to set a minimum for the minimum Days of Cover that we calculated for every week for every SKU. We think that a minimum Days of Cover lower than x is not realistic, therefore if the Days of Cover of a week of an SKU is lower than x, we set the Days of Cover equal to x.

5.3.3 New Days of Cover per classification

To calculate a minimum Days of Cover for every classification for the VMQ-method and the AA-method we look at the classification of every SKU in every quarter and the average Days of Cover that we have calculated for that SKU in that quarter. To illustrate an example if SKU 1 is classified as AX in quarter 1 (average DoC is 5) and SKU 2 is classified as AX in quarter 4 (average DoC is 4), then we calculate the Days of Cover for classification AX by taking the average of both, which is ($\frac{4+5}{2}$ =) 4.5. Then for both quarters of these SKUs, we will make sure in the production plan that the Days of Cover will always be higher than 4.5. Below in Figure 14 the new minimum Days of Cover is given for every classification using our method. We show the current minimum Days of Cover that Grolsch maintains and the new minimum Days of Cover that we propose for every classification. As a side note, we should mention that the current minimum Days of Cover per classification is based on our classification. The new minimum Days of Cover that we propose, as visible in Figure 14, show that the difference between A, B, and C is significant as the minimum Days of Cover for all A products is higher than the minimum Days of Cover for all B products regardless of the XYZ classification. For the C products, the minimum Days of Cover is also lower than for all the B products, except for the classification CZ. Moreover, we can see that the XYZ classification does not have a significant impact on the minimum Days of Cover, except for classification CZ. As classification CZ shows to be an exemption we have looked into why these minimum Days of Cover deviate from the general trend that we see. We found that classification CZ shows an exceptionally high minimum Days of Cover due to the fact that SKUs with a very seasonal demand pattern still show a very high standard deviation of the forecast error during low season when the sold volume in HL drops a lot. Percentage-wise the drop in the average weekly sold volume is much higher than the drop in the standard deviation of the forecast error of these SKUs, which makes the fact that a rather high minimum Days of Cover is calculated for these SKUs.

In general we can argue that the minimum Days of Cover are very dependent on the target Stock Availability percentage, as we did not differ in this for the XYZ classification, but we did differ in this target for the ABC classification. Moreover, when classified as an A product we need an average minimum Days of Cover of 200% of the regular minimum Days of Cover (for 99.5% Stock Availability), when classified as a B product we need an average minimum Days of Cover of 160% of the regular minimum Days of Cover (for 98.5% Stock Availability), and when classified as a C product we need an average minimum Days of Cover of 147% to 160% of the regular minimum Days of Cover (for 97.5% Stock Availability).

Classification	Current minimum DoC	New minimum DoC
AX	100%	193%
AY	100%	200%
AZ	100%	193%
BX	100%	160%
BY	113%	167%
BZ	100%	153%
CX	100%	147%
CY	87%	140%
CZ	100%	187%

Figure 14: The minimum Days of Cover per classification that is currently maintained by Grolsch and the minimum Days of Cover per classification that we propose with our new method in percentage of the regular minimum Days of Cover.

5.3.4 New Days of Cover per SKU

As we have a minimum Days of Cover per classification such that we differ the minimum Days of Cover per classification we also have a method where we calculate one minimum Days of Cover per SKU that is valid for the entire year. The AA-method uses the minimum Days of Cover per quarter given in Figure 14 to calculate a minimum Days of Cover per SKU for the entire year and the ANA-method uses the minimum Days of Cover per week of each SKU to calculate an average over all 52 weeks in order to come to a minimum Days of Cover for each SKU for the entire year. From the new minimum Days of Cover per SKU we notice that for both the AA-method and the ANA-method the minimum Days of Cover are much higher than the current minimum Days of Cover that Grolsch is using. The current minimum Days of Cover are on average 109% of the regular minimum Days of Cover, whilst the average for the AA-method and the ANA-method are 163% and 174%, respectively. Moreover, we see as expected that the minimum Days of Cover for the ANA-method shows a much bigger difference in the lowest minimum Days of Cover and the highest minimum Days of Cover than when we aggregate the minimum Days of Cover by classification.

5.4 New tactical production plans

Using the new minimum Days of Cover per classification and the new minimum Days of Cover per SKU, we want to simulate the effect it has on the Stock Availability percentage and the (inventory-related operational) costs of Grolsch. Before we can simulate the stock levels of Grolsch we need to make new production plans for 1 year ahead based on the new minimum Days of Cover allocations. As mentioned in Section 4.3 the team lead of the Supply Chain Planning makes these new production plans. In order to increase the minimum Days of Cover the Supply Chain Planning team lead increased the opening stock and where needed the production quantities were adjusted, such that all of the constraints are still satisfied. The following situation is an example of when the production quantities are adjusted. Consider a seasonal SKU of which we produce much more on stock than we are able to sell before the end of the season due to the increased opening stock. In this case, we reduce the last production quantity at the end of the season and we add this reduced quantity again later that year as the total produced quantity will have to remain the same as the total forecasted quantity.

5.5 Input distribution forecast errors

To simulate the forecast errors for the SKUs we need to have an input distribution on which the forecast error per week will be based. To find out with which theoretical probability density function we can best generate the forecast error, we have performed Pearson's Chi-Squared test on the forecast errors per week that were given from 2020 up until the third quarter of 2022. After having performed this test we found out that the normal distribution might not be the best distribution to generate the forecast errors with, as only 33% of the Filling Line 2 SKUs would not reject the hypothesis that the forecast errors follow a normal distribution (with a significance of 5%). Nevertheless, we already based the safety stock calculations on a Normal-distribution and for some SKUs the Normal-distribution is in fact a good approximation. However, we do not see clear relations between the type of SKU and whether it follows a normal distribution or not. We would have expected to see that SKUs with a very seasonal demand pattern, which are often harder to forecast, would not show a normal distribution of the forecast errors. On the contrary, we would have expected that SKUs following a stable demand pattern over the entire year would have a forecast error distribution that does look similar to a normal distribution. However, both are not the case. In addition, the current data set is subject to some events that have a big impact on the forecast, and demand distribution like COVID-19 (we tried to avoid this as much as possible), and the national prevention agreement (a law from the government that alcoholic beverages can only be reduced a maximum of 25% of its normal price in retail when giving discounts). Therefore, we use the normal distribution in the simulation to generate the forecast errors. For a more elaborate description of how we applied Pearson's Chi-Squared test to the data, we refer to Appendix A.

5.6 Generating the forecast errors and the demand

To generate the forecast errors within the simulation we are drawing a number from a normal distribution with mean μ, and standard deviation σ. For μ we assume here that this is 0, as we assume that the demand planning adjusts the forecast such that it fluctuates around 0. The σ is calculated based on the forecast errors per week of the SKUs from the previous year using the MSE method. The forecast per week for the next year that we would like to simulate is taken from the file that Grolsch currently has available. The absolute generated forecast error cannot be greater than the forecast, because negative demand should not be possible. Moreover, if we set a lower bound for the forecast error (to prevent negative demand) we also need to set an upper bound for the forecast error otherwise, the average forecast error would have a positive bias. A distribution with a positive bias would be unrealistic and incorrect since the forecast error is then not fully normally distributed with an average of 0. The tactical planning of Grolsch indicated that they want to assume a forecast error that is 0 on average. Therefore, we have set an upper bound for the generated forecast error. The forecast error cannot exceed the forecast for each week. The upper and lower bound mostly affect the demand of the SKUs in a week during which the forecast is rather low and the standard deviation of the forecast error is relatively high. Based on the available forecast per week, and the generated forecast errors per week we can calculate the demand per week. The demand per week then depends on the Stock Availability. In Section 5.8.3 we describe in more detail how we handle demand if we are out of stock. Based on the forecast, the forecast errors, and the demand per week we can calculate all of these per day. First, we calculate the demand per day based on the demand per week. To determine on which working day each hectoliter is sold we draw a random number from 1 to 5 according to the probabilities shown in Table 2 (Grolsch only sells on working days). The forecast per day is thus on average equal to the probability of occurrence multiplied by the total weekly forecasted demand.

Working day	Monday	Tuesday	Wednesday	Thursday	Friday
Probability	0.2	0.2	0.2	0.2	0.2

Table 2: The distribution of the demand over the weekdays

5.7 Generate the scheduled weekday

If the production is planned for a certain week, then the scheduler needs to schedule the production somewhere in that week. However, the specific scheduling time is not known by the tactical planning. Therefore, we need to generate the day that the production is scheduled for each production SKU. We assume here that every SKU can be placed in every position of the weekly schedule on the filling line with an equal chance. So for example, if we have 6 SKUs to be scheduled on Filling Line 2 in week 1, then the first SKU has a probability of $\frac{1}{6}$ of being produced first in week 1, but the first SKU also has a probability of $\frac{1}{6}$ of being produced the last in week 1. Based on the position of the SKU within the weekly schedule we look at the volume in hectoliters that is scheduled of each SKU. The volume in hectoliters that has been produced before the SKU determines on which day the production batch becomes available in stock. In Equation 35 we show how we calculate $ProductionDay_{j,m,pos}$, which represents the day number in the week on which the production batch of SKU j which is scheduled in week m and in position number pos in the weekly schedule becomes available in stock. Normally we should also introduce a subscript for the specific Filling Line as every Filling Line has its own weekly schedule however, we leave this subscript out of the formula given the fact that we focus our research on Filling Line 2 only. In the formula in Equation 35 $SKUVolume_{j,m,u}$ represents the volume in HL that is scheduled of SKU j in week m, which is scheduled in position number u of that week. $TotalVolume_m$ represents the total volume in HL that is scheduled in week m on the filling line. Moreover, the number 7 in the equation represents the 7 working days that we have available on Filling Line 2 as we work in 5 shifts over the entire year. For the first position in the schedule, we set the day that (part of) the produced batch size is available on day 1 of the week. If the position in the weekly schedule of the batch is higher than 1 we calculate what fraction of the total HL has been produced before in week m to calculate how many days have passed before we start with batch number *pos* in the weekly schedule, and then we round up the number of days that we calculated. We assume that after the batch has started the full batch is in stock, because once the batch starts production most of the produced batches are almost immediately available in stock (at least enough to fulfill the orders of that day).

$$ProductionDay_{j,m,pos} = \begin{cases} 1, & \text{if } pos = 1 \\ \left\lceil 7 \cdot \frac{\sum_{u=1}^{pos-1} SKUVolume_{j,m,u}}{TotalVolume_m} \right\rceil, & \text{otherwise} \end{cases} \tag{35}$$

5.8 Calculating the stock levels and the operational costs

Based on the simulated forecast errors and production day of the week we can calculate the stock levels and therefore the resulting Stock Availability percentages and operational costs of Grolsch. Below we describe step by step how we calculate the output within our simulation. We start in Section 5.8.1 with the calculation of the opening stock. Next, in Section 5.8.2 and in Section 5.8.3 we describe how we calculate the number of overstockings and understockings. In Section 5.8.4 we describe how we calculate the Stock Availability percentage(s) before we describe how we calculate the stock level in the warehouse in terms of pallets in Section 5.8.5. Finally, we elaborate on how we calculate the total operational costs in Section 5.8.6.

5.8.1 Calculating the daily opening stock

With the demand per day and the production per day, we can calculate the daily changes in the opening stock level. The opening stock of the next day is calculated by adding the production and opening stock of today and subtracting the sales of today. In Equation 36 the calculation of the daily opening stock is shown, where $\pi_{j,m}$ equals the production batch finished on day m of SKU j, $\rho_{j,m}$ equals the number of sales on day m of SKU j, and $\omega_{j,m}$ equals the opening stock of day m of SKU j. The opening stock on the first day of the simulation is calculated using a combination of the initial stock with which the production plan is made and the batches that are in stock. In the next section, Section 5.8.2, we explain why we need to work with batches on stock and we explain further how the opening stock of the first day is calculated.

$$\omega_{j,m+1} = \omega_{j,m} + \pi_{j,m} - \rho_{j,m} \tag{36}$$

5.8.2 Calculating the overstockings

As we have to deal with perishable SKUs in inventory we keep track of the age of each production batch within the inventory. When making the production plan tactical planning takes into account an opening stock for each SKU. The opening stock of each SKU can consist of multiple batches with different production dates and thus different expiration dates. To simulate the age of the batch at the beginning of the year we draw a random number using an exponential distribution with x days being the average age of a batch, where the age of the batch is between 0 days and the shelf life of the SKU in days. We came to an exponential distribution with an average batch age of x due to an analysis that we have done on the age of the batches in stock that we had gotten on the first of December of Grolsch. We have chosen to split the stock into batches of y HL each, hence if an SKU has $2.5 \cdot y$ HL in stock on day 1 we split this $2.5 \cdot y$ HL into 3 batches of which 2 batches contain y HL and 1 batch contains $\frac{1}{2}y$ HL. For each of these batches, we then draw a random age from the exponential distribution.

At the start of every day we first check the age of each batch. If the age exceeds the shelf life of the SKU, which is 1/3 of the expiration date, we consider it an overstocking. The production plan is made in such a way that the total production per SKU over the year equals the total demand per SKU over the year. Therefore, we do not subtract an overstocking from the total stock level, but we do note the obsolescence. If we would subtract the obsoletes from the total stock level and we receive demand after the products have been declared obsolete we would see both a high amount of over- and understockings and a very erratic stock movement. Moreover, tactical planning would normally interfere in such a situation up front, and the noted overstockings would already lead to higher obsolescence costs which affect the quality of the production plan in the simulation anyway. To showcase what the effect is when products cannot be sold once they have passed 1/3 of their expiration time we have done a test in the sensitivity analysis in Section 6.3.2.

5.8.3 Calculating the understockings

We assume that the incoming orders are satisfied first thing in the morning, which is also often the case at Grolsch, and after that, the produced batches are available in stock. Moreover, we assume that all of the batch sizes are sold by means of the FIFO method, which means that the oldest batches will be used first. The understockings are calculated by subtracting the demand from the opening stock. The demand of SKU j on day m is given by $\zeta_{j,m}$. The understocking cannot be negative, therefore if the result of the calculation is negative, we take the understocking to be 0. Below in Equation 37 the understocking calculation is shown, where $U_{j,m}$ represents the understockings on day m for SKU j. The description of the other variables is given in Section 5.8.1. We discussed in Section 5.8.2 that we do not subtract overstockings from the stock level. For the same reasons we choose to not consider the understockings as lost sales, but as back orders. By treating the understockings as back orders we can register the understockings when they occur on each day for each SKU, but we will allow the stock levels to go below 0 (at least the theoretical ones). Allowing the stock levels to go below 0 also means that we will first fulfill the back orders before being able to fulfill the new incoming sales orders.

$$U_{j,m} = \max\{\zeta_{j,m} - \omega_{j,m}, 0\} \tag{37}$$

5.8.4 Stock availability

To calculate the stock availability of a specific SKU on a specific day we check if demand occurred for that specific SKU on that specific day. If there is in fact realized demand on that day for that specific SKU, then we check the opening stock level of that SKU. If the opening stock level is lower than the demand for that day, then we set the Stock Availability of that day for that SKU equal to 0. In all other cases, we set the Stock Availability to 1. This way we can aggregate the stock availability both per SKU and per day, and it enables us to calculate a stock availability percentage for all SKUs for 1 year. We can calculate the Stock Availability for SKU j on day m ($SA_{j,m}$) as shown in Equation 38.

$$SA_{j,m} = \begin{cases} 0, & \text{if } \omega_{j,m} \leq \zeta_{j,m} \\ 1, & \text{otherwise} \end{cases} \tag{38}$$

5.8.5 Warehousing stock levels

The stock levels that we calculate as described above in Section 5.8.1 are expressed in hectoliters. However, the warehousing department uses the number of pallets to express the total stock level as the number of pallets is a better indication of the capacity utilization of the warehouse. Not every pallet fits the same amount of hectoliters of each SKU, hence we use the number of hectoliters per pallet of an SKU to express the stock level of each SKU in pallets. Next, we can sum over the SKUs to calculate the total stock level. Negative stock levels are of course not summed, as it is physically impossible to have a negative stock.

5.8.6 Total costs

To calculate the total costs we need to calculate the total holding costs and the total overstocking costs. We have already calculated the number of overstockings, and the stock level per SKU per day in pallets. The obsolescence costs we calculate by using the formula shown in Equation 39, where M_j represents the profit margin of SKU j, $OS_{j,m}$ represents the number of hectoliters that of SKU j that exceeds $\frac{1}{3}$ of its expiration time on day m, and $\Lambda_{OS_{j,m}}$ represents the total overstocking costs of day m of SKU j. Remember from Section 2.2.2 that the obsolescence costs were estimated at 29% of the gross profit margin of the product at Grolsch.

$$\Lambda_{OS_{j,m}} = OS_{j,m} \cdot 0.29 \cdot M_j \tag{39}$$

Finally, to calculate the holding costs we use the formula shown in Equation 34 in Section 4.3.

5.9 Conclusion

By means of a combination of the extended ABC and the XYZ classification, we have classified every Filling Line 2 SKU. Using the ABC classification we have set a service level target, and we have calculated the safety stock level in hectoliters for every week for every SKU before converting it into a minimum Days of Cover every week by dividing it by the average weekly demand and multiplying the division by 5. Using the classification that we have done and the average Days of Cover that we calculated for every SKU per quarter we can calculate an average minimum Days of Cover per classification for the VMQ-method and the AA-method. We can see that the minimum Days of Cover per classification follow the expected pattern, such that minimum Days of Cover for the A classifications (which have a higher service level) are higher than the B classifications and (most) C classifications. In addition, we see that if we look at the average new minimum Days of Cover we need on average a minimum Days of Cover of 200% of the regular minimum Days of Cover in order to reach 99.5% Stock Availability (for A products), we need a minimum Days of Cover of 160% of the regular minimum Days of Cover in order to reach 98.5% (for B products), and we need a minimum Days of Cover of 147% to 160% of the regular minimum Days of Cover in order to reach 97.5% (for C products). For the ANA-method we calculate a fixed minimum Days of Cover per SKU by averaging the Days of Cover that we calculated for the SKU per week. Comparing the current minimum DoC to our newly calculated minimum DoC we observe that the current minimum DoC is lower than any other new minimum DoC. Therefore, if it appears that our method to calculate the new minimum Days of Cover would perform better Grolsch would need more storage space within its warehouses. To evaluate the optimality of the new minimum Days of Cover for each classification we need to simulate the effects, but to simulate the effects we first need to make new production plans based on the new minimum Days of Cover allocations.

Using the new minimum Days of Cover allocations we create a 1-year ahead production plan for 2023. The Supply Chain Planning team lead makes the new production plans by changing the opening stock of the original production plan. Compared to the original production plan the opening stock is increased and if needed the production quantities are changed, such that all constraints of the production plan are satisfied and that the produced quantities are exactly the same as the forecasted sold quantities of 2023. The production plans are used together with the forecast and a normally distributed forecast error with mean 0 and standard deviation σ. Although the normal distribution is not the best distribution to simulate the forecast errors we have chosen to use this distribution, because the calculations are based upon this distribution. The simulation outputs a total Stock Availability percentage and a total value for the operational inventory-related costs. In addition, we can see the progress of the stock level in the warehouse of Grolsch that results from the production plans. The simulation does have some flaws and does not reflect the reality entirely, because we did not simulate the production delays (yet) and we have not taken along the fact that the tactical planning of Grolsch can intervene during the year when the Days of Cover drops below the minimum Days of Cover following the realized demand and the production schedule. However, as the 1-year ahead plans are made using the minimum Days of Cover we can already draw conclusions on the optimality of the minimum Days of Cover (per classification) in the next chapter.

6 Results

In this Chapter, we discuss the results of the old safety stock allocation method and the new safety stock allocation method. We start this chapter by discussing the number of replications that are needed in order to get reliable results in Section 6.1. Then we dive into the outcome of the simulation of both the old safety stock allocation method and all other 3 safety stock allocation methods in Section 6.2. Next, we test the robustness of the solutions by changing several parameters, settings, or assumptions within our simulation. In Section 6.3 we describe what these changes mean for the optimality of each of the safety stock allocation methods. In Section 6.4 we discuss our recommendation to Grolsch and we describe here how we would advise Grolsch to implement this recommendation. Finally, we conclude this chapter in Section 6.5.

6.1 Number of replications

The simulation uses random number streams in order to randomly generate numbers from distributions. In case we do not change the random number stream we would get the same results every time that we run the simulation. In case we do change the random number stream we can simulate the effect of variability in real life on the same input data. In order to know how many times we need to change the random number stream to get reliable results we need to perform a test. In Appendix B we have performed the relative error test, such that we know how many simulation runs we need to do in order to get reliable results. We have used different outputs of the simulation. We have used the stock level of all SKUs on the last day, the Stock Availability percentage, the total costs, the total number of hectoliters that have passed 1/3 of the expiration date, and the total number of hectoliters that Grolsch could not deliver on time. We found out that we need to do at least 232 replications to get reliable results and to have a simulation run time that is not too long (232 replications would take us about 23 minutes). With 232 replications we would have a relative error of a maximum of 5% for the most important outputs (Stock Availability percentage and the total costs).

6.2 Results

In this section, we first describe the difference between the outcomes of the simulation of the old production plan and the production plan of the VMQ-method in Section 6.2.1. We then describe the outcomes of the simulation using the production plan of the AA-method and the ANA-method which both use a higher fixed minimum Days of Cover in Section 6.2.2.

6.2.1 Old production plan and VMQ-method

After running 232 replications with the current production plan that is based upon the current minimum Days of Cover that Grolsch uses per SKU and the new production plan that is based upon VMQ-method we could make boxplots of the simulation results. Below in Figure 15 we can see the boxplot of the Stock Availability ratio of both the new and the old production plan. The average Stock Availability percentage for the old production plan is 97.6%, whereas the average Stock Availability percentage for the VMQ-method is on average 98.3%. As we expected we see a higher Stock Availability percentage using the VMQ-method. Nevertheless, this Stock Availability percentage is still not higher or equal to the 98.5% that we aimed for. In Paragraph 6.2.1 we analyse what causes the Stock Availability percentage of the VMQ-method to be better and what causes the Stock Availability percentage to be still below target.

In Figure 16 we visualized the boxplot of the total costs for both the old production plan and the VMQ-method. In Figure 16 we can see that the VMQ-method leads to higher total costs compared to the old production plan. The new production plan using the VMQ-method has an average total cost that is 20.2% higher than the total costs of the old production plan. All in all, the VMQ-method is performing better in terms of the Stock Availability percentage, but the VMQ-method will cost Grolsch more money. We had expected already that an increase in Stock Availability percentage would come with a higher cost, but we want to know where these costs are incurred. In Paragraph 6.2.1 we, therefore, analyse the higher costs in more depth to see what causes underly the higher total costs of the new production plan using the VMQ-method.

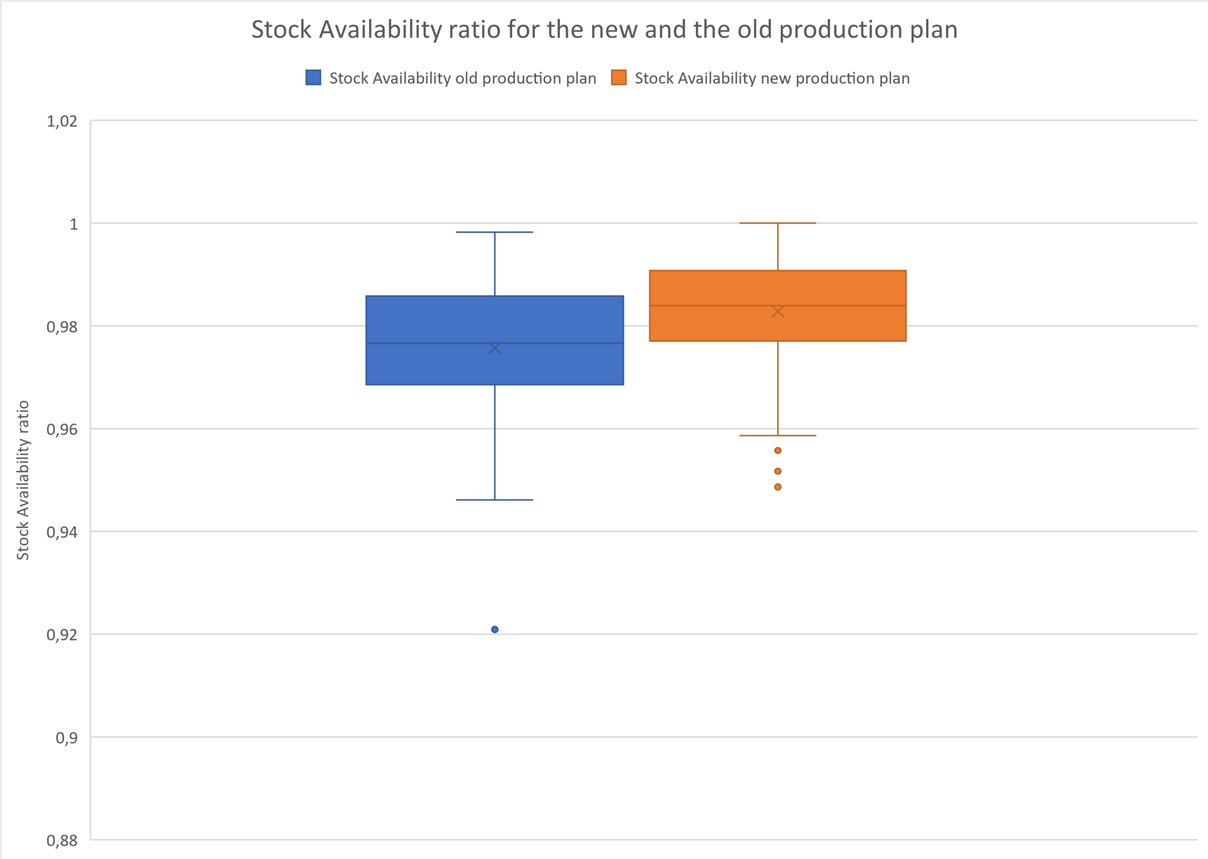


Figure 15: The boxplots that show the Stock Availability ratio for the old production plan and the new production plan using the VMQ-method. The boxplots are made based on the 232 data points, where each data point represents the average Stock Availability ratio of all SKUs over 2023 of a different replication.

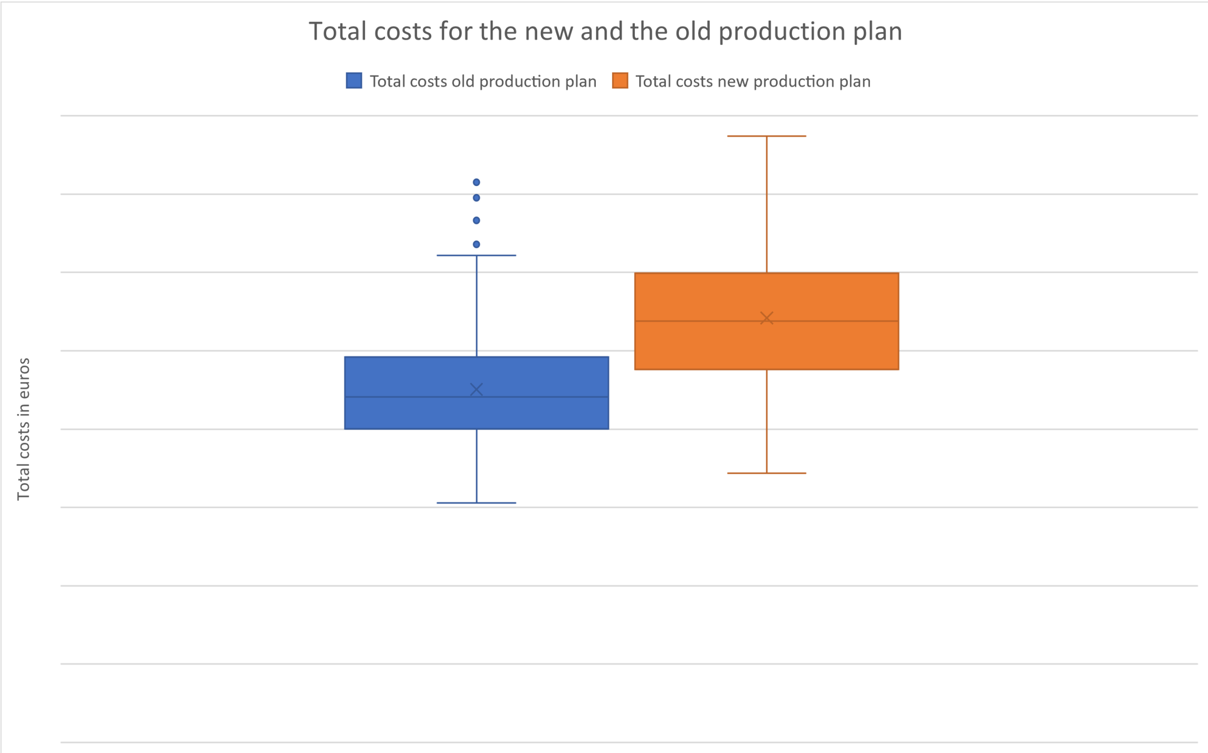


Figure 16: The boxplots that show the total costs for the old production plan and the new production plan using the VMQ-method in euros. The boxplots are made based on the 232 data points, where each data point represents the total inventory-related costs of all SKUs over 2023 of a different replication.

Analysis Stock Availability percentage

When looking at the number of understockings of the old plan and the new plan on SKU level we notice that for almost every SKU the number of understockings has decreased. On average the number of understockings per SKU decreased by 24%. For some SKUs we see only a small decrease in understocking volume and sometimes even an increase. This is especially the case for SKUs with a very seasonal demand pattern with great fluctuations in the forecast per week. Remember from Section 4.2 that we aggregated the Days of Cover per classification and then based the Days of Cover for the SKU for that specific quarter on this aggregated value. We see that for some SKUs the aggregated Days of Cover are too low to reach the Stock Availability target. Moreover, we set a maximum Days of Cover for each SKU for each week of R, which is sometimes just below the Days of Cover that would be optimal according to our calculations. Both the maximum Days of Cover and the aggregation of the Days of Cover per classification in combination with very seasonal demand patterns of some SKUs make the fact that the Stock Availability target of 98.5% is, although very close to 98.3%, not reached.

The limitations of our approach, considering the VMQ-method is less effective for SKUs that are subject to seasonal fluctuations in demand, imply that the VMQ-method is more effective in addressing SKUs that are less affected by seasonal fluctuations in demand.

Analysis higher total costs

To know what causes the higher total inventory-related costs of the new production plan we need to know per cost type what happened in both simulations. Therefore, we have analysed the total costs in boxplots too for the old and the new production plan using the VMQ-method. Below in Figure 17 the cost division of the total costs is visible.

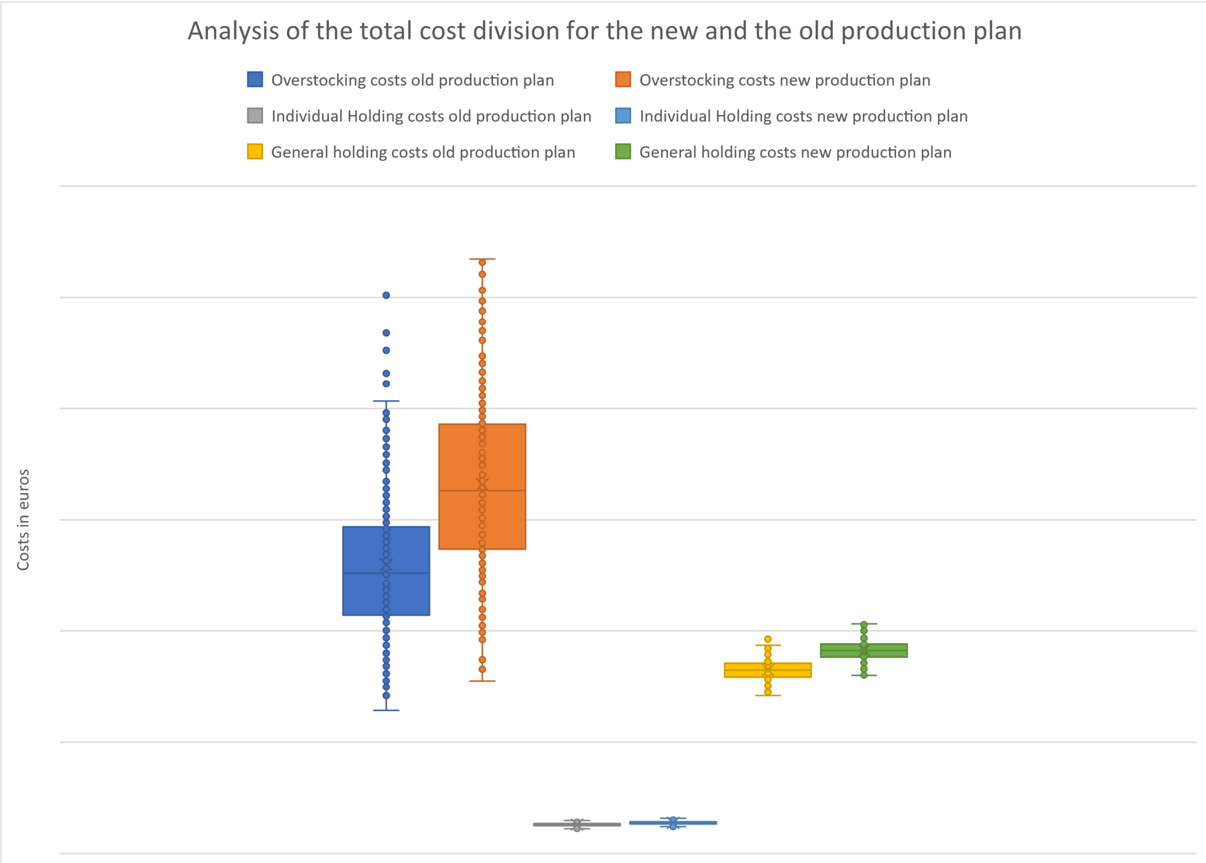


Figure 17: The boxplots show how the total costs for the old production plan and the new production plan using the VMQ-method are built up in euros. The boxplots are made based on the 232 data points, where each data point represents either the total obsolescence costs of all SKUs over 2023, or the total costs of commuting the pallets to the harbour over 2023 (general holding costs), or the costs for keeping all stock on the shelves for all SKUs over 2023 (individual holding costs).

In Figure 17 we see that the new production plan leads to both higher obsolescence (overstocking) costs, higher general holding costs (for commuting), and higher individual holding costs (storage costs for keeping the product on the shelves). In the figure, we can see that the overstocking costs increased a lot with the new production plan compared to the old production plan. The obsolescence costs increased with 27.8%, which accounts for almost 80% of the total increase in costs. The average volume of overstockings increased by 32%. We see that the obsoletes for seasonal SKUs with a rather short shelf life increase a lot when simulating our new production plan. Later in Section 6.4.1 we show a more extensive analysis regarding this.

6.2.2 Fixed versus variable minimum DoC

After we have tried varying the minimum Days of Cover per quarter for each SKU we calculated a new fixed minimum Days of Cover per SKU using 2 different methods. In both methods, we do not differ the minimum Days of Cover per quarter. Running the simulation using the Average Aggregated method gives us better results than using the VMQ-method regarding Stock Availability, but the AA-method is also a lot more expensive. In Figure 18 we show the difference between having a minimum Days of Cover per quarter and between averaging these 4 different Days of Cover per quarter such that we have one Days of Cover per SKU for the entire year (the AA-method). We see that the Average Aggregated method clearly leads to a better Stock Availability percentage. The Stock Availability percentage is calculated at 99.0% compared to 98.3% in case we use different Days of Cover per quarter. The Stock Availability mainly increased for SKUs that have a very seasonal demand pattern, which shows that a fixed minimum Days of Cover works very well to adjust the absolute safety stock level to the forecast, especially for seasonal SKUs. A varying minimum Days of Cover per quarter then only leads to more extreme fluctuations in the absolute safety stock level, and these larger fluctuations have a negative effect on the average Stock Availability percentage.

In Figure 19 we also see that the higher Stock Availability percentage comes with quite a price tag. Using a fixed minimum Days of Cover for the entire year with the AA-method results in a total cost increase of 58.5% compared to the total costs of the old production plan. The cost increase is mainly caused by an increase in obsolescence costs. We see that using the AA-method for seasonal SKUs indeed works to increase the Stock Availability of those SKUs. However, this leads to an unproportionally high number of hectoliters that passes 1/3 of its expiration time before it is sold. We see that the number of hectoliters that have passed 1/3 of their expiration date is not as much caused by the seasonal SKUs, but mainly by the SKUs that show a more stable demand pattern. The SKUs with a rather short shelf life show a large absolute increase in the number of overstockings, whereas the relative increase is mostly caused by SKUs with a very seasonal demand pattern of which the Stock Availability percentage has improved also. We consider a seasonal demand pattern to be present if the sales of the best quarter of the SKU are at least 25% higher than the sales of the worst quarter of the SKU.

The Average Non-Aggregated method leads to an even higher Stock Availability percentage with an average of 99.3%. The ANA-method leads to a total cost increase of 63.9% compared to the total costs of the old production plan, which is roughly 3.4% higher than the total costs of the AA-method. The ANA-method would seem to be a better option as it has a 0.3% higher Stock Availability percentage for rather low marginal costs. However, a pitfall of this method is that it is often overfitted to the current dataset which makes this method less robust in practice. In general, we see that for SKUs that have large seasonal fluctuations in their demand pattern, the ANA-method works better. As a lot of these SKUs do not have a large volume that is sold, whereas every SKU is considered equally important when calculating the Stock Availability the obsolescence costs do not increase a lot. A sensitivity analysis should point out if the AA-method or the ANA-method would be a better option to use.

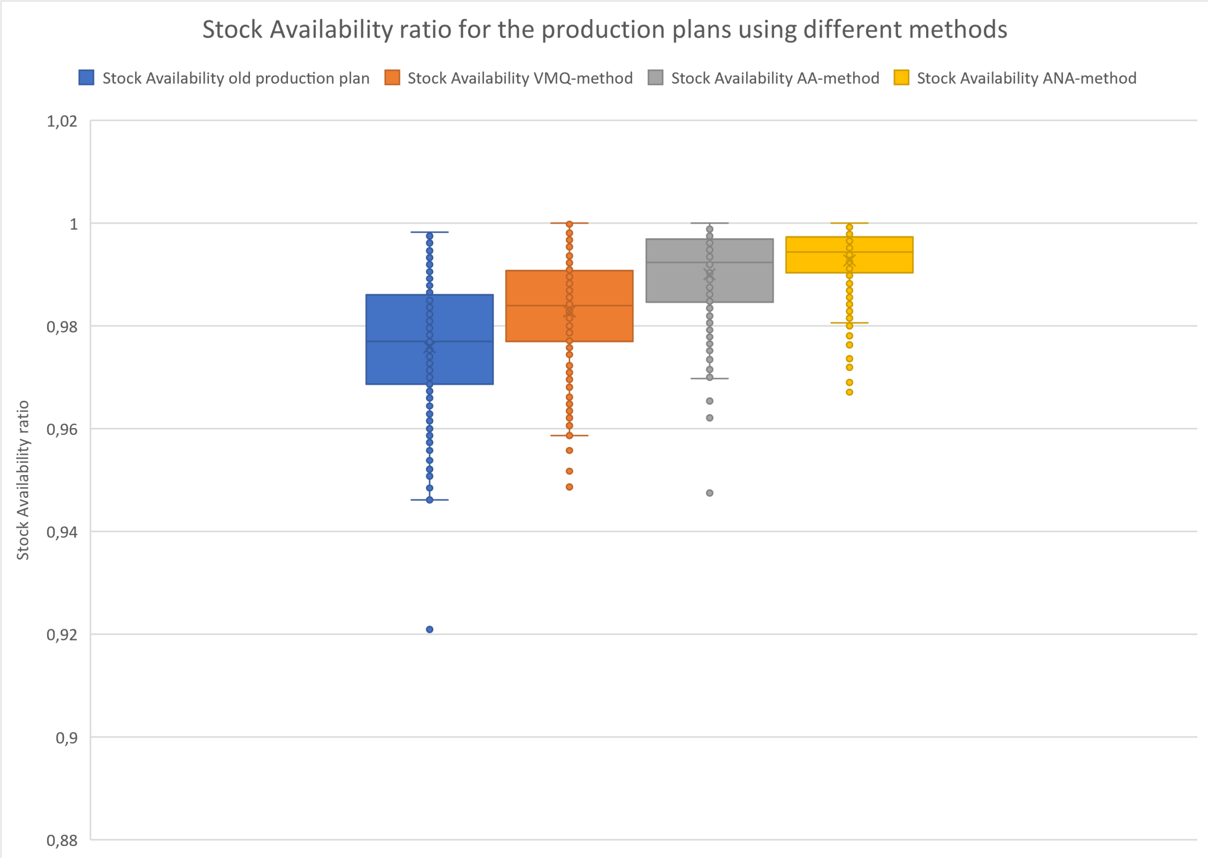


Figure 18: The boxplots that show the Stock Availability ratio for the new production plan using a different minimum Days of Cover per quarter (VMQ-method) and the new production plan using a minimum Days of Cover that is equal for each quarter (the AA-method and the ANA-method). The boxplots are made based on 232 data points, where each data point represents the average Stock Availability ratio of all SKUs over 2023 of a different replication.

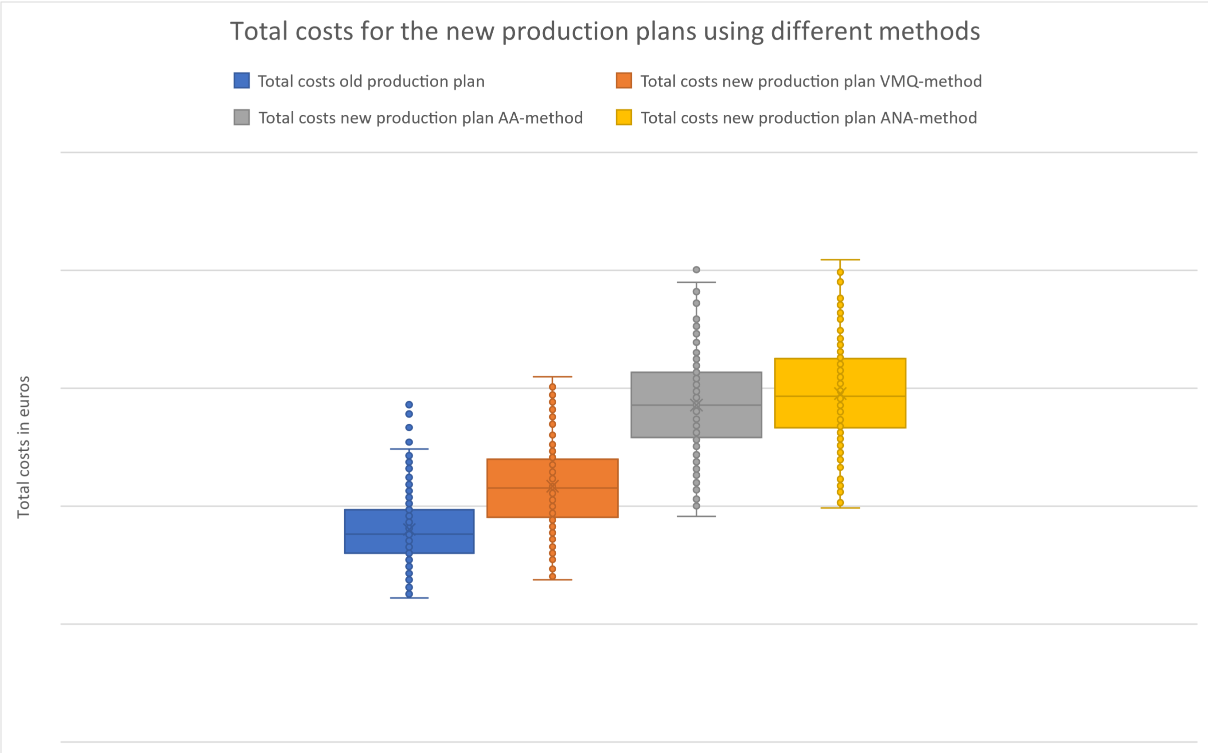


Figure 19: The boxplots that show the total costs for the new production plan using a different minimum Days of Cover per quarter (VMQ-method) and the new production plan using a minimum Days of Cover that is equal for each quarter in euros (the AA-method and the ANA-method). The boxplots are made based on the 232 data points, where each data point represents the total inventory-related costs of all SKUs over 2023 of a different replication.

To summarize all of the results of each method we show the most important results below in Table 3 and in the graph in Figure 20. The results show how that the closer we come to 100% Stock Availability, the more we have to pay per Stock Availability percentage.

	Old production plan	**VMQ-method**	**AA-method**	**ANA-method**	**Target**
Stock Availability %	97.6%	98.3%	99.0%	99.3%	98.5%
Total costs	100%	120.2%	158.5%	163.9%	N.A.
Paid per Stock Availability percent	100%	119.4%	156.2%	161.1%	N.A.

Table 3: The table with the most important results following from the old production plan and all 3 other methods.

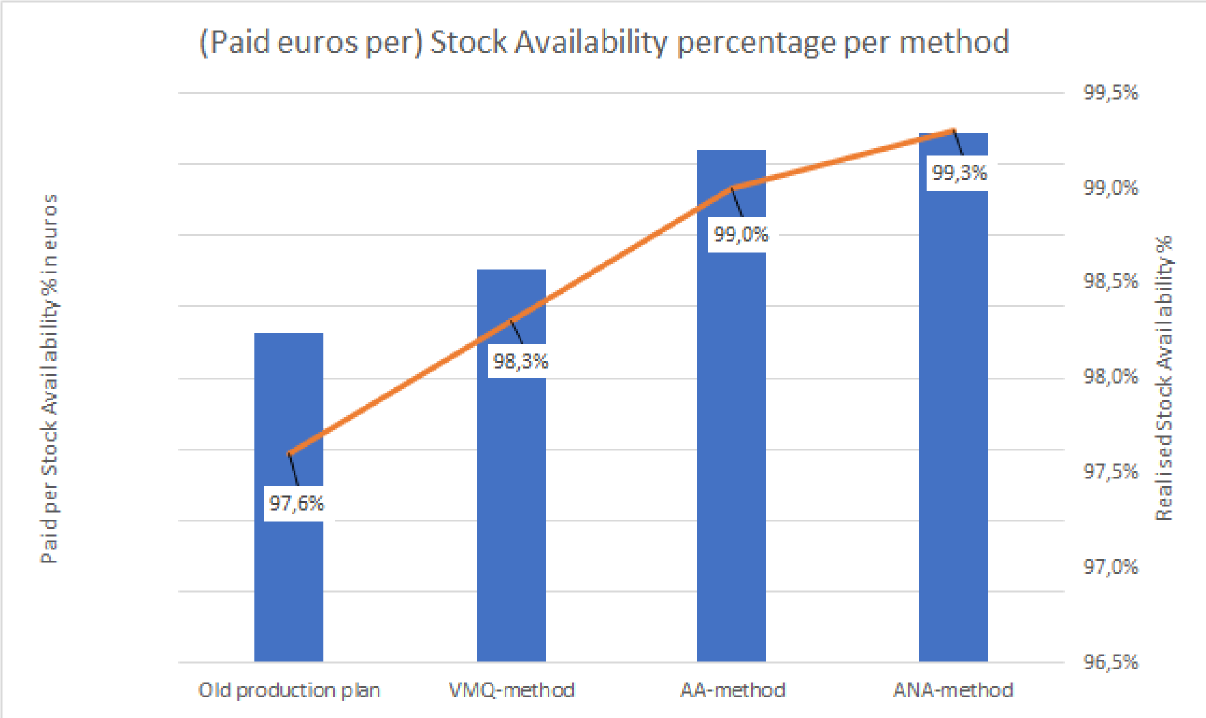


Figure 20: This graph shows how the increase in euros for every percentage of Stock Availability that we would want to have. We can see that the closer we come to 100%, the more expensive each percentage is.

6.3 Sensitivity analysis

With the first results known we perform some sensitivity analyses using the 4 production plans to see which method is more robust and to see what the effect would be on the optimality of the outcomes in case the situation changes. We first want to check what the effect would be on the optimality of each of the Days of Cover in case the production delays are taken along in the simulation, but mainly we want to incorporate the production delays in order to get an indication of the total stock level that we would need in case of each of the methods is used. The effect of the production delays is shown and explained in Section 6.3.1. Moreover, we want to see what the effect would be on the optimality of the production plans (mainly on the Stock Availability percentage) in case the obsolete products are considered to be spoiled such that they are subtracted from the stock level and cannot be sold to customers anymore. This analysis and the results are described in Section 6.3.2. Next, we perform a sensitivity analysis using a different forecast error distribution. We keep using the normal distribution, but by changing the standard deviation of the forecast error we check what the effect would be on the optimality of all 4 production plans. The results of this sensitivity analysis are shown and explained in Section 6.3.3. Using the outcomes of the sensitivity analyses we know which method we would recommend Grolsch to use.

6.3.1 Taking along production delays within the simulation

Grolsch has a KPI called the production tracker to keep track of the reliability of the packaging plan. The production tracker is a percentage that indicates how much percent of the initially scheduled volume is truly filled on the production line. For every batch that was planned on Filling Line 2 over 2022, we have divided the actual filled quantity by the scheduled quantity such that we get a percentage that indicates the reliability of the packaging plan. We assume that this percentage follows a normal distribution and we therefore calculate the average percentage over all batches and the standard deviation over all batches. The average reliability per batch was x% and the standard deviation was y%. We set a lower bound of 0% (as we cannot produce a negative amount) and to keep the distribution symmetrical we use an upper bound of $2 \cdot x\%$. By drawing a random percentage from the normal distribution we can simulate the production delay in the simulation. Below in Figure 21 we see what the production delay does to the Stock Availability of the 4 production plans and in Figure 22 we see what the production delay does to the total costs of the 4 production plans. It is relevant to highlight that it is rather difficult to incorporate the production delay within the simulation. Moreover, the planning department would normally act on production delays, but simulating the decisions of the planning department would be even more difficult. Therefore the results below of the Stock Availability percentage and the total costs might give a distorted view of reality. The Stock Availability percentage namely does not come near the Stock Availability percentage that Grolsch targets. This method of incorporating the production delays is mostly used in order to get an approximation of the number of pallet locations that would be needed and to measure the robustness of the production plans if production is delayed. The results below do show the added value of the Supply Chain Planning department to some extent as the realised Stock Availability percentage was a lot higher over 2022 (and the beginning of 2023) than the Stock Availability percentages shown below taking into account production delays.

When looking at the results taking into account production delays we see that the average total costs are lower for all production plans, which is logical considering the fact that when we have produced less we have fewer products in stock that can expire. The range of the total costs for each method with production delays is higher, in particular, it has a lot more upward outliers than the total costs without production delays. The total costs thus drop almost for sure in case we take along the production delays (the total costs drop about 50% on average for each production plan). The total costs drop of course due to the fact that we have less in stock as production produces about $100 - x\%$ less than we planned for so we have fewer obsolescence costs and we do not have to commute to the harbour as often as the warehouse is not always full. The Stock Availability percentages drop substantially when the production delays are taken into account. The Stock Availability percentages drop with about 30% or more and the range of the Stock Availability percentage for each method is a lot wider. It is noteworthy that the AA-method and the ANA-method both show a higher decrease in absolute costs in case production delays come into play whilst the Stock Availability percentages for both methods remain higher. Therefore, we can conclude that the AA-method and the ANA-method still perform better in case production delays are taken into account.

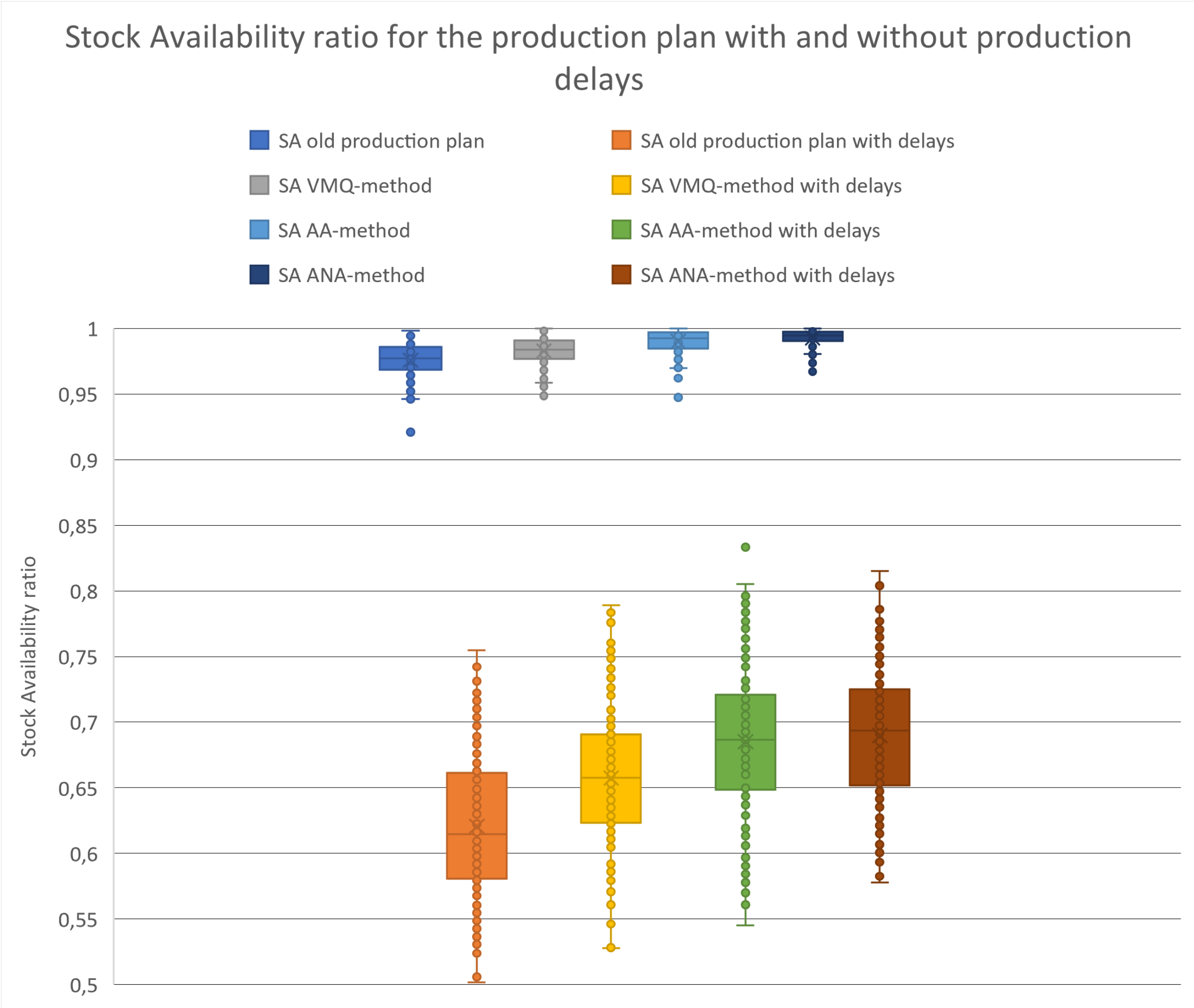


Figure 21: The Stock Availability ratios of the production plans using different methods with and without production delay to assess their robustness.

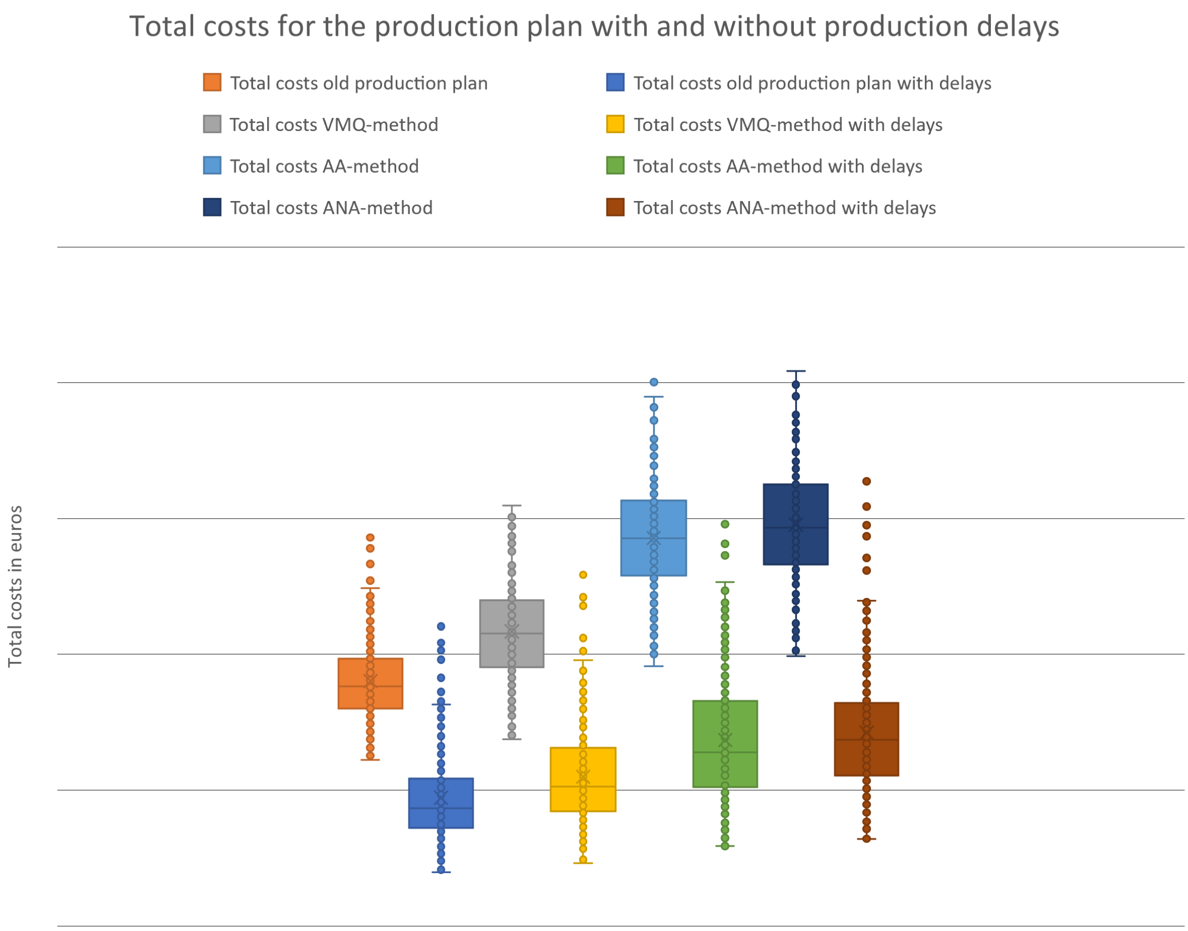


Figure 22: The total costs of the production plans using different methods with and without production delay to assess their robustness.

Number of pallet locations needed with production delays

For the old production plan, we estimate that we would need roughly 16,782 pallet locations during the high season. For the production plan using different Days of Cover per quarter, we estimate that we would need roughly 19,442 pallet locations during the peak season. The AA-method would need roughly 22,518 pallet locations during the peak season and the ANA-method would need about 22,993 pallet locations during the high season. In Section 2.1.6 we already said that we had a total practical warehousing capacity available of 23,000 pallet locations. The estimation of this number of pallet locations needed, when already taking into account production delays, indicates that the current warehousing capacity of Grolsch should be sufficient to reach its Stock Availability percentage target, despite the fact that the A(N)A-method approaches the limit of the warehousing capacity of Grolsch.

We have calculated the estimation of the number of pallet locations that would be needed for all 4 methods as follows. We have calculated in our simulation for each run what the maximum number of pallet locations needed would be to store the inventory on hand of the Filling Line 2 SKUs. Moreover, we divide the maximum needed warehouse capacity for the Filling Line 2 SKUs by the percentage of pallet locations that are reserved for Filling Line 2 SKUs in the old production plan. The division results in an estimation of the number of pallet locations that we would need during peak season if we apply this method for all SKUs on all filling lines.

6.3.2 Removing obsoletes from inventory

In our simulation, we assume that all inventory that has passed 1/3 of its expiration time can still be sold. However, in practice, only a certain percentage of all inventory that passed 1/3 of the expiration time can be sold as not every customer agrees to receive an SKU that has passed 1/3 of its expiration time. Therefore, we have done a comparison where all stock that passed 1/3 of its expiration time is noted as obsolete and directly removed from stock. The results of this comparison are visible below in Figure 23.

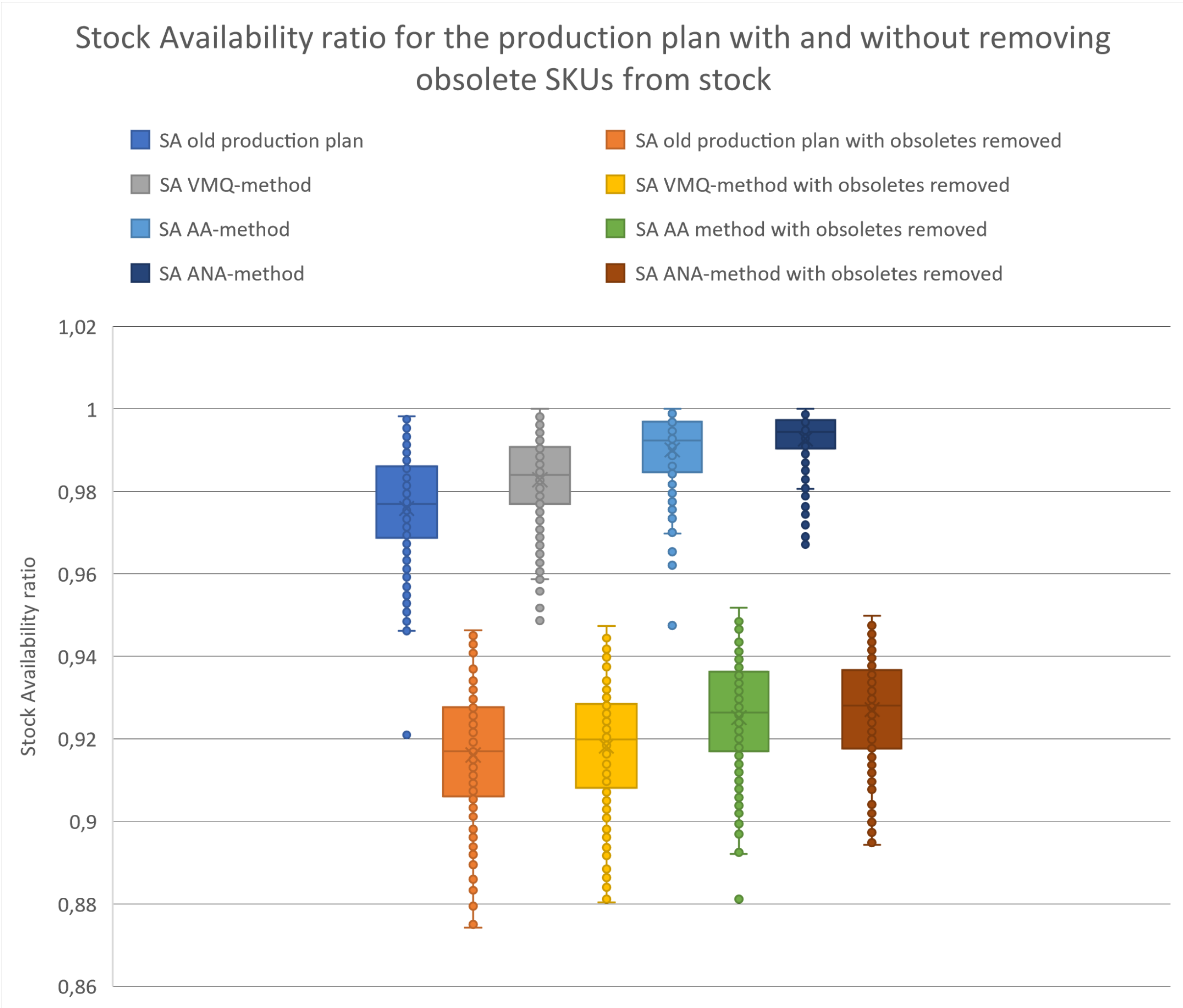


Figure 23: The Stock Availability ratios of the production plans using different methods with and without obsoletes removed from stock after they have passed 1/3 of their expiration time.

We can see in Figure 23 that if we remove the obsoletes from stock in case the SKUs have passed 1/3 of their expiration time that we end up with a lower Stock Availability percentage. The difference is significant where the average Stock Availability percentage drops by 6 to 7% depending on the method used. This shows that the perishability of the SKUs has a large influence on the achieved Stock Availability percentage whereas this is not taken into account within the safety stock calculations. We also see that the AA-method and the ANA-method do not significantly differ in Stock Availability percentage and that the difference in absolute value between the Stock Availability percentages for each method decreases as we take into account that obsoletes cannot be sold (directly).

6.3.3 Changing the standard deviation of the forecast error

(The standard deviation of) the forecast errors can change a lot over time. Therefore we have to test the robustness of all of the methods to see to what extent each method would remain optimal if the forecast error distribution, or more specifically the standard deviation of the forecast error, changes. We have chosen to change the standard deviation of the forecast error of each SKU with a fixed percentage for each scenario. We have 11 scenarios in total and all of the scenarios that we have used are visible below in Table 4. We have chosen to increase and decrease the standard deviation of the forecast error by the same percentage. However, instead of a 100% decrease in the standard deviation of the forecast error, we have chosen to set the maximum decrease at 90%. This decision is based on the observation that a forecast error of 0 almost always results in a Stock Availability of 100%.

Scenario number	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
Change of standard deviation	-90%	-50%	-25%	-10%	-5%	No change	+5%	+10%	+25%	+50%	+100%

Table 4: The table shows all the scenarios that we ran for each production plan. The second row represents the change in percentage of the standard deviation of the forecast error of each SKU compared to the standard deviation of the forecast error of each SKU over 2022.

We have run 11 simulations per production plan where in each scenario each SKU has a different standard deviation of the forecast error. We have visualized the results by means of 3 graphs. Below in Figure 24 the effect of the standard deviation of the forecast error on the Stock Availability percentage is shown, in Figure 25 it is shown to what extent the standard deviation of the forecast error has an effect on the total costs of each production plan and in Figure 26 we show what the effect of the standard deviation of the forecast error is on the number of euros that we need to pay per Stock Availability percentage.

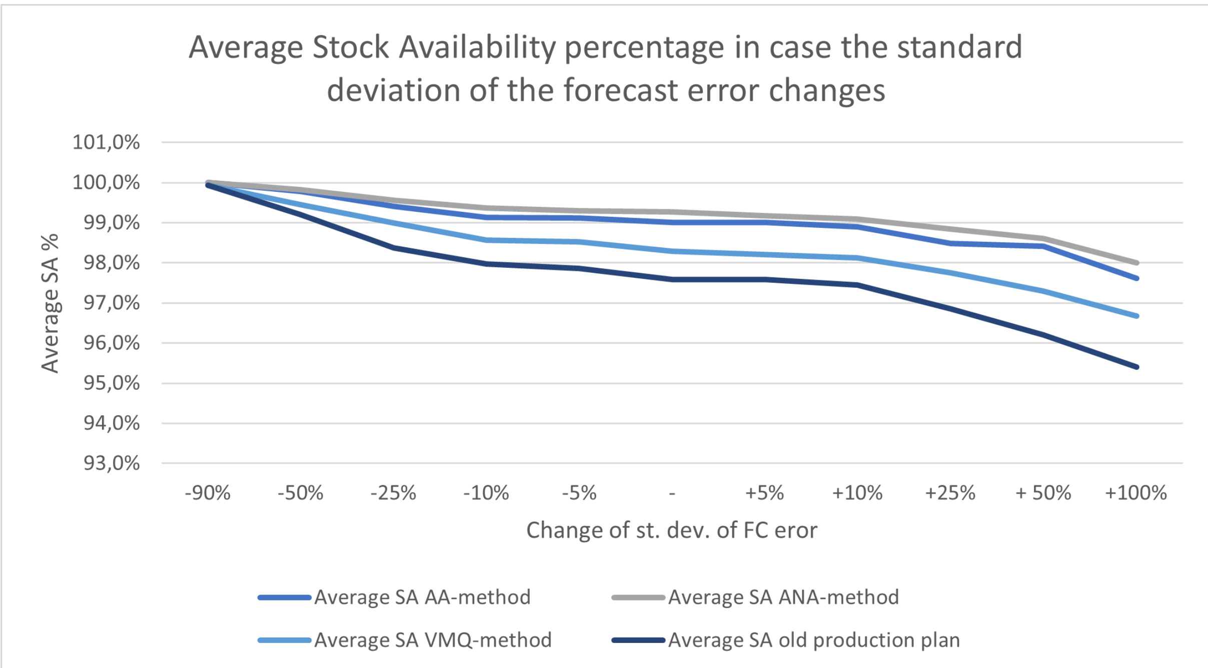


Figure 24: The effect of the standard deviation of the forecast error on the average Stock Availability percentage for each production plan for each scenario. The different scenarios, where each scenario represents a change in percentage of the standard deviation of the forecast error, are shown on the x-axis.

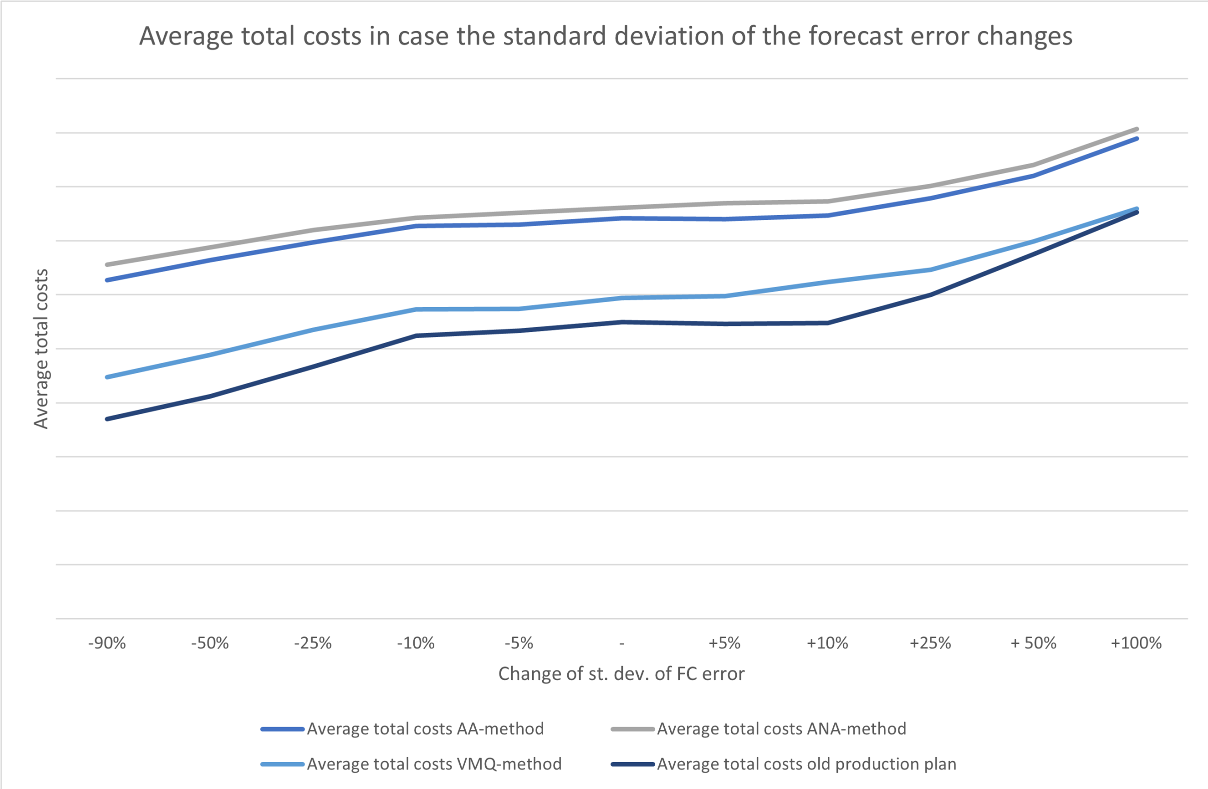


Figure 25: The effect of the standard deviation of the forecast error on the average total costs for each production plan for each scenario. The different scenarios, where each scenario represents a change in percentage of the standard deviation of the forecast error, are shown on the x-axis.

The graph in Figure 24 shows that the ANA-method performs the best in terms of Stock Availability percentage in each situation. The average Stock Availability percentage is the highest. The AA-method performs a little bit worse than the ANA-method however the difference is not significant. The ANA-method even shows an average Stock Availability percentage of 98% when the standard deviation of the forecast error doubles. We can also see that a higher standard deviation of the forecast error leads to the fact that the difference in optimality becomes much larger between each of the production plans. The fact that the difference between the old production plan and the 3 new production plans becomes larger is not odd, as the old production plan has much less safety stock such that when the standard deviation of the forecast error increases we will run out of stock much more often and much faster than with the other 3 production plans. It is noticeable that the difference in the average Stock Availability percentage between the production plan of the VMQ-method and the A(N)A-method becomes bigger as the standard deviation of the forecast error increases. This observation strengthens the conclusion that a variable Days of Cover per quarter per SKU is less optimal.

The graph in Figure 25 shows the effect that the standard deviation of the forecast error has on the total costs of each of the 4 production plans. The average total costs are clearly much higher for the AA-method and the ANA-method compared to the other 2 production plans, which is not odd given the fact that both the AA-method and the ANA-method have a higher Stock Availability percentage. We do see that the higher the standard deviation of the forecast error, the smaller the gap between the average total costs compared between the A(N)a-method and the other 2 production plans. It is worth mentioning that the average total costs increase when the Stock Availability percentage decreases. Normally, you would expect to see a decrease in the total costs when the Stock Availability percentage increases. However, in this case, a higher standard deviation of the forecast error also means that more SKUs can have a much lower demand than forecasted. Therefore, more SKUs will have more in inventory that cannot be sold within 1/3 of the expiration time such that the obsolescence costs rise. Thus due to randomness and very large fluctuations in the forecast error, some SKUs become obsolete very quickly whilst some SKUs become unavailable very quickly. Moreover, in the total costs we do not take along the 'costs' of products being unavailable such that they cannot be sold.

To make a comparison between the combination of the total costs and the Stock Availability percentage we have also added Figure 26. This figure shows that we would always pay the most per Stock Availability percentage for the ANA-method, but that the difference becomes smaller when the standard deviation of the forecast error increases. It is also noteworthy that the production plan using the VMQ-method becomes less optimal than the production plan using the old minimum Days of Cover in case the standard deviation of the forecast error increases.

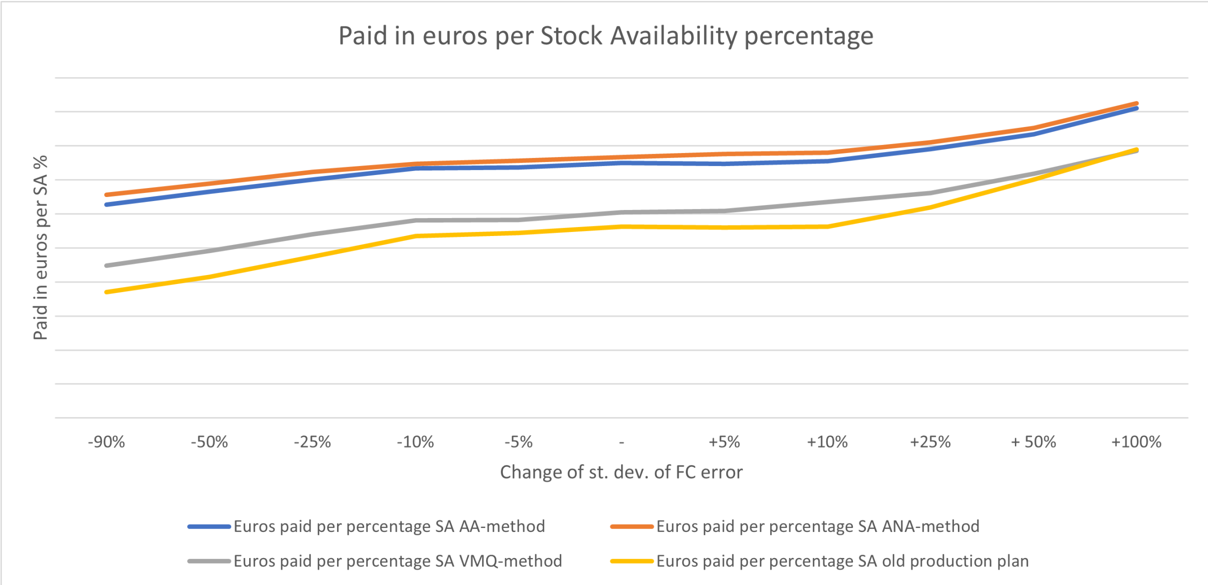


Figure 26: The amount that is paid in euros per Stock Availability percentage for different scenarios. The different scenarios, where each scenario represents a change in percentage of the standard deviation of the forecast error, are shown on the x-axis.

6.4 Recommendations and implementation

6.4.1 Analysis results per SKU category

In Paragraph 6.2.1 we already noticed that seasonal SKUs with a shorter shelf life show a high number of obsoletes which leads to a big increase in the total costs for the production plan using the VMQ-method. For the AA- and the ANA-method we notice the same. In this section, we analyse if we need to change/increase the minimum Days of Cover for each SKU category. First, we analyse the seasonal SKUs, and then we analyse the non-seasonal SKUs. We leave the AA-method out of this analysis as the ANA-method and the AA-method show more or less the same results, and the ANA-method performs better in terms of Stock Availability percentage. Moreover, the sensitivity analysis showed that the ANA-method performs better in every situation regarding the Stock Availability percentage than the AA-method.

Seasonal SKUs

We have 5 different shelf lives for the Filling Line 2 SKUs. The shortest shelf life we call shelf life A, and the longest shelf life we call shelf life E within this report. In the graph in Figure 27 we can see that the SKUs with shelf life A are the only ones that perform above target with the old production plan (99.45%), and the Stock Availability percentages do not improve a lot for these SKUs using the other methods. Moreover, we see in the graph in Figure 28 that the number of obsoletes increases a lot for the ANA-method thus it would not be a good idea to apply this method to these SKUs and increase their minimum Days of Cover. The VMQ-method does perform a little better in terms of Stock Availability percentage and also slightly better in terms of obsolescence costs. However, the difference in obsolescence costs and Stock Availability percentage is not really significant, and for half of the SKUs with shelf life A the method performs well whilst for the other half of the SKUs the method does not perform well. Therefore, we would not advise Grolsch to lower the old minimum Days of Cover of the seasonal SKUs with shelf life A, as the old production plan already shows a higher Stock Availability percentage than we are aiming for, whilst the obsolescence costs are quite high already.

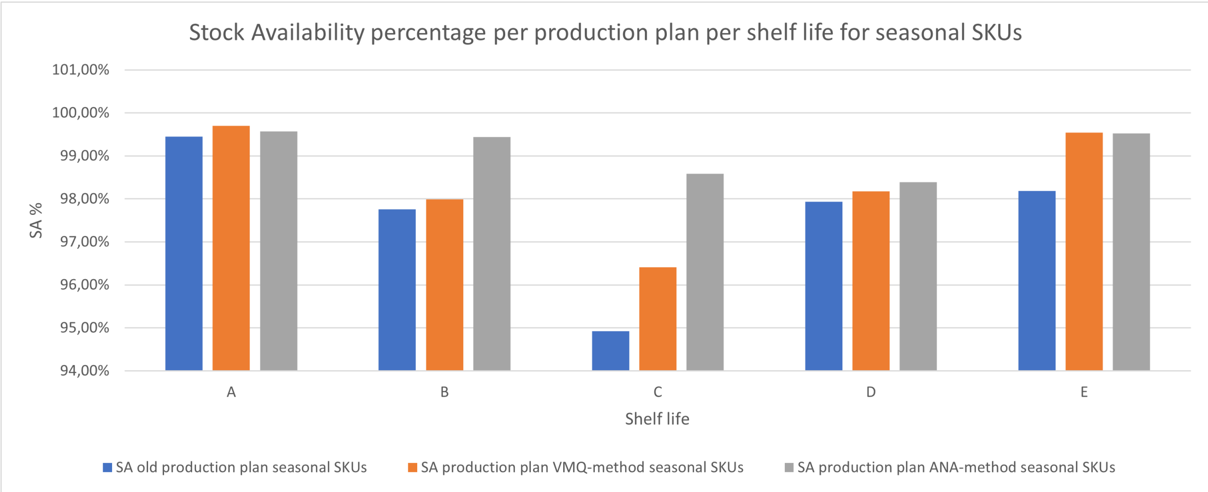


Figure 27: The Stock Availability percentage achieved within the simulation per method for the SKUs with a seasonal demand pattern categorized by shelf life. Shelf life A is the shortest shelf life, whereas shelf life E can be stocked in inventory the longest without becoming obsolete.

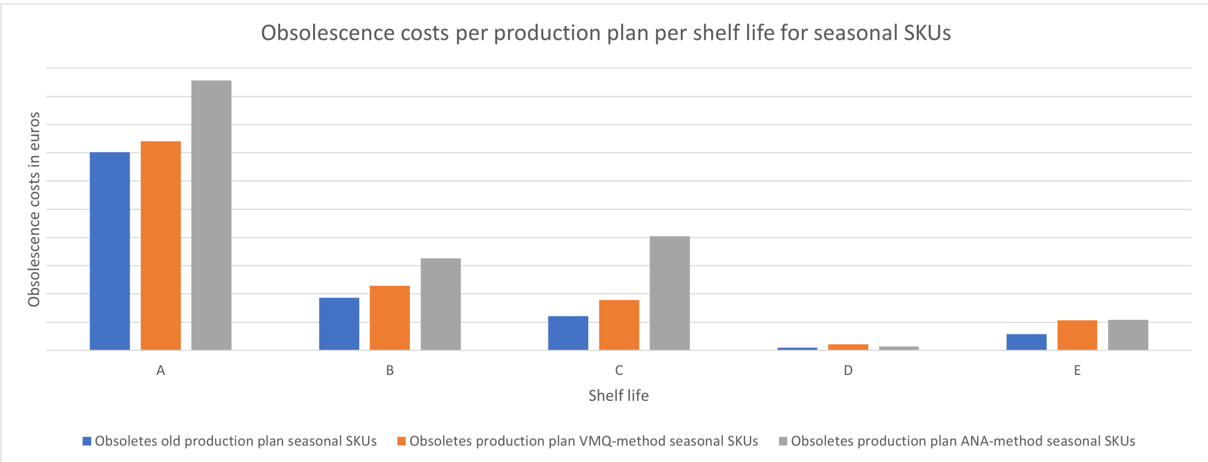


Figure 28: The obsolescence costs achieved within the simulation per method for the SKUs with a seasonal demand pattern categorized by shelf life. Shelf life A is the shortest shelf life, whereas shelf life E can be stocked in inventory the longest without becoming obsolete.

For all seasonal SKUs with shelf life B or longer the Stock Availability percentages do not reach their target, especially for the SKUs with shelf life C (94.92%). Using the VMQ-method we cannot always reach the Stock Availability targets, but with the ANA-method we can reach most of the Stock Availability targets for the SKUs with almost all shelf lives longer than shelf life B. For SKUs with shelf life D and E, we do not see a significant increase in the number of obsoletes. Therefore, we would advise Grolsch to increase the minimum Days of Cover at least for SKUs with a shelf life longer than shelf life C in order to reach the Stock Availability target of 98.5%. However, for the SKUs with shelf life B and C, we do see a significant increase in the obsolescence costs.

Therefore, we analysed the obsolescence costs per additional Stock Availability percentage for all shelf lives in the graph in Figure 29. We see in this graph that we have to pay a reasonable amount more in obsolescence costs per additional Stock Availability percentage for SKUs with shelf life B and C and the difference is not significant, so we would advise Grolsch to increase the minimum Days of Cover for the seasonal SKUs with shelf life B, C, D, and E.

Figure 29: The additional obsolescence costs that Grolsch would have to pay in case the ANA-method is applied to SKUs with a seasonal demand pattern categorized by shelf life. Shelf life A is the shortest shelf life, whereas shelf life E can be stocked in inventory the longest without becoming obsolete.

Non-seasonal SKUs

The non-seasonal SKUs show that the SKUs with shelf life B longer already reach the Stock Availability target using the old production plan so it is not necessary to change these minimum Days of Cover, as shown in the graph in Figure 30. For non-seasonal SKUs with shelf life A and B, we do see a significant increase in the Stock Availability percentage when both the other methods are used. However, we also see a significant increase in obsolescence costs as can be seen in Figure 31. The significant increase in obsolescence costs is a reason for us not to advise Grolsch to increase the minimum Days of Cover for these SKUs. We do see that the VMQ-method leads to a better Stock Availability percentage, whilst the obsolescence costs do not significantly increase in case the shelf life of the non-seasonal SKU is equal shelf life B. However, this is only 1 SKU and we do not see any other clear pattern that using a varying minimum Days of Cover would have a positive effect on these SKUs. Therefore, we would advise Grolsch to keep the old minimum Days of Cover for the non-seasonal SKUs.

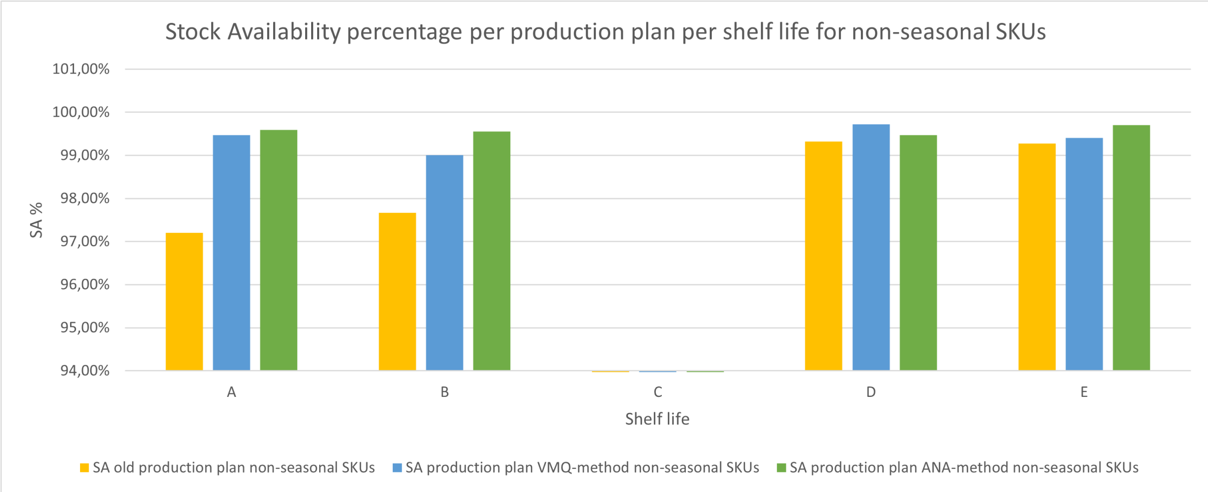


Figure 30: The Stock Availability percentage achieved within the simulation per method for the SKUs with a non-seasonal demand pattern categorized by shelf life. Shelf life A is the shortest shelf life, whereas shelf life E can be stocked in inventory the longest without becoming obsolete.

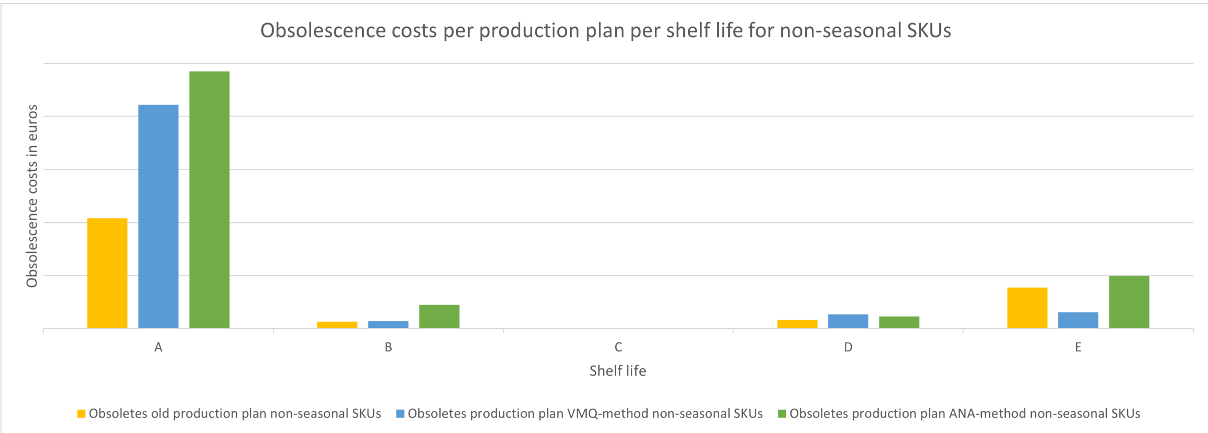


Figure 31: The obsolescence costs achieved within the simulation per method for the SKUs with a non-seasonal demand pattern categorized by shelf life. Shelf life A is the shortest shelf life, whereas shelf life E can be stocked in inventory the longest without becoming obsolete. It should be noted here that the highest vertical gridline within this graph is 2.5 times as high as the highest vertical gridline in the graph of the obsolescence costs of the seasonal SKUs.

Results

In order to know for Grolsch what the consequences are of the advised method, where they will apply the ANA-method to the seasonal SKUs with a shelf life longer than shelf life B and lower the minimum Days of Cover to 67% of the regular minimum Days of Cover for the seasonal SKUs with a shelf life shorter than shelf life B we have run an additional simulation. The non-seasonal SKUs keep the same minimum Days of Cover. We find that using this method results in an average Stock Availability percentage of 98.9% and the average total costs are 29.6% higher than the total costs of the current production plan. According to Kamp (2018) the understocking costs are 35% of the profit margin of a product (as not every SKU that is not sold is a lost sale, but a lot of times SKUs are backordered for example). Therefore, in case we subtract the additional sales that we made in euros due to the additional availability of the SKUs we come to a total cost increase of 18%. As this method still costs a lot more money we have also tried a simulation run where we apply the ANA-method to the seasonal SKUs with a shelf life longer than shelf life B, but we have set a maximum for the minimum

Days of Cover of 167% of the regular minimum Days of Cover as some SKUs have a very high Days of Cover which leads to a lot of obsoletes for these seasonal SKUs with a longer shelf life. Using this method we found an average Stock Availability percentage of 98.6% and a total cost that is 10% higher than the total costs of the old production plan. Subtracting the additional sales that we made in euros due to the additional availability we find that Grolsch has to pay 1.35% more than they are currently paying for the current minimum Days of Cover allocation.

6.4.2 Recommendation

By changing the production plan of the seasonal SKUs as follows Grolsch can improve the Stock Availability percentage such that it reaches its target against minimum operational costs:

- Set the minimum Days of Cover for the seasonal SKUs with a shelf life shorter than shelf life B equal to 67% of the regular minimum Days of Cover.
- Use the ANA-method to calculate the optimal minimum Days of Cover for the seasonal SKUs with shelf life B or longer and set a maximum for the minimum Days of Cover for each SKU of 167% of the regular minimum Days of Cover.
- Keep the old minimum Days of Cover for the non-seasonal SKUs.

Using the recommendations above will in the short term lead to an average Stock Availability percentage of 98.6% with a total cost that is 10% higher. This means that we have reached the targeted 98.5% Stock Availability and Grolsch will have to pay 1.35% more for an additional Stock Availability percentage. The 1.35% cost increase already took into account the additional sales that Grolsch would receive due to the higher Stock Availability. Moreover, we estimate we would need 19,789 pallet locations for this method, which is far lower than we have capacity available for within Grolsch.

The goal of this research was to reach 98.5% Stock Availability against minimal operational costs. It appears that to reach the Stock Availability percentage of 98.5% Grolsch would have to pay more even when taking into account the lost sales. We recommend Grolsch to adjust the minimum Days of Cover based even if the costs slightly increase due to this decision. The fact is that the beer market is quite competitive. In the beer market, the dedicated space in the (physical) retail stores and the promotions are very important for the sales of the products. In order to maintain, or even rather increase, market share the availability of the products is very important as the availability of the products determines whether retailers will dedicate (more) space to the brand or launch (more) promotions with the brand. Moreover, we simply see that most of the SKUs with a very seasonal demand pattern are rather hard to forecast as a lot of them are very weather-dependent. The SKUs that are very hard to forecast show that the current minimum Days of Cover are simply not high enough to reach the target Stock Availability percentage.

In the long-term we would thus recommend to Grolsch to take along the shelf life and the seasonality of the demand pattern in the calculations of the minimum Days of Cover as both these factors show to be of importance regarding the achieved Stock Availability percentage.

6.4.3 Implementation

We recommend Grolsch to first change the minimum Days of Cover for the Filling Line 2 SKUs that follow a seasonal demand pattern to evaluate the effect that these new minimum Days of Cover have. It is important for the (tactical) planning of Grolsch to discuss the change of the minimum Days of Cover and its consequences with the most important departments/stakeholders which we identified are the next ones: warehousing, finance, sales, packaging, quality, and supply chain. Furthermore, after implementation of the new minimum Days of Cover Grolsch should keep an eye on the following KPIs to properly evaluate the optimality of the new Days of Cover: the schedule stability, the Stock Availability percentage (especially of the SKUs of which the minimum Days of Cover have been changed), the obsolescence costs, the commuting costs, and the warehouse utilization.

Schedule stability
With a higher minimum Days of Cover for the SKUs with a longer shelf life (which are many more SKUs than the ones with the short shelf life) the Supply Chain Planning would need to do fewer (last minute) plan adjustments as the risk of running out of stock is a lot lower. Therefore the schedule stability, which indicates to what extent the schedule that was fixed on Friday afternoon the week before remains the same throughout the entire week itself, should increase over time. It is also especially important then to analyse for which SKUs the production batches are changed the most.

Stock Availability percentage
The Stock Availability percentage is important to keep an eye on, especially for the SKUs for which we changed the minimum Days of Cover. It is important for these SKUs to check if each SKU reaches its target Stock Availability percentage based on the ABC classification. Remember that the target Stock Availability percentages are 99.5%, 98.5%, and 97.5% for classifications A, B, and C, respectively. In case of a consistently lower Stock Availability percentage, it might be good to evaluate if the minimum Days of Cover are still optimal.

Obsolescence costs
The obsolescence costs should also be observed closely, in particular for the SKUs for which we applied a higher minimum Days of Cover. In case we see a large rise in obsolescence costs of the SKUs of which we increased the minimum Days of Cover in combination with a very high consistent Stock Availability percentage we should evaluate if we might need to set a lower Days of Cover.

Commuting costs & warehousing utilization
Warehousing utilization and commuting costs are often interrelated. The warehousing department often starts with commuting if the warehousing utilization reaches a certain number of pallet locations (about 18,000 pallet locations), such that the warehouse in the brewery cannot keep all in stock. Therefore, it is important to keep an eye on both and if both are (consistently) very high we should evaluate if we might need to decrease the minimum Days of Cover for some SKUs. These SKUs do not necessarily need to be the ones of which we increased the new minimum Days of Cover, but it is important to check what SKUs make up the largest percentage of the inventory in stock over time.

In case the implementation of the new minimum Days of Cover allocation proves to be successful on Filling Line 2 we would advise the tactical planning of Grolsch to first look at the products of Filling Line 8. Our advice for Filling Line 8 SKUs comes from the fact that this Filling Line produces a lot of different (seasonal) SKUs according to a Make-To-Forecast inventory policy for the domestic market as well. For Filling Line 8 we think that it would also be good to decrease the minimum Days of Cover for seasonal SKUs with a shorter shelf life, whilst increasing the minimum Days of Cover of seasonal SKUs with a longer shelf life. However, we would advise Grolsch to take a close look at where they would set the thresholds. Namely, a difference of at least 25% between the best and the worst quarter in terms of sales volume in HL might be a good threshold for (non-)seasonality for the Filling Line 2 SKUs, just like the threshold set on shelf life B to make a difference between a short and long shelf life. However, for another filling line like Filling Line 8, this might be different. Therefore, to assess this we would advise Grolsch to look into the sales data to assess what should be considered a 'seasonal SKU' on that filling line and we would advise Grolsch to look into the obsolescence costs to assess where the line should be drawn between a short shelf life and a long shelf life.

If implementation for Filling Line 2 and 8 both appear to be a success then we would advise Grolsch to look if it would be worth it to implement our method on Filling Line 1 SKUs as well. Filling Line 1 only has fewer (seasonal) SKUs that are destined for the Dutch market, so it might be less relevant for this filling line. The other filling lines produce almost no (seasonal) SKUs to forecast for the domestic market. Therefore, for the other filling lines, it would not be worth it in our opinion to discover the option of implementing our new method.

6.5 Conclusion

The simulation shows us that the new production plans using the VMQ-method, the AA-method, and the ANA-method lead to higher Stock Availability percentages. The Stock Availability percentages increased from 97.6% to 98.3%, 99.0%, and 99.3%, respectively. The increase in Stock Availability percentage leads to a total cost increase of 20.2%, 58.5%, and 63.9% compared to the total costs of the old production plan for the VMQ-method, the AA-method, and the ANA-method, respectively. The cost increase is mainly due to higher obsolescence costs. A side note to the cost increase is that the total costs do not take into consideration the additional availability of the products which leads to less stock-out costs or better said which leads to additional revenue. We noticed that the higher costs are mostly caused by a high number of obsoletes for SKUs with a shorter shelf life.

From the sensitivity analysis we have learned that removing obsolete products from stock (instead of assuming that we can still sell the obsolete products to our customers) leads to a Stock Availability percentage that is about 6-7% lower, in case the standard deviation doubles we see that we Stock Availability percentage drops with about 1-2%, and when taking into account production delays the Stock Availability percentage decreases by about 30% or more. Two side notes here should be that within the simulation, we did not change the production plan in the simulation to the realized sales and the production delays as would happen in practice within Grolsch, and it is difficult to incorporate the production delays of Grolsch within our simulation so we used the best and easiest method that was at our disposal. The total costs also drop by about 50% in case we take into account the production delays, and in case the standard deviation of the forecast error changes we do see a significant increase in the total costs. Overall, the ANA-method performs best in terms of Stock Availability percentage, but this method also comes with the highest total costs.

We found that our methods, although providing the desired target Stock Availability percentage, still lead to a lot of additional costs mainly due to high obsolescence costs. Therefore, after analysing the results we found that this is caused by 2 factors, namely the shelf life and the seasonality of the demand pattern. We, therefore, changed the minimum Days of Cover based on these 2 criteria. We only changed the minimum Days of Cover of the seasonal SKUs, as higher minimum Days of Cover of the non-seasonal SKUs mostly led to additional (obsolescence) costs without significant improvement of the Stock Availability percentage. For seasonal SKUs with a shorter shelf life shorter than shelf life B, we decreased the minimum Days of Cover to 67% of the regular minimum Days of Cover as the old minimum Days of Cover already led to quite high (obsolescence) costs whilst easily reaching the target Stock Availability percentage. For seasonal SKUs with a shelf life longer than shelf life B we used the ANA-method to increase the minimum Days of Cover. Some SKUs showed to have very high minimum Days of Cover with the ANA-method such that it led to high obsolescence costs, so we set a maximum of 167% of the regular minimum Days of Cover for the new minimum Days of Cover for each SKU. An SKU is considered to have a seasonal demand pattern if there is more than a 25% difference between the best and the worst quarter in terms of sales volume in HL. We found that applying this method would lead to a Stock Availability percentage of 98.6% and a total cost increase of 10%. Taking into account the additional sales that we did not lose due to additional Stock Availability the total costs increased by 1.35% compared to the total costs of the old production plan, for in total 1% additional Stock Availability.

Our new method would cost Grolsch money. However, we have to take into account the following 2 things. The competitive beer market and therefore dedicated space in the retail and promotions of the brand are very important to keep and gain market share. Availability of the products is an important factor for the retailers to dedicate space and launch promotions with Grolsch. Moreover, the current minimum Days of Cover for the seasonal SKUs are simply not always high enough to reach the service level targets of Grolsch. Changing the minimum Days of Cover of these seasonal SKUs with a longer shelf life would lead to minimal additional costs. Therefore, we recommend Grolsch to implement our new method, starting with the SKUs of Filling Line 2 (for the domestic MTF products that are not product X or product Y). To implement this method we would advise Grolsch to keep an eye on the next KPIs: the schedule stability, the Stock Availability percentage (especially of the SKUs of which the minimum Days of Cover have been changed), the obsolescence costs, the commuting costs, and the warehouse utilization. If this method is extended to products of other Filling Lines we would advise Grolsch to first use it on Filling Line 8 SKUs and then Filling Line 1 SKUs. For implementation on other

Filling Lines Grolsch should evaluate what would be a reasonable threshold to consider it to be a seasonal SKU and where the threshold is exactly of a long shelf life and a short shelf life for other Filling Lines (especially since the gap between shelf life A and B is rather big).

7 Conclusion

In the following chapter, we answer the main research question that we formulated in Section 1.3.1. The question that we formulated was the following one:

How can Grolsch improve its safety stock allocation for its Finished Goods such that the service level targets are reached against minimum operational costs?

To answer this main research question we start off this chapter by elaborating on our most important findings in this research in Section 7.1. In Section 7.2 we discuss how these findings should be interpreted and how these findings contribute to the scientific literature before we acknowledge the weaknesses and the constraints of our research in Section 7.3. We end this chapter with Section 7.4 where we outline possible future research directions.

7.1 Main results

Our target in this research was to reach the Stock Availability percentage of 98.5% against minimal operational costs, as Grolsch is currently not able to reach this target. Therefore, we calculated a new minimum Days of Cover for the SKUs of Filling Line 2 that are made to forecast, sold in the domestic market, and which are not product X or product Y.

By using a static safety stock calculation we first calculated the minimum Days of Cover per SKU per week. Based on this number per week we used 3 different methods to come to a minimum Days of Cover allocation:

1. The first method is called the VMQ-method (Variable Minimum Days of Cover per Quarter). We classify every SKU per quarter based on the combination of the ABC and the XYZ classification. We can calculate an average minimum Days of Cover per quarter per SKU based on the weekly minimum Days of Cover per SKU. As every SKU has a different classification per quarter we can then calculate an average minimum Days of Cover per classification and we can then assign this aggregated minimum Days of Cover per classification to the corresponding combination of the SKU and the quarter.
2. The second method is called the AA-method (Average Aggregated) and uses the aggregated minimum Days of Cover of the first method that we calculated per quarter per SKU. Based on the minimum Days of Cover per quarter we calculate an average minimum Days of Cover for the entire year for each SKU.
3. The third method is called the ANA-method (Average Non-Aggregated) and uses the minimum Days of Cover per week per SKU and then calculates the average minimum Days of Cover per SKU over all 52 weeks, such that every SKU has its separate fixed minimum Days of Cover for the entire year. In this method, we do not aggregate the minimum Days of Cover based on the classification, which we did using the AA-method.

Using the 3 methods described above to get a new minimum Days of Cover allocation the team lead of the Supply Chain Planning made new production plans based on these new minimum Days of Cover. The production plans, including the (old) production plan using the current minimum Days of Cover, are simulated such that they can be evaluated.

After simulation of the old production plan we found that the current minimum Days of Cover lead to a Stock Availability percentage of 97.6%. The VMQ-method, using a variable minimum Days of Cover per quarter, leads to a realised Stock Availability of 98.3%, and compared to the old production plan Grolsch would pay an additional 20.2% for a Stock Availability that is 0.7% higher.

A fixed Days of Cover during the entire year leads to a higher Stock Availability percentage than varying the minimum Days of Cover per SKU per quarter. However, we see that keeping a fixed Days of Cover during the entire year for each SKU leads to much higher costs, especially the obsolescence costs show a big increase. Compared to the original production plan we would have to pay at least 55% more. This cost increase is a significant amount.

A minimum Days of Cover calculated by using the ANA-method thus leads to a higher Stock Availability percentage but this also leads to much higher total costs. Also, the sensitivity analysis shows that the ANA-method performs the best in terms of the Stock Availability percentage and this method also shows the highest total costs. However, the higher total costs are caused mostly by higher obsolescence costs and we noticed that 2 characteristics of the SKUs are important for the optimality of the new minimum Days of Cover allocation. The shelf life of the SKU and the seasonality of the demand pattern of the SKU. For the non-seasonal SKUs we noticed that the Stock Availability percentage using the old minimum Days of Cover almost all reached the target already and additional minimum Days of Cover would lead to unnecessarily high obsolescence costs. Moreover, the seasonal SKUs with a shorter shelf life (shelf life A) showed to have quite high obsolescence costs, whilst the Stock Availability percentage is already higher than the target. On the contrary, the obsolescence costs for the seasonal SKUs with a longer shelf life (shelf life B or longer) show to have quite low obsolescence costs and most of them do not reach the target Stock Availability percentage. Therefore, we ran another simulation where we kept the old minimum Days of Cover for the non-seasonal SKUs, lowered the minimum Days of Cover of the seasonal SKUs with a short shelf life to 67% of the regular minimum Days of Cover, and increased the minimum Days of Cover for the seasonal SKUs with a longer shelf life using the ANA-method. As the ANA-method showed very high minimum Days of Cover for some SKUs we have set a maximum of 167% of the regular minimum Days of Cover. Running this simulation led to a Stock Availability percentage of 98.6% and total cost increase of 10% and if we reduce the additional sales that Grolsch will earn due to the higher product availability Grolsch would pay bottom line an additional 1.35% compared to the current total costs.

Even though Grolsch would have to pay for the additional Stock Availability we advise Grolsch to change the minimum Days of Cover of the seasonal SKUs as we have just mentioned. The product availability is an important part of the service to customers. If the product availability is higher then the customers in the retail branch will be more prone to organize promotions with Grolsch and to dedicate more space to Grolsch its products. Both the promotions and the dedicated space in the retail stores are important factors for the market share that Grolsch gains and keeps in a very competitive beer market. Moreover, we simply see that the current minimum Days of Cover for seasonal SKUs with a longer shelf life are not high enough to reach their target Stock Availability percentage, whilst the seasonal SKUs with a shorter shelf life lead to high unnecessary obsolescence costs.

To implement this method we would advise Grolsch to start by implementing this method for the SKUs of Filling Line 2 that are made to forecast, sold in the domestic market, and which are not product X or product Y. If the new minimum Days of Cover are implemented the tactical planning of Grolsch should keep an eye on the next KPIs: the schedule stability, the Stock Availability percentage, the obsolescence costs, the commuting costs, and the warehouse utilization. The Stock Availability percentage is the most important one together with the obsolescence costs and the warehouse utilization. These should together determine if the minimum Days of Cover might need adjustments. If this implementation on Filling Line 2 appears to be a success we would advise Grolsch to implement this method for Filling Line 8 first and then for Filling Line 1 SKUs. If implementation on other filling line SKUs is desired then the tactical planning of Grolsch should first look into what is considered a seasonal SKU on this filling line and what the threshold would be for a long shelf life and a short shelf life. For SKUs on other filling lines, this might be different than for Filling Line 2 SKUs.

7.2 Discussion

In principle, a dynamic safety stock allocation (and therefore a dynamic reorder point) is meant to better cope with fluctuations in demand forecast such that it can be applied very well for products that demonstrate a seasonal demand pattern. In the literature, there is still little to find on dynamic reorder point policies for (R,S,Q) inventory control policies. We have shown that, by using a static reorder point calculation of the (R,S,Q) inventory model and solving this iteratively for every week for every SKU, we are able to calculate a dynamic safety stock level. Following the simulation we found that these calculations can lead to the target Stock Availability percentage (98.5% in our case). Moreover, we found out that the perishability of the products has a great influence on the optimality of the dynamic reorder point. Grolsch should therefore take into account the perishability when determining the optimal safety stock level of the SKUs. Joore (2021) already established that if the service level is higher we will see a higher percentage of SKUs that surpass 1/3 of their expiration time, so we will see a big cost increase due to obsolescence. Moreover, we found that the shorter the shelf life the more impact perishability has on the achieved service level. So to take into account the perishability of the SKUs Grolsch should find out exactly what the effect would be of the (target) service level and the shelf life on the obsolescence costs of its SKUs.

Where the dynamic reorder point is established to better cope with fluctuations in demand forecast such that it can be applied for seasonal products we hypothesised that for some SKUs it might be relevant to differ the minimum Days of Cover per quarter. We reasoned that the standard deviation of the forecast error for those SKUs would be percentage-wise very different per quarter such that we would expect to prevent (unnecessary) obsoletes during low season whilst decreasing stock-out risks during high season. Nevertheless, our research showed that a variable minimum Days of Cover per quarter per SKU is suboptimal for almost all SKUs compared to a fixed minimum Days of Cover for the entire year for the SKU, especially for seasonal SKUs. The reason that the variable minimum Days of Cover per quarter are suboptimal is due to the fact that the absolute safety stock levels fluctuate much more with the varying minimum Days of Cover per quarter. These large fluctuations make the fact that the safety stock level is not always sufficient to have enough in stock, especially during the low season of the SKU during which the absolute safety stock level is much lower.

Many of the (static) safety stock calculations within the literature use the assumption that the demand (or the forecast error) follows a normal distribution with mean μ and standard deviation σ. In our research, we found that for a lot of SKUs we have to reject the hypothesis that the demand follows a normal distribution. More often the absolute forecast error follows an exponential distribution. It is of interest to note that the literature lacks methods using a different distribution than the normal distribution for demand and forecast errors.

In our research we used a combination of the ABC and the XYZ classification and we based the minimum Days of Cover on the classification per quarter for each SKU. We can conclude that using the classification and aggregating the minimum Days of Cover over the SKUs gives a good, although not perfect, indication of the minimum Days of Cover that should be attained in order to reach the target Stock Availability. This means that if we want to use a dynamic safety stock level for an SKU that has the same classification based on the ABC (and XYZ) classification we have a good indication of what this dynamic safety stock level should be, also for New Product Developments given we can make a good estimation of the forecast (error) and the lot size.
Within our simulation we assumed that the average forecast error distribution is 0, as we assume that based on the forecast data of last year the demand planning will adjust the (average) forecast accordingly. However, when calculating the coefficient of variation ($CV = \frac{\sigma}{\mu}$) of the forecast errors we took μ to be equal to the absolute average forecast error, which is an inconsistent assumption within our research. Reflecting afterward it would have been a better option to take the μ to be equal to the average sales of the SKU however, we did not have a sufficient amount of time anymore to change this at the end of our research. The fact that the coefficient of variation has been calculated assuming a forecast bias could indicate that the XYZ classification might not be optimally allocated and this could have influenced our conclusion that the minimum Days of Cover per classification gives us suboptimal results.

7.3 Limitations

First off we calculated several minimum Days of Cover allocations and we have based the production plans on these minimum Days of Cover allocations, which we simulated. Simulating a production plan that is based on the minimum Days of Cover (and other constraints and inputs) and simulating the stock level based solely on the reorder point and a fixed production batch size are of course two different things. When translating the minimum Days of Cover to a production plan we have to take into account capacity restrictions, minimum batch sizes, etc. Moreover, based on a minimum Days of Cover allocation the production plan can be adjusted in many ways in order to satisfy all restrictions. To minimize the risk of having a biased production plan based on the person making it we have increased the opening stock as much as possible and only adjusted the production quantities where necessary without dissatisfying any restriction. However, this still leaves room for interpretation, so the results are partly based on the person making the production plan with the new minimum

Days of Cover.

We processed a lot of information and uncertainties within our simulation, but in practice some things will still deviate from the situation that we have outlined in our simulation. Normally in practice, the (tactical) planning department can intervene in the production plan based on the sales, production delays, and other issues. Because it would be close to impossible to process this in our simulation within the time given for the research we did not take this along in the simulation. Moreover, in practice, tactical planning often plans for Days of Cover that are below the minimum Days of Cover due to various reasons and constraints for the production planning. In our case, we did not take this into account within the simulation. Finally, the production delays are very hard to incorporate within our simulation. We have now mainly used the production delays within the sensitivity analysis to get an indication of the total number of pallet locations that would be needed in the warehouse. However, we assumed a normal distribution here with the mean μ and the standard deviation σ based on the operational standards of Filling Line 2 in 2022. The operational standards are often subject to change and we assume that for each batch the production delay is independent, which is most probably not true. This means that, although we have some indication, we do not know for sure what the exact effect of the production delays is on the Stock Availability percentage and the total costs. Especially since tactical planning often acts on the production delays/advances by lowering or increasing a flexible batch (the flexible batch is often different per week) or by moving the production from an SKU to another week. These planning decisions are difficult to simulate.

Within our simulation we assumed that obsolete products can still be sold as regular demand, such that we do not register a stock-out in case we only have products available that have passed 1/3 of the expiration time. The same goes for stock-outs. If a stock-out occurs we assume that demand is backordered, which is not always the case for Grolsch. This means that we might have a higher or lower Stock Availability percentage reached within the simulation than we would have in practice. In case of a stock-out that should be a lost sale in practice, we should have a higher Stock Availability percentage in practice (and higher total costs). In case of an obsolete product that cannot be sold anymore (against a discount price) we could have a lower Stock Availability percentage in practice (and we would definitely have higher total costs).

Speaking of costs, the percentage of the gross profit margin (29%) that we used to determine the obsolescence costs is based on old research from 2019. It might be that these costs are currently very different. For the holding costs in this research, we have kept it relatively simple as we have only taken into account the costs of commuting. Normally, if stock levels are higher warehousing would need more personnel to internally relocate the pallets. This is currently not taken into account for the holding costs, because we simply did not have a good estimation of when and how many pallets would need to be relocated internally and how many extra personnel we would need for this. On top of that Grolsch currently has to commute to the harbour due to lack of space at their own warehouse. If Grolsch is able to increase the warehousing storage capacity within the brewery they do not have to commute (as many) pallets anymore. In such a case the total variable costs would change and fixed costs would increase such that a new trade-off should be made.

Some additional points that are important to note about this research are the following:

- In this research we have mainly focused on Filling Line 2 products that are made to forecast for the domestic market, excluding 2 SKUs which are product X and product Y. For products of other filling lines, we might thus have different results.
- We assume an infinite warehousing storage capacity. We considered the storage capacity to be an output of our research instead of a constraint.
- When the production plan is made based on the minimum Days of Cover we merely looked at in which week we are able to produce a brown bottle or a green bottle (this is normally also the case at Grolsch), but we did not take into account other aspects of the optimality of the production schedule.

7.4 Further research

We noticed during our research that when the production plan is made based on the minimum Days of Cover the tactical planning follows a rough approach to come to a new production plan for next year. We have tried to formalise a step-wise approach within our research, but this did not lead to a realistic production plan. As a part of standardization and to make a production plan that is as efficient as possible I would advise Grolsch to look into how they can standardize the making of a realistic production plan such that the quality of the production plan does not depend as much on the person making it anymore. By making a relatively simple algorithm within VBA or another programming language the plan could be easily optimized.

We assumed in our research that the forecast error distribution is normally distributed with the mean (μ) being 0, such that the forecast is not biased partly as a wish of Grolsch. However, in practice, we saw that in 2022 the forecast was biased (we often saw a positive bias, hence demand was over-forecasted) and we often saw that the forecast error distribution did not follow a normal distribution. It would be worth finding out for Grolsch what a positive bias of the forecast and a different distribution (like the gamma distribution or the exponential distribution of the absolute forecast errors) would do to the optimality of the safety stocks. It would be interesting to know if it would be more optimal to attain a fixed minimum Days of Cover or to differ the minimum Days of Cover per quarter for each SKU in that situation as well. Furthermore, it would be interesting to see if the new recommended method we propose would then still be optimal.

Currently, we have taken a fixed percentage of the gross profit margin to incur as a cost in case a product passes 1/3 of its expiration time. This percentage was based on research that was performed at Grolsch back in 2019. It would be worth researching if this percentage would still be a good approximation to use for the obsolescence costs of an SKU.

Grolsch has multiple times faced the problem that their warehouse is fully utilized, such that they have to stop their stock build (especially during the run-ups to the summer vacation period and the holiday season in December). It would be good to properly research how much storage capacity Grolsch would need to store all its products and build up stock in the run-up to these peak moments in sales. Moreover, commuting the pallets to the storage location in the harbour is rather inefficient and costs Grolsch a lot of money. Therefore, it would be worth it for Grolsch in our opinion to search for storage locations that are located closer to the brewery.

Within our research, we have determined the optimal safety stock allocation for the SKUs, but we left the optimal batch size out of the scope of this research. In our opinion, it would be worth the effort to do research to find out the optimal batch sizes for each SKU, especially in light of obsolescence.

Another topic worth researching is the effect of the service level (target) of an SKU and the length of the shelf life of an SKU on the obsolescence (costs) of the SKU. Based on our research and the research of Joore (2021) we hypothesise that a higher service level and shorter shelf life lead to higher obsolescence costs. It would be interesting for Grolsch to know the exact effect of the 2 factors on the obsolescence costs, such that Grolsch can better align the minimum Days of Cover to these costs.

References

Axsäter, S. (2006). *Inventory control* (2nd ed.). Springer. https://doi.org/10.1007/0-387-33331-2

Bacchetti, A., Plebani, F., Saccani, N., & Syntetos, A. (2013). Empirically-driven hierarchical classification of stock keeping units [Focusing on Inventories: Research and Applications]. *International Journal of Production Economics*, *143*(2), 263–274. https://doi.org/10.1016/j.ijpe.2012.06.010

Balaji, K., & Senthil Kumar, V. (2014). Multicriteria inventory abc classification in an automobile rubber components manufacturing industry [Variety Management in Manufacturing]. *Procedia CIRP*, *17*, 463–468. https://doi.org/10.1016/j.procir.2014.02.044

Barros, J., Cortez, P., & Carvalho, M. (2021). A systematic literature review about dimensioning safety stock under uncertainties and risks in the procurement process. *Operations Research Perspectives*, *8*, 100192. https://doi.org/10.1016/j.orp.2021.100192

Chopra, S., & Meindl, P. (2018). *Supply chain management: Strategy, planning, and operation, global edition* (7th ed.). Pearson Education. https://doi.org/10.1016/j.pursup.2013.07.003

Gonçalves, J., Sameiro Carvalho, M., & Cortez, P. (2020). Operations research models and methods for safety stock determination: A review. *Operations Research Perspectives*, *7*, 100164. https://doi.org/10.1016/j.orp.2020.100164

Joore, E. (2021). *Modelling the trade-off between service level and waste of perishable goods at food retailers* [Master graduation thesis regarding inventory control of perishable goods that has been previously performed at Slimstock by an alumnus of the study Industrial Engineering & Management at the University of Twente. The thesis can be found via: http://essay.utwente.nl/86238/1/Joore_MA_BMS.pdf].

Kamp, K. (2018). *Inventory control at grolsch : A master thesis which analyzes inventory control at grolsch and proposes a model to determine optimal levels of safety stock* [Master graduation thesis regarding inventory control that has been previously performed at Grolsch by an alumnus of the study Industrial Engineering & Management at the University of Twente. The thesis can be found via: http://essay.utwente.nl/74736/].

Nareshchandra, P., & Desai, D. (2019). Inventory categorization techniques for effective inventory management. *Journal of Emerging Technologies and Innovative Research (JETIR)*, *6*(1), 689–700. https://doi.org/doi.one/10.1729/Journal.19365

Prak, D., Teunter, R., & Syntetos, A. (2017). On the calculation of safety stocks when demand is forecasted. *European Journal of Operational Research*, *256*(2), 454–461. https://doi.org/10.1016/j.ejor.2016.06.035

Schöniger, S., Snellen, H., & Tschöper, A. (2022). Cost of capital study 2022 [https://kpmg.com/de/en/home/insights/2022/10/cost-of-capital-study-2022.html].

Silver, E., Pyke, D., & Thomas, D. J. (2016). *Inventory and production management in supply chains* (4th ed.). CRC Press. https://doi.org/10.1201/9781315374406

t2informatik GmbH. (2023). What is xyz analysis? [https://t2informatik.de/en/smartpedia/xyz-analysis/].

Wikipedia. (2023). Moment (mathematics) [https://en.wikipedia.org/wiki/Moment_(mathematics)].

Yang, L., Li, H., Campbell, J., & Sweeney, D. (2017). Integrated multi-period dynamic inventory classification and control. *International Journal of Production Economics*, *189*, 86–96. https://doi.org/10.1016/j.ijpe.2017.04.010

Appendices

A The distribution of the Forecast Errors

By means of a quick analysis of the forecast error pattern of a few SKUs, we applied the Chi-Squared test for the Normal-distribution, the Gamma-distribution, and the exponential distribution. For the gamma-distribution we had to adjust the data set a bit, as the gamma-distribution cannot be negative. To make a Gamma-distribution we recalculated every entry by adding the absolute minimum of the data set to the original value of the entry. For the exponential distribution, we have taken the absolute forecast errors as was mentioned earlier in Section 5.5. From the data set, we first calculated the number of bins by number of bins $= \sqrt{\upsilon}$, where υ equals the number of observations in the data set. The bin length is then equal to $\lceil \frac{\text{Min}-\text{Max}}{\text{number of bins}} \rceil$, where Min equals the minimum value of the data set, Max equals the maximum value of the data set, and the $\lceil \cdot \rceil$ rounds up variable $\cdot$ to the nearest integer. With the number of bins, and the bin sizes known we count the number of observations of the data set that are in each bin. Next, based on the distribution that we would like to check we can calculate the expected number of observations within each bin. For the Normal-distribution this would be done for example by calculating the probability that an observation is lower than the higher boundary of the bin, which is done using the average and standard deviation of the data set as μ and σ, respectively. By multiplying the probability with the total number of observations (υ) we can calculate the expected number of observations per interval. Based on the expected number of observations per interval for the distribution that we want to check, and the true number of observations per interval we can create a graph like the one below in Figure 32 that is made for a random SKU of Grolsch. This is the first visual check to evaluate the fit of the particular distribution.

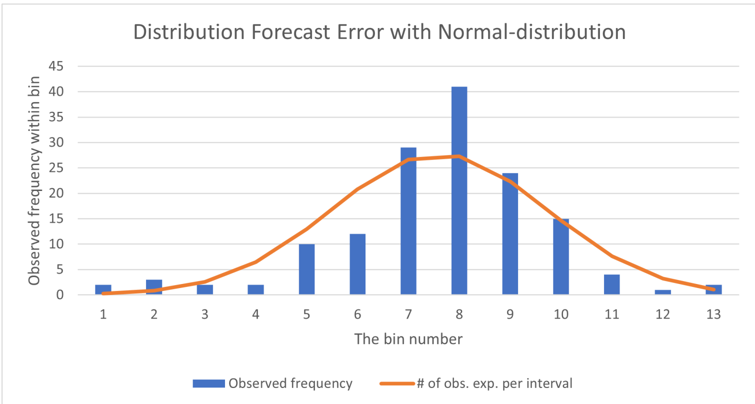


Figure 32: An example of the visual check for the distribution of a random SKU of Grolsch. In this example, we checked the distribution of the SKU for the Normal-distribution. The orange line shows how the graph would look like for this data set if it is normally distributed. The blue bars represent the true number of observations within each bin. The total number of bins is 13, and the total number of observations is 148.

For Pearson's Chi-Squared test we need to first calculate the probability of an observation being in a bin, assuming a uniform distribution. The probability is calculated by dividing the bin number by the total number of bins. Then the higher boundary of the bin is calculated by using the probability of the uniform distribution in the inverse function of the distribution that we want to check. The observed number of observations within this bin is then calculated, and the expected number of observations is then calculated by assuming a uniform distribution (total number of observations divided by the number of bins). Based on both the expected number of observations and the observed number of observations we can calculate a relative error for each bin. The error is calculated by squaring the difference between the observed value and the expected value and dividing it by the expected value. The sum of the relative error for all the bins represents the value that we need to test. The value is tested by the test statistic that is calculated by the inverse of the right-tailed Chi-Squared distribution, where the degrees of freedom are given by the number of bins - 1, and we have taken 0.05 as significance. If the value to test is lower than the value of the test statistic, then we do not reject the hypothesis that the data set follows the distribution that we are checking for. Otherwise, we do reject the hypothesis that the data set follows the distribution we are checking for.

To visually check for the fit of the distribution we have made a Q-Q plot. The Q-Q plot sets a point in the graph for every observation. We first sort all of the observations from low to high and we set this value as the x-value of the data point in the graph. Next, we calculate the expected value for the entry with the inverse of the distribution that we want to check for, where the probability used here equals the observation number divided by the total number of observations. That way we also have the expected value for the observation when it follows the distribution that we want to check for from low to high. The y-value of the data point then equals the expected value. For a perfect fit of the distribution, we should then see a perfectly straight linear line with an angle of 90 degrees on both the x-, and y-axis. An example of a random SKU is given below in Figure 33. We removed the values on the x-, and y-axis due to confidentiality.

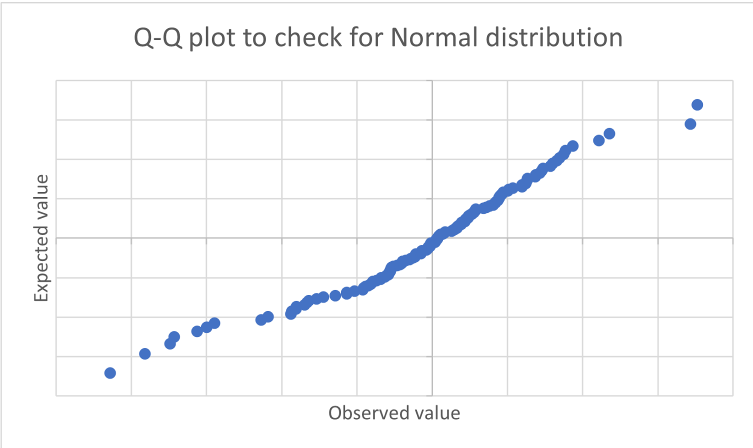
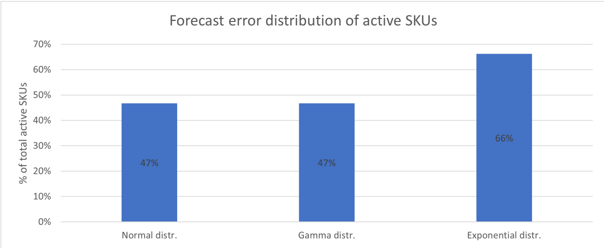


Figure 33: An example of the QQ-plot to check for the distribution of a random SKU of Grolsch. In this example, the observed value is given on the x-axis, and the expected value is given on the y-axis. For a perfect fit, we would see a straight linear line from the bottom left to the upper right, under an angle of 90 degrees from both the x-, and y-axis. The total number of observations for this example equals 148. The values on the x-, and y-axis have been removed due to confidentiality.

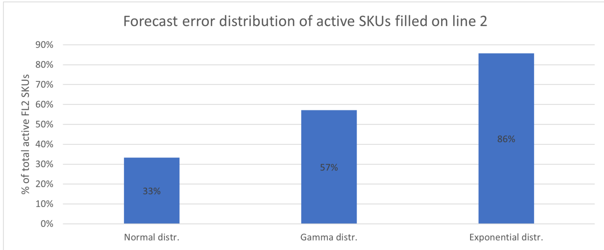
We should note that we filtered the data set for all of the entries that had a forecast of 0, and if an SKU had a lot of forecast errors that were 0 we also filtered these. We filtered the entries that had a forecast of 0 because we noticed sometimes that when an SKU is not actively sold, some sales were still reported. We have asked the demand planning and we came to the conclusion that these sales are sold at a cheaper price or these stocks are considered spoiled due to obsolescence. For some SKUs, we also filtered the data set for 0, only if the forecast errors were 0 a lot of times. We have done this because for some SKUs the demand was such low that the frequency of 0 influenced the distribution a lot.

Results

With Pearson's Chi-Squared test we found that with 47% of the active SKUs we do not reject the hypothesis that the forecast error pattern follows a Gamma- or Normal-distribution with 5% significance. Moreover, for 66% of the SKUs, we do not reject the hypothesis that the absolute forecast error follows an exponential distribution. For the SKUs that are filled on line 2, we can even conclude that we do not reject an exponential distribution for the absolute forecast errors of 86% of the SKUs. For the Normal-distribution this is even only $\frac{1}{3}$. The percentages mentioned are also visible in Figure 34 below.



(a) The percentage of active SKUs of which the forecast error pattern can be modelled by each theoretical distribution.



(b) The percentage of active SKUs filled on line 2 of which the forecast error pattern can be modelled by each theoretical distribution.

Figure 34: The percentage of SKUs of which the forecast error pattern can be modeled by the theoretical distributions, based on Pearson's Chi-Squared test with 5% significance.

B The number of replications

In order to prevent getting inconclusive results from our simulation we need to run multiple simulations, so we can differ the random number stream in every run. To know when the results of the simulation should be conclusive we have to run a large number of replications. In our case, we use five different (important) outputs to determine the number of replications that we need to get reliable results. We use the stock level of all SKUs on the last day, the Stock Availability percentage, the total costs, the total number of hectoliters that have passed 1/3 of the expiration date, and the total number of hectoliters that Grolsch could not deliver on time.

We use the relative error method to determine the number of replications that we need to do. In order to use the relative error method we first need to put the results of the output in an array where every row represents the outcome of a simulation run. Next, we calculate the rolling variance and the rolling average of the output over the number of replications and we calculate the value of the test statistic. The test statistic value is calculated after every additional replication using the left-tailed inverse of the Student's t-distribution with a probability of 97.5% and ϵ degrees of freedom, where ϵ represents the row number (i.e. the number of replications that we have used to calculate the rolling variance of that row). Then we calculate the Confidence Interval Half Width, which is calculated by multiplying the t-value with the square root of the rolling variance divided by the row number. The relative error is calculated by dividing the Confidence Interval Half-Width by the rolling average. The relative error is calculated for every row number (i.e. after every additional replication), and once the relative error is below the prime of the so-called maximum relative error ($\delta^{'}$) we have a minimum number of replications that we need to do in order to get reliable results. We have set the maximum relative error (δ) at 5%. To get the prime of the maximum relative error we need to calculate it as follows: $\delta^{'} = \frac{\delta}{1+\delta}$.

After having calculated the relative error after each additional replication for the first 1,000 replications for each of the 5 different outputs we have found different numbers of replications for each output. The total stock level of all SKUs on the last day indicated that we would need at least 69 replications. The Stock Availability percentage indicated that we would need at least 3 replications. The total costs indicated that we would need at least 58 replications. The total number of hectoliters that have passed 1/3 of their expiration date indicated that we would need at least 232 replications. Finally, the total number of hectoliters that we could not deliver on time to the customers indicated that we would need at least more than 1,000 replications. Even in case we would change the maximum relative error to 10% we would need 441 replications already. With 232 replications we would have a maximum relative error of 12.9%, but we take for granted a higher maximum relative error for the number of hectoliters that is understocked. The number of hectoliters that are understocked is not a completely unbiased measure to assess the number of replications needed, as the sales and production batch sizes per SKU are very different such that the total number of hectoliters that are under- and overstocked often depends very much on a few SKUs. However, we want to get a maximum relative error as low as possible for these outputs as well as long as the runtime is reasonable (which is about half an hour in our opinion).

As visible the number of replications to get reliable results for each output differs a lot. For us, the total costs and the Stock Availability percentage are both the most important outputs of the simulation. Moreover, we want to do several sensitivity analyses, hence we should limit the number of replications in order to prevent extremely high run times. It takes about 6 seconds to run 1 replication.

In order to keep the outcomes reliable we have chosen to run at least 232 replications. We have chosen to run 232 replications, as this gives us a reliable outcome for the most important outputs. In case we also want to go below a maximum relative error of 5% for both the total number of hectoliters that have passed 1/3 of the expiration date and the total number of hectoliters that Grolsch could not deliver on time to the customers we would need a lot more replications. With 232 replications we keep the run time of 1 experiment below half an hour which we think would be reasonable.