IMPROVING PRODUCT OBSOLESCENCE CONTROL AT KONINKLIJKE GROLSCH

Master thesis Industrial Engineering and Management

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Document	Master thesis
Title	Improving product obsolescence control at Koninklijke Grolsch
Summary	Development of an obsolescence control model that measures expected product obsolescence, and generates insights into possible interventions regarding product obsolescence and their effects on costs and service.
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MANAGEMENT SUMMARY

This research has been executed in response to the high inventory losses Grolsch experienced during the previous year. After diving into the inventory losses data of 2019, it appears that almost half (43%) of the total inventory losses during the year 2019 is caused by obsolescence of finished goods, with a total amount of € X. However, since the supply chain planning department only has influence on the obsolescence of finished goods that are made to forecast, it is chosen to focus on these inventory losses during this research, that together made up 48% of the inventory losses due to obsolete finished goods. Obsolescence arises if excess stock reaches its final delivery date to the customer before it is sold. At the moment, there already exists a standard obsolescence control procedure. However, a drawback of this procedure is that it only pinpoints products that already almost reach their final delivery date. If lucky, these products can be sold for a discount price. However, the procedure only mitigates the negative effects of obsolescence, but does not allow more pro-actively action in order to avoid obsolescence. It appears that, at the moment, there is insufficient insight into expected product obsolescence, and so insufficient anticipation to this expected obsolescence is possible, what eventually leads to the high inventory losses. Goal of this research is therefore to better foresee product obsolescence, and to develop a calculation model that generates insight into possible actions regarding product obsolescence and their effects on costs on service.

Current situation analysis

Before a solution model will be developed, first of all a root cause analysis is executed in order to generate insight into the root causes of product obsolescence. After diving deeper into the inventory losses data of 2019, it appears that only 12% of the total inventory losses in hectolitres is caused by semi-finished products, while a much higher volume (88%) is caused by finished goods. However, in general finished goods contain far more added value than semi-finished goods, what means that in case of high expected obsolescence, probably costs could be saved by disposing beer earlier in the production process. Besides this, it appears that products with particular characteristics (slow movers, seasonal products, products with ending sales seasons, and newly introduced products) relatively encountered more obsolescence than other products. Two underlying causes have been found that can explain this. First of all, it appears that structurally overforecasting was an overall problem during the year 2019. However, since the improvement of demand forecasting is an ongoing project, this is no solution direction. The second underlying cause, the interplay between minimum batch sizes and demand volumes, however appears to be a good starting point for further research.

It appears that for brew to order (BTO) products - of which demand volumes in general are already lower than their minimum brewing sizes - on average 18.2% of the produced beer had become obsolete during the year 2019, while this was only 1.6% for the brew to forecast (BTF) products of which demand volumes in general are higher than their minimum brewing sizes. The X BTO products encountered total inventory losses of € X, while the X BTF products encountered total inventory losses of € X during the year 2019. Since the few BTO products – that probably often were restricted by their minimum brewing sizes - in general encountered much more obsolescence, it is hypothesized that part of the obsolescence of these products could have been avoided by applying early disposal of semi-finished beer to these BTO products. We will further focus on examining the impact of early disposal of semi-finished beer on BTO products during this research. It needs to be kept in mind that besides the € X of inventory losses due to obsolete BTO products, also € X of disposal costs need to be taken into account for the BTO products as a direct result of obsolescence. This leads to total costs of € X on which we have influence during this research.

Solution design

The model that is developed to tackle the earlier mentioned root cause is two-fold: a monitoring dashboard measures the expected obsolescence of products, where after the proposed intervention method is examined by the optimization tool. The heuristic developed for the monitoring model is a more complex, extended version of the classical newsboy problem, that now incorporates multiple product batches. Due to fast changing demand forecasts (and so also fast changing production plans), it is decided to focus on short term prediction. Therefore, the monitoring model incorporates a maximum of 1 next planned production batch at a time besides the already available starting stock. With help of the most updated production plan and demand forecast, and by incorporating demand variability in the form of historical forecast deviations, the expected obsolescence per product is calculated. Sensitivity analysis reveals that regarding the expected demand variable, a decrease of 10% already results in an average increase of 85% of the model outcome, while an increase of 10% already results in an average decrease of 26% of the model outcome. Regarding the coefficient of variation of demand variable, a decrease of 10% already results in an average decrease of 29% of the model outcome, while an increase of 10% already results in an average increase of 38% of the model outcome. It therefore can be concluded that a small change in expected demand as well as in the coefficient of variation of demand already can lead to quite some high changes in the model outcome, and so these input variables to a large extent can contribute to the accuracy of the prediction model. This underlines the impact, and so the importance, of the use of accurate demand forecasts and the right forecast deviations per product.

After monitoring, the optimization tool gives an insight into the impact of early disposal of semi-finished beer on products with highest expected obsolescence, and calculates the optimal batch size at which total costs regarding expected obsolescence of finished goods and early disposal of semi-finished beer are minimal. Hereby, only the packaging batch size serves as decision variable, and all other variables -such as the production week, and with which other products a product is sharing its beer during production (also called the product's differentiation characteristics) - are kept constant (fixed). Besides early disposal, if a product is sharing its semi-finished beer with other products during production, also a redivision of semi-finished beer over multiple end products is considered, as long as the redivision fits within the current differentiation characteristics of the products.

Results

In order to examine if early disposal could have been beneficial for the X BTO products during the year 2019, the batch sizes of the X production moments of these BTO products are simulated and optimized by our model. Due to limitations of our model (e.g. single period mathematical model suitable for short term predictions, not for yearly predictions) and the unavailability of data (e.g. weekly obsolescence data) unfortunately we cannot calculate the yearly possible cost savings due to optimization. This means we cannot sum up the different production moments per product since optimization of one production moment could have influenced subsequent production moments. However, after separately optimizing the production moments, we can conclude that for 9 of the 18 production moments optimization resulted in cost savings, and that for 6 of these 9 optimized production moments the cost savings were quite significant in comparison to the € X of actual inventory losses and disposal costs of all BTO products of the year 2019. This can be noticed from the column "Cost savings due to optimization" from Table 1 on the next page. The cost savings are a result of early disposal of semi-finished beer, of a redivision of semi-finished beer over multiple end products, or of a combination of both interventions.

SKU(s)	Production moment	Cost savings due to optimization	Caused by…	Extra set up costs	Final cost savings
92301	Wk. 3	€ X	Early disposal	€ X	€ X
	Wk. 15	€ X	Early disposal	€ X	€ X
92318	Wk. 5	€ X	Early disposal	€ X	€ X
92356 & 92318	Wk. 20	€ X	Redivision of beer	€ X	€ X
92376 & 92378	Wk. 32	€ X	Redivision of beer	€ X	€ X
92239 & 92089	Wk. 14	€ X	Redivision of beer	€ X	€ X
	Wk. 18	€ X	Redivision of beer	€ X	€ X
92298	Wk. 3	€ X	Early disposal	€ X	€ X
92298 & 92306	Wk. 26	€ X	Early disposal & redivision of beer	€ X	€ X

Table 1 Optimization results of production moments of BTO products from the year 2019

It appears that reducing expected obsolescence by applying early disposal also results in higher chances of running out of stock. This means that reproductions need to take place earlier, and so more and smaller production batches are necessary throughout the year, resulting in higher set up costs of the production lines. After subtracting these extra set up costs from the earlier determined cost savings due to optimization, it appears that the cost savings remain relatively high for the 6 production moments with relatively high possible cost savings due to optimization, but decreases to almost nothing (or even end up in losses) for the 3 production moments with relatively low possible cost savings due to optimization, as can be noticed from the column "Final cost savings" in Table 1. Since the extra set up costs are not negligible, it is not unwise to keep them in mind during batch size optimization. Although as earlier mentioned we cannot sum up all the production moments, it can be noticed that if per product (pair) only the last production moment would have been optimized during the year 2019 – and so they would not have been influenced by earlier optimizations, what means that they now can be summed up – already 18% (€ X) of the total actual costs could have been saved. Besides this, taking into account the fact that the cost savings of some separate production moments already are significantly high in comparison to the total costs of € X (for example the cost savings of product 92138 at week 5 (€ X) already would cover 39% of the total costs), it seems that probably quite a large part of the total inventory losses and disposal costs of all BTO products could have been saved during the year 2019 by applying batch size optimization to all BTO products.

Recommendations

Since probably quite a large part of the total inventory losses and disposal costs of all BTO products could have been saved during the year 2019 by applying batch size optimization to these kind of products, it is recommended for Grolsch to start making use of the obsolescence control model. Besides the positive effects of early disposal of semi-finished beer and/or a redivision of semi-finished beer on the BTO products that are examined by the optimization tool, using the monitoring tool can bring with it some more positive effects that are not mentioned yet. Since expected obsolescence can now be foreseen earlier in time, more interventions are possible regarding obsolescence, like for example deferring production, or stimulating (discount) sales. The application and impact of these interventions need some further research, and can be examined during the start of using the obsolescence control model. Since these interventions are also applicable to BTF products, and these BTF products made up a larger part of the inventory losses, it is even more interesting to apply the monitoring tool to all kind of products, and research more intervention methods. Besides this, there also can be focused on improvement of the obsolescence control model. Hereby, improvement of the monitoring model (by improving the accuracy of the input variables demand forecast and demand variability) needs some more attention than improvement of the optimization model (by including extra set up costs as penalty costs, and allowing lower minimum batch sizes) since the monitoring model affects BTO- as well as BTF products, while the optimization model only affects BTO products that make up a smaller part of the total inventory losses of obsolete MTF finished goods.

PREFACE

With this thesis I finish my master Industrial Engineering and Management at the University of Twente, and thereby I also finish my student time in Enschede. I am thankful for the great time and everything I learned these years, during as well as outside my study.

First of all I want to thank Koninklijke Grolsch for giving me the opportunity to write my thesis at their company. The colleagues at the Supply Chain Planning department were very welcoming and helpful, and combining an internship with my master thesis was a great learning experience I will be grateful for the rest of my working life.

My special thanks go to my supervisors from the University of Twente and my external supervisor from Koninklijke Grolsch for all the guidance, support, and critical feedback during the execution of my research. Despite the limiting conditions due to Corona, they still helped me through the whole process. It was nice working with you.

Moreover, I want to thank my family and friends for supporting me during the writing of my master thesis, and helping me finish my research.

Kirsten Endeman

Enschede, 30th November 2020

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ABBREVIATIONS

Abbreviation	Meaning
MTO	Made To Order
MTF	Made To Forecast
BTO	Brew To Order
BTF	Brew To Forecast
MinDoC	Minimum Days of Cover
DoC	Days of Cover
MinBrew	Minimum Brewing batch size
MinFiltr	Minimum Filtration batch size
MinPack	Minimum Packaging batch size
SKU	Stock Keeping Unit
ESS	Ending Sales Season
COGS	Costs Of Goods Sold
VMI-system	Vendor Managed Inventory System
NPD	New Product Development

CHAPTER 1: INTRODUCTION

1.1 RESEARCH CONTEXT

Koninklijke Grolsch, a subsidiary of Asahi Breweries Europe Group, is a Dutch brewery that produces different kind of beers, such as the well-known Premium Pilsner, but also more special beers and non-alcoholic beers from which its popularity is increasing these days. Grolsch is the third biggest Dutch beer brand, and has a market share of 14% in the Netherlands. Its product portfolio is diverse, and includes different brands such as its own brand name Grolsch, but also brand names as Peroni, Kornuit, De Klok, Grimbergen, Asahi Dry and Meantime. The company focusses on two markets: the domestic market and the export market. Per year, around 2/3 of the products is sold in the Netherlands, and most of those products are made to forecast. Besides this, per year around 1/3 of the products is exported, and more than half of the total amount of those export products are made to order. Within the domestic market, Grolsch focusses on "on-trade" clients (bars, restaurants, etc.) as well as "off-trade" clients (retail). This research will take place at the Supply Chain Planning department of Grolsch, that deals with all different kind of products mentioned above. The Supply Chain Planning department consists of the teams tactical planning, production planning, and material planning, and works closely together with all other departments from the company.

1.2 RESEARCH MOTIVATION

At the moment, Grolsch is facing high inventory losses. The company wrote off € X as total inventory losses during the year 2019 (excl. wholesale and export). These inventory losses consist of the losses of finished goods, semi-finished goods, ingredients, raw materials such as packaging and merchandise products together that were intended for production or sale but were written off and disposed instead. Figure 1 shows the division of the net inventory losses of 2019 over the different material types. As can be noticed, the great majority (€ X) of inventory losses is caused by finished goods and so needs the most attention. A striking fact revealed after studying the inventory losses data, is that the undefined material losses, that encounter quite some inventory losses (12 %), are mainly caused by one printing production error. For this reason, we will not elaborate further on these undefined material inventory losses. For the other materials it holds that, since the impact of these materials on the total inventory losses is relatively low, we do not dive deeper into these inventory losses.

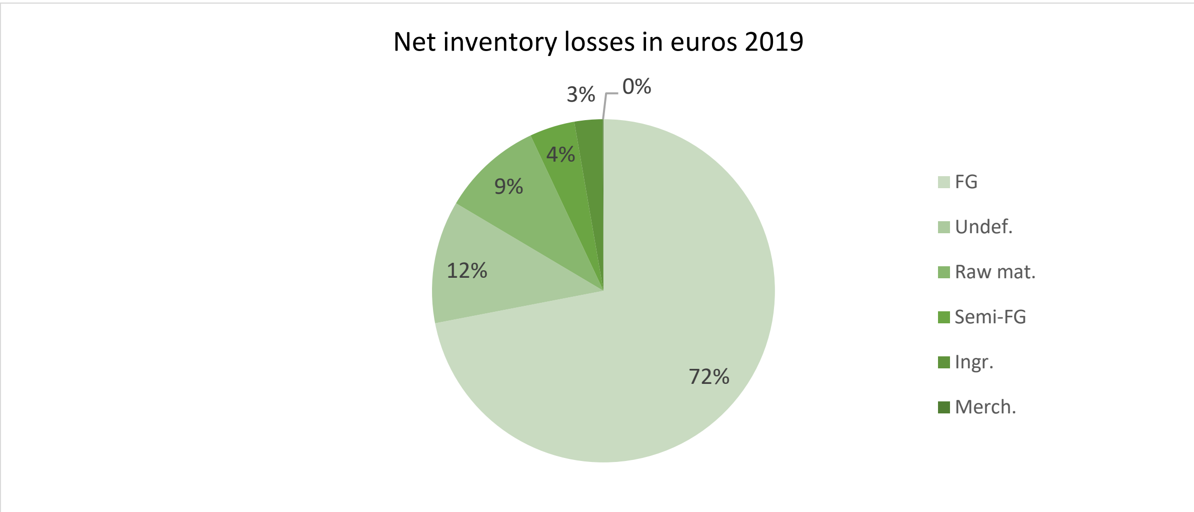

Figure 1 Division of inventory losses in euros for the year 2019 over the different material types

Inventory losses can arise for a lot of reasons. For example, stock can become obsolete or outdated before it is sold, but also problems such as stock damages or quality issues can cause inventory losses. At the company, costs can be written off at different cost centres. Most of these cost centres refer to a department within the company. However, basically a cost centre does not say everything about the cause of costs. Usually multiple reasons for inventory losses can be found at one cost centre. Furthermore, often no reason is given in the data system for a write-off. For this reason it is difficult to get a clear insight into the biggest causes of inventory losses. When diving somewhat deeper into the inventory losses of finished goods, it turns out most of these losses (60.3%) are written off at the commercial cost centre (€ X), as can be seen in Figure 2.

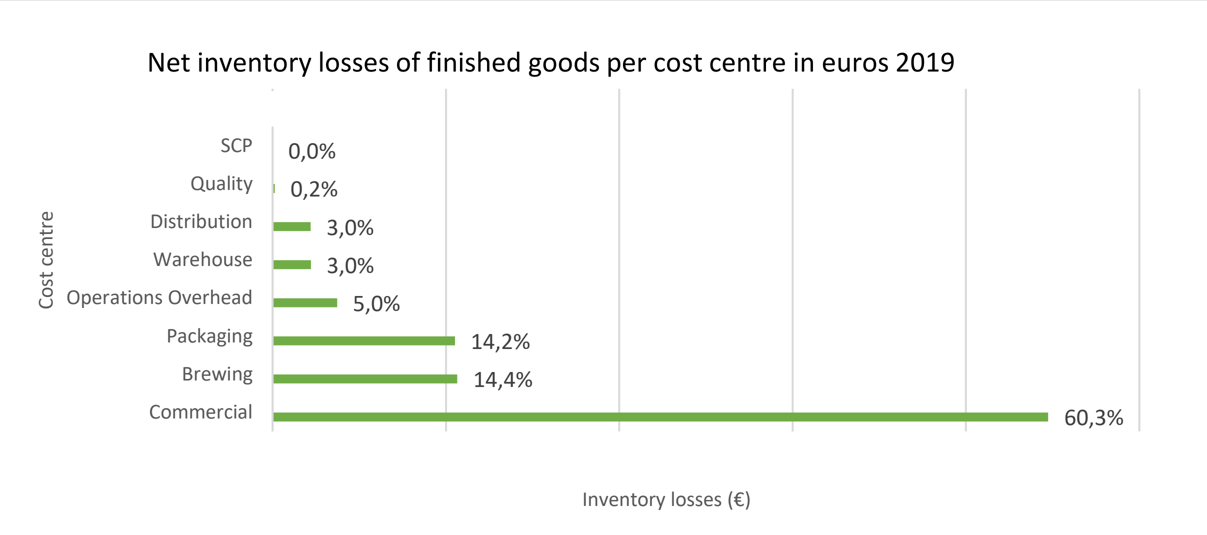

Figure 2 Division of inventory losses of finished goods over different cost centers in euros over the year 2019

For the majority of the commercial finished goods inventory losses no cause is given in the data set, while a minority of these losses are caused by residual beer and obsolete cellar beer. After interviewing some employees it is stated that the commercial losses of finished goods most probably comprise losses due to finished goods that passed their final delivery date to the customer (retailers and restaurants/bars) and so are declared as obsolete. Therefore it is assumed that all the commercial finished goods inventory losses, also those without any given cause, are caused by product obsolescence. Furthermore it is assumed that the finished goods inventory losses written off at most of the other departments are not caused by product obsolescence since the products at these departments are still in production and so cannot have become obsolete already. The few reasons that are given in the data set for those non-commercial losses confirm this, and refer to causes such as damages, quality issues, or production errors. Since a greater part of the finished goods inventory losses could be saved at the commercial cost centre, and since the causes that occur at other departments lay outside the scope of this research at the Supply Chain Planning department, we will focus on reducing the obsolescence of finished goods, also called products or stock keeping units (SKUs) during this further research.

1.3 Problem description

To get more insight into the problem of high obsolescence of finished goods at Grolsch, first of all we will dig somewhat deeper into product obsolescence and its causes and consequences. This information is gathered by means of interviews. Here after, according to Heerkens & van Winden (2012), a problem cluster has been generated that displays all causes and consequences and the relationships between each other, as displayed in Figure 3.

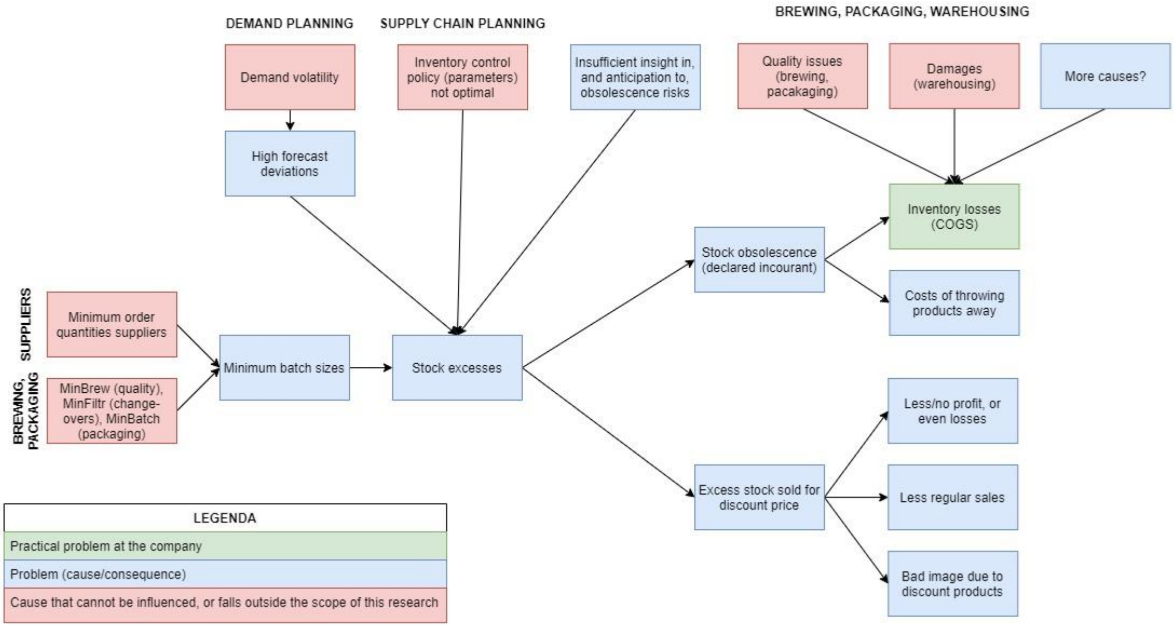

Figure 3 Problem cluster product obsolescence

1.3.1 Minimum batch sizes

One of the causes of product obsolescence, indicated by employees, are minimum batch sizes. There can be found different causes for these minimum batch sizes. First of all, some SKU-specific ingredients are bounded to minimum order quantities of suppliers. Since some of these ingredients are perishable (e.g. yeast), they needs to be used quickly after reception. Second, some processes require minimum batch quantities. During brewing, a minimal amount of ingredients is necessary to reach the quality standards of the final brew. Furthermore, to keep filtration processes efficient by avoiding too much change-overs, the filtration processes are bounded to minimum durations, and so indirect to minimum batch sizes. The same applies for packaging, during which bottles are filled with the final (matured) beer. These packaging processes are bounded to a minimum duration of 3 hours. During the interviews it is stated that obsolescence is especially a problem for slow moving products with a low sales volume, since for most of these products the minimum batch sizes are relatively large in comparison to their sales. The same applies to seasonal products that have low demand at the end of their season, and are not sellable anymore from a certain moment in time. Eventually, the imbalance between available stock and sales can result in stockouts or stock excesses. Stock excesses, for its part, can cause product obsolescence of it becomes expired.

1.3.2 Demand volatility

Forecasts on SKU-level are created by the demand planning department on weekly as well as monthly basis. After interviewing the demand planning department, it appears that especially new products ("New Product Developments", NPDs) can have a quite high variation in demand. The relatively unpredictable demand for these products is difficult to forecast and so can result in quite high forecast deviations. For example, according to the demand planning department, NPDs have an average forecast accuracy of X%, in comparison to a forecast accuracy of around X% for fast movers with a more stable demand pattern. Too optimistic forecasts can result in stock excesses, and therefore can cause product obsolescence. Currently, the demand planning department is busy with improving their demand forecasting methods. For this reason, it is no option to focus on forecasting optimization during this research.

1.3.3 Inventory control

The inventory control system, that is used by the tactical planning team to manage its inventories while meeting customer demand, influences the product stock levels. On weekly basis a tactical production plan is created/updated by the tactical planning team, using the demand forecasts from the Demand Planning department as input. One of the inventory control parameters the tactical planning team determines are the production batch sizes. Another parameter that is determined by the tactical planning team and that influences the amount of stock of different products is the service level ("minimum days of cover", MinDoC) per product. The MinDoC represents the amount of days that needs to be covered with available inventory, and covers the production lead time plus safety stock. The MinDoC is determined by product classification, which is based on the importance and flexibility of a product. Since the tactical planning team is already busy with optimizing the MinDoCs for all the SKUs, this solution direction falls outside the scope of this research. The idea of the tactical planning system is to plan production automatically if the inventory of a product drops below the MinDoC. However, the build-in solver for the production batch sizes is not used at the moment since it does not approach the right production quantities yet. This is because currently the solver does not include all the important constraints per product yet. For this reason, the tactical planning team is busy with integrating all the necessary constraints per product, and optimizing the batch quantity-solver in their planning system. Until the moment this solver works optimal, production quantities still have to be determined manually. When the MinDoC of a product is estimated by the system to be threatened, the tactical planners have to puzzle with (multiples of) minimum batch quantities, until the MinDoC of the product is covered again. This process is time-consuming and sensitive to errors. However, since the tactical planners are optimizing their batch quantity-solver at the moment, also here is no room for optimization left for this research.

1.3.4 Stock excesses

As already mentioned, an imbalance between available stock and sales can lead to stock excesses. An imbalance also can turn out into stockouts, but since this research focusses on inventory losses due to product obsolescence, stockouts will be left outside the scope. Considering stock excesses, there comes a moment in time that stock reaches its final delivery date to the client (1/3 of the total shelf life) due to perishability. To give an indication, the shelf life of beer in kegs is around 1-2 months, for premium lager this is around 3 months, and special beers have a shelf life of around 6 months. When the stock age of a product is higher than 1/3, but lower than 2/3, of its shelf life, two actions are possible. First of all, sometimes clients are willing to buy expired products for a discount price. As an exception, if the quality of a product that passed 2/3 of its shelf life is still good enough, it sometimes even can be decided by the Quality Manager to still release the product for sale at a discount price. Second, in the case that no clients are interested in buying expired products for a discount price, products will be declared obsolete. In this case, the company loses all the direct costs that are made to produce the product, also called the costs of goods sold (COGS). On top of this, it costs the company money to transport obsolete products to the harbour, manually open them, and throw away the beer and (part of the) material. Both costs are directly related to product obsolescence. In the case of discount sales, it depends on the given discount if the company is directly losing money on the product or not. If the discount selling price does not compensate the costs already made, the company is losing money on the product. Also excise duties (in Dutch: "accijnzen") are kept in mind while determining the discount price of products. When products are sold, the excise duty makes part of the selling price. However, when throwing away the products instead of selling them, Grolsch does not have to pay this excise duty. For this reason, it is sometimes even cheaper to throw away a product, than selling it for a lower price, but with excise duty, to a customer. Besides costs directly related to obsolete and discount products, Grolsch also faces more indirect costs. For example by throwing away products or selling products for a discount price, the company loses potential profit. Besides this, discount products can act as substitution goods and could have a negative impact on the sales of regular products, and besides this could damage the brand image.

1.3.5 Insufficient insight in, and anticipation to, expected obsolescence

In order to control product obsolescence, currently once per week an obsolete list is updated by the customer service department. This list displays all the products that are threatened to reach their final delivery date within 5 weeks, and that do not have enough demand forecasted to consume all the stock left. During the weekly Retail Operations Meeting (ROM), all products with high expected obsolescence are discussed, and it is decided if these products can be sold for a discount price, or will be declared obsolete. To give an indication, Premium lager is in stock for on average 4 days, while a special beer such as Radler has an average DoC of 15 days.

Before we dive further into Grolsch' current obsolescence control procedure, first of all the definition of expected obsolescence will be given in order to clarify what is meant with this term during this research. With <u>expected obsolescence</u>, during this research **the expected amount of hectolitres of beer** is meant **that could not have been sold before it reached its final delivery date to the customer, and also could not have been sold for a discount price after reaching its final delivery date. These products are declared obsolete and need to be disposed**. More information about obsolescence will be discussed further in the report.

A first shortcoming of the current obsolescence control procedure of Grolsch is that the expected obsolescence is only calculated with help of the expected demand forecast, but demand variability is not taken into account yet. Since demand sometimes can be very fluctuating, it would be smart to also include demand variability in order to estimate product obsolescence.

Another shortcoming of the current obsolescence control procedure, is that it only pinpoints finished goods that are almost at the end of their lifecycle (5 weeks before final delivery date) and that are threatened to become obsolete. The procedure does not take into account all the other stock (remaining finished goods, semi-finished goods) and planned products for production that are already threatened to become obsolete in the future. When also taking into account this expected obsolescence, interventions could take place earlier in time in order to reduce future stock obsolescence. Besides selling finished goods for a discount price, or throwing them away at the end of the process, there is a wish to find out what the effects can be of interventions that take place more early in the planning/production process. For example, planned production batches could be cancelled/adjusted, but also later in the process, it could be decided to abort production and throw away (part of the) semi-finished products before making any more costs. At the moment there is not enough insight in all possible actions to take against obsolescence and their possible effects on costs and service.

A third shortcoming is the lack of insight in stock ages (versus shelf life) of available stock at the tactical planning program. Stock ages can be found per product in SAP, but looking up for this information per product takes too much time during production planning. Currently, the tactical planning program displays a standard maximum stock age per product, in other words the standard amount of days from end of production (packaging) until final delivery date to the customer. This maximum stock age can be kept in mind while planning new production batches, since the DoC must not be higher than the maximum stock age of the planned product. However, the tactical planning program lacks insight in the stock age of planned products that are already packaged (and its perishability is started yet). This means it cannot be controlled easily from the production plan if products on stock almost reach their final delivery date to the customer. Therefore, obsolescence (for example caused by demand changes) cannot be foreseen easily. This makes early anticipation to expected obsolescence more difficult. On top of this, stock of a certain product can consist of different batches with different expiration dates. First come first served is applied to stock, so there is no need to worry about the treatment of stock. However, the lack of insight into the stock ages of different batches in the tactical planning program makes obsolescence control even more difficult.

Finally, after interviewing some employees, it turned out that at the moment, the communication between the Demand Planning, Supply Chain Planning and Sales departments about expected obsolescence, possible interventions and their effects, can be better and more effective. The current product obsolescence procedure is not sufficient enough. By more combining important information, knowledge and opinions from different departments, decision making regarding product obsolescence would be less complex and more well-founded.

1.3.6 Other causes of inventory losses

Also other causes of inventory losses are revealed during interviews. As earlier described, for example during production and packaging, products can be rejected due to quality issues, or during transportation and warehousing, damages can result in product obsolescence. Even more causes of inventory losses could be possible but those are not revealed during the interviews or not find in the inventory losses data. However, since it is already decided to focus on the cause product obsolescence, those other causes of inventory losses are irrelevant during this further research.

1.3.7 Core problem

As already described, excess stock of finished goods that reaches its final delivery date to the customer can become obsolete or, if lucky, sold for a discount price. As can be noticed in the problem cluster, most of the found causes for excess stock cannot be influenced, or fall outside the scope of this research. Only the cause related to insight in and anticipation to expected obsolescence remains. Solving this planning-related problem would be of interest to the supply chain planning department where this research takes place. For this reason, there will be focussed on the following core problem during this research: "**At the moment, insufficient insight into expected product obsolescence, and insufficient anticipation to expected product obsolescence, eventually leads too high costs.**"

1.4 Research goal, questions and approach

According to the formulated core problem, the goal of this research will be as follows:

> "To better foresee product obsolescence, and to develop a calculation model that generates insight into possible actions regarding product obsolescence and their effects on costs and service"

In other words, the main research question will be: "**How do we better foresee product obsolescence, and how do we generate insight into possible actions regarding product obsolescence and their effects on costs and service?**" Intervention scenarios to products for which much obsolescence is expected can be analysed by means of a calculation model, and its effects (e.g. costs and service) can be used to support decision making regarding product obsolescence. In this way, the research will contribute to a new way of obsolescence control by different departments. Several sub-questions are developed, and by answering these questions, the main research question will be answered, and so the research goal will be achieved. The sub-questions and a plan of approach to answer these questions, are discussed in this chapter.

Chapter 2: Current situation analysis

a) How much product obsolescence did Grolsch encounter during the year 2019, and what were the negative effects of this product obsolescence for Grolsch?

First of all, it needs to be determined which negative effects are directly related to product obsolescence, and so needs to be measured. Here after, information about the amount of obsolescence and its negative effects can be gathered by means of a quantitative analysis of obsolete cost data from the year 2019.

b) Which products encountered the highest obsolescence during the year 2019, and what are the root causes of product obsolescence?

From the 2019 obsolete cost data set it can be examined which products encountered the highest obsolescence during the year 2019, and so require most attention during this research. Here after, a root cause analysis can be executed to the obsolescence data from 2019. At a later stage in the research, tackling one of these root causes can serve as possible interventions against (the negative effects of) product obsolescence.

c) How does Grolsch - and in particular the tactical planning team - currently tries to foresee, and anticipate to product obsolescence, and which intervention methods are currently applied to products for which much obsolescence is expected?

By conducting interviews with the tactical planning team and other important stakeholders, the current way of production planning and estimating product obsolescence can be studied, and it could be examined which intervention methods against obsolescence currently take place at which moments (e.g. during planning, production, or when products are already on stock).

d) Which intervention methods are furthermore possible in order to reduce (the negative effects of) product obsolescence?

By conducting interviews with the tactical planning team and other important stakeholders, it can also be examined which other intervention methods against obsolescence are possible, and why these methods are not (yet) applied at Grolsch. Here after, one of these solution directions will be chosen to focus on further during this research.

Chapter 3: Solution design

a) What will be the scope of the solution model? Which restrictions needs to be taken into account, and which assumptions will be made?

In order to design a model for our proposed solution direction, first of all it needs to be determined how the model will broadly work, for which kind of products in which kind of situations the model is applicable, and if there are restrictions within the company that needs to be taken into account. Also some assumptions needs to be made in order to simplify the problem and prevent the model from becoming too detailed. The determined scope, restrictions, and assumptions together function as a framework within which a solution model can be created.

b) What does the conceptual model look like, and which in- and output data is desired for this model?

While taking into account the earlier determined model scope, restrictions, and assumptions, a conceptual model is developed by means of the black box method. The solution model is now seen as a black box with its desired inputs and outputs, without knowing their internal workings yet. First of all the desired model output is determined, after which it is determined which input data will be needed to generate this output data. Also it will be described in broad terms at this section how this output data will be generated. However, deepening of the exact relations between in- and output data will take place at a later stage of this research.

c) According to the literature, how can product obsolescence be estimated by also taking into account the demand variability, and how is this technique applicable to our model? How does the earlier proposed intervention method, and its impact on expected obsolescence and corresponding costs, will be examined by the model?

A literature review can provide insight in ways to estimate product obsolescence by also taking into account the demand variability, and one of these ways can be used to develop an obsolescence prediction model. After developing a certain calculation model, it also needs to be determined how the earlier proposed intervention method will be included into the model, in order to apply optimization to the current situation and examine the effects of this intervention on the outcome of the model.

d) How should the model be verified and validated?

In order to examine if the model is credible, it has to be ensured that the implementation of the model is correct, and find errors are fixed. Besides this, to ensure the accuracy of the model's representation of the real system, historical data (from 2019) can be tested on the model, and its outcomes can be compared to the real outcomes of 2019.

e) What are the results of model verification and validation?

After executing the steps in above mentioned research sub-question, the verification and validation results needs to be studied in order to determine if the model indeed can be considered as verified and validated.

Chapter 4: Results

a) How are the optimization results of the applied intervention method generated by the model?

Before optimization is applied, it needs to be determined into which situations and for which products of the year 2019 will be intervened. Here after, the (decision) variables that will be changed during optimization need to be determined.

b) What are the optimization results of the applied intervention method in terms of expected obsolescence and its corresponding costs?

It is interesting to examine if application of the intervention method indeed would have resulted in improvements regarding expected obsolescence and its corresponding costs, and if so, how much improvement could have been reached.

c) What are the additional effects of the applied intervention method?

Besides the effects on expected obsolescence and its corresponding costs, an intervention probably also brings along other side effects that need to be taken into account as well. This will be done in this section.

d) Would application of the intervention method (and so use of the optimization model) have been useful for the year 2019?

In order to determine if application of the intervention method (and so: use of the optimization model) would have been beneficial for the year 2019, the effects on expected obsolescence, its corresponding costs, and other side effects need to be compared to the actual costs and effects.

Chapter 5: Sensitivity analysis

a) What is the impact of changing input variables on the model outcome?

First of all it needs to be determined which input variables will be adjusted during the sensitivity analysis. In general, these will be the variables the company has some influence on, so that adjustments to these variables actually might be put into practice if that would be desired. After slightly increasing and decreasing the current input variable values, it can be concluded for which changes in input variable the model outcome is the most sensitive, and which changes result in desired model outcome improvements.

b) What other changes can be applied to the model in order to examine potential improvement of the model outcome?

Besides adjusting the above mentioned input variables, perhaps also other small adjustments can be made to the model (e.g. to particular parameters of the model) in order to try to improve the model outcome. The results of this second sensitivity analysis will be discussed in this section.

1.5 Research scope and limitations

As already mentioned, during this research we will be focusing on product obsolescence of finished goods. The proposed obsolescence control model that will be developed during this research is only applicable to those finished goods, and its semi-finished goods earlier in the process, but in reality, also material obsolescence is a problem at Grolsch. However, the inventory losses of finished goods are much higher than that of material, and besides this, obsolescence control of material is much more complex since different SKUs often share the same types of material. It is for these reasons that it is chosen to only focus on finished goods, and its semi-finished goods, during this further research.

1.6 Deliverables

At the end, the research will result in the following deliverables:

- A root cause analysis of product obsolescence;
- A calculation model that generates insight into expected product obsolescence and different possible interventions and its effects, in order to support product obsolescence control;
- A new proposed obsolescence control procedure.

CHAPTER 2: CURRENT SITUATION ANALYSIS

In order to improve obsolescence control at Grolsch, first of all insight into the problem and its impact is needed. In Chapter 1, by means of qualitative interviews and data analysis, possible causes and consequences of product obsolescence are revealed. The next step in this research is to quantify the problem and to reveal the most important causes of product obsolescence by more profound data analysis. Finally, this chapter describes the current way Grolsch tries to control product obsolescence, and which interventions furthermore could take place to reduce product obsolescence.

2.1 QUANTIFYING THE PROBLEM

As input for this research, a data set containing the inventory losses in euros at Grolsch over the year 2019 is used. There is chosen for a minimal period of one year, since the seasonal demand patterns of products will fall within one year. It can be discussed if an observation of the obsolescence of one year is enough to draw conclusions about obsolescence and its causes, since for example in this case you will only have inventory losses data of 1 season for seasonal products. However, since the product portfolio is changing fast, it will take too much time to dive into inventory losses data of multiple years and take into account all the product code changes that took place within those years. For this reason there is chosen to dive into the data of the most recent year (2019). It is assumed that this year reflects the current situation (product portfolio, demand, etc.) the best.

2.1.1 Finished- and semi-finished goods inventory losses

In Chapter 1, it is determined to focus on finished goods obsolescence during this further research, since this problem causes the most inventory losses. However, a remarkable fact that is discovered in the inventory losses data, is that the commercial finished goods inventory losses in 2019 due to obsolescence (almost € X) were much higher than the inventory losses caused by semi-finished goods in 2019 (almost € X, only 20% of the obsolete finished goods inventory losses). This big difference needs some further investigation. Before diving further into inventory losses data of finished- and semi-finished goods, first of all it is explained which types of semi-finished goods exist by means of a description of the production process of beer.

The production process of beer usually takes around X weeks, and in short at four stages of this process different semi-finished goods can be found. First of all, from mashed malt and water a liquid extract called **wort** is produced. Together with hop, this liquid is boiled at the brewing installations. Immediately after brewing, the liquid is cooled, and yeast is added where after fermentation of the product takes place. This fermentation takes around X till X weeks and results in **fermented (young) beer**. Hereafter, the fermented beer has to be stabilized ("lagered") at lager tanks, and after ca. X weeks (min. X/max. X weeks) the liquid is turned into **matured (lager) beer**. This matured beer is then filtrated (X hL/h) at the filtration lines. The matured beer is blended with a specific amount of water, and also compounds are added if needed in order to create a special taste. Hereafter the **filtrated (bright) beer** is stored into bright beer tanks. After spending X-X days in the bright beer tanks, the beer is **packaged** at the production lines into bottles, cans, or kegs. This is the turning point from semi-finished goods into finished goods.

At the moment, X different brew streams exist, using different wort types. These X different worts result in X different fermented beers, and after this in X different matured beers. Here after, during the last two stages of the production process, differentiation takes place. Around X different filtrated beers arise from the X different matured beers. Since most of the filtrated beers are packaged into multiple different packages, the amount of different packaged finished products is a higher than the amount of different filtrated beers produced. From the X different filtrated beers, finally X[1] different end products can be produced. In Appendix I, an overview of all the different wort-, filtrated beer- and end product types can be found. The table gives insight into the differentiation of brew streams. It can be noticed that sometimes differentiation takes place between filtrated beers destined for kegs and filtrated beers destined for bottles and cans. For example there exists the filtrated beer type X kegs and the filtrated beer type X bottles and cans. Both originate from the brew stream X, but for keg beer another percentage of carbon dioxide is needed than for beer in cans or bottles, and so different filtrated beer types are needed. It needs to be kept in mind that when a product is already being produced, the differentiation of matured beer over filtrated beer types, or filtrated beer over packaging types, cannot be changed anymore.

After studying the inventory losses data in terms of hectolitres as well as costs, it is determined that the total amount of disposed beer in 2019 (more than X hL) is around 0.6% of the total amount of beer produced that year (X hL), and in the case of semi-finished goods, more beer is disposed earlier in the process in the form of matured beer, and no wort or fermented beer have been written off in 2019. Besides this, it turns out that the biggest reason for the big difference in amount of inventory losses of finished- and semi-finished goods in 2019 – as already spoke about in Chapter 1 - is caused by a much larger volume of finished goods written off (almost X hL) in comparison to the volume of semi-finished goods disposed earlier in the process (almost X hL), as can be seen in Table 2.

Inventory losses finished- and semi-finished goods 2019				
Material type	Inventory losses in euros	% of total inventory losses in euros	Inventory losses in hectolitres	% of total inventory losses in hectolitres
Matured beer	€ X	6 %	X hL	9 %
Filtrated beer	€ X	3 %	X hL	3 %
Finished goods	€ X	91 %	X hL	88 %
Total	*€ X*	*100 %*	*X hL*	*100 %*

Table 2 Inventory losses in terms of hectoliters and euros of finished and semi-finished goods over the year 2019

In Appendix II, information about the cost price calculations can be found. It needs to be kept in mind that the inventory losses are expressed in terms of variable costs of goods sold (COGS), and so more indirect/fixed costs (personnel, maintenance, IT, etc.) are not taken into account yet. This means that the final COGS are sometimes much higher for some products. However, to give a good indication of the direct inventory losses, only the variable COGS are displayed. Besides this it is difficult to determine the final COGS per semi-finished as well as finished product, since the fixed costs made per product then have to be divided over the different stages of the production process. This division can differ a lot per product, and is difficult to determine. Considering the inventory losses data of 2019 as shown in Table 2, there was just a little difference in average price per hectolitre between disposed finished- and semi-finished products. Roughly speaking, considering Table 2, the variable COGS of disposed matured beer was on average € X/hL, while that of disposed filtrated beer was on average 1.4 times as high (€ X/hL) and that of disposed packaged beer 1.55 times as high (€ X/hL) during the year 2019. It seems like the added value on finished goods did not had that much effect on the big difference in amount of inventory losses between finished- and semi-finished goods, while the volume of thrown away beer was far more determinative. However, after interviewing employees and diving into the cost price calculation data, it becomes clear that this was specifically the case for these disposed products, since in general more expensive semi-finished goods, and less expensive finished goods has been thrown away during the year 2019. This can be explained by the fact that more expensive, special

[1] However, looking at the packaging data of 2019, in total only X different finished products are packaged.

beers more often do not share their brew stream with other products, and so are tend to be disposed if more is produced than necessary. However, after diving into the cost price calculation data, as described in Appendix II, it appears that in general finished products contain a lot more added value than semi-finished products. In Appendix II, an explanation about the cost price calculations and this conclusion can be found, and it is proven that throwing away beer earlier in the process still could lead to quite some reduction of the final obsolescence costs.

2.1.2 Impact of product obsolescence

In order to calculate the impact of product obsolescence in 2019, first of all the scope of this research is brought back to the part of product obsolescence that can be influenced by the supply chain planning department. This means that all import beer, but also all made to order products (e.g. tank beer) are left aside during this research. It is decided to only focus on made to forecast products, since in the case of made to order products the client is responsible for the amount of products produced and so also for their obsolescence. Therefore the new amount of **inventory losses** we will focus on are those only caused by made to forecast (MTF) products, and can be found in Table 3. These products can be intended for the domestic market as well for the export market, and for retail as well as for restaurants/bars. Together these products make up for X hL what is almost half of the total inventory losses due to finished goods in 2019, with a price of € X what is almost half of the total inventory losses due to finished goods in euros in 2019.

As discussed in Chapter 1, a few times a year finished goods that are declared obsolete are transported to the harbour and are disposed. For the year 2019, the total disposal costs were almost € X. These disposal costs include transport costs, as well as costs to manually opening packages and disposing the beer. Also these **disposal costs** have to be taken into account when calculating the direct impact of product obsolescence. The disposal costs are not calculated per product, but are expressed in terms of total disposal costs per month for all disposed products together. For this reason, we assumed that the disposal costs can be divided over all the obsolete finished goods according to their disposed volume of obsolete beer, and so the disposal costs for MTF products can be calculated and are also shown in Table 3.

Finally, also **extra production costs due to disposal** have to be taken into account when calculating the direct impact of obsolescence. In order to calculate these costs, first of all it is determined[2] which MTF products did not have ending sales seasons in 2019, and so were produced throughout the whole year. For these products (X of the X obsolete products) it can be assumed that if expired stock had been disposed, at a later moment in time this batch had to be produced all over again. For this reason, the disposed volumes of obsolete beer of these products (X hL) are multiplied with their variable COGS again, and are taken into account as costs of extra production, as can be seen in Table 3.

Finally, it can be concluded that during 2019 the direct impact of obsolete MTF products was equal to **€ X** as can be noticed in Table 3 on the next page.

[2] It is assumed that a product had an ending sales season if the product had no sales during at least 2 consecutive months (or 1 month if the month before/after had almost zero sales), and consecutive sales without zero sales during its sales season.

Direct impact of obsolescence	Costs
Inventory write-offs due to obsolescence (X hL)	€ X
Disposal costs (X/X hL * € X)	€ X
Costs of extra production (X hL)	€ X
Total	*€ X*

Table 3 Impact of obsolete MTF products in terms of direct costs (€) over the year 2019

As described in Chapter 1, besides disposing excess stock that passed its final delivery date, sometimes if the company is lucky a customer can be found who wants to buy those products that reached their final delivery date to the customer for a discount price. These are the products expected to become obsolete that are discussed during the weekly ROM-procedure as earlier described. ThSe lost profits (extra discounts) matter in the case of discount sales, since this excess stock was already assigned to a client. The missed profit opportunities of the products sold for discount price are calculated by taking the difference between a product's original sales price and its discount price. This results in a total amount of lost profits due to discount sales of almost **€ X** during the year 2019. These lost profits definitely needs to be taken into account during this research since they also give insight into the impact of expired excess stock, though they cannot be added that easily to the direct impact costs shown in Table 3. The reason for this is that the lost profits due to discount sales are a more indirect effect and therefore not suited to be compared one to one with the direct impact costs. However, tackling the problem of stock obsolescence, and so reducing the amount of excess stock passing its final delivery date, will besides less product obsolescence also result into less expired stock needed to be sold for a discount price, and so less lost profits due to discount sales. This means it suffices to focus on reducing product obsolescence during this further research.

2.1.3 Conclusion

1. The big difference between inventory losses of finished- and semi-finished goods in 2019 can for the greater part be explained by the fact that a much higher volume of finished goods has been thrown away;
2. The higher added values on finished goods were not that determinative in 2019 since relatively seen more expensive filtrated beer, and cheaper finished goods have been thrown away;
3. However, in general finished goods contain far more added value than semi-finished goods, and it would still be beneficial to throw away products earlier in the production process;
4. The direct impact of obsolete products (the supply chain planning department can influence) consists of the inventory write-offs due to obsolescence, disposal costs and costs of extra production, and the total costs were equal to more than € X in 2019.
5. The total amount of lost profits due to discount sales of expired products were almost € X. By tackling the problem of obsolete stock, also less discount products will needed to be sold, and so these losses will decrease.

2.2 Root cause analysis

After quantifying the problem, it is time to examine which products encountered the most obsolescence during the year 2019 by means of a Pareto analysis, and to examine what the real impact of the proposed causes - that arose from the interviews in Chapter 1 - were on product obsolescence by means of a root cause analysis. However, it is important to make a distinction between product characteristics and underlying causes of obsolescence. From the interviews in Chapter 1 potential causes of obsolescence as well as product characteristics that are possibly sensitive to obsolescence are mentioned. A recap of these causes and product characteristics is given below.

Potential causes and product characteristics affecting product obsolescence:

1. Slow moving products;
2. Seasonal products;
3. Products with ending sales seasons;
4. New Product Developments;
5. High forecast deviations (4);
6. Minimum batch size restrictions in combination with low demand volumes (1,2,3,4).

It becomes clear that the first 4 proposed causes are in fact product characteristics thought to be sensitive to obsolescence, while causes 5 and 6 are indeed potential underlying causes of product obsolescence. The kind of products with specific product characteristics thought to be affected by certain underlying causes as discussed during the interviews, are mentioned in between brackets after these underlying causes. The remaining potential causes of product obsolescence that were revealed during the interviews but are not discussed above are already examined and left outside scope in Chapter 1 since their effect was not significant enough or not possible to influence during this research (e.g. damages, quality issues, etc.), or will be examined at a later stage since they are not measurable but have to do with the current way of working at Grolsch.

During this chapter, first of all by means of a Pareto analysis it will be determined which products encountered the most inventory losses due to obsolescence during the year 2019. Also it will be examined if specific characteristics (1-4) proposed in Chapter 1 are more common amongst those products with high inventory losses due to obsolescence. Hereafter we go more into depth of the underlying causes 5 and 6 by means of a root cause analysis. During this analysis there will be searched for quantitative relations between obsolescence and potential causes. Per underlying cause, also the kind of products with particular characteristics thought to affected by these causes are discussed.

In Chapter 2.1, the scope of this research is already delimited to commercial inventory losses data of MTF products only. However, the discount products sold in 2019 would also have become obsolete if there would have been no client willing to buy them for a discount price at that moment. For this reason, these discount products needs to be taken into account as well. This will be done by expressing the volumes (hL) of sold MTF products for a discount price as variable COGS as well, and also use this as input data for the analyses. During the Pareto analysis, these variable COGS are directly used as input data. This means that the total amount of inventory losses we will focus on now is somewhat higher than the earlier mentioned € X inventory losses caused by product obsolescence. Also including the variable COGS of products sold for a discount price now results in total costs of € X. During this root cause analysis, we will further focus on these total inventory losses caused by obsolete products as well as by products sold for a discount price. However, in order to prevent the product price from influencing the root causes, during the root cause analyses not the net inventory losses but the relative inventory losses per product are needed. Besides this, also all the causes and characteristics mentioned above needs to be expressed as variables before they can be analysed. In Appendix III, a detailed description can be found about how these variables are determined and which assumptions are made.

2.2.1 Pareto analysis of problem SKUs

According to the Pareto principle – roughly 80 % of the effects come from 20 % of the products – a chart is created that represents the net inventory losses due to obsolescence per product in descending order by bars, and the cumulative total of inventory losses by line, as can be seen in Figure 4. It is decided to determine the problem products regarding obsolescence in terms of costs instead of hectolitres, since in the end we want to reduce the amount of costs due to obsolescence. Also it is determined not to execute a Pareto analysis per brew stream, since most of the brew streams are on the basis of a lot of different finished goods (e.g. from the the Pils Domestic brew stream X different finished products are created). In this way it is difficult to look for specific causes of the high inventory losses due to obsolescence.

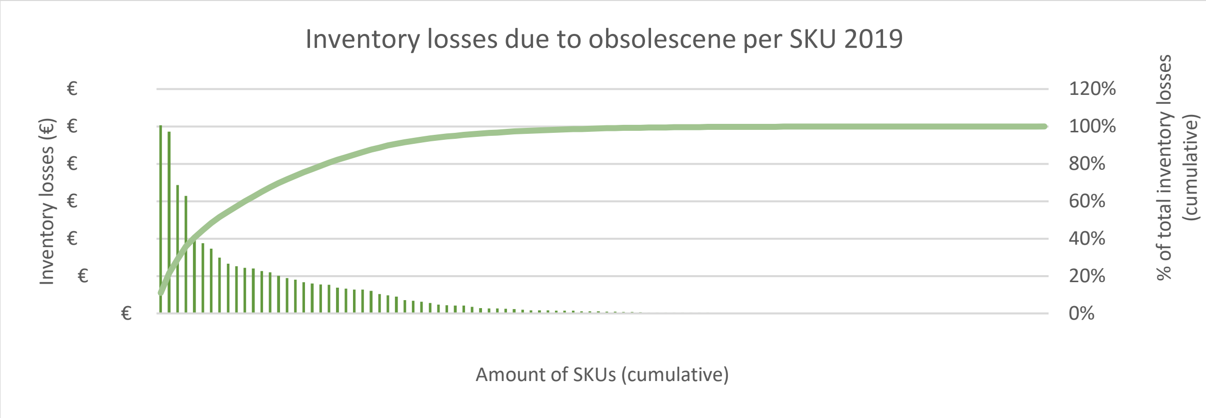

Figure 4 Pareto chart inventory losses due to obsolescence per SKU 2019

From the chart it can be noticed that X of the X products (21.5 %) are responsible for almost € X (83.5 %) of the total inventory losses, and so the Pareto rule applies to this situation. It means these top 21.5 % products need the most attention. To examine if the specific product characteristics proposed in Chapter 1 are more common amongst those products with high inventory losses due to obsolescence, the frequency of these characteristics is compared between only the top 21.5% obsolete products and all obsolete products together. The results can be found in Figure 5. Due to confidentiality, only the mutual differences are shown in this report. In Appendix III information can be found about the classification of NPDs, slow movers, seasonal products and ending sales seasons.

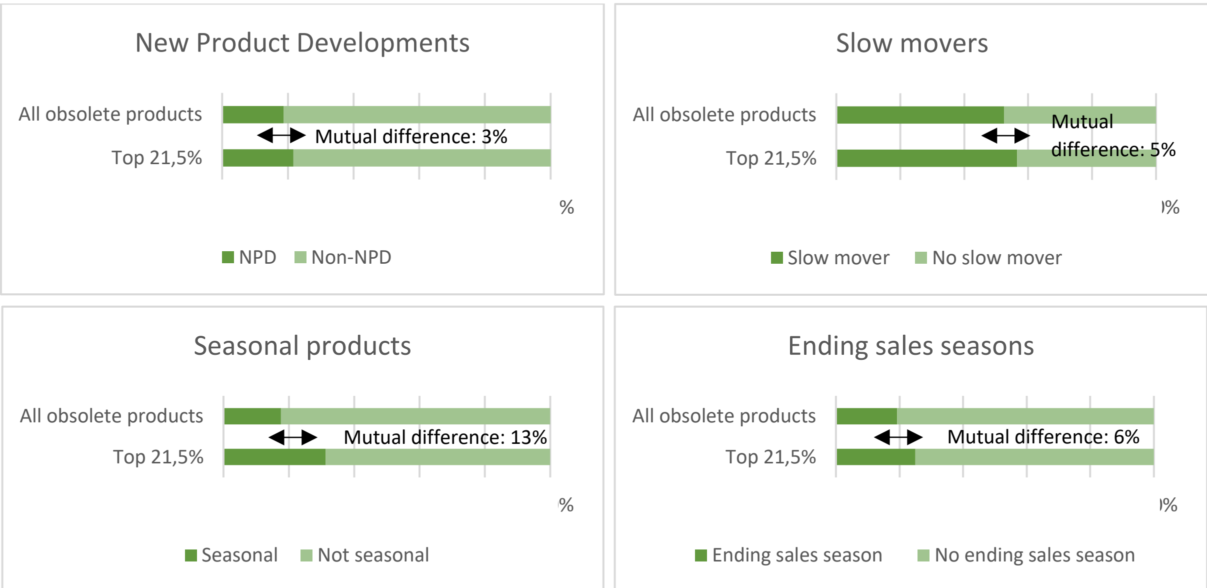

Figure 5 Product characteristics amongst top 21,5% obsolete products vs. all obsolete products

As can be noticed in Figure 5, all 4 earlier mentioned product characteristics are indeed more common amongst the top 21.5 % products that encountered more inventory losses due to obsolescence, and so products with these characteristics need more focus. However, in Figure 5 only classifications (slow mover yes/no, and seasonal yes/no) are taken into account, but there is not yet searched for quantitative relations between how products score on these characteristics and their obsolescence. Besides this, by using the inventory losses due to obsolescence as input data, product prices can affect the relations. Therefore, in Appendix IV these quantitative relations are also examined, but now with the relative obsolescence (obsolescence in hL vs. production volume per product per year) as input data. However, these quantitative relations cannot be examined for NDPs and products with ending sales seasons, since products are just NPD or not, or have an ending sales season or not, there is no value in between. From the quantitative relations analyses of Appendix IV it can indeed be proven that there are relations between obsolescence and sales volume /seasonality. Also it is proven that ending sales seasons sometimes play a part at highly obsolete seasonal products, but sometimes also not. However, ending sales seasons have to be taken into account as a separate product characteristic, since there are also non-seasonal products with ending sales seasons.

After examining the relations between different products with specific characteristics and obsolescence, it is now interesting to examine if the earlier proposed causes indeed underlie these highly obsolete products with specific characteristics, and what the impact of these proposed causes was on obsolescence. Therefore, during the next two sections we go more into depth of the underlying causes.

2.2.2 High forecast deviations

During the interviews it is stated that high forecast deviations can cause obsolescence. It is speculated this is especially the case for NPDs, since these products do not have enough historical data to base their forecast on. During this section, first of all the quantitative relations between obsolescence and high forecast deviations will be examined, where after it is examined if NPDs indeed faced high forecast deviations and were more overforecasted in general as speculated during the interviews.

Forecast accuracy

In order to examine if high forecast deviations were indeed a cause for product obsolescence, the product's forecast accuracies are necessary. Two ways of measuring forecast accuracies are considered, the mean absolute percentage error (MAPE) and the bias as percentage of the total sales (bias %). The MAPE gives insight in the overall forecast accuracy of a product, what means that it treats over- as well as underforecasting and makes no distinction between them but takes the absolute error. However, only overforecasting is expected to have an effect on product obsolescence, and so therefore it is more interesting to use a forecast accuracy measure that makes a distinction between over- and underforecasting. Therefore it is chosen to only examine the relation between relative obsolescence and bias % during this research. The results can be found in Figure 6. A negative bias % means that in general the forecast was higher than the sales, and so a product has been overforecasted in general.

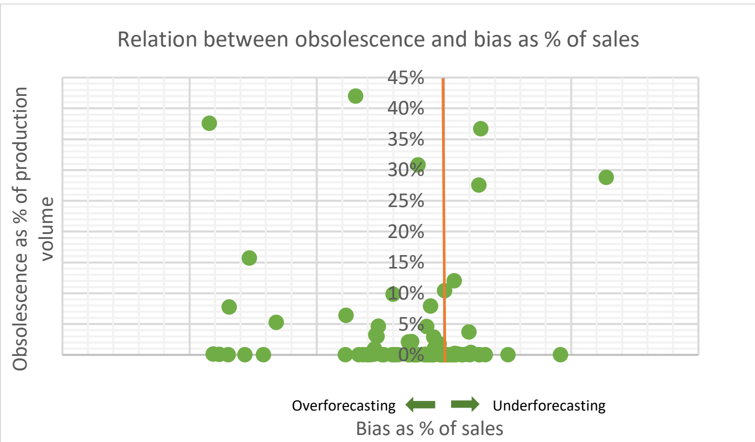

Figure 6 Relative obsolescence vs. bias as % of sales of SKUs sold in 2019

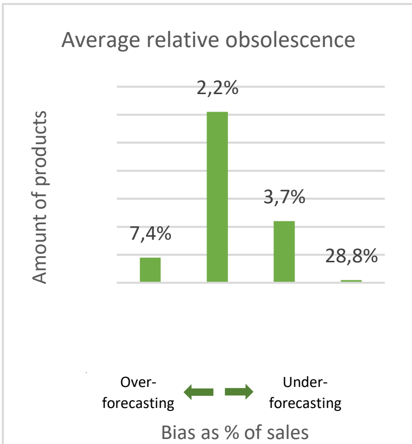

Figure 7 Average relative obsolescence of SKUs sold in 2019

As can be noticed in Figure 6, underforecasted as well as overforecasted products encountered obsolescence. From Figure 7 – where the bias as % of sales is subdivided into 4 groups – it can be seen that the X products that were strongly overforecasted (bias % between -X % and -X %) encountered on average more obsolescence than the other products that were less overforecasted or underforecasted, as expected during the interviews. Except for 1 strongly underforecasted product during the year 2019 that still encountered much obsolescence (X %), but this is rather an exception than a rule. However, no strong negative relation is visible between bias as % of sales and average relative obsolescence. For example the average relative obsolescence of slightly underforecasted products (bias % between 0% and 50%) is higher than that of slightly overforecasted products (bias between -50 % and 0 %). Although there can be found a relation between the most strongly overforecasted products and higher obsolescence, in general no strong negative relation can be found between bias as % of sales and obsolescence. However, from the data it seems like **structurally too much demand is overforecasted during the year 2019**. Considering all products sold in 2019, X % of all products were in general overforecasted and only X % of all products were in general underforecasted. The average bias % of all products together was -X %. After interviewing some employees it can indeed be confirmed that the forecasts in 2019 were in general too optimistic. However, since at the moment the demand planning department is focusing on producing more realistic demand forecasts, there is no improvement potential here for this research.

Product characteristics vs. forecast accuracy

As explained in Appendix III, a product is classified as NPD if it is a new created product, and does not have enough historical sales data to base its forecasts on. It is now interesting to examine if NPDs indeed were more overforecasted in general as speculated during the interviews, what could be an explanation of their higher amount of average relative obsolescence. Therefore, the average relative obsolescence and average bias as % of sales of NPDs are compared with that of non-NPDs. Although during the interviews the other mentioned product characteristics were not thought to experience relatively higher forecast deviations, it is interesting to examine if this is indeed true. Therefore the average relative obsolescence and average bias as % of sales of products with these characteristics are examined as well, and all information is displayed in Table 4.

Product characteristic	Average relative obsolescence	Average bias as % of sales	Under- vs. overforecasted
NPD	X %	- X %	X % vs. X %
Non-NPD	X %	- X %	X % vs. X %
Seasonal	X %	- X %	X % vs. X %
Not seasonal	X %	- X %	X % vs. X %
Ending sales season	X %	- X %	X % vs. X %
No ending sales season	X %	- X %	X % vs. X %
Slow mover	X %	- X %	X % vs. X %
No slow mover	X %	- X %	X % vs. X %

Table 4 Obsolescence and forecast measures of products with specific characteristics 2019

From Table 4 it can be concluded that **NPDs indeed in general encountered relatively seen more obsolescence than non-NPDs**, and so need some more attention when focusing on obsolescence reduction. It also can be noticed from Table 4 that **NPDs were in general more (often) overforecasted than non-NPDs**. This is in line with the expectations mentioned during the interviews. It also can be noticed from Table 4 that the products that comply with one of the other specified characteristics (seasonality, ending sales seasons and slow movers) indeed also encountered relatively seen more obsolescence, and so need some more attention when focusing on obsolescence reduction. Besides this, it can be noticed that also these products in general were more (often) overforecasted than products that do not comply with the specific characteristics. One exception applies to the products with ending sales seasons that were in general less overforecasted than products sold throughout the year. An explanation for this could be the fact that demand planners are more cautious with the forecasts for products that are at the end of their sales season since it is known these products are prone to become obsolete.

In general, it can be concluded that structurally overforecasting was an overall problem during the year 2019. However, since the optimization of forecasts is already an ongoing project at the demand planning department, it is interesting to examine the impact of minimum batch size quantities in combination with low demand volumes to product obsolescence, as will be done during the next section.

2.2.3 Minimum batch size restrictions in combination with low demand volumes

Besides high forecast deviations, a second underlying cause of obsolescence mentioned during the interviews are minimum batch size restrictions in combination with low demand volumes. If the demand volume of a product is lower than the minimum batch size it needs to comply with, obsolescence can arise quite easily. Minimum batch sizes or low demand volumes are therefore no standalone causes of obsolescence, but the interplay between them can cause obsolescence. For example, a product with relatively high demand volumes still can encounter obsolescence if the batch sizes it needs to comply with are still higher than these demand volumes. For this research it is interesting to examine if the combination of demand volumes lower than the minimum batch sizes indeed led to more obsolescence as expected. During this section, we first will dive somewhat deeper into minimum batch size restrictions, after which the relation together with lower demand volumes on obsolescence will be discussed.

Minimum batch size restrictions in combination with low demand volumes

Minimum batch size restrictions apply to three different stages during the production process - during brewing, filtration and packaging - and these restrictions also differ per product. From now on, the minimum batch size for brewing will be called “MinBrew”, for filtration “MinFiltr”, and for packaging “MinPack”. For this part of the research, brewing-, filtration-, and packaging data from 2019 is available. However, it is not that simple to link these data sets with each other, since the divisions of matured beer over the different filtrated beer types are not linear due to dilution[3]. Analysing the different production steps and divisions of beer over the different products during the year 2019 will therefore be too complex. For this reason it is chosen to leave aside the brewing- and filtration data and only focus on the packaging data of products during this part of the research. The packaging data of 2019 contains the packaging batch sizes in hectolitres per week per product. It is assumed that in general a maximum of one batch is packaged per product per week, and so the weekly data in general represents one packaging batch per product. Only for the Premium Pilsner an exception applies, since this product in general is packaged more than once per week. For this reason, with help of the average packaging speed, the average batch size per week is calculated for Premium Pilsner and is used as input for this analysis.

Although during this part of the research there will only be focussed on packaging data, still all three minimum batch size restrictions needs to be taken into account per product, since all restrictions can affect the packaging batch sizes of products. One can imagine that, if a minimum batch size of a product later in the production process is larger than a minimum batch size of a product earlier in the process,

[3] Blending fermented beer with water until the desired alcohol percentage is reached.

still there cannot be produced less than this minimum batch size later in the production process. In other words, at least the MinPack volume of a product needs to be brewed/fermented/lagered/filtrated/packaged, at least the MinFiltr volume of a product needs to be brewed/fermented/lagered/filtrated, and at least the MinBrew volume of a product needs to be brewed. However, application of the batch size restrictions is not that simple as it seems. Through differentiation during the production process, the semi-finished beer volumes that differ per production stage all need to comply with the batch size restrictions by themselves. In Figure 8 an overview can be found of the differentiation possibilities during the production process.

Figure 8 Differentiation and minimum batch sizes in the production process of beer

As earlier explained and as can be seen in Figure 8, differentiation can take place after lagering, whereby the matured beer is divided over different filtrated beer types that belong to the same brew stream. Besides this, differentiation can take place after filtration, whereby the filtrated beer is divided over different packaging types of the product (bottles, cans, kegs, etc.). In the case of smaller minimum batch size(s) during a later production stage, there is a possibility to share or dispose part of the production batch in the meantime. It can be assumed that between brewing and filtration, disposal of matured beer can take place, but that in general – with a few exceptions - all the beer that is filtrated will be packaged, and so disposal of filtrated beer can be excluded as an option. The reason for this is that it takes a few weeks after brewing before beer will be filtrated, while packaging occurs often almost immediately after filtration, and so disposing beer between brewing and filtration is much more logical than between filtration and packaging. The same holds for packaged products that are transported to the warehouse immediately after packaging, and so only disposal of packaged beer that is already on stock for a while is taken into account as an option. Therefore, for this research only the disposal of matured beer and finished goods matters.

It needs to be kept in mind that in the case of early disposal of semi-finished products, at least the minimum batch size later in the process need to remain. After interviews with the tactical planning team it appears that there is an expectation that disposing beer in the meantime could be a solution for products with demand volumes lower than their minimum batch sizes in order to avoid obsolescence. One can imagine that especially products that do not share a brew stream with other products and so cannot share their semi-finished goods during production, often have to do with demand volumes lower than the minimum batch sizes. It is stated during the interviews that disposing products in the meantime as a way to avoid obsolescence does not happen often at the moment, and if it happens the decision about how much beer is disposed at which moment is often not well-founded as already described during Chapter 1.

Within Grolsch, there is made a distinction between two different types of products: **Brew To Forecast (BTF) products** and **Brew To Order (BTO) products**. One must beware of the difference between “brew to order/forecast” and “make to order/forecast”. The characteristic “make to order/forecast” indicates whether production of a product is based on actual orders of a client (here: retailers or restaurants/bars) or on sales forecasts made by the company itself. However, ultimately, in both cases it is about the external demand of the client. “How much beer do we need to package in order to fulfil (received or predicted) demand of the client?” On the contrary, the characteristic “brew to order/forecast" is about the <u>internal</u> demand of departments within Grolsch. "How much beer does the brewing department need to brew in order to comply with the packaging plans?" This internal demand also can be based on internal orders as well as forecasts. As one can understand from above mentioned information, BTO products as well as BTF products both can be either make to order or make to forecast. As earlier mentioned, during this research there is only focussed on make to forecast products, since the Supply Chain Planning department has no influence on client's orders. As explained, these make to forecast products can be either divided into the category BTO or BTF.

When looking at the packaging data set of 2019, in total X BTO products are present in the data, while the remaining X products are BTF products. As explained earlier, BTO products are products for which often volumes needs to be produced that are lower than their minimum brewing batch sizes, and so these batch size restrictions for brewing are often bonding. For this reason, the minimum brewing batch size restrictions of these BTO products are always kept in mind during production planning. BTO products are often products that do not undergo differentiation during their production process, but arise from only 1 liquid and 1 packaging type. These products are produced at once and beer is not shared with other products in the meantime. However, there also exists products that do undergo differentiation, but still often are restricted by their minimum batch size restrictions since demand is often lower. For this reason these products are called BTO products as well. On the other hand, there also exist products that do not undergo differentiation during their production process, but often experience demand volumes higher than their batch size restrictions. For these kind of products the minimum brewing batch sizes are often not restricting, and so these products are not called BTO products. BTF products are products for which brewing batch size restrictions often do not play a role since their production volumes are often higher than their minimum brewing batch sizes. A document is drawn up by the tactical planning team, in which products are classified as BTO/BTF. In this document, BTO products are provided with their MinBrew volume, in order to keep in mind during production planning. This does not mean that BTF products do not have a MinBrew volume, but since for these products in general always more than this MinBrew volume is produced, the MinBrew volume in general does not matter for them and so does not needs to be displayed during production planning.

For this part of the research it is interesting to examine if there is a relation between demand volumes lower than minimum batch sizes and obsolescence. Therefore, also information about the differentiation characteristics per particular production moment is necessary in order to calculate with the right demand (production) volumes per (semi-finished) product per production stage. This information is not immediately available from the data base but needs to be figured out with help of the differentiation possibilities per product and the demand forecasts at the particular production moments. It appears that figuring out the differentiation characteristics of all beer streams at particular production moments throughout the year 2019 is complex and time-consuming. Besides this, demand volumes can fluctuate a lot during the year (e.g. in the case of seasonal products and/or products with ending sales seasons), what means that the right demand volumes of particular production moments needs to be linked to their corresponding obsolescence. However, it appears to be difficult to link the right demand volumes of particular production moments to their corresponding obsolescence. Due to these complications and time limitations, it is decided not to search for quantitative relations anymore between demand volumes that lower than minimum batch sizes and obsolescence, but to carry out the analysis in a different way, as mentioned below .

As earlier mentioned, BTO products are – in comparison to BTF products - most of the time restricted by their MinBrew volume, because their demand volumes are often lower than their minimum brewing batch sizes. Since during this analysis we look for products of which demand volumes are lower than the minimum batch sizes, it is decided to focus on the BTO products that in general comply with this characteristic. It is now examined if there is a relation between BTO products and obsolescence. When diving into the packaging and obsolescence data of the year 2019, it appears that in all cases the MinBrew volume was packaged during the year 2019, and no early disposal already took place. Besides this, it becomes clear that during the year 2019, BTO products encountered less total inventory losses due to obsolescence as can be noticed in Table 5. However, this is quite logical since BTO products are in a large minority.

BTO/BTF SKUs	Inventory losses (€)	Inventory losses (hL)	Average inventory losses (hL)	Average relative obsolescence
X BTO SKUs	€ X (39%)	X hL (31%)	X hL/product	X %
X BTF SKUs	€ X (61%)	X hL (69%)	X hL/ product	X %

Table 5 Obsolescence information brew to order (BTO) vs. brew to forecast (BTF) products 2019

However, as also can be noticed from Table 5, **the average relative obsolescence of BTO products was much higher than that of BTF products, and therefore it can be concluded that the few BTO products indeed encountered in general much more obsolescence**. Besides this, it also can be concluded that for these BTO products – that were probably restricted by their minimum batch sizes and for which no early disposal took place- **part of the obsolescence could have been avoided by applying early disposal of BTO semi-finished goods**.

Product characteristics vs. minimum batch size restrictions in combination with low demand volumes

As mentioned during the interviews, slow movers, seasonal products, and products with ending sales seasons – products that encounter in general more obsolescence - are thought to be affected by minimum batch size restrictions in combination with low demand volumes. What these products have in common, is the fact that they all three encounter low demand volumes during a certain period. Slow movers encounter low demand volumes throughout the whole year, while seasonal products without ending sales seasons encounter low demand volumes outside their peak moments, and products with ending sales seasons can encounter problems with low batch sizes needed at the end of their sales season. Besides this, it is stated during the interviews that NPDs on the other hand are mainly affected by their minimum batch size restrictions, since NPDs are often BTO products. Although it is difficult or even impossible to prove that there is a relation between obsolescence and demand volumes lower than the minimum batch sizes as earlier mentioned, it is still remarkable that it are exactly the products with relatively low demand volumes during a certain period that encountered relatively high obsolescence during the year 2019. Therefore, it is plausible that the relatively low demand volumes (in combination with minimum batch size restrictions) of slow movers, seasonal products, and products with ending sales seasons, had impact on the obsolescence amongst those kind of products.

Since for BTO products statements can be made about how obsolescence could have been avoided during the year 2019 by means of early disposal of matured beer, it is interesting to examine if most of the NPDs that encountered relatively high obsolescence were indeed BTO products as stated during the interviews. After data analysis, it turns out that **NPDs are relatively seen much more common amongst BTO products than amongst BTF products, and that in general the obsolescence amongst BTO NPDs is much higher than amongst BTF NPDs**, as can be seen in Table 6. Therefore it is plausible that, besides the earlier mentioned overforecasting amongst NPDs, the BTO characteristic (bounded to batch size restrictions) in combination with lower demand volumes, can be seen as a cause for the relatively higher obsolescence amongst NPDs.

BTO/BTF NPD	Amount of BTO/BTF NPDs vs. total amount of BTO/BTF products (NPD and non-NPD)	Inventory losses (€)	Average relative obsolescence
BTO NPDs	X%	€ X	8.3 %
BTF NPDs	X%	€ X	3.0 %

Table 6 Obsolescence information brew to order (BTO) vs. brew to forecast (BTF) NPDs 2019

2.2.4 Conclusion

1. There needs to be made a clear distinction between real underlying causes of obsolescence, and products with particular characteristics affected by those causes;
2. 21.5 % of the products are responsible for 83.5 % of the total inventory losses due to obsolescence, and amongst these top 21.5 % products the proposed characteristics thought to be sensitive to obsolescence are indeed more common;
3. Slow movers, seasonal products, products with ending sales seasons, and NPDs indeed encountered in general more relative obsolescence, and quantitative relations can be found between relative obsolescence and seasonality/demand volume. Extra attention to those kind of products is therefore recommended when focusing on reducing obsolescence;
4. The ending sales season characteristic needs to be taken into account separately from seasonality, since products that encounter obsolescence can be seasonal and have an ending sales season, but also can have just one of the two characteristics affecting obsolescence;
5. Overforecasting was a structural problem during the year 2019 amongst all products. As stated during the interviews, especially NPDs were indeed more (often) overforecasted than non-NPDs, probably due to its lack of historical data;
6. Forecasting improvement is currently an ongoing project, and so no improvement potential lays here for this research. For this reason there will be focused on the second proposed underlying cause: the interplay between minimum batch sizes and demand volumes;
7. It is difficult to prove that there is a relation between obsolescence and demand volumes lower than minimum batch sizes, since this also depends on the differentiation characteristics of matured beer with different filtrated beer types at the particular production moments during the year 2019. Besides this, it is difficult to link the demand volumes of the particular production moments during the year 2019 to the right corresponding obsolescence. Because generating these insights is too complex and takes too much time for this part of the analysis, it is decided to carry out the analysis in a different way, by focusing on BTO products of which in general their demand volume is already lower than their minimum batch sizes;
8. From the packaging data it can be concluded that in all cases BTO matured beer has not been disposed in the meantime, while on average BTO products encountered much more obsolescence than BTF products. Therefore, it is hypothesized that early disposal of matured beer would have been a good solution for these BTO products in order to avoid obsolescence;
9. NPDs are relatively seen much more common amongst BTO products than amongst BTF products, and so they more often need to comply with minimum batch size restrictions. This, together with lower demand volumes, could besides overforecasting be an explanation of the relatively high obsolescence amongst NPDs;
10. It is remarkable that products that encountered relatively lower demand volumes throughout - or at particular moments during - the year (slow movers, seasonal products, and products with ending sales seasons) in general encountered relatively high obsolescence. It cannot be proven easily, but it is plausible that the obsolescence of these products can be explained by their relatively low demand volumes in comparison to their minimum batch size restrictions.

2.3 Current way of obsolescence control

In order to create some more insight into the current way of obsolescence control, it will be examined how at the moment expected product obsolescence is measured. Besides this, a process flowchart will be created that displays the current obsolescence control procedure, from demand planning until sales, and the ways to avoid obsolescence that are applied at the moment. The information from this chapter can support the development of a solution to reduce obsolescence.

2.3.1 Tactical planning and obsolescence control

As earlier mentioned, on weekly basis a tactical production plan is created/updated by the tactical planning team, using the demand forecasts from the demand planning department as input. This demand forecast is a representation of the real estimated demand, sometimes adjusted by sales targets. However, prevention from stockouts and stock excesses is not incorporated in the demand forecast yet, but is applied by the tactical planners.

Prevention from stockouts

First of all, it is tried to avoid stockouts with help of the minimum days of cover (MinDoC)-value per product. This MinDoC-value represents the minimum amount of days that needs to be covered with available inventory, and encompasses the safety stock. Currently, optimization of these MinDoCs per product takes place by the tactical planning team. The MinDoC of a product is based on a few things, such as e.g. product classifications as earlier mentioned (based on a product's importance and flexibility), but also a product's forecast accuracy is kept in mind while determining the MinDoC of a product. This product's forecast accuracy is not incorporated quantitatively, but is based on experience. Products that had higher forecast deviations in the past, are considered more risky and so a higher MinDoC has been assigned to them.

Since production cannot be planned automatically by the system yet (however, the development of an automatic batch size-solver is an ongoing project), at the moment production quantities are determined manually by the tactical planners. First of all the demand forecast is loaded into the program, where after it warns the user if the DoC – the amount of days that can be covered with available stock, based on the current demand forecast - of a product drops below the MinDoC. The difference between MinDoC and DoC, is that the MinDoC only encompasses safety stock, while the DoC encompasses demand during lead time as well. Hereafter, the tactical planners have to puzzle with (multiples of) minimum batch quantities, until the MinDoC of a product is covered again. For products that do not share their brew stream with other filtrated beer types (often BTO), often the minimum batch size (MinBrew) is planned. However, the planning of products that share a brew stream with other products (often BTF) is somewhat more difficult. For these products it is checked if also other products of the same brew stream are needed during the same period, and if this is the case, the production of these products is planned together. In this case the MinBrew restriction often plays no role.

Prevention from stock excesses

At the moment, no real obsolescence estimation takes place during tactical planning. As earlier mentioned, currently the tactical planning program displays a standard maximum age of shelf life per product that equals 1/3 of its total shelf life. It can be seen as the maximum amount of days from end of production (packaging) until final delivery date (1/3 shelf life) to the customer. Also per product the DoC is displayed. If during the planning of new production batches the DoC of a product becomes higher than the maximum stock age, and so there will be planned on obsolescence, the system gives a warning. In some cases, obsolescence cannot be avoided due to minimum batch size restrictions. As already mentioned, therefore sometimes it is planned to dispose some beer already after brewing, but currently this does not happen often, and if it happens it is often not based on quantitative facts (e.g. on estimated obsolescence) but mere speculation. This current way of obsolescence control has a few shortcomings.

First of all, the system only warns if there is planned on obsolescence. The expected obsolescence is only calculated with help of the expected demand forecast, but demand variability is not taken into account, what can influence the expected obsolescence of a product. Since demand sometimes can be very fluctuating, it would be smart to also include demand variability in order to estimate product obsolescence. Hereby the expression (expected obsolescence) stays the same, but the way to determine it (now including demand variability) differentiates from the earlier applied method. Only considering the expected demand, but not taking into account demand variability, makes decision making regarding product obsolescence, e.g. about early disposal of beer, less well-founded.

Second, as already mentioned, the system lacks insight into the stock ages of different product batches that are already on stock, and from which its perishability is already started. This information can be found in SAP, but looking up for this information per product separately takes much time during production planning. This means it cannot be controlled easily if products already on stock almost reach their final delivery date to the customer, especially since demand forecasts are changing constantly. This makes production planning and inventory management even more difficult.

2.3.2 Obsolescence control process flowchart

In Figure 9 at the next page, a process flowchart displays the current way of obsolescence control, from demand forecasting until sales. Also all the earlier found problems related to product obsolescence are incorporated in this chart. The interventions regarding obsolescence that are applied at the moment, are expressed in terms of decision moments (6 and 11).

(6) First of all after the brewing process (between brewing and filtration) it can be decided to intervene early in the process and throw away the brewed beer instead of moving on to the next step (filtration). At this stage there exist no standard procedure regarding obsolescence control. Decisions take place ad hoc, often by e-mail or calls, but are not based on quantitative facts (e.g. on expected obsolescence).

(11) The second decision moment is the earlier described weekly Retail Operations Meeting (ROM). This procedure is more standardized, however it only incorporates products reaching their final delivery date within 5 weeks and so a lot of products are left outside the scope of this current procedure.

Also per stage in the diagram, the average directly related costs/hL product are added. It can be noticed that these costs increase during every stage of the production process, and so how later in the process disposal of beer takes place, how less costs can be saved. In order to calculate the average directly related costs per hectoliter product during the different stages (brewing, packaging, and warehousing), the variable COGS per product, as well as the disposal costs and reproduction costs earlier mentioned in Chapter 2.1 are taken into account. The costs are build up per stage as follows:

- Brewing: as earlier mentioned, only the disposal of matured beer as semi-finished good is taken into account. For this reason the average variable COGS of matured beer (€ X/hL) are taken into account during this stage of the production process;
- Packaging: after packaging, normally products will immediately be put on stock. No finished goods will be thrown away between the packaging and storage stages. However, to generate insight into the increasing added values during the production process, the average directly related costs are mentioned at this stage anyway. Therefore the average variable COGS of finished goods (€ X/hL, 4.2 times higher than for brewing) is used. Besides this, it costs money

to dispose finished goods, and so also the average disposal costs per hectoliter are added at this stage. The average disposal costs are € X/pallet, and on average a pallet contains 6 hL beer, what results in average disposal costs of € X/hL. In total, the average directly related costs to dispose packaged products will therefore be € X/hL;

- Warehousing: the next possible moment to dispose products after brewing is during their storage. In the case of an ending sales season, products do not have to be produced again, and the earlier mentioned average directly related costs to dispose packaged products (€ X/hL, 1.1 times higher than for packaging) applies. However, if products have an ending sales season, reproduction costs needs to be taken into account as well. These reproduction costs are equal to the earlier mentioned variable COGS of a product. Therefore, the average directly related costs of a disposed and newly reproduced product are € X/hL.

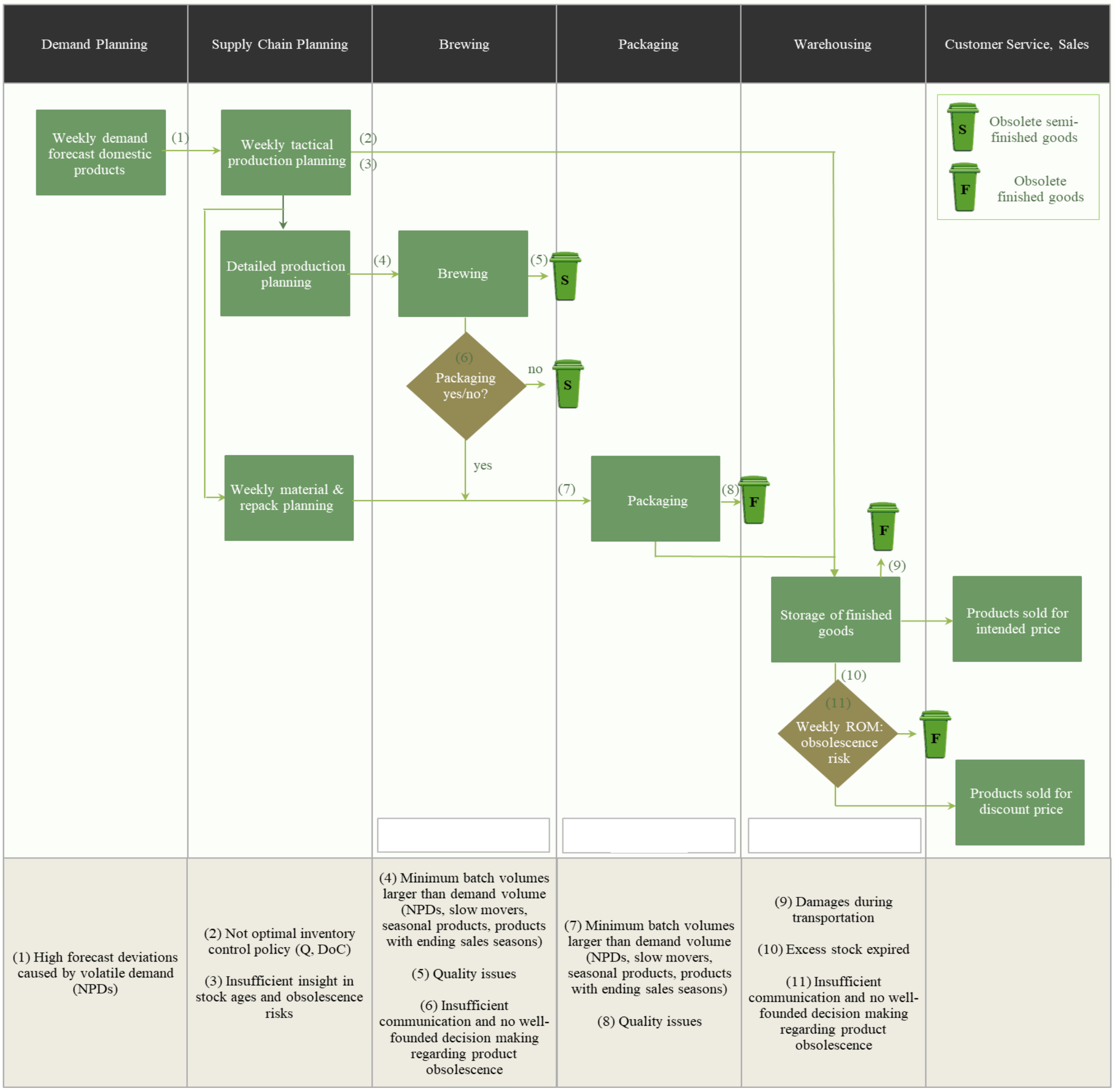

Figure 9 Process flowchart of the production process and current obsolescence control procedure

2.3.3 Conclusion

1. The current tactical planning system tries to prevent newly planned products from becoming out of stock or obsolete, by warning the planner if a newly planned product has insufficient (safety) stock (if DoC < MinDoC), or too much stock (if DoC > shelf life) in relation to its demand forecast;
2. At the moment, expected obsolescence is only calculated with help of the most updated demand forecast, but demand variability is not taken into account yet. Especially since demand can be very fluctuating, decision-making regarding obsolescence (e.g. about early disposal) is less well-founded in this way. Therefore, it would be smart to also include demand variability during the calculation of expected obsolescence;
3. The lack of insight into the stock ages of different product batches that are already on stock makes production planning and inventory management more difficult, especially since demand forecasts are constantly changing;
4. The ROM-procedure only incorporates products on stock reaching their final delivery date within 5 weeks, and so a lot of products on stock are still left outside the scope of obsolescence control.

2.4 Solution directions

Until now, insight is created into the problem of product obsolescence and its causes. Now it is time to examine the different solution directions in order to reduce the negative effects of product obsolescence. The different solution directions will be discussed in this chapter, where after one solution direction is chosen to focus on during further research.

It is already decided to not focus on causes such as damages and quality issues since these problems take place at other departments and therefore fall outside the scope of this research. Causes that occur during demand planning and tactical production planning and inventory management remain, and therefore possible solutions in these directions will be discussed.

2.4.1 Optimizing demand forecasting process

From the root cause analysis it became clear that overforecasting was a structural problem during the year 2019, what can be an explanation of the obsolescence that year. However, since – as already explained - producing more realistic demand forecasts is an ongoing project at the moment, this is no solution direction for further research.

2.4.2 Vendor Managed Inventory system

Another solution there can be thought of is a Vendor Managed Inventory (VMI) system, where the client (in this case: retailer) shares its inventory data with the supplier (Grolsch), and the supplier is responsible for optimization of the client's inventory. With help of the VMI-system, excess stock can be prevented. However, part of Grolsch' clients already work with a VMI-system, and during the interviews it is stated that the remaining retailers are not interested in implementing a VMI-system. When implementing a VMI-system, Grolsch' clients (retailers) have to bear part of the implementation costs. Although reduction of excess stock can be very valuable for Grolsch, the retailers only benefit from improved service levels as a result of the VMI-system. However, it appears from the interviews that since at the moment Grolsch' service levels are already quite high, retailers do not think the costs of implementing a VMI-system would outweigh the possible optimization of service levels. For further research it could be interesting to examine if clients are willing to implement a VMI-system if Grolsch offers to pay (most of) the costs, and if the benefits of such a VMI-system regarding excess stock reduction would outweigh the costs of implementation for Grolsch.

2.4.3 Lowering minimum batch sizes

Besides demand forecasting, it also became clear that minimum batch size restrictions in combination with lower demand volumes made optimal production planning more difficult and caused obsolescence amongst products. As mentioned in Chapter 2.2.3, minimum batch size restrictions play a role at the beginning, as well as at the end of a production process. One solution direction of which can be thought of is lowering the minimum batch sizes.

Minimum brewing batch sizes in the beginning of the production process are set in order to maintain a constant quality of the beer. Since a good product quality is a prerequisite, it is not possible to apply significant adjustments to these restrictions. On the contrary, significant adjustments are possible to the minimum batch sizes at the end of the production process (during packaging). These minimum packaging batch sizes have to do with the efficiency of the packaging lines. Different departments together have agreed on a rule of thumb that says a packaging line needs to produce a minimum of 3 hours straight to be efficient. It would be interesting to examine if it is maybe beneficial to lower the minimum hours of packaging per batch, and so the minimum packaging batch size volumes, and allow more change-overs in between batches. When lowering the MinPack volumes of products, less stock needs to be planned on obsolescence beforehand.

To examine how much inventory losses savings could take place for the year 2019 within this solution direction, first of all it is determined how many times MinPack was the highest batch size restriction for products during the year 2019. It turns out that from the products of which all required data was available, almost half of the products produced in 2019 (44%) had their highest batch size restriction in the end of the production process, and together they made up 31% of the total inventory losses in hectoliters, and 23% of the total inventory losses in euros. This in comparison to the other half the products (56%) that had their highest batch size restriction at the beginning of the production process, and together made up 69% of the total inventory losses in hectoliters, and 77% of the total inventory losses in euros. This means that the total inventory losses due to obsolescence amongst products with the highest batch size restrictions in the beginning of their production process were higher than that of products with the highest batch size restriction at the end of their production process, and so more inventory losses savings are possible by focusing on the former products with highest minimum batch size restrictions in the beginning of the production process.

During the next sections, solution directions regarding restrictions at the beginning of the production process are examined and discussed more thoroughly. However, the inventory losses of products with the highest batch size restriction at the end of the production process are certainly not negligible, and therefore this is still an interesting alternative solution direction for further research. Perhaps it is possible that, by lowering the MinPack batch sizes, still a lot of obsolescence reduction can be achieved quite easily. However, since a variety of different factors are involved at the packaging stage, examining the impact of lowering MinPack sizes will take some time. First of all, allowing more change-overs during packaging will negatively affect the efficiency of the packaging lines, and this loss of factory efficiency in its turn will have impact on a lot of other things. For example, in total more time is needed to produce the same amount of products, more cleaning needs to take place in between batches, etc. All these effects needs to be identified when examining this solution direction. For this reason we remain with the solution direction regarding restrictions at the beginning of the production process, but keep in mind the other solution direction of lowering MinPack values for possible further research.

2.4.4 Product postponement

One of the solutions possible to apply earlier in the production process is product postponement. In this way, product completion can be delayed, such that it fits demand as good as possible and expected obsolescence can be minimized. A way to apply product postponement is by letting more products share their brew stream with each other. From one matured beer type in this way more filtrated beer types can be produced, and the same applies to filtrated beer types resulting in different packaged products. This would make production planning more flexible, since the production of more products can be combined, and less products need to comply with the minimum batch size restrictions on their own. As already mentioned, especially NPDs often do not share their brew stream with other products. The reason for this is that after development of these new products in the test brewery, most off the time they have been added separately to the product portfolio. It would be very interesting to examine possibilities of including (new) products in other already existing brew streams. However, after some interviews it becomes clear that this is already an ongoing project at the brewing department. For this reason, this solution direction will not be further examined during this project.

2.4.5 Early disposal of semi-finished products

One remaining solution direction regarding minimum batch size restrictions in the beginning of the production process is the disposal of semi-finished products early in the production process. Since the earlier mentioned product postponement is not something to focus on during this project, it is decided to focus on early disposal of semi-finished products. This solution is suitable for products of which the minimum batch sizes in the beginning of the production process are higher than those at the end of the process. Especially for BTO products that often are bounded to their MinBrew volumes as mentioned in Chapter 2.2.3, early disposal is expected to be a good way to avoid product obsolescence later in the process. An advantage of this solution direction, is that it can be combined with generating insight into expected product obsolescence and into possible interventions and their effects where is also a lack of at the moment.

As earlier mentioned, during tactical planning it is already tried not to plan on obsolescence (DoC < shelf life). However, also taking into account the demand variability when calculating expected obsolescence will support the planning process and decision-making regarding product obsolescence, and makes it more well-founded. For products with high expected obsolescence, it can be determined what the effects are on expected obsolescence when disposing part of the matured beer earlier in the process. Of course during early disposal, the remaining beer volumes still need to comply with the minimum batch size restrictions of the next production steps as earlier mentioned. If during an early stage expected obsolescence is already noticed, but it appears that no early disposal of these products is possible (e.g. due to higher minimum batch sizes at the end of the production process), departments can already be warned (e.g. the sales department) and other intervention possibilities can be discussed. In this way, interventions such as for example marketing campaigns can already be planned, to avoid future discount sales of expired stock and/or obsolescence. Since for this research we cannot be provided with sensitive product price data, it is not possible to calculate the expected effects of these marketing campaigns, and so this intervention scenario cannot be incorporated quantitatively into the solution model. However, during this research a standard procedure can be developed to support the discussion between different departments about different intervention possibilities (early disposal, marketing campaigns) for products with high expected obsolescence.

2.4.6 Conclusion

1. Demand forecasting optimization is an ongoing project, and so no solution direction for this research. The same holds for product postponement. Also implementation of a VMI-system is no possibility since clients or not interested to invest in such a system;
2. Applying significant adjustments to the minimum brewing batch sizes is no possibility due to quality restrictions, but for the minimum packaging batch sizes this can be a solution direction;
3. However, it appears that for the year 2019 more inventory losses are caused by the products with the highest minimum batch size restrictions in the beginning of the production process instead of the products with the highest minimum batch size restrictions at the end of the process, and so we will focus on these former products with more cost savings potential;
4. Since product postponement is already an ongoing development, it is chosen to focus on another solution direction at the beginning of the production process: early disposal of semi-finished goods;
5. The final solution model will calculate expected product obsolescence and will generate insight into the effects of early disposal of matured beer on expected obsolescence.

Chapter 3: Solution design

As described in Chapter 2.4.5, it is decided to focus on early disposal of semi-finished products in order to try to reduce product obsolescence. This chapter will discuss the idea of the solution model that incorporates the chosen solution direction, and will explain more thoroughly how the proposed model works.

3.1 Model scope, restrictions and assumptions

The idea of this solution direction is to create a model that is two-fold: it monitors the expected obsolescence of products, where after the effects of early interventions on the expected obsolescence of products can be examined. At the end of the research, an obsolescence monitoring model as well as a decision model that tries to reduce expected obsolescence will be delivered.

Since the monitoring model needs to take into account the expected obsolescence of all products at Grolsch – products planned to be produced as well as products already on stock – the new production plan as well as already available stock data is used as input data to the model. Products that are already in production are not taken into account in the solution model, since these products would probably already have been treated by the model during previous production planning. For all the products – on stock as well as still planned to be produced - the expected obsolescence will be calculated by the monitoring model. During monitoring, per product a distinction can be made between expected obsolescence caused by current available stock as well as expected obsolescence caused by the products planned to be produced.

Expected obsolescence caused by current available stock

- Regarding finished goods that are already produced and on stock, in the best case obsolescence is foreseen well in advance and can still tried to be avoided. For example after discussion between different departments, it can be decided to stimulate sales by way of a marketing campaign in order to prevent products from becoming obsolete. In the worst case products already have reached – or do almost reach - their final delivery date (such as the products that appear at the ROM procedure) and are sold for a discount price or are disposed. Since both actions (discount sales as well as disposal of obsolete finished goods) are reactive and only mitigate the negative effects of obsolescence, they are not taken into account as early intervention possibilities in the decision model.

Expected obsolescence caused by products planned to be produced

- For products planned to be produced but with already high expected obsolescence, besides the already mentioned reactive actions also proactive actions are possible before production takes place, in order to avoid stock excesses at a later stadium. For this reason these kind of products are selected from the monitoring model and are used as input to the decision model that tries to reduce expected obsolescence. As earlier explained, the decision model will examine the effects of planned disposal of matured beer. From now on we will call the decision model the early disposal decision model.

A restriction that needs to be kept in mind is the fact that generally there is never planned on stockouts for products (DoC => MinDoC). Especially in the case of NPDs, from which its success amongst other things depends on a good market introduction. In general, for normal products a DoC between X-X days is maintained, while for NPDs some safety is incorporated into their DoC, what leads to a DoC of around X days.

However, an exception to this rule applies to products at the end of their sales season. In this case often it is agreed with the client (retailer) that from a certain moment no new production batches will take place and a product is only available while stock lasts. In this way, bypass of the stockout restriction is possible, and excess stock is avoided.

Although the model focusses on obsolescence reduction and besides this the tactical planner probably will intervene in time in order to prevent a product from being out of stock, it is decided to still also calculate the expected understocking per product batch. The reason for this is because the understocking at a particular moment can be seen as stock that still needs to be produced in the future to fulfil the remaining demand. At Grolsch, unfulfilled demand is not treated as lost sales, but as backlogged sales that needs to be fulfilled at a later moment in time. Therefore it is important to also take into account the expected understocking of product batches during the calculation of the final expected overstocking per product. During Chapter 3.3.2, where the mathematical model of the monitoring system will be discussed, the need for calculation of expected understocking will be further explained.

Starting stock of semi-finished products is not taken into account in the model, since semi-finished products that are not used during production almost immediately become obsolete and will not be kept in stock.

The First In First Out (FIFO) principle has been applied to products on stock. This means that the oldest product batches (that have the earliest final delivery date) are sold first.

Furthermore it is assumed that the production lead time can be neglected in the model, since the few days filtration and packaging takes is much less than the period from week zero until the final delivery date of a new production batch.

3.2 Conceptual model

In order to develop the model, first of all a conceptual model is developed that represents the system. A visualization of the conceptual model can be found in Figure 10. Here after the necessary input- and output data of the model is discussed, and it is explained how the model works. Since besides expected obsolescence, also expected understocking is relevant in order to calculate the final expected obsolescence as earlier explained, from now on we will talk about expected over-and understocking instead of expected obsolescence only.

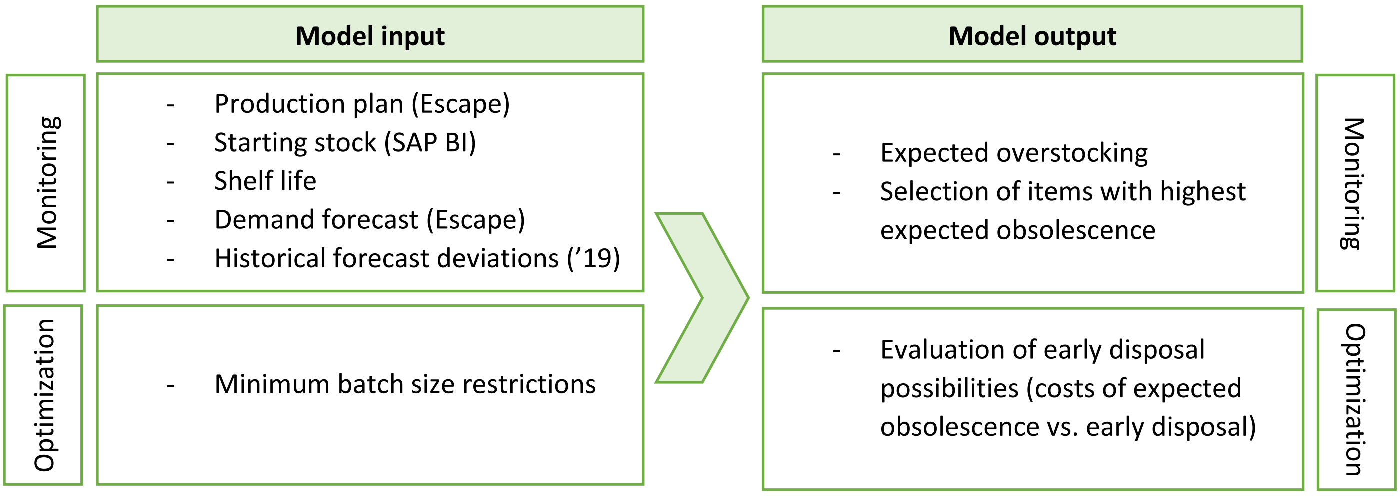

Figure 10 Conceptual model of monitoring- and optimization model

Production plan

Since newly planned production batches can cause obsolescence, first of all the production plan is used as input to the model. This production plan comprises the packaging plan in hectoliters per product on a weekly basis. For this reason the expected over- and understocking per product is also calculated on a weekly basis within our model.

It is chosen to only use the next planned production batch per product as input to the model, since production plans change the entire time due to demand (forecast) changes. This means that the further into the future we look (and so the more production batches we would take into account), the less accurate the expected obsolescence calculated by the model would be. The strength of this model lies in generating an insight into the expected obsolescence of products as good as possible from a certain moment, given a certain starting stock level and the most updated production- and sales plan at that moment. This means that the model will not simulate an entire period with multiple production moments. Furthermore, after interviewing supply chain planning staff it is decided to only look for a next production batch that takes place within 13 weeks from the monitoring moment on, since after these 13 weeks the production plan becomes too flexible, what can negatively impact the accuracy of the model. This means that planned production batches that fall outside the next 13 weeks, are not taken into account in the model.

Since the proposed model is only useful for make to forecast products – the obsolescence of make to order products is a responsibility for the client himself – make to order products are filtered out from the input data set. Also tank beer is filtered out from the input data set since the supply chain planning department cannot influence these kind of products.

Starting stock

Since besides newly planned production batches, also the expected over- and understocking of already existing stock can be measured, this current stock - called starting stock - needs to be taken into account as well in the model. A product can have multiple batches in stock with different production dates, and so with different final delivery dates. Therefore, all these different batches needs to be taken into account separately. The input data of starting stock consists of information per product batch about the production week and the amount of hectoliters on stock at the moment of monitoring. Just as has been done at the products planned to be produced, make to order products and tank beer are filtered out from the starting stock data, as explained above.

Shelf life

In order to determine the expected obsolescence of a product, information about a product's shelf life is needed. As earlier mentioned, after 1/3 of a product's total shelf life has passed by, a product's final delivery date to the client has been reached and a product will be declared obsolete. Per product batch (starting stock as well as newly planned products) the final delivery date can be calculated with help of the shelf life of a product. The shelf lives are expressed in weeks since the model also calculates weekly expected over- and understocking. If information about the shelf life of a product is missing, we take the average shelf life of all products from the product portfolio together (15 weeks).

Demand forecast

In order to calculate the expected over-and understocking per product, the expected demand per product is needed. Therefore, the most recent updated sales forecast of weekly demand in hectoliters will be used as input data. During interviews it is suggested that demand is normally distributed. In Appendix V it is verified that the hypothesized normal distribution indeed adequately describes the demand data, and so normally distributed demand is assumed for this model. As input for the model, the expected (mean) demand (μ) of a product from the current monitoring moment until the final delivery date of the last product batch is needed, since after this moment the last product batch has become obsolete and the calculation has ended. Since planned production batches will always be the newest product batches on stock (newer than starting stock), the planned production batch can always be considered as the last product batch reaching its final delivery date in the model. Therefore, demand data is needed from the monitoring (current) moment until the final delivery date of the next production batch. However, if a product is not included in the production plan of the next 13 weeks, but still has got some starting stock, the last product batch taken into account in the model equals the starting stock batch with latest final delivery date. Then, demand data is needed from the monitoring (current) moment until the final delivery date of this starting stock batch with latest final delivery date.

Historical forecast deviations

As already mentioned the expected demand from the monitoring (current) moment until the final delivery date of the last starting stock/next production batch is used as input data to the model. This expected demand comes along with a certain forecast accuracy, and so also demand variability needs to be taken into account in the model. The forecast accuracy of a product can be determined with help of historical sales and forecast data. A choice that needs to be made is what historical data will be used in order to calculate the standard deviation of a product's expected demand. From interviews it appears that tactical planning decisions are often based on historical data from a maximum of one year ago, since the product portfolio is changing rapidly. Due to these rapidly changing products, it is chosen to also base the standard deviations of expected demand on historical data from a maximum of one year ago (in this case: the year 2019).

Furthermore it is assumed that forecasts are unbiased. As earlier explained, during the year 2019 forecasts were structurally overforecasted. However, since Grolsch is striving for more realistic forecasts at the moment, probably the current/future forecasts will be less biased.

In order to calculate the standard deviation over a certain period L (σ_L), first of all the forecast accuracy method needs to be determined. Silver, Pyke and Thomas (2017) discuss three widely used forecast accuracy methods: the Mean Square Error (MSE), the Mean Absolute Deviation (MAD) and the Mean Absolute Percent Error (MAPE). Only the last called MAPE is not affected by the magnitude of the demand volumes since it expresses the variability as a percentage. Since demand can fluctuate a lot, and so can differ strongly from the demand a year ago, it is chosen to work with relative deviations (MAPE) instead of absolute deviations, and multiply these relative deviations with the expected demand in order to obtain the standard deviations that can be used as input to our model. Therefore, first of all per product the MAPE is calculated (1), with n = 52 weeks (here: over the year 2019), x_t = actual sales in week t, and $\hat{x}_{t-1,t}$ = forecast for week t 1 week in advance.

$$MAPE_n = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{x_t - \hat{x}_{t-1,t}}{x_t}\right| \qquad (1)$$

After calculating the MAPE per product, the coefficient of variation for 1 week ahead needs to be calculated. As described in Silver, Pyke and Thomas (2017), the relationship between MAD and σ_1 is not as simple, but that in the case of normal distributed demand the σ_1 can estimated as follows (2).

$$\sigma_1 = 1.25\, MAD \qquad (2)$$

However, since we need to calculate the relative instead of absolute deviations, we assume the coefficient of variation for 1 week ahead CV(1) to be calculated as follows (3).

$$CV(1) = 1.25\, MAPE \qquad (3)$$

Until now, the forecast update interval equals 1 week. However, since we look ahead a few weeks from the monitoring (current) moment until the final delivery date of the last starting stock batch/ next production batch, the CV(1) needs to be converted to CV(L), the coefficient of variation for L weeks ahead. According to Silver, Pyke and Thomas (2017), assuming that in an L period the forecast errors in consecutive periods are independent and each have a standard deviation of σ_1, a good way to approximate the σ_L is as follows (4).

$$\sigma_L = \sqrt{L}\,\sigma_1 \tag{4}$$

Since with stationary demand the following holds (5),

$$\mu_L = L\mu_1 \tag{5}$$

and besides this the coefficient of variation can be determined by the following relation between mean and standard deviation (6),

$$CV = \frac{\sigma}{\mu} \tag{6}$$

the coefficient of variation for L weeks ahead can be calculated as follows (7).

$$CV(L) = \frac{\sigma_L}{\mu_L} = \frac{\sqrt{L}\,\sigma_1}{L\mu_1} = \frac{\sqrt{L}\,\sigma_1}{L\mu_1} = \sqrt{L}^{-1} CV(1) = \frac{CV(1)}{\sqrt{L}} \tag{7}$$

After calculating the coefficient of variation of a product's demand over L weeks, this CV(L) can be multiplied with the earlier mentioned expected demand over the L weeks (μ_L) to obtain the standard deviation over the L weeks (8).

$$\sigma_L = CV(L) * \mu_L \tag{8}$$

A problem occurs for products that have limited/no historical data to calculate their coefficient of variation from. In short the following situations are possible for products:

1. NPDs with limited/no historical data due to limited/no earlier sales;
2. Non-NPDs with limited/no historical data due to error in data base;
3. Non-NPDs with enough historical data.

Only in the last case, the above mentioned method is suitable to calculate the coefficient of variation of a product. However, for NPDs as well as non-NPDs with limited/no historical data another method needs to be found to determine their coefficient of variation of expected demand. Different solutions can be thought of for these products. An option for NPDs would be to calculate the coefficient of variation from recent demand data for NPDs that are already have been sold a few weeks. It is recommended not to base this σ on sales data of the first 10 weeks after launch, since a product's demand pattern will form from around the 10th week onwards, after the first two packaging and delivery moments have taken place. However, besides the fact that not all NPDs already own demand data from 10 weeks, another drawback of this solution is that demand can be quite erratic, especially in the first weeks after launch of a new product. This makes demand forecasting more difficult, and so also can result in very changeable forecast deviations, what can give a distorted picture of the current standard deviation of a product's demand forecast.

For this reason, another method is investigated that uses historical data of products with similar characteristics, to estimate the standard deviation of an item with limited/no historical data. The idea of this method is to find an empirical relationship between the standard deviation (σ_1) and the demand level (a) by means of regression analysis. According to Silver, Pyke, and Thomas (2017), for many organizations the following power function relationship gives a reasonable fit (9)

$$\sigma_1 = c_1 a^{c_2} \qquad (9)$$

or equivalently expressed in a linear relationship (10)

$$log\ \sigma_1 = log\ c_1 + c_2 \log a \qquad (10)$$

However, for our problem we need the coefficient of variation instead of the standard deviation of demand. Therefore, it needs to be investigated if the proposed relationship between demand level and standard deviation can be rewritten in such a way that it applies to our problem. Since the demand level (a) represents the expected demand per year (μ), and besides this in general equation (6) applies, the following can be stated (11).

$$CV(1) = \frac{\sigma_1}{a} = \frac{c_1 a^{c_2}}{a} = c_1 a^{c_2 - 1} \qquad (11)$$

As can be noticed, still a power function holds as relationship between the demand level and (now) the coefficient of variation. Therefore, it is assumed that the method discussed in Silver, Pyke, and Thomas (2017) is also applicable to our situation in which we need to determine the coefficient of variation instead of the standard deviation of demand. However, since it is easier to assess a relationship between two variables by means of a straight line instead of a power graph, it is chosen to draw the ln-ln graph of the coefficient of variation vs. demand volume. This has been done for NPDs as well as for non-NPDs of which no(t) (enough) historical data was available.

NPDs with limited/no historical data

After filtering out some outliers from the demand- and coefficient of variation data of all products that were classified as NPD during the year 2019, with help of the remaining data an ln-ln plot is created as can be found in Figure 23 of Appendix VI. As can be noticed from the graph, the data does not follow a clear straight line what means that the linear model does not fit well to the data. This also becomes clear from the really low R-squared value of only 0.X. An explanation for the weak relationship between demand level and coefficient of variation of demand of NPDs of 2019 is that the forecast accuracy of NPDs heavily depends on the success of a product introduction. However, it is almost not predictable if a product will become a success on the market or not, what results in very variable forecast accuracies. Besides this, there is only limited data available of NPDs (X NPDs during the year 2019) what makes the outcome of the applied linear regression less reliable.

Due to this lack of data, and above all since it appears that there is almost no relation between demand volume and coefficient of variation of demand for NPDs of 2019, it is decided there is no point in defining an equation for the coefficient of variation for NPDs by means of regression analysis as discussed by Silver, Pyke, and Thomas (2017). However, still the coefficient of variation of demand for NPDs of this current year (2020) is needed as input value for the model. For this reason it is determined to just simply calculate the average MAPE-value of all NPDs of the year 2019 (in this case: X%), and to use this value to calculate the standard deviation over the L weeks per product in the same way as already described in equations (3) until (8). As an indication, the average MAPE-value of all NPDs of 2019 was X%, while that of all non-NPDs during the same year was “only” X%.

Non-NPDs with limited/no historical data

The same regression analysis has been applied to all products that were classified as non-NPD during the year 2019. After filtering out some outliers from the demand- and coefficient of variation data, the linear regression results in the ln-ln plot that can be found in Figure 24 of Appendix VI. In comparison to Figure 23, now a more clear straight line is visible. This also appears from the higher R-squared value, of 0.X. Although the relationship is not extremely strong, the clearer straight line and the higher R-squared value indicate some relation between demand level and coefficient of variation for non-NPDs during the year 2019, and so we will build further on these results.

It is interesting to examine if, amongst these non-NPDs, there can be found groups of products with similar characteristics of which the relationship between demand level and coefficient of variation is even higher. It is chosen to focus on two other product characteristics that were already mentioned during interviews as possible factors that complicate forecasting, namely: seasonality and ending sales seasons. It is chosen not to do the same for slow moving/non-slow moving products, since their categorization is based on the same variable as already used for the linear regression (yearly demand volumes). For the seasonal/no seasonal non-NPDs and the non-NPDs with/without ending sales seasons, linear regression has been applied and the resulting ln-ln plots (Figures 25 until 28) can also be found in Appendix VI.

As can be noticed, the graph from seasonal non-NPDs (Figure 25) shows no strong relationship (no clear straight line and a low R-squared value of only 0.X), in comparison to the graph of not seasonal non-NPDs (Figure 26) that shows a stronger relationship (clearer straight line and higher R-squared value of 0.3964). However, the relationship that appears from the graph of not seasonal non-NPDs (Figure 26) seems not stronger than that of all non-NPDs together (Figure 24), and so there will not be further focused on the distinctive characteristic seasonality. Hereafter the characteristic ending sales seasons is investigated. As can be noticed, both graphs (in Figures 27 and 28) show a quite clear straight line and contain a quite strong R-squared value. Non-NPDs with ending sales seasons (Figure 27) perform even better than all non-NPDs together (Figure 24) with an R-squared value of 0.X. However, the graph of non-NPDs with ending sales seasons (Figure 27) is based on only X non-NPDs, what makes it dangerous to draw conclusions from it. Besides this, the graph of non-NPDs with no ending sales seasons (Figure 28) does not show a stronger relationship than that of all non-NPDs together (Figure 24). For these reasons it is decided to let go the idea of grouping non-NPDs during the regression analysis, but focus on the already determined general linear regression results of all non-NPDs of 2019 together. This results in the following power function equation for the coefficient of variation of non-NPDs (12). Also a graph of this equation can be found in Appendix VI in Figure 29.

$$CV(1)_{non-NPDs} = 4.3904\ a^{-0.234} \qquad (12)$$

With help of this equation, at a current moment in time (here: a moment in the year 2020) for every non-NPD with limited/no historical sales data a coefficient of variation for 1 week ahead can be calculated by filling in its yearly expected sales into equation (12). Hereafter, in the same way as has been done earlier, the coefficient of variation for L weeks ahead can calculated (7), and it can be multiplied by the expected demand (µ) during period L to obtain the standard deviation over the L weeks.

A discussion point of the above mentioned methods to calculate the standard deviations of demand for different kind of products, is that it makes use of the historical forecast and actual sales data of one whole year ago (here: the year 2019) starting from week 1 and ending in week 52 of that same year. This means that, for example, in the last week (week 52) of the year 2020, we still calculate a product's MAPE-value with data from the whole year 2019, while actually there is already almost 1 full year of new historical forecast- and actual sales data available of the year 2020. In order to improve the accuracy of the model, it can be considered to use weekly instead of yearly forecast- and actual sales data. Since the monitoring model will be used weekly, in this way the forecast- and actual sales input data will be updated every time the monitoring model is used. For the above mentioned example this would mean that the forecast- and actual sales data from week 52 of the year 2019 until week 51 of the year 2020 will be used. However, a drawback of this method is that it takes a lot of time to load forecast data from the data system and make it suitable for the standard deviation calculations (e.g. detecting and removing unnecessary data, etc.). For this reason it chosen to stay with the decision to use forecast- and actual sales data of one whole year ago, but weekly updating this data could be a possible improvement of the model in the future.

Batch size restrictions

In order to evaluate early disposal possibilities and its impact on expected overstocking, the minimum batch sizes per product are also relevant. These restrictions determine the maximum amount of beer that can be disposed per product. Therefore the minimum brewing-, filtration-, as well as packaging volumes per product are taken into account in the model.

Costs

By including the costs of goods sold of finished- and semi-finished products and disposal costs of finished products, per product the expected costs of obsolescence and possible early disposal of matured beer can be calculated and weighted up against each other.

3.3 Mathematical model

In order to set up a mathematical model for our proposed solution, first of all there will be dived into literature to look for similar problems and possible solution methods.

3.3.1 Newsboy problem

As found in literature, the current problem can be described as a classical newsboy problem. The newsboy problem is a single-period mathematical model used to make decisions about inventory levels of perishable products with fixed prices and uncertain demand. In the case of Grolsch, produced beer should satisfy demand within 1/3 of their shelf life, and any beer left after this period has almost no value (sold for discount price or becoming obsolete). According to the Newsboy problem described by Chopra and Meindl (2013), with help of equations (13) and (14) the expected over- and understock can be calculated given a certain demand forecast.

$$Expected\ overstock = \int_{x=-\infty}^{O} (O - x)\, f(x)\, dx = (O - \mu)F_S\left(\frac{O-\mu}{\sigma}\right) + \sigma f_S\left(\frac{O-\mu}{\sigma}\right) \tag{13}$$

$$Expected\ understock = \int_{x=O}^{\infty} (x - O)\, f(x)\, dx = (\mu - O)[1 - F_S\left(\frac{O-\mu}{\sigma}\right)] + \sigma f_S\left(\frac{O-\mu}{\sigma}\right) \tag{14}$$

The following inputs are considered:

- O = order size (here: stock level)
- μ = expected demand (here: from week 0 until the final delivery date (1/3 of the shelf life) of the latest starting stock batch/first new production batch)
- σ = standard deviation of demand (here: same period, previous year)
- $F_S(x)$ = cumulative distribution function of demand
- $f_S(x)$ = probability density function of demand

If the stock level equals O, an overstock results only if demand $x < O$ (1), and an understock results only if demand $x > O$ (2). Demand's stochasticity is taken into account in the above mentioned newsvendor problem example of Chopra and Meindl (2013). In their example, demand is assumed to be normally distributed, with a mean μ and standard deviation σ. As explained in Appendix V, statistical analysis shows that the Normal distribution is a fair model for our problem, what corresponds to the distribution used in the example of Chopra & Meindl (2013).

3.3.2 Monitoring model

Our problem is more complex than the above mentioned situation described by Chopra & Meindl. Their model only takes into consideration 1 stock level, while in our situation a product can have multiple batches on stock, what makes the expected over- and understock calculations more complex. For this reason a heuristic is developed that tries to model the expected over- and understocking per product as good as possible given a certain starting stock level and production plan. Since the FIFO principle is applied and demand is backlogged, the heuristic starts with the oldest product batch and calculates the expected over- and understocking, given a certain demand forecast between the current moment and the final delivery date of that batch. All the products of this batch that are not consumed before the final delivery date of this batch has been reached become obsolete. On the other hand, the shortage during this period needs to be kept in mind as well since this has to be added to the demand of the next product batch due to backlogging. This process continues until the expected over- and understocking of the latest batch has been calculated. At the end, the product's final obsolescence over the whole period equals the sum of all expected overstocking of the different product batches. Besides this, the final shortage of a product over the whole measuring period only equals the understocking of the last product batch, since shortages of different product batches are passed on until the last product batch has reached its final delivery date.

Mathematical model

There are n=1..N batches on stock with final delivery dates $T_1 < T_2 < \cdots < T_N$

Note: since the heuristic only calculates the expected obsolescence for 1 end product k, and no other products matter during the heuristic developed for the monitoring, during the heuristic we make no distinction between different products and such make no further use of the subscript symbol (end production k) during this general heuristic that can be applied to every end product k. However, during optimization we will make a distinction between products because in this situation this will make sense due to possible differentiation.

Input variables

S_n = stock level of batch n at beginning of planning period
T_0 = beginning of planning period (current moment)
T_n = moment at which stock of batch n becomes obsolete (n=1..N)
T_{N+1} = moment at which last product batch (in case of no production plan) or first production batch ($n+1$) becomes obsolete
$f_n(x)$, $F_n(x)$: Probability Density Function resp. Cumulative Distribution Function of demand in [T_{n-1}, T_n], with T_0=0. This demand is normally distributed with mean μ_n and standard deviation σ_n

Decision variable

Q^P= next planned packaging batch size for end product in hectoliters

Auxiliary variables

S_n'= expected remainder of batch n still available after backlogging. By definition: $S_1' = S_1$
EU_n'= expected remaining shortage of batch n after backlogging

Output

EO_n = expected overstocking of batch n on T_n (n=1..N+1)

EUH_n = expected understocking of batch S_n op T_n (n=1..N+1)

Heuristic

On T_1: Newsboy analysis with available stock S_1 (=S'_1) and demand distribution over T_1.

(Note: if the product has no starting stock, but is included in the production plan, S_1 equals Q).

Define: $z_1 = \frac{S'_1 - \mu_1}{\sigma_1}$

With the standard normal loss function: $G(z) = f_s(z) - z\{1 - F_s(z)\}$

Calculate expected over- and understocking:

$$EO_1 = \sigma_1\{z_1 + G(z_1)\}$$

$$EU_1 = \sigma_1 G(z_1)$$

If next product batch left: update starting stock and shortage for next product batch:

$$S'_n = \max(S_n - EU_{n-1}; 0)$$

$$EU'_{n-1} = \max(EU_n - S_n; 0)$$

On T_n: Newsboy analysis with available stock S'_n , backlogged demand EU'_{n-1} and demand distribution over T_n.

Define: $z_n = \frac{S'_n - \mu_n - EU_{n-1}}{\sigma_n}$

With the standard normal loss function: $G(z) = f_s(z) - z\{1 - F_s(z)\}$

Calculate expected over- and understocking:

$$EO_n = \sigma_n\{z_n + G(z_n)\}$$

$$EU_n = \sigma_n G(z_n)$$

Repeat until second last product batch.

If last product batch left: update starting stock and shortage for last time:

(remember: if last product batch is production batch: $S_{N+1} := Q_k^P$).

$$S'_{N+1} = \max(S_{N+1} - EU_N; 0)$$

$$EU'_N = \max(EU_{N+1} - S_{N+1}; 0)$$

On T_{N+1}: Newsboy analysis with available stock S'_{N+1} , backlogged demand EU'_n and demand distribution over T_{n+1}.

Define: $z_{N+1} = \frac{S'_{N+1} - \mu_{N+1} - EU_N}{\sigma_N}$

With the standard normal loss function: $G(z) = f_s(z) - z\{1 - F_s(z)\}$

Calculate expected over- and understocking:

$$EO_{N+1} = \sigma_{N+1}\{z_{N+1} + G(z_{N+1})\}$$

$$EU_{N+1} = \sigma_{N+1}G(z_{N+1})$$

Here after, the total expected over- and understocking of the product over the particular period can be calculated:

$$EO_{Tot} = EO_1 + EO_n + \cdots + EO_N + EO_{N+1}$$

$$EU_{Tot} = EU_{N+1}$$

However, since as earlier mentioned in general the rule applies that there will not be planned on stockouts, and so it is assumed that in case of threatening shortages production will be planned in time, there is no point in optimization of the expected understocking. In our model, the final expected understocking therefore will not be seen as a performance indicator. Only the intermediate expected understocking of the different product batches will be used as a means to determine the expected overstocking of the next batch (except for the last batch since there is no subsequent batch anymore). This means that only the final expected overstocking of products is used as performance indicator during optimization.

Approximation

For the expected over- and understocking on T_n we only take into account the earlier calculated deterministic expected over- and understocking on T_{n-1} and not the variability of demand. This means we consider these input values for the next batch as deterministic instead of stochastic since otherwise the calculation would become a lot more complex.

Assumptions

Furthermore it is assumed that every production batch is already available from the moment of planning (T_0). In reality this is not always the case, since most of the time the production moment is later than the moment of planning (T_0). However, since first of all existing starting stock needs to be consumed according to the FIFO-principle before the newly produced batch can be touched, and besides this it is assumed that there is not planned on stockouts and so the production planner tries to plan production batches in time, the assumption that no stockouts occur before the next production batch will be released seems quite plausible. However, it is not easy to check if shortages indeed often do not occur before a new production batch is released. First of all, forecasts are on weekly basis and not on daily basis, what means that it is difficult to use the right (amount of) demand as input data. This can cause a distorted picture of the shortages at a particular moment. Besides this, the forecasts are not always accurate and can contain fuzzy demand that does not belong there, what also can cause a distorted picture of the expected shortages. For this reason the assumption is made that production usually is planned in time and there is enough starting stock to fulfil demand before the new production batch is released. However, a way to improve the reliability of the model in the future, is by taking into account the release time of the production batch as well.

3.3.3 Early disposal decision model

After monitoring the expected over- and understocking of products and identifying the products with highest expected obsolescence, it is time to try to reduce the expected obsolescence of these identified products. The previous mentioned monitoring model already made a distinction between expected obsolescence caused by starting stock, and expected obsolescence caused by a new production batch. Since we cannot proactively affect the expected obsolescence caused by starting stock, there will only be focussed on the expected obsolescence caused by newly planned production batches.

As mentioned at the end of Chapter 2, it is chosen to focus on the early disposal of matured beer as a way to try to avoid future product obsolescence. However, this intervention method is not suitable to all kind of products. Early disposal is only possible for products of which the demand (needed brewing batch size) is lower than the MinBrew batch size, and so matured beer can be disposed in the meantime. As earlier mentioned, products that are often affected by their MinBrew batch size and so often produce more than is demanded due to minimum brewing restrictions, are called brew to order (BTO) products. These BTO products are provided with a MinBrew-value in the data system, as a reminder to the planner to always comply to these restrictions. Assuming that indeed in general only the planned production batches of BTO products are affected by the MinBrew batch sizes (and so can be lowered), it is chosen to only focus on BTO products during optimization. For this reason, only the products that are BTO are selected from the products with high expected obsolescence identified during monitoring, and will be examined during optimization.

The planned packaging batch size will be considered as the decision variable that needs to be optimized. It is chosen for the packaging batch size, since the tactical planner always plans with packaged beer volumes, and so the model also focusses on this packaging batch size. The packaging plan of the tactical planner serves as a framework for the brewing planner, who tries to ensure the right amount of demanded beer is brewed in time. Sometimes reconsideration and adaptation of the packaging plan need to take place in order to align the production plans with each other. Although the model focusses on the packaging batch sizes, still the batch size restrictions during all stages of the production process (MinBrew, MinFiltr and MinPack) needs to be kept in mind. This is because of the differentiation possibilities of beers during brewing and filtration, and since it is assumed that the losses during production are so small that these can be neglected, what means that the sum of packaged beer volumes of products belonging to the same brew stream or filtrated beer stream need to comply with the corresponding minimum batch sizes during that stage. First of all the different possible situations regarding differentiation are explained below, where after its corresponding restrictions are explained in the mathematical model of the optimization tool.

Situation 1: No differentiation

Figure 11 Batch size restrictions if no differentiation took place during production

In this first possible situation in which from one matured beer stream, one filtrated beer stream, and also one packaged product is produced, the planned packaging volume of the final product must comply to the MinPack-, MinFiltr-, as well as the MinBrew volume.

Situation 2: Differentiation only at packaging

Figure 12 Batch size restrictions if differentiation only took place at packaging

In this second possible situation in which one matured beer stream results in one filtrated beer stream, but in multiple packaged products, per final product the planned packaging volume must comply to its own MinPack volume, and the total packaged volume belonging to one filtrated beer stream must comply to the MinFiltr- as well as the MinBrew volume.

Situation 3: Differentiation only at filtration

Figure 13 Batch size restrictions if differentiation only took place at filtration

In this third situation, in which one matured beer stream results in multiple filtrated beer streams, but these filtrated beer streams in their turn only result in 1 packaged product, per final product the packaged volume must comply to its own MinPack- and MinFiltr volume, and the total volume of packaged beer belonging to one matured beer stream must comply tot the MinBrew volume.

Situation 4: Differentiation at both filtration and packaging

Figure 14 Batch size restrictions if differentiation took place at filtration as well as packaging

In the last possible situation, in which one matured beer stream results in multiple filtrated beer streams, and these filtrated beer streams in their turn also result in multiple packaged products, per final product the packaged volume must comply to its own MinPack volume, the total packaged volume belonging to one filtrated beer stream must comply to the MinFiltr volume, and the total volume of all packaged beer together belonging to one matured beer stream must comply tot the MinBrew volume.

As earlier mentioned, the packaging batch size (and so the amount of matured beer to dispose that equals the difference between MinBrew and the packaging batch size) of the current packaging plan, will serve as the decision variable for our early disposal decision model. Hereby it is chosen to remain with the current moments of production, since the goal of the optimization model is to optimise the current packaging plan, and not to completely change it by also adjusting all production moments. For this reason it is also decided to remain with the already established differentiation characteristics per planned production moment per production stage during optimization. It could be possible to also reconsider all differentiation possibilities per production moment per production stage, but therefore also often the production moments of the packaging plan should be overhauled in order to combine different products with each other. Considering more decision variables (production moments and differentiation possibilities) would increase the complexity of the model, and so the amount of time needed to establish a good working model. Keeping in mind the goal of the optimization model, and besides this the limited time that is given to execute this research, it is chosen to remain with the packaging batch size as only decision variable, and consider the production moments and the differentiation characteristics per production stage as given.

By varying the packaging batch size (and so the amount of matured beer to dispose), the effect on the expected obsolescence of a product can be examined. As earlier mentioned, the expected understocking of a product will only be used as a means to determine the expected overstocking during the heuristic and will not be used as a final performance indicator for the early disposal decision model. The effects of early disposal and the expected obsolescence that comes along with it, can also be expressed in terms of costs. The direct costs that come along with early disposal of matured beer are the variable costs (COGS) of producing this matured beer. The costs of disposal of matured beer are so low that these can be neglected. Besides this, the direct costs that come along with obsolescence of finished goods are the variable costs (COGS) of producing (incl. packaging) these finished goods, and the costs of disposing these finished goods at the harbour (on average €X/hL).

A way to determine the optimal packaging batch size, is to minimize the above mentioned total direct costs related to obsolescence. The earlier mentioned batch size restrictions should needs to be taken into account during this optimization. The optimization would result in 1 optimal packaging batch size per product. However, it can be questioned if it is smart to base early disposal decisions purely on costs, since also more subjective factors can influence the decisions. For example for some products stockouts are definitely not desired and so a higher amount of expected obsolescence (and its corresponding costs) is accepted. For these kind of products still a packaging batch size higher than its optimal packaging batch size could be desired. For this reason it is chosen to not only calculate 1 optimal batch size per product, but to also express the impact of early disposal of matured beer on expected obsolescence and its corresponding costs by plotting them against each other in a chart. The chart can support decision making about early disposal of matured beer. Per product, with help of a business case the expected obsolescence can be weighed against the corresponding costs and a decision can be made about the final packaging batch size. In the upcoming section the mathematical model behind batch size optimization will be explained, where after in the subsequent section the early disposal decision making support tool with supporting charts will be discussed.

Mathematical model

For the early disposal decision model the same heuristic is applied as used for the monitoring part (as described in Chapter 3.2.2) in order to calculate the expected overstocking for a particular period, but now for multiple batch sizes per product. The following additional information is necessary in order to examine the effects of batch size volume on total costs.

Parameters

MQ_i^B = minimum brewing batch size for matured beer *i* (*i*=1..*I*)
MQ_j^F = minimum filtration batch size for filtrated beer *j* (*j*=1..*J*)
MQ_k^P = minimum packaging batch size for end product *k* (*k* = 1..*K*)

Sets:
F_i = set of filtrated beers that can be produced from matured beer *i* (subset of *j*=1..*J*)
P_j = set of end products that can be produced from filtrated beer *j* (subset of *k*=1..*K*)

The sets F_i are disjunct, and $\bigcup_{i=1..I} F_i = \{1,2,..,J\}$
The sets P_j are disjunct, and $\bigcup_{i=j=1..J} P_j = \{1,2,..,K\}$

c_k = variable COGS per end product *k* (*k* = 1..*K*)
d_k = average disposal cost per end product *k* (*k* = 1..*K*) (on average €7.50/hL as mentioned in Ch. 2.3)
c_i = variable COGS per matured beer *i* (*i*=1..*I*)

Decision variables

Q_i^B = planned brewing batch size for matured beer *i* (*i*=1..*I*)
Q_j^F = planned filtration batch size for filtrated beer *j* (*j*=1..*J*)
Q_k^P = planned packaging batch size for end product *k* (*k* = 1..*K*)

Restrictions

The following equations embody the no losses-constraints and the generalized brewing-, filtration- and packaging batch size restrictions that apply to every product *k* with a certain differentiation characteristic at the moment of production.

Minimum batch sizes:

$$Q_i^B \geq MQ_i^B, i = 1..I \quad (15)$$

$$Q_j^F \geq MQ_j^F, j = 1..J \quad (16)$$

$$Q_k^P \geq MQ_k^P, k = 1..K \quad (17)$$

No losses in the supply chain:

$$Q_i^B = \sum_{j \in F_i} Q_j^F, i = 1..I \quad (18)$$

$$Q_j^F = \sum_{k \in P_j} Q_k^P, j = 1..J \quad (19)$$

However, equations (18) and (19) that embody the no losses-constraints and the minimum batch size constraints can be substituted into the earlier mentioned minimum brewing- and filtration equations (15) and (16). This results in the following equations (20) and (21). The minimum packaging constraints (17) remain the same, but are for the sake of completeness mentioned one more time at the final constraints below (22).

Combined final constraints:

$$\sum_{j \in F_i} Q_j^F \geq MQ_i^B, i = 1..I \quad (20)$$

$$\sum_{k \in P_j} Q_k^P \geq MQ_j^F, j = 1..J \quad (21)$$

$$Q_k^P \geq MQ_k^P, k = 1..K \quad (22)$$

In order to allow early disposal of matured beer during optimization, relaxation of the constraint regarding minimum brewing volumes (20) needs to take place, what means that only the constraints regarding minimum filtration- and packaging volumes (21) and (22) remain during optimization. Equation (20) is now left aside because, if disposal is applied, the batch size will be lower than the MinBrew value.

Performance indicators

Just as has been done during the heuristic of the optimization model, the total expected overstocking of end product *k* over a particular period can be calculated, but now for multiple production quantity values (23).

$$EO_{Tot,k}(Q_k^P) = EO_{1,k}(Q_k^P) + EO_{n,k}(Q_k^P) + \cdots + EO_{N,k}(Q_k^P) + EO_{N+1,k}(Q_k^P) \quad (23)$$

Also per brewing volume the packaged product belongs to the amount of disposed matured beer can be calculated (24). Of course, one can imagine the brewing quantity Q_i^B equals the packaging quantity Q_k^P if no early disposal is planned already, and if the product is not sharing its beer with other products.

$$Amount\ of\ disposed\ matured\ beer\ (Q_i^B) = (MQ_i^B - Q_i^B) \quad (24)$$

Besides the expected overstocking and the amount of disposed matured beer, also the expected costs (25) and (26) per case can be calculated as extra information to support decision making, resulting in the total costs (27).

$$Costs\ of\ expected\ obsolescence\ (Q_k^P) = (c_k + d_k) * EO_{Tot,k}(Q_k^P) \qquad (25)$$

$$Costs\ of\ early\ disposal\ (Q_i^B) = c_i * \left(MQ_i^B - Q_i^B\right) \qquad (26)$$

$$Total\ costs\ (Q_k^P, Q_i^B) = (c_k + d_k) * EO_{Tot,k}(Q_k^P) + c_i * \left(MQ_i^B - Q_i^B\right) \qquad (27)$$

Here after, the total costs can be minimized by adjusting the packaging batch size Q_k^P.

Early disposal decision making support tool

After it is explained how the underlying heuristic of the model works, now it is time to discuss the early disposal decision making support tool. Goal of the tool is to support decision making regarding the batch sizes of BTO products with high expected obsolescence. One by one for these products the effects of their batch size on the total costs (expected obsolescence costs + early disposal costs) per product can be examined, and as mentioned in the previous section the optimal batch size can be calculated with one click by minimizing the total costs. An example of the charts shown on the dashboard of the early disposal decision making support tool can be found in Figure 15. The old batch size from the production plan (here: X hL) and its corresponding total costs are already displayed with a yellow mark on the total costs graph. By adjusting the batch size in the orange cell of the table (e.g. by filling in the optimal batch size), the impact of the batch size (and so the early disposal quantity of matured beer) on expected obsolescence and its corresponding total costs can be examined, and will be displayed with a green mark on the graph (here: optimal batch size X hL). With help of the graph and table of Figure 15, the tactical planner can determine which batch size to apply.

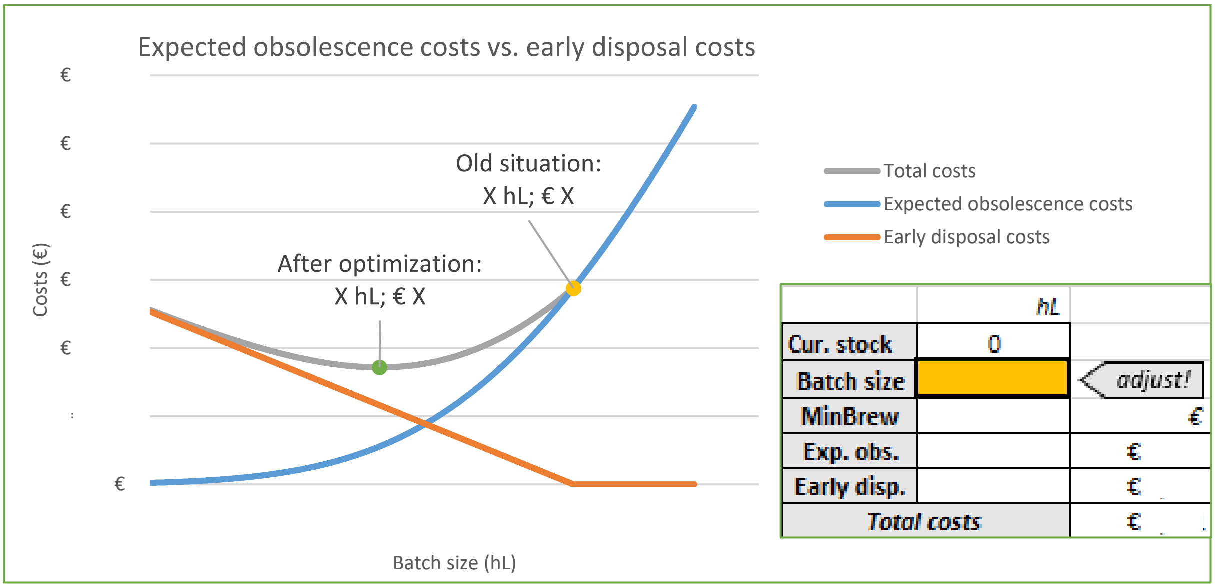

Figure 15 Optimization tool dashboard: graph with total direct costs related to obsolescence vs. packaging batch size, and table with effects of (adjustable) packaging batch size on stock level and costs

After reviewing the model and dashboard with the tactical planning team, it appears that besides the already shown chart and graph in Figure 15 some insight is desirable into the weekly expected inventory level, since this would give the planner more feeling about the effect of the chosen production batch size on the inventory level. For this reason, also a weekly expected inventory level chart is created for the dashboard. An example of such a chart can be seen in Figure 16. It needs to be kept in mind that the chart of Figure 16 is just an example of a situation, and is not related to the situation displayed in Figure 15. The chart of Figure 16 displays weekly point estimates of the expected inventory level, calculated by weekly subtracting the expected demand from on hand stock, starting with the starting stock level at the current week (here: week 13) and also taking into account the next new production batch (here: week 15). If there is no starting stock available at the current week, the expected inventory level of course starts at zero hL.

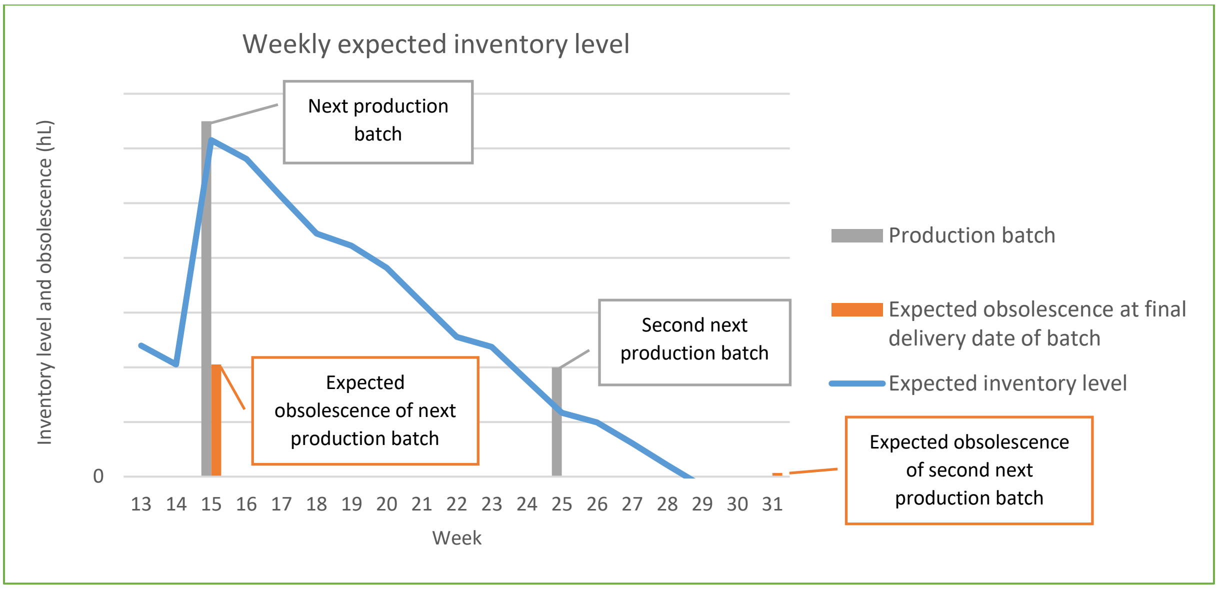

Figure 16 Weekly expected inventory level (point estimates) and expected obsolescence (stochastically)

Although a strong peak in expected inventory level probably will stand for a new released production batch, nonetheless it is useful to show the exact amount of planned production in the chart of Figure 16. This is done by the grey bar (here: next production batch of X hL at week 15). Although - as earlier mentioned in Chapter 3 - only the next planned production batch is taken into account in the heuristic, it is decided to still also display the subsequent planned production batches in the chart since this will give some more insight into the future inventory level (here: second production batch of X hL at week 25). However, since monitoring and optimization is only based on the next planned production batch, only the next planned production batch is incorporated into the expected inventory level point estimate calculations. The subsequent production batches in the chart should only be regarded as indicative.

Also orange bars are displayed in the chart of Figure 16. These orange bars represent the expected obsolescence calculated by the heuristic. As already described in Chapter 3, the heuristic does not calculate the amount of expected overstocking per week, but per final delivery date of each product batch. In order to calculate weekly expected obsolescence, adjustments are required to the algorithms of the heuristic. Due to limited time it is decided not to apply these adjustments to the algorithms, but to stick with the current calculations of expected overstocking per final delivery date of each product batch, and to only display the expected overstocking levels at these final delivery dates in the chart. For example, in the situation displayed in Figure 16, 1 starting stock batch is available, resulting in an expected obsolescence level of X hectolitres at its final delivery date in week 15. Besides this, the next batch causing obsolescence is the next planned production batch of week 15, with an expected obsolescence level of 7 hectolitres at its final delivery date in week 31. Summing up both displayed expected obsolescence levels would result in the total expected obsolescence as also calculated by the model. Since the heuristic only takes into account the next planned production batch, also only for this first production batch the expected obsolescence is displayed in the chart, and not for the subsequent production batches.

It needs to be kept in mind by the tactical planner that the chart of Figure 16 only displays weekly point estimates based on the most updated starting stock level, expected demand, and production plan. The expected inventory level is determined deterministically, and does not take into account demand variability such as the heuristic does in order to calculate the expected overstocking. It is for this reason that expected overstocking is possible at the final delivery date of the next production batch (just as expected understocking is possible at the same time), while the point estimate of the expected inventory already reached its zero level a few weeks before, as is the case in Figure 16. Although combining deterministically determined inventory level point estimates as well as stochastically determined obsolescence into one chart makes it somewhat more complex to understand for the tactical planner, it is decided to still stick to this idea since it is interesting to relate the different product batches with their expected obsolescence in one chart and put them in perspective to the inventory level.

Last but not least, the dashboard contains a bar chart that provides some more insight into the inventory level versus expected demand. The bar chart displays the release dates and final delivery dates of the different product batches (starting stock and/or the next production batch) that are taken into account by the heuristic, and the expected demand volumes during these periods. In Figure 17, an example of such a bar chart can be found. Also this chart is just an example of a situation, and is not related to the situations displayed in Figure 15 or 16. As can be noticed from Figure 17, in this situation the starting stock level ("Stock 1") of X hectolitres that is available from the current moment (week 13) reaches its final delivery date at week 15. The demand from week 13 until week 15 is expected to be X hectolitres. At week 15 a new production batch ("Q") is planned to be released with a volume of X hectolitres. The expected demand volume from the release date until the final delivery date of this production batch (at week 31) equals X hectolitres. When studying this bar chart, it needs to be kept in mind by the tactical planner that stochasticity is not taken into account at the displayed demand. Also it needs to be kept in mind that – although this bar chart displays the actual week at which the next production batch is released –the heuristic still assumes that this production batch is already available at the current moment (here: week 13) as already described.

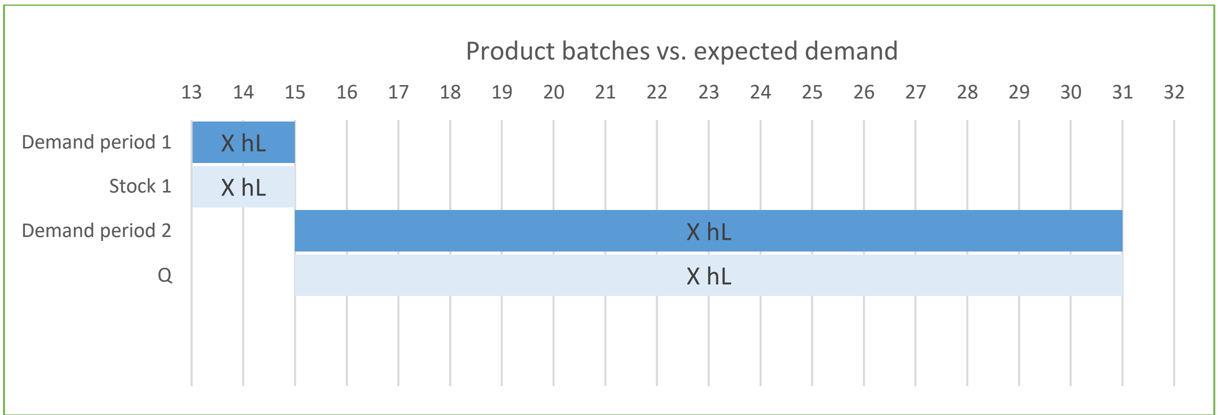

Figure 17 Optimization tool dashboard: final delivery dates of product batches vs. expected demand

3.4 Model verification and validation

First of all, together with an employee from the supply chain planning department it is tested if the model meets the expectations. After it appears that this is the case and the model is verified, validation follows. By validating the monitoring model, the correctness of the model will be checked. Does the outcome of the predictive monitoring model correspond more or less with reality? Does the model give a reliable insight into the expected obsolescence of products? Therefore, the expected obsolescence of historical production batches needs to be calculated and compared to the actual obsolescence data. Also the products sold for a discount price are incorporated in this actual obsolescence data since these products also were declared obsolete, but were able to be sold for a discount price instead of being disposed at the harbour.

3.4.1 Validation model

As earlier mentioned, the strength of our monitoring model lays in predicting obsolescence at a certain moment for a limited time period (within a maximum period that equals the shelf life of a product) given the most accurate demand forecast for that moment. This means that the model is not created with the intention to predict the obsolescence for one whole year resulting from multiple production batches. However, since per product only the total obsolescence data of one whole year (here: the year 2019) is available instead of for example per week, there needs to be find a way to still approach the total yearly obsolescence of products with our short term prediction model. Therefore, it is decided to take week 1 of the year 2019 as starting week within our validation model (or the first production week of the year if there is no starting stock available in week 1), and instead of including only 1 production batch, now all production batches are putted in chronological order behind the starting stock batches. The long term validation model now predicts the expected over- and understocking for a given starting stock level and multiple production batches in the same way as the short term monitoring model did for a given starting stock level and a maximum of one production batch. However, it needs to be kept in mind that including multiple production batches into the model and extending the prediction period can negatively affect the accuracy of the final model outcome. At the next section, first of all the input data of the validation model will be discussed, where after in the subsequent section the reliability of this validation model will be further discussed. Here after we will focus on the validation results.

3.4.2 Input data used for validation

As already described, the expected obsolescence of historical production batches needs to be calculated and compared to the actual obsolescence data for that same period. Since there will be focussed on historical batches during validation, and besides this the validation model works differently than the monitoring model as discussed above, other input data is needed during validation.

Production moments and quantity

For this research, we have chosen to focus on the production during the year 2019 since we are also provided with the obsolescence data of this year. Since production plans are updated weekly, for example production moments can be shifted to one week later or can even be removed from the plan. If we would use the constantly updated production plans for our validation model, this would give a distorted picture of the real production moments that year (due to overlapping or missing production moments). For this reason, it chosen to use the actual production moments with the actual production batch sizes during the year 2019.

Expected demand

Since demand forecast are also constantly changing, but the decisions about production quantities are always based on the most recent demand forecast, it is important that the demand forecast input data in our validation model is updated at every final production quantity decision moment. This is always two weeks before real production takes place, due to the frozen time window for production planning. When a production moment

Forecast deviations

Unfortunately, forecast data of the year 2018 is unavailable in the data base. Therefore, it is chosen to use the same forecast deviations data as used for our current monitoring model as input for the validation model. This means that the actual forecast deviations of the year 2019 are also used to simulate the obsolescence of that same year. It is not the most desirable situation and it can be questioned if this can cause overfitting of the model. However, since – as earlier discussed - we make use of the average forecast deviations of demand of products over a whole year instead of the actual forecast deviations at particular moments for products, and these deviations in general vary a lot during the year, we assume that the risk of overfitting is not extremely high and therefore the assumption can be made.

3.4.3 Drawbacks and limitations of the (validation) model

As earlier mentioned, a drawback of this more long term prediction modelling during validation is that it is less accurate than short term prediction modelling during monitoring. During validation, still the assumption applies that every batch is already available from the first week, and so no stockouts occur until the end of the prediction period. Earlier, we decided that the assumption that the planner always plans a new production batch in time before a stockout occurs is acceptable for 1 production batch. However, assuming this for all production batches during a year of course has a greater impact on the reliability of the model outcome than making this assumption for only one production batch. Besides this, the heuristic makes use of more assumptions that can affect the accuracy of the model outcome. For example, during the heuristic every calculated expected understocking per batch is deterministically affecting the demand for the next batch. One can imagine that the further into the future we look with our model, the more impact intermediate over- and understocking deviations have on the reliability of the final outcome of the model.

Besides this, the quality of the model outcome also depends on the quality of the demand forecast. Of course the model takes into account demand variability in the form of standard deviations of demand. However, this will always be an average approximation of demand variability, with a maximum of one week ahead average standard deviation per product. Outliers in demand deviations are therefore not used in the model, and so if the actual sales for a product at a particular moment differed strongly from its demand forecast input data, the prediction model already can give a much different result.

Furthermore, a lack of data can influence the results of the model. This applies to the input data used for our model as well as the actual obsolescence data to compare the model results with. For example, not all products are provided with a shelf life, or sometimes the production data of starting stock is missing, what can affect the accuracy of the model outcome. Besides this, it is possible that some obsolescence data is incorrectly stored into the data system, what means that it is not entirely sure that the model outcome is compared to the real situation.

3.4.4 Validation results

For the validation of every single product, manually the starting stock level at the first prediction week needs to be searched in the data base and loaded into the model, and the same holds for the constantly updating sales plans per production decision moment. One can imagine that when setting up a validation model for a product with a lot of production moments during the year, many sales plans needs to be searched for and loaded into the model and for every production decision moment manually the right weeks of expected demand needs to be selected. Since this process takes quite some time and needs to be done accurately since it is prone to errors but there is limited time, it is decided not to validate all products that encountered obsolescence during the year 2019, but to focus on few products that together caused a majority of the obsolescence.

Therefore, X products are selected from the X products that encountered obsolescence during the year 2019 and/or were sold for a discount price. These products (7% of the total amount of obsolete/discount products during the year 2019) together make up for more than half (53%) of the total inventory losses and discount sales expressed in hectolitres. The results of the validation are shown in Table 7 on the next page. How the prediction model performs in comparison to the actual situation is shown per product by the absolute- and relative deviations in the two last columns. The relative deviation is calculated by dividing the absolute deviation by the total actual obsolescence. This means that over predicted products have a positive relative deviation, and under predicted products have a negative relative deviation. A relative deviation of 0% would mean that a product's obsolescence is perfectly predicted.

As can be noticed from Table 7, for some products the obsolescence predicted by the validation model is close to the actual obsolescence during the year 2019. On the contrary, there are also products of which the obsolescence predicted by the validation model is much higher or lower than the actual obsolescence. There is looked for common characteristics amongst products that probably can explain these high deviations between predicted obsolescence and reality. However, seasonality appears as much amongst the good as well as bad predicted products, and the same applies to yearly sales volumes, and the yearly amount of production moments. Only one of the products of Table 7 is classified as NPD during the year 2019, but the obsolescence of this product is predicted quite well (relative deviation of - X%), and so also newness is excluded as explanation for the high deviations between predicted obsolescence and reality.

Note: "obs." stands for obsolescence, "FGs" stands for finished goods.

SKU	Number of production batches	Total disposal FGs '19	Total discount sales '19	Total actual obs. '19	Total predicted obs. '19	Deviation	Relative deviation
92089	2	X hL	-	X hL	X hL	+ X hL	+ X%
92137	1	X hL	-	X hL	X hL	- X hL	- X%
91207	7	X hL	X hL	X hL	X hL	- X hL	- X%
92192	11	X hL	X hL	X hL	X hL	- X hL	- X%
92301	2	X hL	-	X hL	X hL	- X hL	- X%
92193	15	X hL	-	X hL	X hL	+ X hL	+ X%
92126	4	X hL	X hL	X hL	X hL	+ X hL	+ X%
92520	5	X hL	-	X hL	X hL	- X hL	- X%
90983	21	X hL	-	X hL	X hL	+ X hL	+ X%
92346	4	X hL	-	X hL	X hL	- X hL	- X%
Total				*X hL*	*X hL*		

Table 7 Validation results expected obsolescence vs. actual obsolescence 2019

Therefore, there is focussed on the different drawbacks and limitations of the (validation) model discussed in the previous section. After some research it is found out that for most of the products encountering high relative deviations in Table 7, the actual sales during the year 2019 indeed sometimes varied a lot from the two weeks ahead demand forecast, what can explain the high differences between prediction and reality. At some moments the actual sales were even 100% more or less than its corresponding forecast. Besides this, if there is no historical forecast- and sales data available of a product, its yearly forecasted sales is used as input data to determine a value for its standard deviation. This means that sometimes also the standard deviation value can be based on a really bad forecast, what also affects the accuracy of the model.

As already mentioned, these extremely high outliers in demand variability can almost never be reached by the prediction model since we work with averaged demand variability per product. This means that when a given 2 weeks ahead forecast is extremely bad, the incorporated average demand variabilities often cannot on their own meet these extremely high demand outliers. As already mentioned, it is not the task of the supply chain planning department to improve the demand forecasts. Only forecast deviation risk can be incorporated into the model by means of standard deviations of demand based on historical forecast deviations. Therefore, it needs to be accepted that the accuracy of the prediction model still depends to a large extent on the accuracy of the 2 weeks ahead demand forecast. The model only tries to predict obsolescence as good as possible given the most recent demand forecast and the historical forecast deviations as input data.

However, as also can be noticed from Table 7, despite the sometimes high individual deviations, the total amount of predicted obsolescence (X hL) is quite close to (1.13 times the) the total actual amount of obsolescence (X hL) during the year 2019. This means that, although some predictions vary significantly from reality, on average the validation model gives quite a good result. It can also be noticed from the results that products are not structurally over- or under predicted. The predicted obsolescence of some products are higher than reality, while that of others are lower. Therefore, it is assumed that the deviations are not a result from an error in the model but are most probably caused by the earlier mentioned bad forecasts.

3.5 Conclusion

1. The model that is created is two-fold: a monitoring dashboard measures the expected obsolescence of products, where after the optimization tool gives an insight into the impact of early disposal of matured beer, and calculates the optimal batch size at which total costs regarding expected obsolescence of finished goods and early disposal of matured beer are minimal;
2. Obsolescence can be caused by starting stock as well as by a newly planned production batch. Only for the latter proactive actions – such as early disposal of matured beer – are possible in order to avoid future obsolescence;
3. It is chosen to work with relative deviations instead of absolute deviations, and multiply them with expected demand in order to generate standard deviation input data per product;
4. For products with limited/no historical data, by means of regression analysis the standard deviation of demand is estimated by using historical data of products with similar characteristics;
5. Only for NPDs – for which the regression analysis does not work – the average coefficient of variation of demand of all NPDs of 2019 is used as input data;
6. The heuristic developed for the monitoring model is a more complex, extended version of the classical newsboy problem, that incorporates multiple product batches;
7. The packaging batch size is considered as the decision variable of the model. All other variables – such as the moments of production and the product's differentiation characteristics of matured/filtrated beer– are considered as given and cannot be changed;
8. With the future user it is checked that the model meets all expectations and so the model can be considered as verified;
9. Although some individual predictions of the monitoring model vary significantly from reality, the total amount of predicted obsolescence is quite close to reality;
10. Besides this, the model did not structurally over- or under predict. This suggests that the individual deviations of the validation model are not a result of a model error;
11. A better explanation of the deviations could probably be the fact that the model's accuracy to a large extend depends on the quality of the demand forecast, and besides this the fact that quite some assumptions are made within the model, what means that the model can never perfectly reflect reality and deviating outcomes are inevitable.

CHAPTER 4: RESULTS

After verifying and validating the monitoring model, it is time to examine the effects of early disposal of matured beer by using the early disposal decision making support tool. During the next sections the optimization model and the choice for input data will be explained, where after the results and conclusions will follow.

4.1 OPTIMIZATION MODEL

Unfortunately it is not possible to generate yearly optimization results for products, since the improved batch sizes of products – that are determined per single production quantity decision moment given the most recent sales forecast at that moment – would already have affected the next production moments. Regarding validation, the actual production plan can be used as input data since also the actual production quantities are used. However, during optimization, every change in production quantity would have affected the expected moment of understocking of a product, and so the moment at which the next production batch needed to take place. Therefore, the combination of optimized production batch sizes with old fixed production moments would give unrealistic results regarding expected obsolescence since probably the next productions would have taken place at different moments with different production quantities.

For this reason it is chosen not to determine the yearly optimization results and compare them to the yearly validation results, but to treat every production quantity decision as a stand-alone decision and not combine them with other decision moments. This means the optimization effects will be examined separately per stand-alone production quantity decision moment. Every single production quantity decision moment (2 weeks before actual production took place) per product that took place during the year 2019 is simulated by the monitoring model, and the expected over- and understocking at the final delivery date of each planned production batch and its corresponding costs are calculated, given the most updated sales plan at that particular decision moment. Hereafter, with help of the early disposal decision making tool a new, optimal batch size is determined, resulting in new expected over- and understocking and corresponding costs. Here after, the results from the old and new batch size can be compared to each other per production quantity decision moment of a product.

4.2 INPUT DATA USED FOR OPTIMIZATION

In general, the same input data as used during validation of the year 2019, can be used during optimization of that same year. This for example applies to the forecast deviations input data. However, the first difference is now that per production quantity decision moment (that only incorporates 1 next planned production batch) also only 1 updated sales plan is necessary, instead of the multiple updated sales plans for the multiple subsequent production moments during validation. A second difference with the validation model is that during optimization per production quantity decision moment the starting stock level needs to be updated too since we now consider these decision moments as independent from the previous decision moments. The third difference with validation is the fact that during optimization, now a new (optimized) production batch size is used.

During the year 2019, as earlier mentioned X BTO products have been produced. It is chosen to focus on the optimization of the production quantities of these BTO products, each containing one or multiple production moments during the year 2019. Some of the production moments of these products took place at the end of the year 2019, what means that the final delivery dates of these batches – and so the moments they became obsolete - took place in the next year (2020). Therefore, these production moments are excluded during optimization. As earlier mentioned, during optimization the current differentiation characteristics per planned production moment are maintained. After diving into the packaging data and discussing with the tactical planning team about the differentiation characteristics of the production moments of these BTO products, it appears that X of the X BTO products (67%) were sharing their matured beer with each other during production (namely the pairs 92356 & 92318, 92376 & 92378, 92089 & 92239, an 92298 & 92306), and the products of the last called three pairs also shared their filtrated beer with each other. The sharing of matured- and filtrated beer over these product pairs are also applied during optimization. Besides early disposal, also a different division of matured- and filtrated beer over the final products is considered for these product pairs.

4.3 Optimization results

Since every decision moment is examined independently from the other decision moments and is only based on the most updated sales- and production plan at that moment, the optimization results are also displayed separately per product per production quantity decision moment in Appendix VII. Only for the first mentioned product in Appendix VII as an example the dashboard decision support charts are displayed per decision moment. However, since displaying these dashboards for all products would take up a lot of space in this report, for the other products only the results tables are shown in Appendix VII. A summary of the optimization results can be found in Table 8 on the next page.

In the column "Old batch size" the old (actual) batch sizes of the year 2019 can be found per production moment. In the next column "Optimal batch size" the optimized batch size quantity per production moment can be found, determined by minimizing the sum of the costs of expected obsolescence of finished goods (COGS finished goods + transportation costs) and the costs of early disposal of matured beer (COGS matured beer), as already explained in the mathematical model of Chapter 3. In both columns it is also mentioned if the batch size was equal to the minimum brewing batch size ("MB") of the product, and if/ how much disposal ("disp.") took place. Here after, the earlier mentioned total costs - caused by the old (actual) and the new (optimal) batch sizes that served as input variables to our monitoring model - are displayed, where after in the last column the changes in total costs are displayed by comparing the old and the new (optimal) situation.

It needs to be kept in mind that the cost savings generated at the different production moments cannot be summed up per product, since optimization of one production moment probably would have affected the stock level, and so the next production moment in terms of timing and production quantity (what means that probably less costs could have been saved at the next production moment). Therefore, we keep looking at the cost savings separately per production moment.

First of all, as can be noticed from the results in Table 8**, during almost all production moments during the year 2019 the minimum brewing quantities were brewed for the BTO products and in no case early disposal of matured beer took place**. When looking at the actual production data of 2019, sometimes the actual batch quantities of BTO products were about a few dozen hectolitres lower than the minimum brewing volumes. It is assumed that in these cases small losses occurred during the production process leading to actual packaging volumes slightly lower than the minimum brewing volumes. However, since we assumed that these losses are so small they can be neglected, the actual starting values (the minimum brewing volumes) at these moments are used as input variables to the monitoring model.

Note: “MB” stands for MinBrew, “MF” stands for MinFiltr, “MP” stands for MinPack, and “disp.” stands for disposal. Orange text represents the amount of matured disposed (if this was the case).

	SKU(s) – decision moment week	Old batch size	Optimal batch size	Old total costs	New total costs	Change in costs
MB = X MF = X MP = X	92301 - wk. 3	X hL (MB, no disp.)	X hL (X hL disp.)	€ X	€ X	- € X (- 40.4%)
	92301 – wk. 15	X hL (MB, no disp.)	X hL (X hL disp.)	€ X	€ X	- € X (- 11.5%)
MB = X MF = X MP = X	92135 – wk. 11	X hL (MB, no disp.)	X hL (MB, no disp.)	€ X	€ X	-
	92135 – wk. 22	X hL (MB, no disp.)	X hL (MB, no disp.)	€ X	€ X	-
	92135 – wk. 32	X hL (MB, no disp.)	X hL (MB, no disp.)	€ X	€ X	-
MB = X MF = X MP = X	92160 – wk. 13	X hL (MB, no disp.)	X hL (MB, no disp.)	€ X	€ X	-
MB = X MF = X MP = X	92346 – wk. 19	X hL (MB, no disp.)	X hL (MB, no disp.)	€ X	€ X	-
	92346 – wk. 22	X hL (MB, no disp.)	X hL (MB, no disp.)	€ X	€ X	-
	92346 – wk. 25	X hL (MB, no disp.)	X hL (MB, no disp.)	€ X	€ X	-
	92346 – wk. 29	X hL (MB, no disp.)	X hL (MB, no disp.)	€ X	€ X	-
MB = X $MF_{'56}$ = X $MF_{'18}$ = X $MP_{'56}$ = X $MP_{'18}$ = X	92318 – wk. 5	X hL (No disp.)	X hL (X hL disp.)	€ X	€ X	- € X (- 48.6%)
	92356 & 92318 – wk. 20	X hL = X hL + X hL (MB, no disp.)	X hL = X hL + X hL (MB, no disp.)	€ X	€ X	- € X (- 7.5%)
	92318 – wk. 24	X hL (MB, no disp.)	X hL (MB, no disp.)	€ X	€ X	-
MB = X MF = X $MP_{'76}$ = X $MP_{'78}$ = X	92376 & 92378 – wk. 32	X hL = X hL + X hL (MB, no disp.)	X hL = X hL + X hL (MB, no disp.)	€ X	€ X	- € X (- 33.0%)
MB = X MF = X $MP_{'39}$ = X $MP_{'89}$ = X	92239 & 92089 – wk. 14	X hL = X hL + X hL (MB, no disp.)	X hL X hL + X hL (MB, no disp.)	€ X	€ X	- € X (- 0.32%)
	92239 & 92089 – wk. 18	X hL = X hL + X hL (MB, no disp.)	X hL = X hL + X hL (MB, no disp.)	€ X	€ X	- € X (- 12.6%)
MB = X MF = X $MP_{'98}$ = X $MP_{'06}$ = X	92298 – wk. 3	X hL (MB, no disp.)	X hL (X hL disp.)	€ X	€ X	- € X (- 5.2%)
	92298 & 92306 – wk. 26	X hL = X hL + X hL (MB, no disp.)	X hL = X hL + X hL (149 hL disp.)	€ X	€ X	- € X (- 19.2%)

Table 8 Summary optimization results

During discussion of the results we make a distinction between products that did not share their matured- and/or filtrated beer with other products during production, and products that did share their matured- and/or filtrated beer with other products (in pairs in the case of the year 2019) during production. There are also some cases where products shared their beer during one moment and did not share their beer during other moments. These products will be discussed in both sections.

Products that did not share their beer during production
Looking at Table 8, it can be noticed that at both production moments of product 92301 cost savings (€ X and € X) would have been possible due to early disposal of matured beer. Also during 1 production moment of product 92318, a significant amount of cost savings would have been possible (€ X) by applying early disposal, and the same applies for 1 production moment of product 92298, but now with almost negligible cost savings (€ X). Furthermore it can be noticed from Table 8 that during 9 production moments, of the products 92135, 92160, 92346, and 92318, no cost savings were possible by means of batch size optimization. The batch sizes remain equal to the minimum brewing volumes after optimization, what means that no optimization was possible anymore. One reason that optimization was not possible for these products could be that disposing matured beer would have been more expensive than some extra obsolescence (e.g. due to a low expected obsolescence value). Another explanation can be the fact that for some of these products the minimum filtration volume equals the minimum brewing quantity, what means that although the minimum brewing volume restriction is released, still no disposal is possible for these products anyway.

Product pairs that shared their beer during production
Looking at the product pairs that shared their beer with each other during production, it appears that for all 5 shared production moments cost savings would have been possible. Regarding the first 4 production moments of product pairs 92356 & 92318, 92376 & 92378, and 92239 & 92089, these cost savings are not a result of early disposal of matured beer (the brewing volumes remained equal to the minimum brewing volumes after optimization), but of a redivision of beer over the final products. However, in essence the same thing is going on, namely that regarding the expected obsolescence and its corresponding costs it seems cheaper to produce less of a product, but instead of disposing the remaining matured beer in order to save costs, it now appears costs can be saved by moving beer to the other product that shares production. Some cost savings generated by a redivision of beer were quite significant (€ X, € X, and € X) while others were not (€ X and € X). For the last mentioned production moment in Table 8 from product pair 92298 & 92306, it appears that instead of only a redivision of beer, now a combination of a redivision of beer and early disposal of matured beer could have led to cost savings (of € X) during this production moment. Probably the expected demand was so low in comparison to the minimum batch volumes, that early disposal could have been beneficial for this case.

When diving into the actual sales data of 2019, it can be noticed that for some of these cases the actual sales were lower than expected and so in reality lower batch sizes could have been applied during the year 2019. This again underlines the importance of accurate demand forecasts when using this model. However, this is easy to say in hindsight, and besides this it is also true the other way around: for some products actual demand appeared to be higher and so less low batch sizes would have been better. It needs to be kept in mind that with help of the model one tries to make the best batch size decision at a certain moment based on the most updated sales- and production plan at that moment. The same applies to our optimization results. The actual demand was not known yet at the production quantity decision moments of our model, and therefore the only thing the model does is providing insight into the best batch size decisions at certain moments given the most recent sales- and production plans at these moments.

4.4 IMPACT OF OPTIMIZATION ON EXPECTED UNDERSTOCKING

As becomes clear from the results, decreasing product batch sizes by applying early disposal of matured beer and/or by redividing matured over products that share the same brew steam, indeed in some cases seems to be a good preventive action to save costs regarding expected obsolescence. However, as also can be noticed from the optimization results displayed in the tables of Appendix VII, in our model always a price needs to be paid for the reduction of expected obsolescence, in the form of an increased chance of running out of stock (higher expected understocking). For example this can be noticed from the stock level charts of the first mentioned product in Figures 31 and 32 of Appendix VII, where the stock levels are expected to reach their zero level much faster after batch size optimization. This means that by applying lower batch size volumes, given the same demand forecasts, reproductions need to take place earlier in order to prevent the product from running out of stock, and so as a result more and smaller production batches should take place throughout the year.

More and smaller production batches also will bring with them extra costs due to more change-overs at the production lines that need to take place in between different production batches. However, after discussion with the tactical planning team it is decided not to include penalty costs for higher expected understocking levels or more production moments during the year into the goal function of the optimization model. First of all, according to the tactical planning team, in general alarm bells will start ringing and action is necessary if a stockout is expected to occur within 2 or 3 weeks (when the MinDoC of a product is threatened). A product that for example runs out of stock within 18 weeks instead of 21 weeks (as can be noticed in for example Figures 32 and 33) is no big problem for a tactical planner at that moment since there is still enough time to anticipate in time with a newly planned production batch. As can be noticed from the results (e.g. from Figures 33 and 36), products with lowered batch sizes reach their zero stock level somewhat earlier than they did before optimization, however, the difference is not significant and stockouts within 2 or 3 weeks are not expected. Therefore, including penalty costs for higher expected understocking levels/ more production moments during the year is not of value for the tactical planning team. They prefer to only base their batch size decisions on costs directly related to obsolescence, namely the earlier mentioned variable COGS and disposal costs of finished goods, and the variable COGS of matured beer. Besides this, due to rapidly changing sales- and production plans, it is hard to say how many more production moments will be needed for a given year, and what the impact will be on the total costs. For this reason it is difficult to determine how much penalty costs associated with more production moments exactly needs to be taken into account per case. Wrong costs could give a distorted picture and could lead to wrong decisions regarding batch sizes.

Although it is decided not to include penalty costs for higher expected understocking levels/more production moments during the year into the goal function of the optimization model, an indication can be given for our research regarding the year 2019. As discussed in the previous section, we cannot sum up the cost savings per production moment of one product, since optimization of one production moment probably would have affected the next production moments. Therefore, we considered the optimization per production moment separately, given the certain starting stock level at that moment, and not taking into account the subsequent productions. For the same reason, we cannot calculate the yearly extra needed production moments (and so extra set-up costs) per product due to optimization, so also here we have to look for the extra set-up costs separately per optimized production moment.

For the 9 optimized production moments of Table 8 where early disposal and/or a redivision of beer took place in order to save costs, an estimation of the extra set up costs due to optimization is shown in Table 9 below. A detailed explanation of the calculations can be found in Appendix VIII. It needs to be noticed that every time an optimized batch size of a production moment is taken into account, the batch sizes of the other production moments of that same product are kept constant (remain their actual value) since we look at every production moment separately. This means that no conclusions can be made about the impact of all optimized production moments together on extra set-up costs.

SKU(s)	Production moment	Cost savings due to optimization	Extra set up costs	*Final cost savings*
92301	Wk. 3	€ X	€ X	€ X
	Wk. 15	€ X	€ X	€ X
92138	Wk. 5	€ X	€ X	*€ X*
92356 & 92318	Wk. 20	€ X	€ X	*- € X (loss)*
92376 & 92378	Wk. 32	€ X	€ X	*€ X*
92239 & 92089	Wk. 14	€ X	€ X	*- € X (loss)*
	Wk. 18	€ X	€ X	*€ X*
92298	Wk. 3	€ X	€ X	*€ X*
92298 & 92306	Wk. 26	€ X	€ X	*€ X*

Table 9 Estimated extra set up costs due to necessary reproductions caused by batch size optimization during the year 2019

As can be noticed from Table 9, it appears that **for the 6 production moments with relatively high possible cost savings due to optimization, these cost savings remain relatively high after subtraction of the extra set up costs, and so batch size optimization remains beneficial for these production moments**. However, it also appears from Table 9 that in general **for the 3 production moments with relatively low possible cost savings due to optimization, these cost savings were already so low that subtraction of the extra set up costs ended up in little cost savings or even in losses.** Therefore, it can be concluded that for these kind of production moments, batch size optimization appears to be not beneficial. Also it appears from Table 9 that **relatively high possible cost savings due to optimization as well as relatively low possible cost savings due to optimization occur at products that did not share their beer with other products during production as well as at product pairs, and so both kind of products need attention during optimization**.

It needs to be kept in mind that these calculations only give an indication of the expected extra set up costs due to reproduction if batch size optimization would have been applied at 1 production moment of a product during the year 2019. We do not know what the effect of more optimized production moments together of a product could have been on necessary reproduction as already discussed. Besides this, perhaps it would have been possible to cover extra needed production for some products by already planned production batches of products from the same brew stream, or perhaps agreements with the client could have been made to quit sales (and so production) earlier in time. It is difficult to make statements about this, and therefore above mentioned estimated extra set up costs only serve as an indication. Also it needs to be kept in mind that of course the actual yearly demand (and so the yearly production plan) was not known yet at every single production quantity decision moment. This means that one could not have known at these decision moments if extra production would have been necessary that year by applying batch size optimization. Although the calculations of the estimated extra set up costs have some drawbacks and limitations, it still can be concluded that **it is not unwise to also keep in mind the average set up costs of the production line when considering batch size optimization of a product.** Lowering batch sizes must be reconsidered if the cost savings due to optimization are not significantly higher than the estimated extra set up costs due to optimization.

Although it is determined together with the planning team not to include extra set up costs caused by optimization as penalty costs into the model due to limited time during this research and the desire to focus on direct impact of batch size optimization, **a refinement of the model in the form of including these extra set up costs could be of interest during further research**, since – although in most of the cases the extra set up costs have no big impact on the cost savings - it appears that these extra set up costs are also not negligible, and in some cases will even result in losses.

Last but not least, it needs to be kept in mind that demand can change rapidly and sometimes even the 2 weeks ahead demand forecast can already very heavily from the actual sales. As already discussed in Chapter 3, this extremely fluctuating demand cannot always be captured by the model. One can imagine that, although quite some understocking is expected, **taking the stockout risk (but plan a new production batch in time if this appears to be necessary in the upcoming weeks) and so produce in smaller batches and react faster to changing demand can sometimes be a good solution to products**. It is the task of the production planner to make a trade-off between the effects of expected obsolescence and stockouts as good as possible with help of the early disposal decision making support tool.

4.5 Usefulness of the optimization model

Although the final cost savings are determined separately per production moment while the variables of the other production moments of that product are kept constant, and so the cost savings of the different production moments cannot summed up per product, still it is interesting to compare the potential cost savings per production moment to the actual obsolete costs of te year 2019. As mentioned in Chapter 1, we started with € X of total inventory losses during the year 2019. Here after, we narrowed our scope to 43% of the total inventory losses that were only caused by obsolete finished goods (€ X), where after the scope is even more narrowed by only focussing on almost half of these total inventory losses (€ X, X hL) caused by made to forecast (MTF) products that can be influenced by the supply chain planning department. From these inventory losses caused by obsolete MTF products, 39% was caused by X brew to order (BTO) products (in comparison to 61% caused by X brew to forecast (BTF) products), with total inventory losses of € X during the year 2019 (X hL). During optimization, we only focused on these BTO products, and therefore, we will compare our final BTO products cost savings due to optimization to these actual inventory losses of all BTO products of the year 2019. However, one thing needs to be remembered, namely the fact that the total costs used during optimization include the variable COGS of finished goods, the disposal costs of finished goods as well as the disposal costs of semi-finished goods. To keep it simple we now assume that no early disposal took place for the X BTO products during the year 2019. However, when also taking into account the disposal costs of finished goods (€ X/hL), this means that the total actual costs of obsolete and disposed BTO products during the year 2019 was equal to (€ X * X) + € X = **€ X**.

As earlier mentioned we cannot compare the sum of all the final BTO products cost savings due to optimization with the sum of the actual inventory losses and disposal costs of all BTO products of the year 2019, however, **we can say that the cost savings of some separate production moments already are quite significant in comparison to the sum of the actual inventory losses and disposal costs of all BTO products of the year 2019.** Take for example the production moment of product 92138 in week 5: the final cost savings of € 21,914 already covers 39% of the total actual inventory losses and disposal costs of BTO products of the year 2019.

We can also approach this in another way. If you for example only take into account the potential cost savings of the last production moment per product/ product pair (and so assume that all earlier production moments are not optimized, what means that optimized production moments did not influence each other), a statement can be made about what cost savings possibly could have been made during the year 2019 by only optimizing the last production moment per product/product pair. Therefore we take week 15 of product 92301 (€ X), week 32 of product pair 92376 & 92378 (€ X), week 18 of product pair 92239 & 92089 (€ X), and week 26 of product pair 92298 & 92306 (€ X). Optimized production moments that resulted in losses we do not take into account. The total potential cost savings of these different production moments can be summed up since they were not influenced by earlier optimizations. The sum of these cost savings (€ X) is already 18% of the sum of the actual inventory losses and disposal costs of all BTO products of the year 2019 (€ X). Assuming that probably even more cost savings could have been possible during the year 2019 by also applying batch size optimization to the other production moments (for example the cost savings of € X for the production moment of product 92138 in week 5 are not taken into account yet here), it seems that **probably quite a large part of the total inventory losses and disposal costs of all BTO products could have been saved during the year 2019 by applying batch size optimization**.

4.5 Conclusion

1. Optimization has been applied to 14 production moments from the X BTO products produced during the year 2019. The optimization results per production moment cannot be summed up per product since they would have affected each other, and therefore they need to be studied separately;
2. Optimization is applied to products that did not share their beer with other products during production, as well as to products that shared their beer with other products during production (here: product pairs). This means that besides early disposal, for the product pairs also a redivision of semi-finished beer over their end products is considered during optimization, as long as the solution fits within the current differentiation characteristics of the products;
3. It appears that the biggest cost savings would have been possible at the products that did not share their beer with other products during production by applying early disposal of matured beer. However, during the other production moments of products that did not share their beer with other products during production, no cost savings were possible by means of batch size optimization, sometimes due to the fact that the expected obsolescence was already so low that disposing matured beer would be more expensive than an increase in expected obsolescence, and sometimes due to the fact that the minimum filtration volume was equal to the minimum brewing volume and so early disposal was not possible anyway;
4. Also it appears that for all product pairs some cost savings would have been possible. However, at most of these production moments these cost savings were not a result of early disposal of matured beer, but of a redivision of beer over final products. Some cost savings generated by a redivision of beer were quite significant while others were not. For 1 production moment of a product pair, a combination of early disposal and a redivision of beer probably would have led to cost savings.
5. A reduction in expected obsolescence will always lead to an increase in expected understocking, wat in its turn will lead to more and smaller production batches planned throughout the year, and so ultimately in more set up costs of the production lines;

6. It appears that for production moments with relatively high possible cost savings due to optimization, these cost savings remain relatively high after subtraction of the extra set up costs, and so batch size optimization remains beneficial for these production moments. However, for production moments with relatively low possible cost savings due to optimization, batch size optimization appears to be not beneficial, since the cost savings of these production moments were already so low that subtraction of the extra set up costs ended up in little cost savings or even in losses. Relatively high- as well as relatively low possible cost savings occurred at products that did not share their beer with other products as well as at product pairs, and so both kind of products need attention during batch size optimization;
7. It is not unwise to also keep in mind the set up costs when considering batch size optimization, since it appears that – although in most of the cases the extra set up costs have no big impact on the cost savings - these extra set up costs are not negligible, and in some cases even result in losses instead of cost savings. For this reason, including extra set up costs as penalty costs into the optimization model could be an interesting refinement of the model during further research;
8. Producing in smaller batches, accepting the stockout risk, and reacting faster to changing demand can sometimes be an attractive solution to products, especially in the case of uncertainty/rapidly changing demand;
9. The costs we had influence on during our research were the actual costs of obsolete and disposed made to forecast (MTF) brew to order (BTO) products during the year 2019, with a total amount of € X.
10. Although the cost savings per production moment due to optimization cannot be summed up per product since the optimized production moments would have influenced each other, still it can be noticed that the cost savings of some separate production moments already are quite significant in comparison to the sum of the actual inventory losses and disposal costs of all BTO products of the year 2019. For example, the cost savings of product 92138 at week 5 (€ X) already would cover 39% of the total actual inventory losses and disposal costs of BTO products of the year 2019;
11. Besides this, if per product only the last production moment would have been optimized during the year 2019 – and so they would not have been influenced by earlier optimizations, what means they now can be summed up – already 18% (€ X) of the sum of the actual inventory losses and disposal costs of all BTO products of the year 2019 could have been saved;
12. Therefore, it seems that probably quite a large part of the total inventory losses and disposal costs of all BTO products could have been saved during the year 2019 by applying batch size optimization to these BTO products.

CHAPTER 5: SENSITIVITY ANALYSIS

During the sensitivity analysis of the model it is examined how strongly the model outcome changes as a result of a small change (+/- 10%) of the basic input variable value. As earlier mentioned, the following input variables are available in our model:

1. Starting stock level of batch *n* at beginning of planning period;
2. Production moment (week) of batch *n;*
3. Packaging batch size *Q*;
4. Planned production moment (week) of batch *Q*;
5. Shelf life of product;
6. Differentiation characteristic of product with other products during brewing and filtration;
7. Expected demand (sales plan);
8. Historical coefficient of variation of demand;
9. Minimum batch size restrictions (MinBrew, MinFiltr, and MinPack).

The goal of the sensitivity analysis is to generate useful insights into the impact of input variables on the model outcome. Therefore, there is no point in adjusting an input variable that cannot be influenced by the company in real life. After considering the 9 above mentioned input variables, it is decided to only focus on (7) the expected demand from the sales plan, (8) the historical coefficient of variation of demand used to incorporate stochasticity of the demand into the model, and (9) the batch size restrictions during the sensitivity analysis. The impact of slightly adjusting these variables on the outcome of the model will be discussed in the next sections.

In Chapter 1 it is simply said that changing the batch size constraints is no option due to quality restrictions. However, after discussion with the tactical planning team it appears that just slightly – not significantly - changing these constraints probably often still can be possible without affecting the quality of the beer. Therefore, it is still interesting to examine the effects of just slightly lowering minimum batch sizes. However, it needs to be kept in mind that the impact of slightly lower minimum batch sizes on the quality of beer must be thoroughly investigated during further research before it actually can be applied.

5.1 IMPACT OF CHANGES IN EXPECTED DEMAND AND COEFFICIENTS OF VARIATION OF DEMAND

As already described during the validation in Chapter 3.4, our prediction model can almost never capture extremely high outliers in demand variability since we work with averaged demand variability per product. As already mentioned, it is not the task of the supply chain planning department to improve the demand forecasts. Only forecast deviation risk can be included in the model by means of historical coefficients of variation of demand. Therefore, it needs to be accepted that the accuracy of the prediction model still depends to a large extent on the accuracy of the most updated demand forecast. The model only tries to predict obsolescence as good as possible given the most recent demand forecast and the historical coefficients of variation of demand as input data. Therefore, it is interesting to examine the effects of these input variables on the outcome of the model.

A first idea that came to mind for this part of the sensitivity analysis, was the idea to examine the impact of a more accurate forecast on the predictability of the model. Therefore, it would have been nice to improve the forecast accuracy of the expected demand input data of the validation model, and examine if this would result in predicted obsolescence closer to the actual obsolescence data of 2019. However, unfortunately it is not possible to turn this idea into reality, since the validation model captures multiple production moments per product. For validation this is no problem, since per production quantity decision moment we worked with the historically most updated demand forecast that was available at that moment. Subsequent production quantity decisions were based on the effects of the earlier made decisions. However, changing the most updated demand forecasts at these production quantity decision moments into the actual demand of that year will not result in a good reflection of the possible new situation. Better insights into the future demand at these moments probably would have resulted in different production quantities, different obsolescence and stockouts, and so also in different subsequent moments of production and their corresponding production quantities. For this reason, it needs to be accepted that, when it is desired to examine the impact of a more accurate forecast on the predictability of the model, this analysis can only be done for a maximum of one production moment of a product at a time. This means that per production moment per product a sensitivity analysis needs to be applied. Therefore, it is decided to continue our analysis with the production moments of BTO products that are already examined during optimization, since these models are already available for use. However, due to limited time, it is chosen not to study the production moments of all X BTO products, but to focus on 8 of the BTO products during the sensitivity analysis: 5 products that did not share their beer with other products, and 4 products (2 pairs) that did share their beer with other products.

Yet, there is another thing that should be noted. The actual obsolescence data – that should have serve as the basic outcome data to compare our results with - is not available for particular periods, but only as a total amount of obsolescence for whole the year 2019. For this reason, the sensitivity analysis needs to be done in a different way. Instead of using the actual obsolescence data of 2019 and showing what the real impact of slightly changes in expected demand and forecast deviations could have been to this obsolescence data, it is decided to execute the sensitivity analysis per production moment more hypothetically. Therefore, per production moment, we take the already calculated expected obsolescence – that is based on the current input data of these models, such as the most updated demand forecast at that production quantity decision moment and the earlier determined historical coefficient of variation of demand – as our baseline outcome, and then one at a time apply slightly changes (-/+ 10%) to the expected demand and historical coefficients of variation of demand to examine the impact on the expected obsolescence. When applying changes to the value of one of the variables, the other variable value is kept constant. However, it needs to be kept in mind that in the model the historical coefficients of variation of demand are multiplied with the expected demand in order to calculate the standard deviation of demand. This means that if the expected demand value is changed, the standard deviation value changes with it. The reverse is not true since the expected demand value is not dependent on the historical coefficients of variation of demand. It also needs to be kept in mind that if besides a new production batch also starting stock is available– resulting in multiple batches in one model - the expected demand or the coefficients of variation of demand of all production batches undergo the same adjustments at the same time.

Per production moment per product, the sensitivity of the expected obsolescence to the changes (-/+ 10%) in expected demand and historical coefficients of variation of demand are calculated. A summary of the absolute and relative changes in expected obsolescence as a reaction to the changes (-/+ 10%) in the so-called input variables are displayed in Tables 10 & 11 on the next page. Also per production moment the difference in percentual change in expected obsolescence after decreasing/increasing the expected demand is calculated, since the model is the most sensitive to the variable that causes the highest increase/decrease in expected obsolescence.

Percentual change in expected demand	-10%	Basis	+10%	-10%	+10%	Increase / decrease
SKU – decision moment week	Change in expected obsolescence			Percentual change in expected obsolescence		
92301 - wk. 3 (792)	X hL	X hL	X hL	+ 27.3%	- 21.0%	48.3%
92301 – wk. 15 (738)	X hL	X hL	X hL	+ 11.9%	- 10.3%	22.2%
92135 – wk. 11 (700)	X hL	X hL	X hL	+ 321.7%	- 75.6%	397.3%
92135 – wk. 22 (700)	X hL	X hL	X hL	+ 243.3%	- 72.2%	315.5%
92135 – wk. 32 (700)	X hL	X hL	X hL	+ 338.7%	- 76.1%	414.8%
92160 – wk. 13 (650)	X hL	X hL	X hL	+ 7.6%	- 4.6%	12.2%
92346 – wk. 19 (400)	X hL	X hL	X hL	+ 19.8%	- 13.9%	33.7%
92346 – wk. 22 (400)	X hL	X hL	X hL	+ 0.9%	+ 0.1%	0.8%
92346 – wk. 25 (400)	X hL	X hL	X hL	+ 10.5%	- 7.5%	18%
92346 – wk. 29 (400)	X hL	X hL	X hL	- 0.5%	+ 1.2%	1.7%
92356 – wk. 20 (350)	X hL	X hL	X hL	+ 23.9%	- 16.2%	40.1%
92318 – wk. 5 (837)	X hL	X hL	X hL	+ 33.3%	- 0.3 %	33. 6%
92318 – wk. 20 (450)	X hL	X hL	X hL	+ 16.7%	- 11.6%	28.3%
92318 – wk. 24 (800)	X hL	X hL	X hL	+ 263.6%	- 68.7%	332.3%
92376 – wk. 32 (650)	X hL	X hL	X hL	+ 29.8%	- 20.0%	49.8%
92378 – wk. 32 (200)	X hL	X hL	X hL	+ 13.1%	- 11.8%	24.9%

Table 10 Sensitivity analysis results input variable expected demand

Percentual change in historical coefficient of variation of demand	-10%	Basis	+10%	-10%	+10%	Increase / decrease
SKU – decision moment week	Change in expected obsolescence			Percentual change in expected obsolescence		
92301 - wk. 3 (792)	X hL	X hL	X hL	- 6.1%	+ 6.2%	12.3%
92301 – wk. 15 (738)	X hL	X hL	X hL	- 2.3%	+ 2.4%	4.7%
92135 – wk. 11 (700)	X hL	X hL	X hL	- 52.0%	+ 78.4%	130.4%
92135 – wk. 22 (700)	X hL	X hL	X hL	- 35.0%	+ 41.8%	76.8%
92135 – wk. 32 (700)	X hL	X hL	X hL	- 55.9%	+ 89.9%	145.8%
92160 – wk. 13 (650)	X hL	X hL	X hL	- 1.1%	+ 1.2%	3.3%
92346 – wk. 19 (400)	X hL	X hL	X hL	- 33.2%	+ 38.9%	72.1%
92346 – wk. 22 (400)	X hL	X hL	X hL	- 47.0%	+ 65.5%	112.5%
92346 – wk. 25 (400)	X hL	X hL	X hL	- 35.9%	+ 43.3%	79.2%
92346 – wk. 29 (400)	X hL	X hL	X hL	- 45.5%	+ 62.0%	107.5%
92356 – wk. 20 (350)	X hL	X hL	X hL	- 41.7%	+ 54.1%	95.8%
92318 – wk. 5 (837)	X hL	X hL	X hL	0.%	0%	0%
92318 – wk. 20 (450)	X hL	X hL	X hL	- 41.7%	+ 54.1%	95.8%
92318 – wk. 24 (800)	X hL	X hL	X hL	- 30.3%	+ 37.4%	67.7%
92376 – wk. 32 (650)	X hL	X hL	X hL	- 31.3%	+ 35.9%	67.2%
92378 – wk. 32 (200)	X hL	X hL	X hL	- 0.9%	+ 1.1%	2%

Table 11 Sensitivity analysis results input variable historical coefficient of variation of demand

As can be noticed from Table 10, **in general the relation between expected demand and expected obsolescence appears to be negative in the monitoring model**. However, it cannot be said that easily that higher demand in general leads to less obsolescence, because it needs to be kept in mind that here only the effect on the outcome of the monitoring model is tested, and not on that of the optimization model. This means that besides changing the expected demand value, all other variables and parameters – including the batch size value – are kept constant, and the batch size is not optimized after changing the expected demand value. Probably, if the batch sizes also were variable during this analysis (as is the case in real life), minimum batch sizes in some cases would be less restricting during higher demand. However, this cannot be examined during this analysis. The negative relation proven by this analysis can just be explained by the fact that if the same amount of products is planned to be produced, while more demand is expected, logically in general less obsolescence will be expected to occur. As can be noticed from Table 10, **sometimes a small change in expected demand already can cause a big change in expected obsolescence** (taking into account the same production quantity). **This indicates the importance of the use of an accurate demand forecast, and a quick response to changing demand.**

On the opposite, as can be noticed from Table 11, **the relation between the coefficient of variation of demand and expected obsolescence appears to be positive**. However, it cannot be said that easily that better forecasts therefore would contribute to a reduction of obsolescence. First of all, also here it needs to be kept in mind that only the effect on the outcome of the monitoring model is tested, not on that of the optimization model, what means that besides changing the coefficient of variation of demand value, all other variables and parameters – including the batch size value – are kept constant, and the batch size is not optimized after changing the coefficient of variation of demand value. Besides this, we cannot say something about how obsolescence could have been reduced by changed forecast errors, since we cannot formulate any statements about the predictability of the model. As already mentioned, the sensitivity analysis per production moment is done hypothetically because the actual obsolescence data per production moment is not available to compare the model outcome with. This means that we can only hypothetically examine the impact of changing an input variable on the model outcome during this analysis, but we cannot make any statements about real obsolescence reduction. Therefore, the only thing we can say about Table 11 is that the positive relation proven by this analysis can be explained by the fact that how less demand variability is taken into account by the heuristic (keeping the production quantity constant), how smaller the chance that – if the (planned) amount of stock is already quite close to the expected demand – stock exceeds expected demand and obsolescence occurs, and so how smaller the expected obsolescence will be.

As also can be noticed from both Tables 10 and 11, regarding the expected demand variable, a decrease of 10% already results in an average increase of 85% of the model outcome, while an increase of 10% already results in an average decrease of 26% of the model outcome. Regarding the coefficient of variation of demand variable, a decrease of 10% already results in an average decrease of 29% of the model outcome, while an increase of 10% already results in an average increase of 38% of the model outcome. It can be noticed that **a small change in expected demand as well as in the coefficient of variation of demand already can lead to quite some high changes in the model outcome.** Thereby, the model is especially sensitive to a decrease in expected demand. **This sensitivity of the model to changes in expected demand and the coefficient of variation of demand underlines the impact, and so the importance, of the use of accurate demand forecasts and the right forecast deviations per product.**

5.2 Impact of changes in minimum batch sizes

In our second analysis, we want to examine the impact of the batch size restrictions on the expected obsolescence and its corresponding costs calculated by the optimization model. A few options are possible to examine: applying early disposal in other stages of the production process, or changing one or multiple batch size constraints.

As already mentioned, the only moment at which early disposal is possible, is after brewing. For this reason, there is no sense in examining the effects of applying disposal after filtration or packaging, and so we drop the first option.

Since our optimization model only makes a trade-off between the costs of early disposal of matured beer and the costs of expected obsolescence of finished goods, of course by changing the minimum brewing constraints so that penalty costs for early disposal of matured beer is not incorporated anymore, the early disposal costs will disappear in the total costs formula. This means a trade-off will no longer be made between costs of expected obsolescence of finished goods and costs of early disposal of matured beer, and so always the lowest possible packaging batch size (zero) resulting in the lowest costs regarding expected obsolescence will be chosen, what is no useful outcome for the tactical planner. Besides this, it is not realistic to remove the minimum brewing constraints, since these constraints are necessary to keep up with the quality standards of the beer. The same applies to the minimum filtration- and packaging batch sizes. For these reasons it is decided to drop the option to remove batch size constraints.

This brings us to a more realistic option: slightly changing the batch size constraints (-/+ 10%) in order to examine the impact on the optimized packaging batch sizes and its corresponding costs regarding expected obsolescence of finished goods and early disposal of matured beer. For almost all products there is no sense in only lowering the minimum packaging batch sizes, since - as earlier mentioned - no disposal takes place in between filtration and packaging, and for almost all BTO products it applies that the minimum filtration batch size is (at least more than 10%) higher than the minimum packaging batch size. However, there is an exception for BTO products that share their filtrated beer stream. For these products there is a possibility that only lowering the minimum packaging batch sizes already pays off. Above all, it is interesting for all products to examine the impact of lowering the minimum brewing- and filtration batch sizes.

Since for this analysis we need to re-optimize the packaging batch size under new batch size restrictions, also for this analysis the optimization models of the 8 BTO products of the year 2019 are used that were also used during the earlier sensitivity analysis about expected demand and the coefficient of variation of demand. The current input data of these models, such as the expected demand and historical coefficients of variance of demand, are kept constant, while only the minimum batch size values are adjusted one at a time, whereafter a new optimized batch size and its corresponding expected obsolescence and costs is calculated. Results of the analysis can be found in the Tables 12, 13, and 14 on the next pages.

Note: “MB” stands for MinBrew, “MF” stands for MinFiltr, “MP” stands for MinPack, “Q” stands for the optimized packaging batch size, and “disp.” is displayed in between brackets after the optimized batch size if early disposal of matured beer is planned. The changed variable is coloured green.

	% change in MB	-10%	Basis	+10%	-10%	+10%
	SKU – decision moment	Change in total costs (expected obsolescence + early disposal)			(Percentual) change in total costs	
MF = X MP = X	**92301**	MB = X	**MB = X**	MB = X		
	Wk. 3	Q = X (disp.)	Q = X (disp.)	Q = X (disp.)		
		€ X	€ X	€ X	- € X (- 18.5%)	+ € X (+ 18.5%)
	Wk. 15	Q = X (disp.)	Q = X (disp.)	Q = X (disp.)		
		€ X	€ X	€ X	- € X (- 3.6%)	+ € X (+ 3.6%)
MF = X MP = X	**92135**	MB = X	**MB = X**	MB = X		
	Wk. 11	Q = X	Q = X	Q = X		
		€ X	€ X	€ X	- € X (- 81.2%)	+ € X (+ 307.2%)
	Wk. 22	Q = X	Q = X	Q = X (disp.)		
		€ X	€ X	€ X	- € X (- 78.3%)	+ € X (+ 176.2%)
	Wk. 32	Q = X	Q = X	Q = X		
		€ X	€ X	€ X	- € X (- 81.6%)	+ € x (+ 321.7%)
MF = X MP = X	**92160**	MB = X	**MB = X**	MB = X		
	Wk. 13	Q = X	Q = X	Q = X		
		€ X	€ x	€ X	- € X (- 0.0%)	+ € X (+ 5.0%)
MF = X MP = X	**92346**	MB = X	**MB = X**	MB = X		
	Wk. 19	Q = X	Q = X	Q = X		
		€ X	€ X	€ X	- € X (- 0.0%)	+ € X (+ 29.4%)
	Wk. 22	Q = X	Q = X	Q = X		
		€ X	€ X	€ X	- € X (- 0.0%)	+ € X (0.0%)
	Wk. 25	Q = X	Q = X	Q = X		
		€ X	€ X	€ X	- € X (- 0.0%)	+ € X (0.0%)
	Wk. 29	Q = X	Q = X	Q = X		
		€ X	€ X	€ X	- € X (- 0.0%)	+ € X (0.0%)
MF = X MP = X	**92318**	MB = X	**MB = X**	MB = X		
	Wk. 5	Q = 350	Q = X	Q = X		
		€ X	€ X	€ X	- € X (- 4.0%)	+ € X (+ 4.0%)
	Wk. 24	Q = X	Q = X	Q = X		
		€ X	€ X	€ X	- € X (- 70.7%)	+ € X (+ 162.7%)
$MF_{'56}$ = X $MF_{'18}$ = X $MP_{'56}$ = X $MP_{'18}$ = X	**92356 & 92318**	MB = X	**MB = X**	MB = X		
	Wk. 20	Q_{92356} = X	Q_{92356} = X	Q_{92356} = X		
		Q_{92318} = X	Q_{92318} = X	Q_{92318} = X		
		$Q_{total} = X$	$Q_{total} = X$	$Q_{total} = X$		
		€ X	€ X	€ X	- € X (- 20.5%)	+ € X (+ 29.4%)
MF = X $MP_{'76}$ = X $MP_{'78}$ = X	**92376 & 92378**	MB = X	**MB = X**	MB = X		
	Wk. 32	Q_{92376} = X	Q_{92376} = X	Q_{92376} = X		
		Q_{92378} = X	Q_{92378} = X	Q_{92378} = X		
		$Q_{total} = X$	$Q_{total} = X$	$Q_{total} = X$		
		€ X	€ X	€ X	- € X (- 15.1%)	+ € X (+ 21.3%)

Table 12 Sensitivity analysis results minimum brewing restrictions

	% change in MF	-10%	Basis	+10%	-10%	+10%
	SKU – decision moment	**Change in total costs (expected obsolescence + early disposal)**			**Percentual change in total costs**	
MB = X MP = X	**92301**	**MF = X**	**MF = X**	**MF = X**		
	Wk. 3	Q = X (disp.)	Q = X (disp.)	Q = X (disp.)		
		€ X	€ X	€ X	- € X (- 0.0%)	+ € X (0.0%)
	Wk. 15	Q = X (disp.)	Q = X (disp.)	Q = X (disp.)		
		€ X	€ X	€ X	- € X (- 0.0%)	+ € X (0.0%)
MB = X MP = X	**92135**	**MF = X**	**MF = X**	**MF = X**		
	Wk. 11	Q = X	Q = X	Q = X		
		€ X	€ X	€ X	- € X (- 0.0%)	+ € X (0.0%)
	Wk. 22	Q = X	Q = X	Q = X		
		€ X	€ X	€ X	- € X (- 0.0%)	+ € X (0.0%)
	Wk. 32	Q = X	Q = X	Q = X		
		€ X	€ X	€ X	- € X (- 0.0%)	+ € X (0.0%)
MB = X MP = X	**92160**	**MF = X**	**MF = X**	**MF = X**		
	Wk. 13	Q = X	Q = X	Q = X		
		€ X	€ X	€ X	- € X (- 0.0%)	+ € X (+ 5.0%)
MB = X MP = X	**92346**	**MF = X**	**MF = X**	**MF = X**		
	Wk. 19	Q = X	Q = X	Q = X		
		€ X	€ X	€ X	- € X (- 0.0%)	+ € X (+ 29.4%)
	Wk. 22	Q = X	Q = X	Q = X		
		€ X	€ X	€ X	- € X (- 0.0%)	+ € X (0.0%)
	Wk. 25	Q = X	Q = X	Q = X		
		€ X	€ X	€ X	- € X (- 0.0%)	+ € X (0.0%)
	Wk. 29	Q = X	Q = X	Q = X		
		€ X	€ X	€ X	- € X (- 0.0%)	+ € X (0.0%)
MB = X MP = X	**92318**	**MF = X**	**MF = X**	**MF = X**		
	Wk. 5	Q = X	Q = X	Q = X		
		€ X	€ X	€ X	- € X (- 6.7%)	+ € X (+ 6.7%)
	Wk. 24	Q = X	Q = X	Q = X		
		€ X	€ X	€ X	- € X (- 0.0%)	+ € X (0.0%)
MB = X MP'_{56} = X MP'_{18} = X	**92356 & 92318**	**MF_{92356} = X** **MF_{92318} = X**	**MF_{92356} = X** **MF_{92318} = X**	**MF_{92356} = X** **MF_{92318} = X**		
	Wk. 20	Q_{92356} = X	Q_{92356} = X	Q_{92356} = X		
		Q_{92318} = X	Q_{92318} = X	Q_{92318} = X		
		Q_{total} = X	Q_{total} = X	Q_{total} = x		
		€ X	€ X	€ X	- € X (- 0.3%)	+ € X (+ 3.5%)
MB = X MP'_{76} = X MP'_{78} = X	**92376 & 92378**	**MF = X**	**MF = X**	**MF = X**		
	Wk. 32	Q_{92376} = X	Q_{92376} = X	Q_{92376} = X		
		Q_{92378} = X	Q_{92378} = X	Q_{92378} = X		
		Q_{total} = X	Q_{total} = X	Q_{total} = X		
		€ X	€ X	€ X	- € X (- 0.0%)	+ € X (0.0%)

Table 13 Sensitivity analysis results minimum filtration restrictions

	% change in MP	-10%	Basis	+10%	-10%	+10%
	SKU – decision moment	**Change in total costs (expected obsolescence + early disposal)**			**Percentual change in total costs**	
MB = X MF = X	**92376 & 92378**	**MP_{92376} = X** **MP_{92378} = X**	**MP_{92376} = X** **MP_{92378} = X**	**MP_{92376} = X** **MP_{92378} = X**		
	Wk. 32	Q_{92376} = X	Q_{92376} = X	Q_{92376} = X		
		Q_{92378} = X	Q_{92378} = X	Q_{92378} = X		
		$Q_{total} = X$	$Q_{total} = X$	$Q_{total} = X$		
		€ X	€ X	€ X	- € X (- 10.7%)	+ € X (+ 12.8%)

Table 14 Sensitivity analysis results minimum packaging restrictions

Slightly changing minimum brewing value

As expected, from Table 12 a positive relation can be noticed between minimum brewing batch sizes and total costs regarding expected obsolescence of finished goods and early disposal of matured beer. **It appears that by slightly lowering the minimum brewing volumes of BTO products, for some cases (orange circled) quite some cost savings can be made**. This can be explained by the fact that in general producing less results in less costs regarding expected obsolescence, and in the case of early disposal less matured beer needs to be disposed (MinBrew – Q) what results in less disposal costs. The fact that it is only possible for a few products, is because for these products the minimum filtration volume is lower than the minimum brewing volume. In all other cases still the minimum filtration volume (and so the actual minimum brewing volume) needs to be produced. In other words, **it does not always make sense to lower the minimum brewing volume, but it seems that for all products of which the minimum filtration volume is lower than the minimum brewing volume, lowering the minimum brewing volume will result in cost savings**. Besides the fact that lowering the batch size restrictions can sometimes lead to cost savings, it needs to be kept in mind that the opposite is true as well. It appears that slightly increasing the minimum brewing volumes in most of the cases also leads to higher costs. Before drawing conclusions about the possible cost savings for some products by lowering their minimum brewing batch sizes, first it needs to be further investigated which other costs play a part when lowering the minimum brewing batch sizes, and if the earlier mentioned cost savings enough outweigh these other costs.

Slightly changing minimum filtration value

As can be noticed from Table 13, also a positive relation can be noticed between minimum filtration batch sizes and total costs regarding expected obsolescence of finished goods and early disposal of matured beer. This can be explained by the fact that a lower minimum filtration volume allows more disposal of matured beer during production, while for a higher minimum filtration volume the opposite is true. Especially in the case of current minimum filtration volumes that are equal to the minimum brewing volumes, an increase in the minimum filtration volumes often leads to higher compulsory minimum batch sizes, and so in higher total costs. Although a lower minimum filtration volume allows more disposal of matured beer during production, it does not mean this will always result in cost savings. As can be noticed from Table 13, the opposite appears to be true. For almost every production moment, it appears that even though the minimum filtration volume is lowered (but the minimum brewing volume remains the same), it is not cheaper to dispose more matured beer in the meantime. The trade-off between costs regarding expected obsolescence and costs regarding early disposal in all cases already lies at the old optimal batch volume. This is even the case for products of which first early disposal was not possible since the actual minimum filtration volume was equal to the actual minimum brewing volume. Even when lowering the minimum filtration volume, early disposal appears to be not beneficial to apply.

However, two exceptions apply here. As can be noticed from Table 13, product 92318 encounters quite some cost savings by lowering the minimum filtration volume. This is probably because – unlike the other products – here the early disposal costs outweigh the costs regarding expected obsolescence. In the old situation before slightly changing the minimum filtration volume, the optimal batch value of this product at this production moment was already equal to the minimum filtration volume. The other exception applies to the product pair that shares its matured beer stream, but does not share its filtrated beer stream (products 92356 & 92318). These products are in general less affected by the shared minimum brewing volume, and so their batch volumes are more often close to the minimum filtration volumes. This means that in general these products would benefit more from a decrease of their minimum filtration volume. However, as also can be noticed from the table, the possible cost savings for this product pair are still not much (only -0.3%). Therefore, **it seems that the impact of lowering the minimum filtration volumes of BTO products on total costs in general is much smaller – or even nothing – in comparison to the impact of lowering the minimum brewing volumes**. An explanation for this can be that the minimum filtration volumes are already so low that not much cost savings can be made anymore here. It also needs to be kept in mind that other costs that play a part by lowering the minimum filtration batch sizes are not taken into account yet. This means that there is a possibility that lowering minimum filtration batch sizes eventually might even result in more costs instead of cost savings when also taking into account other costs that play a part when lowering minimum filtration volumes. This firstly needs to be further researched.

Slightly changing minimum packaging value

As already discussed, for almost all products there is no sense in only lowering the minimum packaging batch sizes, since no disposal takes place in between filtration and packaging and for almost all BTO products it applies that the minimum filtration batch size is (at least more than 10%) higher than the minimum packaging batch size. However, there applies an exception to BTO products that share their filtrated beer stream. These products are in general less affected by the shared minimum brewing- and filtration volumes, and so their batch volumes are more often close to the minimum packaging volumes. This means that in general these products would benefit more from a decrease of their minimum packaging volume. Therefore, it is examined if lowering the minimum packaging batch sizes pays off for these kind of products. As can be noticed from Table 14, indeed some cost savings seem to be possible for products 92376 & 92378 when lowering their minimum packaging batch sizes. However, these cost savings (-10.7%) are quite lower than the average cost savings possible by lowering the minimum brewing batch sizes (on average -24.9% per production moment). Besides this, **the total amount of cost savings reached by lowering minimum packaging batch sizes of BTO products is much lower than those reached by lowering minimum brewing batch sizes,** since for almost all products there is no sense in only lowering the minimum packaging batch sizes. Last but not least, also here it is possible that the total costs that come along with lowering minimum packaging batch sizes - that not have been treated yet – will be higher than the quite small total cost savings that can be reached.

Overall, it can be concluded that when it is desired to generate more cost savings, lowering the minimum brewing volumes of BTO products would be an interesting option to take into consideration. However, when further examining this option, it needs to be kept in mind that lowering batch sizes must not negatively the quality standards of products. Besides lowering one of the batch sizes, one can imagine that combining multiple lower minimum batch sizes for different production stages possibly could result in even more cost savings. Due to limited time, unfortunately this option cannot be researched completely. Researching all different combinations of changed minimum batch sizes would be an interesting direction for further research. However, it is chosen to apply combined changed minimum batch sizes to two production moments for which it looks like it will pay off. These moments will be discussed below.

Combining changed minimum batch sizes

First of all, as already noticed from Table 13, product 92318 is the only product for which the minimum filtration volume has been produced (in week 5), what means that this product is affected by its minimum filtration volume. As already noticed from Table 12, also one of the highest cost savings were possible at this product by lowering the minimum brewing volume. As already mentioned, this product is not affected by its minimum packaging volume in this case. Therefore, it is interesting to examine the effect of changing the minimum brewing- as well as the minimum filtration volume at the same time. The results of this analysis can be found in Table 15 below. It appears that for this case it does matter to lower the minimum brewing- as well as filtration volume at the same time, since even more cost savings can be made in this way (savings of € X compared to savings of € X and € X when lowering respectively the MinBrew and MinFiltr values).

MP = X

% change in MB & MF	**-10%**	**Basis**	**+10%**	**-10%**	**+10%**
SKU – decision moment	**Change in total costs (expected obsolescence + early disposal)**			**Percentual change in total costs**	
92318	MB = X MF = X	MB = X MF = x	MB = X MF = X		
Wk. 5	Q = X	Q = X	Q = X		
	€ X	€ X	€ X	- € X (- 10.6%)	+ € X (+ 10.6%)

Table 15 Sensitivity analysis results minimum brewing- and filtration restrictions

The last production moment that is interesting to further examine is that of product pair 92376 & 92378 in week 32. The production moment of this pair is the only moment at which lowering the minimum packaging volume would pay off, as already noticed from Table 14. Since the product pair in this case is not affected by its shared minimum filtration volume, but it appeared from Table 12 that besides lowering the minimum packaging volume, some cost savings were also possible by lowering the minimum brewing volume, it is decided to examine the effect of changing its minimum brewing- and packaging volumes at the same time. The results of this analysis can be found in Table 16 below. It appears that for this case it does not matter that much to lower the minimum brewing- as well as filtration volume at the same time, since not many more costs (€ X now in comparison to € X when only lowering the MinPack value) or even not any more costs (€ X cost savings now as well as when lowering the MinBrew value).

MF = X

% change in MB & MP	**-10%**	**Basis**	**+10%**	**-10%**	**+10%**
SKU – decision moment	**Change in total costs (expected obsolescence + early disposal)**			**Percentual change in total costs**	
92376 & 92378	MB = X MP_{92376} = X MP_{92378} = X	MB = X MP_{92376} = X MP_{92378} = X	MB = X MP_{92376} = X MP_{92378} = X		
Wk. 32	Q_{92376} = X	Q_{92376} = X	Q_{92376} = X		
	Q_{92378} = X	Q_{92378} = X	Q_{92378} = X		
	$Q_{total} = X$	$Q_{total} = X$	$Q_{total} = X$		
	€ X	€ X	€ X	- € X (- 15.2%)	+ € X (+ 21.3%)

Table 16 Sensitivity analysis results minimum brewing- and packaging restrictions

Regarding both production moments, only for the first mentioned production moment of product 92318 in week 5 it appears that combining the lowering of minimum batch sizes (here: MinBrew and MinFiltr) leads to significantly (€ X till € X) more cost savings. For the other production moment of product pair 92376 & 92378 it appears that almost no extra cost savings can be made by combining the lowering of minimum batch sizes (here: MinBrew and MinPack). Given these results, **it could be interesting to further examine the combination of lower minimum brewing- and filtration volumes at the same time during further research**. However, it needs to be kept in mind that not all production moments of BTO products are already considered during this sensitivity analysis, and so it is recommended to first of all examine all BTO production moments – and check if indeed a combination of lower minimum brewing – and filtration volumes at the same time would be more beneficial - before diving further into this research direction. Also here it needs to be kept in mind that lowering multiple batch sizes must not negatively the quality standards of the products.

5.3 Conclusion

1. The relation between expected demand and expected obsolescence appears to be negative, while it appears to be positive for the coefficient of variation of demand;
2. A small change in one of the variables can already lead to quite some large changes in the model outcome, what underlines the impact, and so the importance, of the use of accurate demand forecasts and the right forecast deviations per product;
3. By slightly lowering the minimum brewing volumes of BTO products, for some products quite some cost savings can be made. This in comparison to the relatively low cost savings generated by lowering the minimum filtration- and packaging volumes;
4. Keeping in mind the additional costs of lowering the minimum batch sizes, that are not taken into account yet, it seems that lowering minimum brewing volumes eventually can result in significant cost savings. Therefore, lowering minimum brewing volumes of BTO products (without negatively influencing the product quality standards) would be an interesting option to further examine;
5. However, it appears that the combination of lower minimum brewing- and filtration volumes at the same time can result in even more cost savings. Therefore, more research in this direction (also here: without negatively influencing the product quality standards) also could be interesting.

Chapter 6: Conclusion

This research has been executed in response to the high inventory losses Grolsch faced during the previous year due to obsolescence of finished goods, with a total value of almost € X. After some interviews with different departments, it appeared that at the moment insufficient insight into expected product obsolescence, and insufficient anticipation to this expected obsolescence, eventually leads to high costs. Therefore, the following research goal was formulated: **"To better foresee expected product obsolescence, and to develop a calculation model that generates insight into possible actions regarding product obsolescence and their effects on costs and service"**. Several sub-questions were developed with the aim to eventually reach the research goal. In this chapter, the sub-questions will be answered one by one in order to conclude this research.

6.1 Current situation analysis

a) How much product obsolescence did Grolsch encounter during the year 2019, and what were the negative effects of this product obsolescence for Grolsch?

The direct impact of obsolete finished goods consists of the inventory write-offs due to obsolescence, disposal costs, and costs of extra production, resulting in a total sum of more than € X for the year 2019. Besides this, the total amount of lost profits due to discount sales of expired products was almost € X that year. A much higher volume of finished goods is disposed in comparison to semi-finished goods. However, in general finished goods contain far more added value than semi-finished goods, what means that in case of high expected obsolescence, probably costs could be saved by disposing beer earlier in the production process.

b) Which products encountered the highest obsolescence during the year 2019, and what are the root causes of product obsolescence?

21.5% of the products were responsible for 83.5% of the total inventory losses due to obsolescence. Amongst those top 21.5%, some particular product characteristics (slow movers, seasonal products, products with ending sales seasons, and NPDs) are more common, and in general products with those particular characteristics also encountered more relative obsolescence. The first underlying cause of product obsolescence that is found is the structural overforecasting of products. The second underlying cause of product obsolescence that is found is the interplay between minimum batch sizes and demand volumes. During the year 2019, BTO products - of which in general the demand volume is already lower than the minimum batch sizes- encountered much more obsolescence than BTF products -of which in general the demand volume is higher than the minimum batch sizes. Therefore, it is hypothesized that early disposal of matured beer would have been a good solution for these BTO products in order to reduce future obsolescence.

c) How does Grolsch - and in particular the tactical planning team - currently tries to foresee, and anticipate to product obsolescence, and which intervention methods are currently applied to products for which much obsolescence is expected?

At the moment, the tactical planning system only warns if there is planned on obsolescence or stockouts, but does not take into account demand variability yet. Also there is a lack of insight into the stock ages of the different product batches that are already on stock. Besides this, at the moment there is only focussed on products reaching their final delivery date within 5 weeks and for which the only *solution is to sell them for a discount price, while actually it is more interesting to focus on other products for which still more pro-active interventions are possible in order to avoid future obsolescence.*

d) Which intervention methods are furthermore possible in order to reduce (the negative effects of) product obsolescence?

Since demand forecasting improvement and product postponement are ongoing projects, these are no solution directions for this research. Lowering minimum brewing volumes is no solution direction due to quality restrictions, however, lowering packaging batch sizes can be a solution direction. Since more inventory losses are caused by products with the highest minimum batch size restrictions in the beginning of the production process instead of at the end, and so these products have more cost savings potential, there will be focussed further on a solution in the beginning of the production process, namely: early disposal of semi-finished goods. The goal of the final solution model is to estimate product obsolescence, and generate insight into the effects of early disposal of matured beer on expected obsolescence.

6.2 Solution design

a) What will be the scope of the solution model? Which restrictions needs to be taken into account, and which assumptions will be made?

The model that is created is two-fold: a monitoring dashboard measures the expected obsolescence of products, where after the optimization tool gives an insight into the impact of early disposal of matured beer, and calculates the optimal batch size at which total costs regarding expected obsolescence of finished goods and early disposal of matured beer are minimal. During monitoring, per product a distinction can be made between expected obsolescence caused by current starting stock, and expected obsolescence caused by the newly planned production batch. Only for this planned production batch, proactive actions – such as early disposal of matured beer – are possible in order to avoid future obsolescence.

b) What does the conceptual model look like, and which in- and output data is desired for this model?

With help of the next planned production batch per product, the currently available starting stock, a product's shelf life, the expected demand, and the coefficient of variation of demand, the expected overstocking per product is calculated by using the monitoring model. It is chosen to work with relative deviations instead of absolute deviations, and multiply them with expected demand in order to generate standard deviation input data per product. For products with limited/no historical data, by means of regression analysis the standard deviation of demand is estimated by using historical data of products with similar characteristics. Only for NPDs this method does not work, and so the coefficient of variation of demand for these kind of products is determined by taking the average coefficient of variation of demand of all NPDs of 2019. Here after, with help of the minimum batch sizes, the costs of goods sold of (semi)- finished goods, the disposal costs of finished goods, and the early disposal costs of matured beer, the early disposal possibilities and its effects on total costs regarding expected obsolescence and early disposal of matured beer are examined by using the optimization tool.

c) According to the literature, how can product obsolescence be estimated by also taking into account the demand variability, and how is this technique applicable to our model? How does the earlier proposed intervention method, and its impact on expected obsolescence and corresponding costs, will be examined by the model?

The heuristic developed for the monitoring model is a more complex, extended version of the classical newsboy problem, that now incorporates multiple product batches. After monitoring the expected obsolescence of products, the optimal batch size per product can be calculated by minimizing the total costs regarding expected obsolescence and early disposal of matured beer, taking into account the moment of production and the product's differentiation characteristics of matured/filtrated beer with other products as given, fixed variables. The early disposal decision making support tool supports decision making regarding batch sizes by showing the effects of different batch sizes on the expected obsolescence and its corresponding costs in charts and tables on a dashboard.

d) How should the model be verified and validated?

After checking with the future user if the model meets all expectations, and so can be considered as verified, the monitoring model is validated by checking if the model outcome corresponds more or less with the actual obsolescence volume of 2019. Since our model is intended for short term predictions, incorporating a maximum of 1 production batch at a time, but the actual obsolescence volume to compare the model's outcome with is only available as a total volume of one whole year (2019), it is decided to transform the monitoring model into a long term prediction model that can be used as validation model per single product. This is done by taking into consideration all batches produced during the year 2019, besides the starting stock batch(es) at week 1. Per product batch within the model, now the most updated sales forecast is used as input data in order to reflect every production quantity decision moment of the previous year as good as possible. It is decided to validate 10 products produced in 2019 that together caused a large part of the total obsolescence of that year.

e) What are the results of model verification and validation?

Although some individual predictions of the monitoring model vary significantly from reality, the total amount of predicted obsolescence is quite close to reality, and the model did not structurally over- or under predict. This suggests that the individual deviations are not a result of a model error. A better explanation of the deviations could probably be the fact that the model's accuracy to a large extend depends on the quality of the demand forecast, and besides this the fact that quite some assumptions are made within the model, what means that the model can never perfectly reflect reality and deviating outcomes are inevitable.

6.3 Results

a) How are the optimization results of the applied intervention method generated by the model?

Per stand-alone production moment, optimization results are generated. It is decided to only optimize the batch sizes of the X available BTO products, since in general only these kind of products often are affected by their minimum brewing volumes and so only for these kind of products early disposal of matured beer often could be desired. During optimization, only the packaging batch size served as decision variable. All other variables (such as the moment of production and the product's differentiation characteristics) have been kept constant (fixed). Besides early disposal, also a redivision of semi-finished beer over the final products was considered when products were sharing their with other products, as long as it fits within the current differentiation characteristics of the products. The *optimization results per production moment could not be summed up per product, since optimization of 1 production moment during the year probably would have affected the next planned productions. Therefore, we studied the optimization effects per separate production moment.*

b) What are the optimization results of the applied intervention method on expected obsolescence and its corresponding costs?

It appears that the biggest cost savings would probably have been possible at the products that did not share their beer with other products during production (4 production moments with cost savings of € X, € X, € X and € X) by applying early disposal of matured beer. However, during the other 9 production moments of products that did not share their beer with other products, no optimization was possible. Regarding the products that shared their beer with other products, optimization by a redivision of beer was possible at all production moments, but at some production moments it probably led to higher cost savings (€ X, € X, and € X) than at other production moments (€ X and € X). For 1 production moment even a combination of early disposal and a redivision of beer would probably have led to cost savings (€ X).

c) What are the additional effects of the applied intervention method?

Always a price needs to be paid for the reduction of expected obsolescence in our model, in the form of an increased chance of running out of stock. This probably would result in more and smaller production batches planned throughout the year, and so in more set up costs of the production lines. Although it is not desired – and also difficult - to include extra set up costs due to optimization into the model, an indication of these costs is calculated manually afterwards. It appears that after subtracting these extra set up costs from the earlier determined cost savings due to optimization, for production moments with relatively high possible cost savings due to optimization, these cost savings remain relatively high after subtraction of the extra set up costs, and so batch size optimization remains beneficial for these production moments. However, for production moments with relatively low possible cost savings due to optimization, batch size optimization appears to be not beneficial, since the cost savings of these production moments were already so low that subtraction of the extra set up costs ended up in little cost savings or even in losses. Since the extra set up costs are not negligible, it is not unwise to keep them in mind during batch size optimization. Furthermore it needs to be kept in mind that sometimes the choice to produce less and in smaller batches and thereby accepting the risk of emerging obsolescence, can appear to be an attractive solution, especially in the case of rapidly changing demand forecasts.

d) Would application of the intervention method (and so use of the optimization model) have been useful for the year 2019?

The costs we had influence on during our research were the actual costs of obsolete and disposed brew to order (BTO) products during the year 2019, with a total amount of € X. Although the cost savings per production moment due to optimization cannot be summed up per product, still it can be noticed that the cost savings of some separate production moments already are quite significant in comparison to the sum of the actual inventory losses and disposal costs of all BTO products of the year 2019. For example, the cost savings of product 92138 at week 5 (€ X) already would cover 39% of the total actual costs. Besides this, if per product only the last production moment would have been optimized during the year 2019 – and so they would not have been influenced by earlier optimizations – already 18% (€ X) of the total actual costs could have been saved. Therefore, it seems that probably quite a large part of the total inventory losses and disposal costs of all BTO products could have been saved during the year 2019 by applying batch size optimization to these kind of products.

6.4 Sensitivity analysis

a) What is the impact of changing input variables on the model outcome?

For the production moments of 8 of the X BTO products of the year 2019, first of all the baseline outcome resulting from the current input variables is calculated, where after a sensitivity analysis has been applied during which the values of expected demand and the coefficient of variation of demand are one for one slightly (10%) decreased and increased. The new model outcomes are than compared to the baseline outcome. The relation between expected demand and expected obsolescence appears to be negative, while the relation between the coefficient of variation of demand and expected obsolescence appears to be positive. It can be noticed that a small change in expected demand as well as in the coefficient of variation of demand already can lead to quite some high changes in the model outcome, and so these input variables to a large extent can contribute to the accuracy of the prediction model. This underlines the impact, and so the importance, of the use of accurate demand forecasts and the right forecast deviations per product.

b) What other changes can be applied to the model in order to examine potential improvement of the model outcome?

Per BTO production moment of the year 2019, first of all the baseline outcome resulting from the earlier optimized batch size based on the current input variables is used, where after the minimum batch sizes are one for one slightly (10%) decreased and increased. The new model outcomes are than compared to the baseline outcome. It appears that by slightly lowering the minimum brewing volumes of BTO products, for some cases quite some cost savings can be made. Furthermore, it appears that in general lowering the minimum filtration- and packaging volumes of BTO products does not result in significant cost savings. Therefore, it can be concluded that when it is desired to generate more cost savings, only lowering the minimum brewing volumes (without negatively influencing the product quality standards) of BTO products would be an interesting option to further examine. However, first it needs to be further examined if the additional costs of lowering minimum brewing volumes would outweigh these cost savings, before it can be concluded that lowering minimum brewing volumes would be beneficial. Besides lowering the minimum batch sizes one for one, also the combination of multiple lower minimum batch sizes at the same time is examined. It appears that probably quite some extra cost savings could have been possible by combining lower minimum brewing- and filtration batch sizes at the same time, and therefore more research in this direction is interesting. However, it is smart to first of all also examine the remaining BTO production moments and their opportunities before the impact of lowering (multiple) batch sizes will be further researched. Also here it needs to be kept in mind that lowering multiple batch sizes must not negatively influence the quality standards of products.

Chapter 7: Discussion, recommendations and further research

This research started with the main research question: "**How do we better foresee product obsolescence, and how do we generate insight into possible actions regarding product obsolescence and their effects on costs and service?**" After some preliminary research it is decided to develop a obsolescence control calculation model that is two-fold: a monitoring model estimates the expected obsolescence of all made to forecast (MTF) products (planned or already on stock) by besides expected demand also taking into account demand variability, where after the optimization tool generates insight into possible interventions against expected obsolescence and its corresponding costs, and can be used to support decision making regarding product obsolescence. The interventions include the early disposal of matured beer, and a redivision of semi-finished beer over different end products in the case of products sharing their beer with other products. In this way, the research contributed to a new way of obsolescence control by different departments.

7.1 General recommendations

At the beginning of this research, the research scope is brought back to the inventory losses caused by obsolescence of made to forecast (MTF) finished goods, products where the supply chain planning department has influence on, with a total actual amount of inventory losses of € X during the year 2019. Here after, it is decided to focus on 39% of these inventory losses (€ X) caused by brew to order (BTO) products, since these products encountered relatively more obsolescence than BTF products. These BTF products made up a greater part (61%) of the finished goods inventory losses, resulting in a total amount of € X. When also taking into account the disposal costs of obsolete BTO products (€ X), the total actual amount of obsolescence and disposal costs of BTO products we have influence on during our research is brought to € X. During the current situation analysis it was hypothesized that early disposal of matured beer would have been a good solution for BTO products in order to avoid obsolescence during the year 2019, since these products – in comparison to BTF products - in general encounter demand volumes lower than their minimum brewing sizes. Therefore, early disposal of matured beer has been researched as a solution direction for BTO products in order to avoid obsolescence. After formulating our model it appears that besides early disposal of matured beer, also redividing semi-finished beer over different end products (and so: adjust product differentiation characteristics) can be taken into account as an intervention during optimization.

Due to limitations of our model (e.g. single period mathematical model suitable for short term predictions, not for yearly predictions) and the unavailability of data (e.g. weekly obsolescence data) unfortunately we cannot calculate the yearly possible cost savings due to optimization. However, after separately optimizing the production moments, we can conclude that the cost savings of some separate production moments already are quite significant in comparison to the € X of actual inventory losses and disposal costs of all BTO products of the year 2019. For example, the cost savings of one production moment (€ X) already would cover 39% of the total actual costs. Besides this, when only applying batch size optimization to every last production moment of a BTO product during the year 2019 (only then the cost savings of all production moments can be summed up since they are not influenced by previous optimizations) already 18% (€ X) of the total costs of obsolescence and disposal of BTO products could have been saved by applying batch size optimization. This means that by applying batch size optimization to all production moments of the year 2019, probably quite a large part of the total inventory losses and disposal costs of all BTO products could have been saved. Since similar type of cost savings can be made in the future with help of this model, it is recommended for the supply chain planning department to make use of the monitoring model from now on in order to earlier warn the tactical planner about expected obsolescence, and to make use of the optimization tool in order to examine the effects of early disposal of matured beer and a redivision of semi-finished beer over end products on expected obsolescence of BTO products and its corresponding costs. There is no point in also applying the optimization model to BTF products, since these products in general almost never experience batch sizes lower than their demand volume. Since our optimization model optimizes batch sizes by making trade-offs between early disposal costs and expected obsolescence costs, but there is no point in applying early disposal of matured beer to BTF products, no trade-offs can be made for these kind of products and so the optimization tool does not make sense for them.

However, besides the above mentioned optimization results for BTO products, it needs to be kept in mind that there are also other positive effects of our model that are not discussed yet. As earlier mentioned, by using the monitoring model, the tactical planner can be earlier warned about expected obsolescence. Besides the pro-active ways to avoid obsolescence by planning early disposal of matured beer or planning a redivision of semi-finished beer over end products, also other ways are possible in order to reduce the negative effects of product obsolescence. For example the production planner can decide to defer planned production, but also more reactive actions are possible such as stimulating sales by starting a marketing campaign on time, or trying to sell products that almost passed their final delivery date for a discount price to the customer earlier in time in order to avoid disposal of finished goods eventually. These actions are also possible for BTF products, and so probably our model could have played a bigger role in reducing (the negative effects of) product obsolescence. Due to limited time, the impact of the other possible actions unfortunately could not have been examined during this research. However, it would be interesting to research this during a pilot study for for example the upcoming year, in which the model will be used for the first time. This means that every week after a new production plan has been released, the tactical planner should run the model in order to monitor expected obsolescence, and discuss possible actions (active as well as pro-active, depending on the kind of product and the state in which it is in, for example planned, in production or on stock) together with colleagues from different departments that are also involved in the decision-making regarding product obsolescence, such as demand planning, marketing and sales, and customer service.

Putting into use the obsolescence control model enables the user to react faster to threatening obsolescence of BTO- as well as BTF products. Since BTF products made up a greater part (61%) of the total inventory losses of obsolete MTF finished goods, with a total amount of inventory losses of € X (and even total costs of € X + € X = € X when also including disposal costs), it would be very interesting to also focus on BTF products during further research since a lot of costs could be saved here. Since early disposal of matured beer is not useful for these kind of products, there need to be searched for other possible pro-active as well as reactive interventions in order to avoid and/or mitigate the negative effects of obsolescence of these kind of products. Also improving the proposed obsolescence control model could be an interesting idea for further research. This probably will be beneficial for BTO- as well as BTF products. In the next sections we will dive somewhat deeper into ways to improve the monitoring- and optimization model.

7.2 Possible future improvements of the monitoring model

As already mentioned in Chapter 3, the strength of the developed expected obsolescence monitoring model lies in short term prediction modelling. The model generates insight into the expected obsolescence of products as good as possible from a certain moment, given a certain starting stock level, the next planned production batch from the most updated production plan, and the expected demand from the most updated sales plan. Including multiple production batches into the model - and so extending the prediction period - can negatively affect the accuracy of the final model outcome due to fast changing demand forecasts. It means that regarding expected obsolescence, the further into the future we look, the less accurate the model outcome will be, and therefore it is chosen to remain with only the next planned production batch to consider within our model. As appears from validation, although some individual predictions of the monitoring model vary significantly from reality, the total amount of predicted obsolescence is quite close to reality. Also the model did not structurally over- or under predict, what suggests that the individual deviations are not a result of a model error.

One explanation for the sometimes still high differences between predicted obsolescence and reality is the fact that the monitoring model outcome to a large extend depends on the two input variables expected demand and demand variability, as also has been proven during the sensitivity analysis. This indicates the need for accurate demand forecasts and use of the right demand variabilities. However, it also needs to be kept in mind that extremely high outliers in demand - resulting from a bad demand forecast – only to a small extent can be approached by the monitoring model by including high demand variabilities. Since we work with the yearly average relative deviations of demand per product (that are multiplied with the expected demand for a particular period), the extremely high outliers in demand can almost never be fully reached by the model. Once more, this underlines the importance of the use of accurate demand forecasts. Although overforecasting was a structural problem during the year 2019, at the moment the demand planning department is optimizing its forecasting methods, and tries to produce more realistic forecasts, what can positively affect the accuracy of our prediction model. Another way to improve the accuracy of the prediction model, is by updating the coefficients of variation of demand for all products more frequently. At the moment, only once per year this input variable is calculated per product. However, it would be interesting to update this input variable weekly, so that more products are provided with their demand variability, and besides this – especially for NPDs with limited historical data– the most recent values can be used as input to the model.

Another explanation for the sometimes high differences between predicted obsolescence and reality are the assumptions that are made in order to simplify the working of our model, like for example the assumption that production batches are already available from the moment of planning (and so no stockouts occur before the production batch will be released). Since the model is built on these assumptions, it will almost never perfectly reflect reality, and deviating outcomes are inevitable. However, since it is expected that these assumptions are not one of the bigger causes of the sometimes high differences between predicted obsolescence and reality, and besides this it is quite complex and would take a lot of time to let the model better correspond to reality by making it more detailed, it is assumed that this refinement of the model is not very interesting for further research.

7.3 Possible future improvements of the optimization model

As mentioned in Chapter 4, a refinement of the optimization model that could be of interest during further research, is also taking into account the fact that optimized (often smaller) batch sizes often lead to more necessary production moments during the year, and so eventually to extra set up costs in between the different production batches at the different production lines. It appeared that these extra set up costs due to optimization were not negligible (and sometimes could even lead to losses instead of cost savings). For this reason, including extra set up costs as penalty costs into the optimization model could be an interesting refinement of the model during further research. However, this further improvement of the optimization model must not take too much time and effort, since it only has some influence on BTO products, but does not affect the BTF products that encountered more obsolescence during the year 2019.

Another possible way to improve the optimization model results would be to allow more decision variables into the model that can be optimized. For example, it can be decided to – besides the packaging batch size - also make the production moments and differentiation characteristics of products variable. However, by taking these steps, the optimization model that first only focussed on batch size optimization within an already provided production plan, will now more and more turn into a stand-alone production planning model with multiple decision variables. It is believed that this is not desired, since our obsolescence control model focusses on monitoring, and improving a current situation, and not on developing a totally new production plan from scratch. Besides this, at the moment Grolsch is already busy with the development of a batch size optimization solver into their tactical planning program. It therefore can be concluded that the company is not looking forward to a totally new production planning tool. Therefore, the option to allow more decision variables into the optimization model during further research is left aside.

As already proven during the sensitivity analysis in Chapter 5, another possible way to achieve more cost savings regarding obsolescence, is by slightly lowering the minimum brewing volumes of the BTO products. However, before applying this measure, first of all it needs to be investigated which other costs play a part when lowering the minimum brewing batch sizes, and if the earlier mentioned potential cost savings enough outweigh these additional costs that need to be made. If this appears to be the case, it would be interesting to examine the effects of lowered minimum brewing volumes. In this context, it would also be interesting to examine the effects of combining lower minimum brewing- and filtration batch sizes at the same time, since during sensitivity analysis it appeared that probably quite some extra cost savings could have been possible in this way. However, it needs to be kept in mind that lowering one or multiple batch sizes is only attractive if this does not negatively influence the quality of products too much. If lower batch sizes strongly negatively influence the quality standards of products, the extra cost savings probably will not outweigh the decrease in product quality, or are not even possible since the minimum quality standards are already reached. For this reason, the impact of lower minimum batch sizes on product quality first of all needs to be investigated. However, also here it applies that this further improvement of the optimization model must not take too much time and effort, since it only has some influence on BTO products, but does not affect the BTF products that encountered more obsolescence during the year 2019.

Another way to bypass the minimum batch sizes for especially BTO products, is by letting more products share their brew stream with each other during production. However, since this research direction already has been examined at the moment by the brewing department, this is no direction for further research for the supply chain planning department.

7.4 Conclusion

Summarized, it is recommended for Grolsch to start making use of the obsolescence control model, monitor expected obsolescence, and besides optimize batch sizes of BTO products - in the form of early disposal of matured beer or a redivision of semi-finished beer over different products - also other pro-active and reactive interventions against the negative effects of BTO- as well as BTF product obsolescence should be investigated. In this way also the obsolescence of BTF products can tried to be tackled, that made up a larger part of the total inventory losses of obsolete MTF finished goods. The different interventions against the negative effects of product obsolescence need to be discussed with employees from different departments that are involved in the decision-making regarding product obsolescence. The optimization model can support decision-making regarding early disposal and/or a redivision of semi-finished beer over different end products during this procedure. Besides putting into use the obsolescence control model and investigate different possible interventions against (the negative effects of) product obsolescence, there also can be focussed on improvement of the obsolescence control model. Hereby, improvement of the monitoring model (by improving the accuracy of the input variables demand forecast and demand variability) needs some more attention than improvement of the optimization model (by including extra set up costs as penalty costs, and allowing lower minimum batch sizes) since the monitoring model affects BTO- as well as BTF products, while the optimization model only affects BTO products that make up a smaller part of the total inventory losses due to obsolete MTF finished goods.

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APPENDIX I: DIFFERENTIATION CHARACTERISTICS OF WORTS, FILTRATED BEERS, AND END PRODUCTS

APPENDIX II: COST PRICE CALCULATIONS OF FINISHED- AND SEMI-FINISHED PRODUCTS

The inventory losses of finished- and semi-finished goods are expressed in terms of variable costs of goods sold (COGS) that encompass the bill of material (BOM) of a product and the costs of manually repacking the product if this was necessary. Indirect costs, such as cleaning and energy costs, but also fixed costs such as operating and maintenance costs, and overhead costs are not included yet in these variable COGS. Roughly speaking, considering Table 1, the price of disposed matured beer was on average € X/hL, while that of disposed filtrated beer was on average € X/hL and that of disposed packaged beer € X/hL. However, taking into account the fact that finished goods contain 100% of the filtrated beer of the previous step, and besides this also include the costs of packages and repacking, the variable COGS of finished goods were expected to be much higher than that of semi-finished goods. Considering these figures, it seems like the disposed volume had more impact on the big difference in obsolescence costs between finished- and semi-finished goods, than the added value on finished goods had. This would imply that disposing filtrated beer instead of packaged beer would not lead to much cost savings. However, this cannot be stated this easily since the cost prices differ strongly from product to product.

After studying the cost price calculation data, it can be noticed that the average variable COGS of finished- and semi-finished goods differ from the average inventory losses per hectolitre in 2019, as can be seen in Table 18. The average variable COGS of filtrated beer are in fact a little bit lower than that of matured beer, since filtration is the only production step in which the price per hectolitre of a product can decrease in comparison to its previous production step due to the blending process with water. The relatively seen high average inventory losses per hectolitre of filtrated beer in 2019 can be explained by the fact that in 2019 in general more expensive filtrated beer – with e.g. special beers with expensive added compounds - have been disposed.

Material type	Average variable COGS / hL	Average inventory losses / hL in 2019
Matured beer	€ X	€X
Filtrated beer	€ X	€ X
Finished goods	€ X	€ X

Table 18 Average variable COGS / hL compared to average inventory losses / hL of finished- and semi-finished goods in 2019

Also it can be noticed from Table 18 that in general the average variable COGS for finished products are much higher than the average inventory losses of finished goods from the inventory losses data of 2019. This can be explained by the fact that a lot of relatively seen cheaper finished goods have been thrown away in 2019, especially cheap tank beer destined for bars and restaurants with variable COGS from € X/hL. Given the fact that in general the variable COGS of finished goods are a lot higher, it can be stated that throwing away products earlier in the process still could lead to quite some reduction of the final obsolescence costs.

To prove the above mentioned statement, all the obsolescence costs of finished goods of 2019 are expressed in terms of the variable COGS of its filtrated beer. By assuming a situation in which all the finished goods would have been thrown away as filtrated beer earlier in the process, the € X of obsolete finished goods would have been decreased with 40% until almost € X of obsolete filtrated beer, and so it can be noticed that the added value on finished goods definitely makes sense.

APPENDIX III: INPUT VARIABLES ROOT CAUSE ANALYSIS

Relative obsolescence

Since the relations between obsolescence and proposed causes and product characteristics are examined, instead of the inventory losses in terms of euros as used during the Pareto analysis, now the net inventory losses in terms of hectolitres are used in order to prevent the product prices from influencing the relations. Besides this, instead of the absolute obsolescence in terms of hectolitres per product, the relative obsolescence per product is used, by expressing the obsolescence per product in hectolitres as a percentage of the total production volume of this product in hectolitres in 2019. During the root cause analysis, the relative obsolescence per product is compared to the defined variables discussed below.

Slow movers

Since it is not sure if the existing classification of slow movers is still correct, first of all it needs to be determined which products were slow movers in 2019. For these calculations the sales data in hectolitres of 2019 is used. It is assumed a product can be categorized as a slow mover if it faces low average demand. However, comparing all products' average sales with each other would give a distorted picture of the real slow movers, since products packaged at different packaging lines can differ strongly in sales volume. Therefore, per product the average sales per month is divided by the average sales per product per month on the packaging line where the product is produced, and this variable is called the sales volume factor. An overview of the different packaging lines, and their average sales volume per month can be found in Table 19.

Packaging line	Products	Average sales/ product/ month
1	X	X hL
2	X	X hL
3	X	X hL
4	X	X hL
5	X	X hL
7	X	X hL
8	X	X hL
20	X	*Not needed for this research*
98	X	X hL
99	X	X hL
CON9	X	X hL

Table 19 Packaging lines and their average sales per product per month based on sales data 2019

It is assumed that if the sales volume factor of a product is beneath 0,5 - and so is minimal a factor 2 times lower than the average sales of all products on the same packaging line – it can be classified as a slow mover.

Seasonality products and ending sales seasons

Since it is not sure if the current classification of seasonal products is still correct, also per product it is determined if it encountered seasonality, and if the product had an ending sales season. To determine if a product was seasonal, a seasonality factor has been calculated. Since product codes change rapidly, and so for quite some products no historical data of previous years was present, and besides this only 40% of the products sold in 2019 were not new or delisted and have sales data of at least 2 full years, it is determined to only use the sales data of 2019. It needs to be kept in mind this could have some negative effect on the accuracy of the seasonality measures.

For every product the 3 consecutive months with the highest total sales volume are determined, and the seasonality factor is calculated by dividing these sales by the total amount of sales per year. Since only data of one year has been used, the months at the end of 2019 are taken together with the months at the beginning of 2019. This means that e.g. December 2019 is taken together with January 2019 and February 2019. It is determined that if more than 50% of the sales of a product took place in those 3 consecutive months, this product can be considered as seasonal. The seasonality factor only can be calculated for products that have sales data over whole the year, so products that were new and/or delisted during the year 2019 are left aside. Since these products together make up halve of the inventory losses, it needs to be kept in mind that this could give a distorted picture of the seasonality among all the products. Besides this, it needs to be kept in mind that besides seasonality, also other things like promotions can influence the buying behaviour of clients, and so in reality the seasonality of some products could differ from these figures.

New product developments

As stated during the interviews, NPDs have little to no demand history, and so they are more difficult to forecast and prone to become under- or overforecasted. However, before this can be verified, first of all it needs to be determined which products that are sold during the year 2019 can be classified as a NPD, since it is not sure if the current NPD classification is still correct. For this research we are provided with the creation dates of SKUs in the data base. It can be assumed that in general a new product is created in the data base around 10 weeks before its first production date, and that usually the first sales will be around 2 weeks after this first production date (so 12 weeks after creation). Also taking into account the fact that a product without historical sales data of 1 full year can be considered as difficult to forecast, we assume that products can be classified as NPD if they are in the first 52+12 = 64 weeks after their creation date. In this way, it is determined per SKU during which weeks of the year 2019 they were classified as non-NPD or NPD, and it is assumed that if products were classified as NPD more than half a year during 2019, they can be seen as NPD on overall. It can be concluded that X% of the products sold in 2019 were NPDs, and the remaining X% can be classified as non-NPD.

Forecast accuracy

Through the eyes of the supply chain planning department it is not accurate to use the most updated forecast value for every week when calculating the forecast accuracy, since there is a frozen horizon of 1 week, what means that in general a week before production the production plan cannot be modified anymore by the planners. For this reason, it is determined that the forecast of wk-2 is leading for the sales of wk0 during the calculation of the forecast accuracy. Since the tactical planners are flexible to adjust their planning until this 1 week before production, this wk-2 forecast is indeed correct to use is input for the forecast accuracy measures. As explained in Chapter 2, the forecast accuracy of products is calculated by means of the bias as percentage of its sales. This measure (28) gives an indication about to what extent a product has been under- or overforecasted.

$$Bias\ \% = \frac{\sum_{wk=1}^{n} Sales - FC}{\sum_{wk=1}^{n} Sales} \qquad (28)$$

It needs to be kept in mind that there will almost always be a deviation between forecast and sales, however the extent to which a product encountered forecast deviations matters. A shortcoming of above mentioned measure is that it cannot be calculated for weeks where the sales were zero because dividing by zero is not possible. For this reason, these weeks are left aside during the calculation of the variables. However, this can give a distorted picture of the forecast accuracies of products, especially for that of slow movers since these products can encounter intermittent demand what is now left aside.

APPENDIX IV: ANALYSES OF QUANTITATIVE RELATIONS

Slow moving products

It appears that from the products sold in 2019, around half of the products (X%) was slow moving, and X% was not slow moving. The relative obsolescence per product versus its sales volume factor can be found in Figure 19.

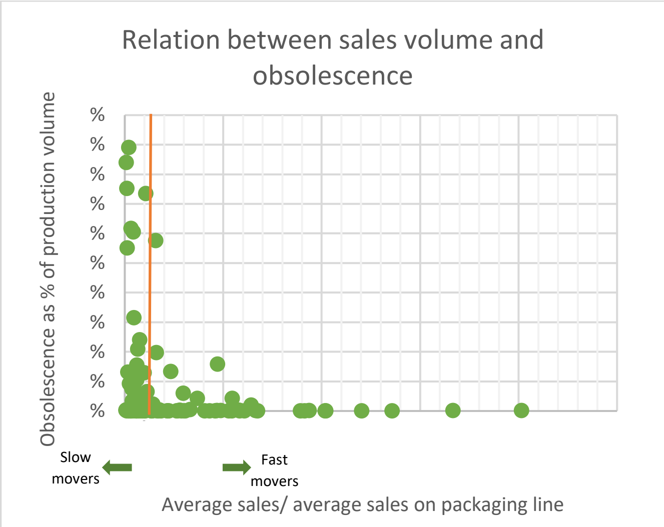

Figure 18 Relative obsolescence vs. sales volume factor of SKUs sold in 2019

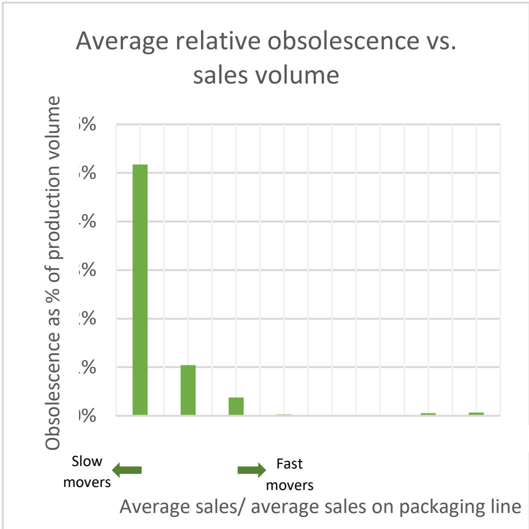

Figure 19 Average relative obsolescence vs. sales volume factor of SKUs sold in 2019

It can be noticed that there is some negative relation between obsolescence and sales volume. The real fast movers encounter relatively seen very little obsolescence, while the products that encountered most obsolescence were slow moving. However, speaking of a very strong negative relation between the two variables is not possible, since the points show no significant clustering in a band. This is because there are also a lot of slow movers that did not encounter much obsolescence. To get some more insight into the relation between sales volume and obsolescence, the average relative obsolescence per sales volume factor is determined. Therefore the volume factors are subdivided into 8 different groups as can be seen in Figure 20. As can be noticed from Figure 19, it can be concluded that in general **the average relative obsolescence is descending as the relative demand volume of a product increases**. This would indicate indeed some negative relation between obsolescence and sales volume, and so it would be smart to pay extra attention to slow moving products when focusing on obsolescence reduction.

Seasonality products and ending sales seasons

It appears that from the products sold in 2019 (excl. new/delisted products and products with missing data) X% were seasonal, and X% were not seasonal. In Figure 20 the relative obsolescence per product versus its seasonality factor can be found.

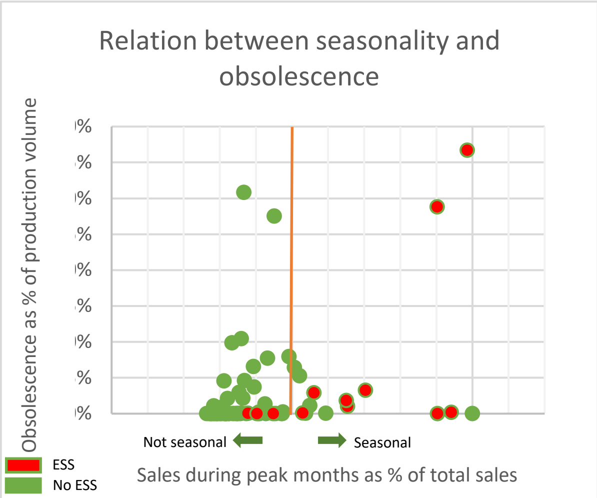

Figure 20 Relative obsolescence vs. seasonality factor of SKUs sold in 2019

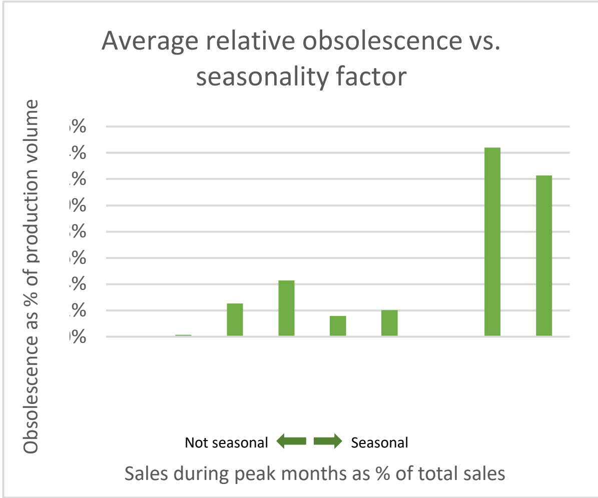

Figure 21 Average relative obsolescence vs. seasonality factor of SKUs sold in 2019

As can be seen in Figure 20, there cannot be spoke of a strong relation between the two variables, since the points show no significant clustering in a band. Strongly seasonal products encounter much as well as few obsolescence. It can be seen that the highest obsolescence is experienced by strongly seasonal products, but also products with a seasonality factor around X% encounter high obsolescence. However, to get some more insight into the relation between seasonality and obsolescence, the average relative obsolescence per seasonality factor is determined. Therefore the seasonality factors are subdivided into 9 different groups as can be seen in Figure 21. Figure 21 supports the conclusion that obsolescence is encountered by seasonal as well as not very seasonal products, but it also can be noticed that **the strongly seasonal products encountered on average much more obsolescence than the products that were not very seasonal**, what can be explained by the fact that there are a lot of non-seasonal products that encounter (almost) no obsolescence. Therefore, it is smart to pay some extra attention to strongly seasonal products when focusing on reducing product obsolescence.

To explain the fact that strongly seasonal products are tend to become obsolete, two reasons arise from the interviews. First of all it is stated that if a strongly seasonal product has little demand volume outside its peak months, at these months a production volume can already be larger than the demand volume due to batch size restrictions. A second explanation is the fact that for products with an ending sales season, it is difficult to not produce too much at the end of the season and avoid stock excesses after the sales season due to also the minimum batch size restrictions. Although the sales patterns of strongly seasonal products and products with ending sales seasons can be very similar – because both have a peak moment and few/no sales during no-peak moments – it is important to look for both characteristics separately, since, as described above, zero sales and almost zero sales are causing obsolescence in a different way. Therefore, also the relation between ending sales seasons (as already described in Chapter 2.1) and obsolescence is examined separately below.

In Figure 20, all products with an ending sales season are coloured red, and it can be noticed that most of the products with ending sales seasons were also seasonal (what seems quite logical). However, there are also a few products with an ending sales season that were not really seasonal, what can be explained by the fact that they had just a few months without sales, and no real peak months. It also can be noticed that products that encountered relatively seen high obsolescence had ending as well as no ending sales seasons. When diving further into the sales data, it can be noticed that **the products with an ending sales season still had an average relative obsolescence of X% while that of the products with sales throughout the whole year was 3.5 times smaller (X%)**, what can be explained by the fact that there are many products without ending sales season that had relatively low/no obsolescence. Therefore, it can be assumed that products with ending sales seasons are also more likely to become obsolete and so also need some extra attention when focusing on obsolescence reduction.

Since in general products with ending sales seasons are strongly seasonal, but this is not always the case (and the other way around: products with ending sales seasons are also not always strongly seasonal), it is smart to look for both characteristics seasonality and ending sales seasons separately from each other when focusing on reducing obsolescence. However, it might be assumed that if a strongly seasonal product with an ending sales season encountered much obsolescence, probably this ending sales season was the reason, and if a strongly seasonal product without ending sales season encountered much obsolescence, the low demand volume during the no-peak months was probably the reason for high obsolescence.

APPENDIX V: PROBABILITY DISTRIBUTION OF DEMAND

During interviews it suggested that demand is normally distributed. However, before this assumption can be made, first of all it needs to verified that the hypothesized normal distribution indeed adequately describes the demand data. One way to generate insight into the form of the underlying distribution is by creating a histogram. However, according to Montgomery and Runger 2011), usually histograms are not really reliable indicators of the distribution form. A more reliable method that is suggested by Montgomery and Runger to determine if the hypothesized distribution adequately describes the data, is a graphical technique called probability plotting. Therefore, first of all the total demand data per week together for all products sold in 2019 (excluding MTO export products, tank beer and import products where the supply chain planning department has no influence on) is arranged in ascending order, and per observed value the observed cumulative frequency (*j*-0.5)/*n* is calculated with *n* as total amount of observations and *j* as observation value 1 until *n*. Here after from these observed cumulative frequencies, the corresponding standardized normal scores z_j are calculated. The theoretical z-scores z_j are plotted against the observed demand, and results in the normal probability plot shown in Figure 22. A trend line has been drawn through the plotted points.

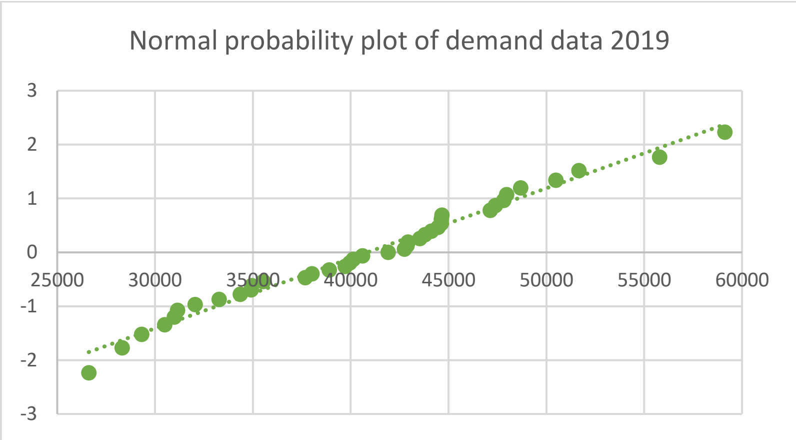

Figure 22 Normal probability plot obtained from standardized normal scores, based on historical demand data (total sales/week during the year 2019)y

As can be noticed from Figure 22, the data points are close to the straight line, and so it seems like a normal distribution adequately describes the demand data. However, to quantitatively proof the hypothesis that demand data is normally distributed, a goodness-of-fit test can be executed based on the chi-square distribution (Montgomery and Runger, 2011). *n=39* observations (weeks) are arranged in a frequency histogram, having *k=14* class intervals. Per *i*th class interval the observed frequency O_i is determined, and the expected frequency E_i is calculated with help of the hypothesized normal distribution. Here after with help of equation (29) the chi-square test statistic is calculated and results in a value of 14.7.

$$X_0^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i} \qquad (29)$$

Also the percentage points $X_{\alpha,v}^2$ of the chi-square distribution with α=0.05 and v=13 degrees of freedom is determined and results in a value of 22.36. The hypothesis that demand is normally distributed would be rejected if $X_0^2 > X_{\alpha,v}^2$. Since in this case the opposite is true ($X_0^2 = 14.7 < X_{\alpha,v}^2$= 22.36), we retain the null hypothesis that demand is normally distributed.

APPENDIX VI: REGRESSION ANALYSIS COEFFICIENT OF VARIATION OF DEMAND

I. NPDs vs. non-NPDs

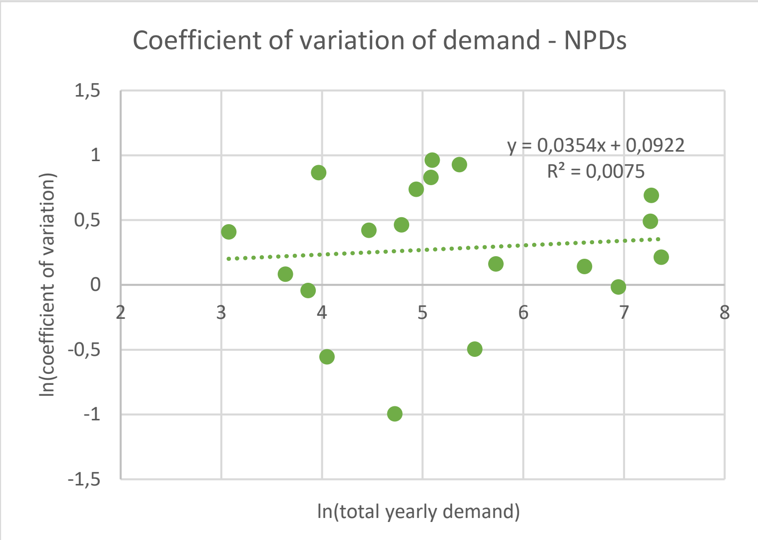

Figure 23 Ln-ln plot coefficient of variation vs. total yearly demand of NPDs 2019

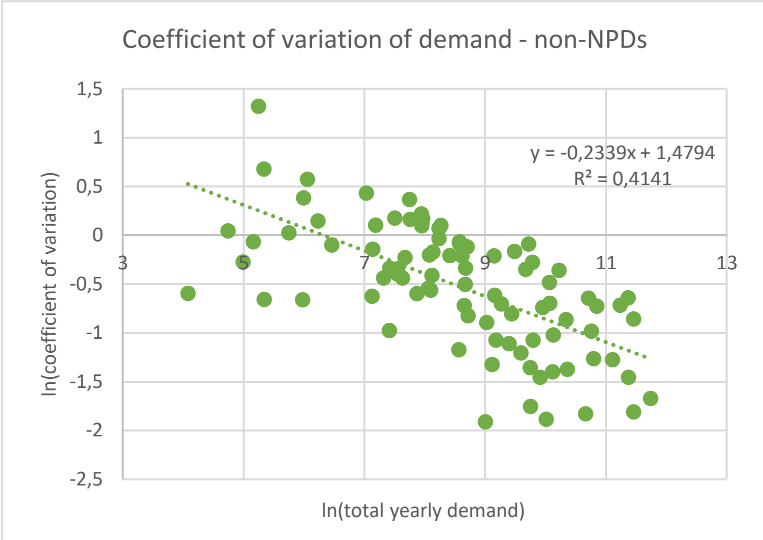

Figure 24 Ln-ln plot coefficient of variation vs. total yearly demand of non-NPDs 2019

II. Non-NPDS, seasonality characteristic

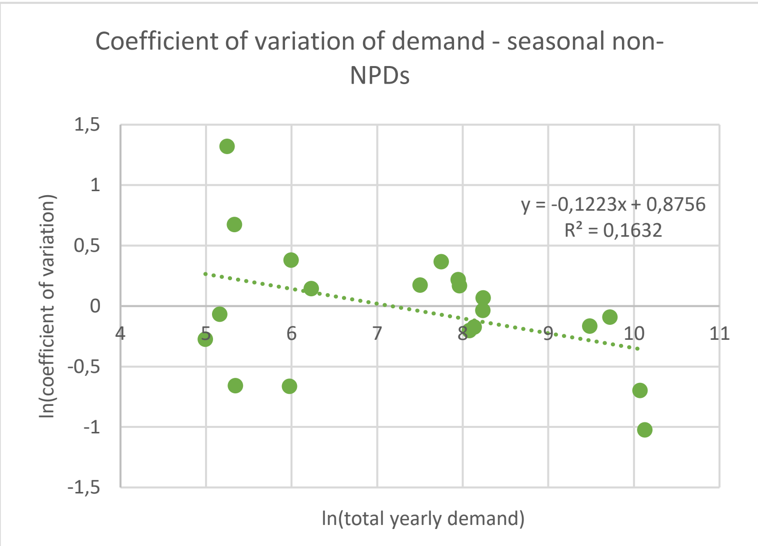

Figure 25 Ln-ln plot coefficient of variation vs. total yearly demand of seasonal non-NPDs 2019

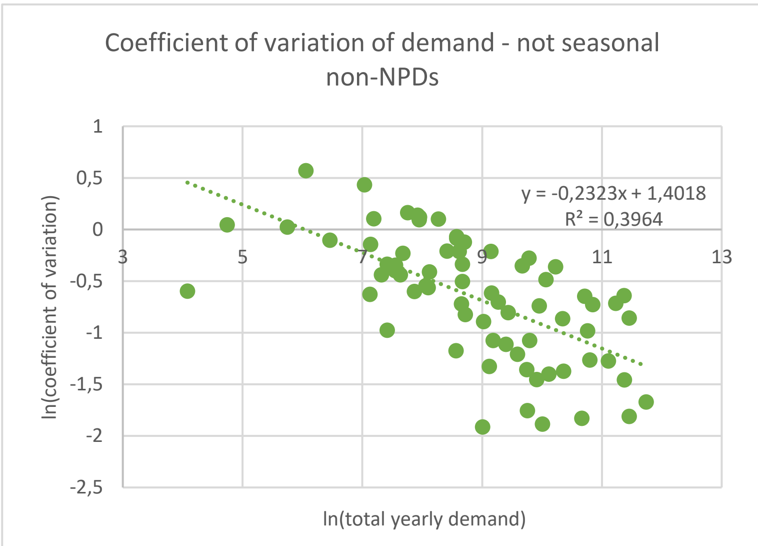

Figure 26 Ln-ln plot coefficient of variation vs. total yearly demand of not seasonal non-NPDs 2019

III. Non-NPDs, ending sales seasons characteristic

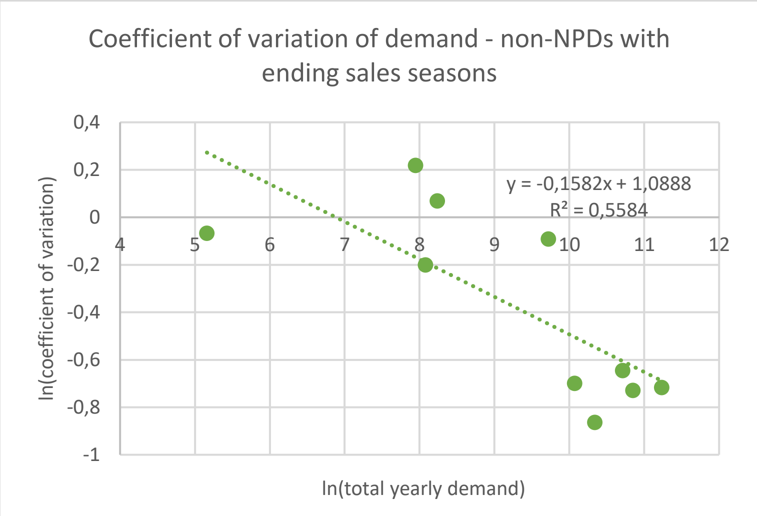

Figure 27 Ln-ln plot coefficient of variation vs. total yearly demand of non-NPDs with ending sales seasons 2019

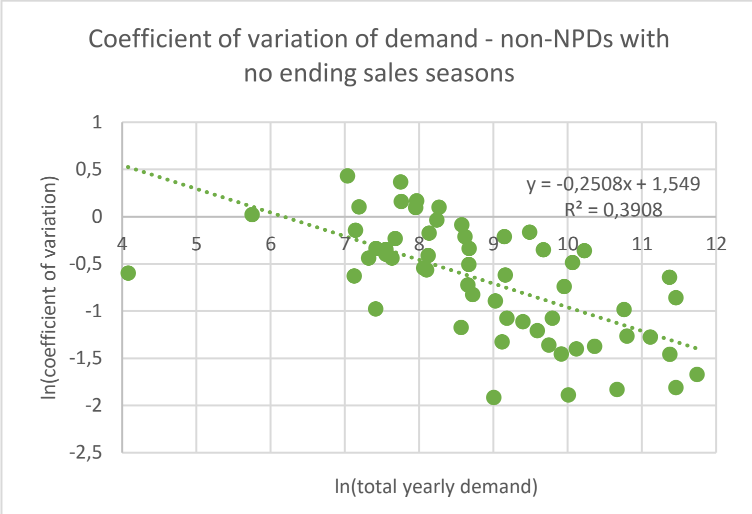

Figure 28 Ln-ln plot coefficient of variation vs. total yearly demand of non-NPDs with no ending sales seasons 2019

III. Non-NPDs, power function graph

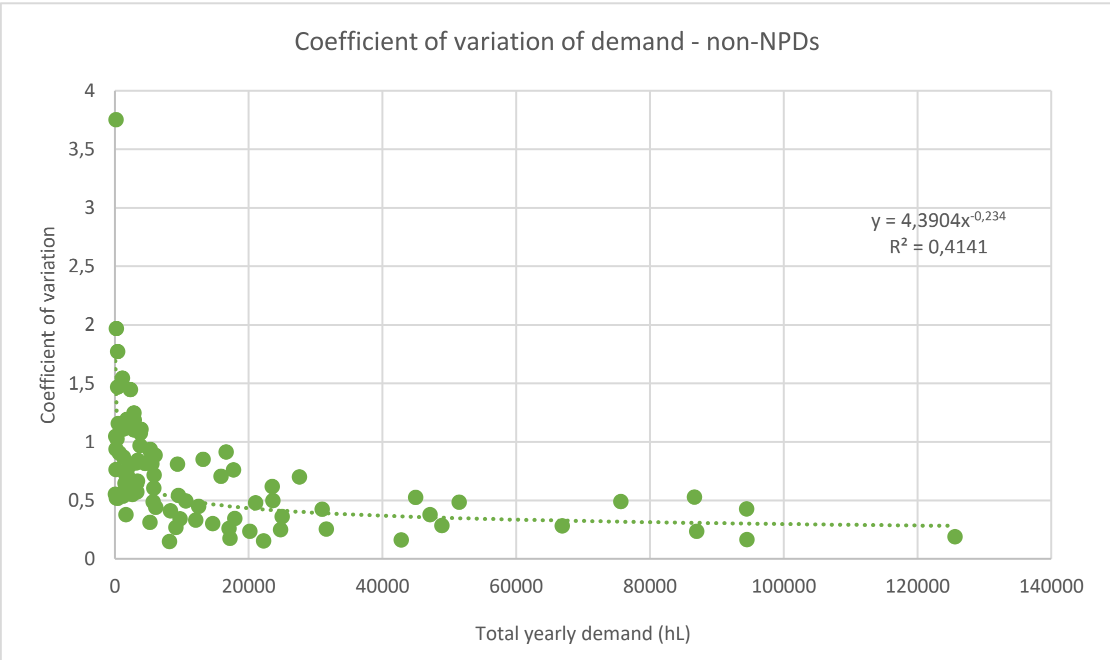

Figure 29 Power function plot coefficient of variation vs. total yearly demand of non-NPDs 2019

Appendix VII: Results of production quantity optimization

In the columns "Old model" results can be found for the expected over- and understocking and its corresponding costs using the old (actual) production quantity as input to our monitoring model. In the columns "Optimization model" the results for the expected over- and understocking and its corresponding costs using the optimized batch size quantity as input to our monitoring model can be found. This optimized batch size is determined by making a trade-off between the costs of expected obsolescence of finished goods (COGS finished goods + transportation costs) and the costs of early disposal of matured beer (COGS matured beer), as already explained in the mathematical model of Chapter 3. Only for the first product (92301) as an example all dashboard decision support charts are displayed per decision moment. However, since displaying these dashboards for all products takes up lots of space, for the other BTO products of the year 2019 only the results tables are shown.

Product 92301

Product 92301 encountered 2 production moments during the year 2019 that had a final delivery date within that same year, at weeks 5 and 17. The production moment in week 42 is not taken into account since its final delivery moment took place in the year 2020. MinBrew batch size: X hectolitres.

Decision moment - week 3	Old model	Optimization model
Batch size (hL)	X	X
Early disposal (hL)	X	X
Early disposal costs	*€ X*	*€ X*
Expected overstocking costs	*€ X*	*€ X*
Total costs	***€ X***	***€ X***
Exp. understocking (hL)	X	X

Table 20 Results before and after batch size optimization - product 92301 decision week 3

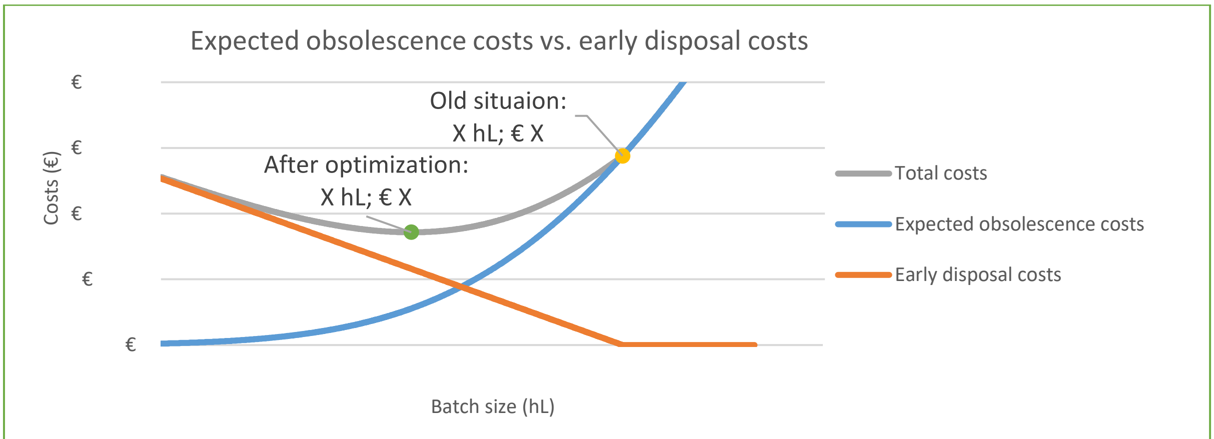

Figure 30 Total costs before and after batch size optimization - product 92301 decision week 3

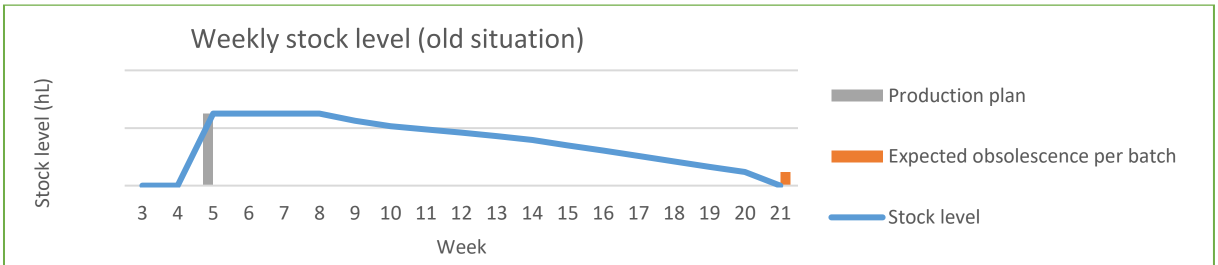

Figure 31 Weekly stock level before batch size optimization - product 92301 decision week 3

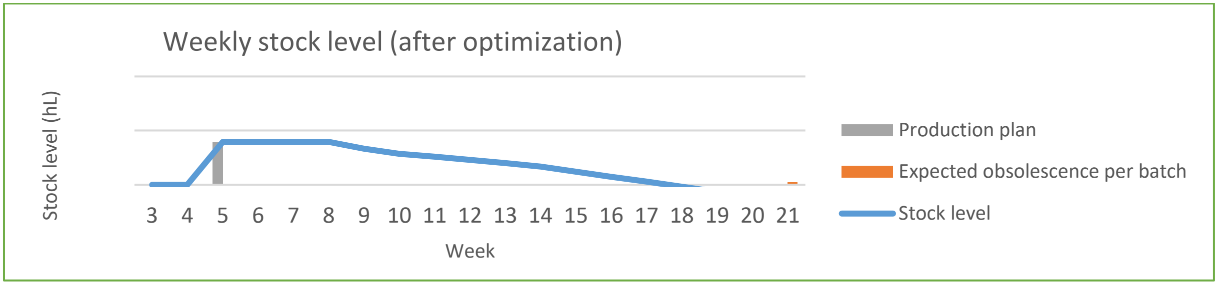

Figure 32 Weekly stock level after batch size optimization - product 92301 decision week 3

Decision moment – week 15	Old model	Optimization model
Batch size (hL)	X	X
Early disposal (hL)	X	X
Early disposal costs	*€ X*	*€ X*
Expected overstocking costs	*€ X*	*€ X*
Total costs	***€ X***	***€ X***
Expected understocking (hL)	X	X

Table 21 Results before and after batch size optimization - product 92301 decision week 15

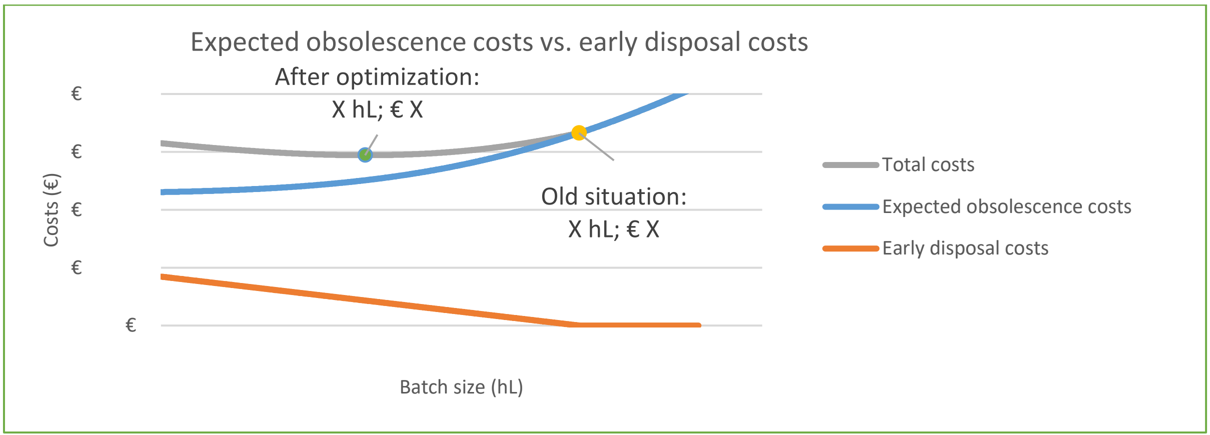

Figure 33 Total costs before and after batch size optimization - product 92301 decision week 15

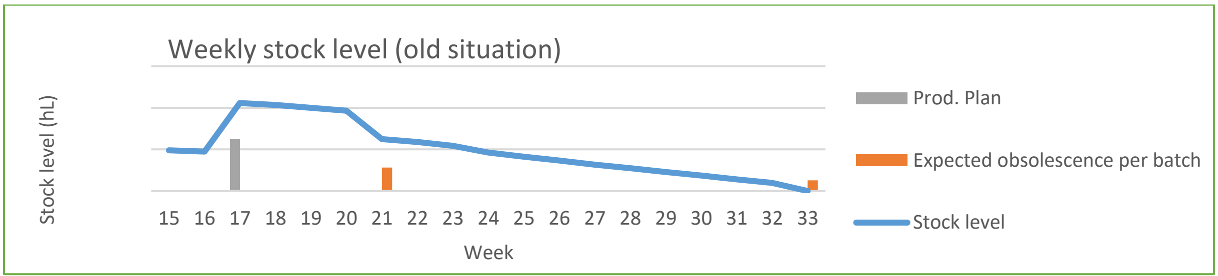

Figure 34 Weekly stock level before batch size optimization - product 92301 decision week 15

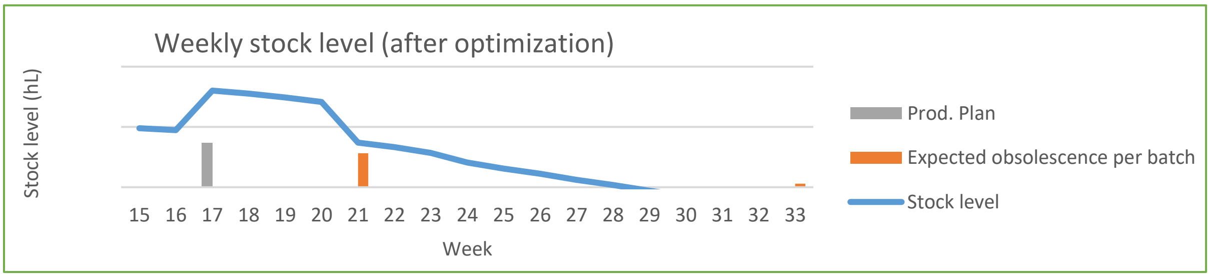

Figure 35 Weekly stock level after batch size optimization - product 92301 decision week 15

Product 92135

Product 92135 encountered 3 production moments during the year 2019 that had a final delivery date within that same year, at weeks 13, 24 and 34. The production moment in week 44 is not taken into account since its final delivery moment took place in the year 2020. MinBrew batch size: X hectolitres.

Decision moment – week 11	Old model	Optimization model
Batch size (hL)	X	X
Early disposal (hL)	X	X
Early disposal costs	*€ X*	*€ X*
Expected overstocking costs	*€ X*	*€ X*
Total costs	***€ X***	***€ X***
Expected understocking (hL)	X	X

Table 22 Results before and after batch size optimization - product 92135 decision week 11

Decision moment - week 22	Old model	Optimization model
Batch size (hL)	X	X
Early disposal (hL)	X	X
Early disposal costs	*€ X*	*€ X*
Expected overstocking costs	*€ X*	*€ X*
Total costs	***€ X***	***€ X***
Expected understocking (hL)	X	X

Table 23 Results before and after batch size optimization - product 92135 decision week 22

Decision moment - week 32	Old model	Optimization model
Batch size (hL)	X	X
Early disposal (hL)	X	X
Early disposal costs	*€ X*	*€ X*
Expected overstocking costs	*€ X*	*€ X*
Total costs	***€ X***	***€ X***
Expected understocking (hL)	X	X

Table 24 Results before and after batch size optimization - product 92135 decision week 32

Product 92160

Product 92160 encountered 1 production moment during the year 2019 that had a final delivery date within that same year, at week 15. MinBrew batch size: X hectolitres.

Decision moment - week 13	Old model	Optimization model
Batch size (hL)	X	X
Early disposal (hL)	X	X
Early disposal costs	*€ X*	*€ X*
Expected overstocking costs	*€ X*	*€ X*
Total costs	***€ X***	***€ X***
Expected understocking (hL)	X	X

Table 25 Results before and after batch size optimization - product 92160 decision week 13

Product 92346

Product 92346 encountered 4 production moments during the year 2019 that had a final delivery date within that same year, at weeks 21, 24, 27 and 31. MinBrew batch size: X hectolitres.

Decision moment - week 19	Old model	Optimization model
Batch size (hL)	X	X
Early disposal (hL)	X	X
Early disposal costs	*€ X*	*€ X*
Expected overstocking costs	*€ X*	*€ X*
Total costs	***€ X***	***€ X***
Expected understocking (hL)	X	X

Table 26 Results before and after batch size optimization - product 92346 decision week 19

Decision moment - week 22	Old model	Optimization model
Batch size (hL)	X	X
Early disposal (hL)	X	X
Early disposal costs	*€ X*	*€ X*
Expected overstocking costs	*€ X*	*€ X*
Total costs	***€ X***	***€ X***
Expected understocking (hL)	X	X

Table 27 Results before and after batch size optimization - product 92346 decision week 22

Decision moment - week 25	Old model	Optimization model
Batch size (hL)	X	X
Early disposal (hL)	X	X
Early disposal costs	*€ X*	*€ X*
Expected overstocking costs	*€ X*	*€ X*
Total costs	***€ X***	***€ X***
Expected understocking (hL)	X	X

Table 28 Results before and after batch size optimization - product 92346 decision week 25

Decision moment - week 29	Old model	Optimization model
Batch size (hL)	X	X
Early disposal (hL)	X	X
Early disposal costs	*€ X*	*€ X*
Expected overstocking costs	*€ X*	*€ X*
Total costs	***€ X***	***€ X***
Expected understocking (hL)	X	X

Table 29 Results before and after batch size optimization - product 92346 decision week 29

Products 92356 & 92318 from same matured beer stream

Sometimes, the packaging of a product that takes place after brewing is postponed for a maximum of two weeks, due to for example technical limitations (unavailability of machines at certain moments) or perishability issues (postponement of the shelf life starting date of packaged products). This was for example the case for products 92356 and 92318 that share the same matured beer stream, what means that the brewing process of both products can be combined and so one brew will be destinated for both products. Product 92356 encountered 1 production moment during the year 2019 that had a final delivery date within that same year, at week 24. Product 92318 encountered 4 production moments during the year 2019 that had their final delivery dates within that same year, at weeks 7, 22, 26 and 30.

In this example, shared brewing took place in week 22, where after only product 92356 was packaged immediately after the brewing process. Part of the brew - destined for product 92318 - remained in the beer tank and was packaged two weeks later. Since during postponement of packaging only the packaging dates of the products differ, but the packaging batch sizes stay the same, still the optimization model for products with a shared brew stream can be applied. Since brewing as well as the first packaging batch takes place in week 22, we take week 20 as the 2 weeks ahead decision moment for the optimization model.

After discussion with the tactical planning team, it appears that for the production of product 92318 in weeks 26 and 30 an exception was allowed, and packaging was postponed 4 weeks instead of 2 weeks. This means that in week 26 brewing took place for both batches, and part of the batch was packaged 4 weeks later. However, for the sake of simplicity there is only worked with a production moment at week 26 for both batches. For this reason, not 3, but 2 extra production moments are taken into account for product 92318 besides the shared brew with product 92356 in week 22. According to the packaging data set, it can be assumed that product 92318 did not share its beer with other products during the production in weeks 7 and 26, since no other beers from the same beer stream were produced during a period of 2 weeks before and 2 weeks after these production moments. It can be noticed that at both production moments the minimum brewing volume has been produced, and so no early disposal took place. MinBrew batch size: X hectolitres.

Decision moment - week 5	Old model	Optimization model
Batch size (hL)	X	X
Early disposal (hL)	X	X
Early disposal costs	*€ X*	*€ X*
Expected overstocking costs	*€ X*	*€ X*
Total costs	***€ X***	***€ X***
Expected understocking (hL)	X	X

Table 30 Results before and after batch size optimization - product 92318 decision week 5

Decision moment - week 20	Old model		Optimization model	
Product	**92356**	**92318**	**92356**	**92318**
Batch size (hL)	X	X	X	X
Total batch size (hL)		X		X
Total early disposal (hL)		X		X
Total early disposal costs		*€ X*		*€ X*
Expected overstocking costs	*€ X*	*€ X*	*€ X*	*€ X*
Total costs		***€ X***		***€ X***
Expected understocking (hL)	X	X	X	X

Table 31 Results before and after batch size optimization - products 92356 and 92318 with shared brew stream at decision week 20

Decision moment - week 24	Old model	Optimization model
Batch size (hL)	X	X
Early disposal (hL)	X	X
Early disposal costs	*€ X*	*€ X*
Expected overstocking costs	*€ X*	*€ X*
Total costs	***€ X***	***€ X***
Expected understocking (hL)	X	X

Table 32 Results before and after batch size optimization - product 92318 decision week 24

Products 92376 & 92378 from same matured- and filtrated beer stream

Product 92376 encountered 1 production moment during the year 2019 that had a final delivery date within that same year, at week 34. Product 92378 encountered 1 production moment during the year 2019 that had a final delivery date within that same year, also at week 34. Both products belong to the same brew stream and so production of one brew destined for both products took place in week 34. MinBrew batch size: X hectolitres.

Decision moment - week 32	Old model		Optimization model	
Product	**92376**	**92378**	**92376**	**92378**
Batch size (hL)	X	X	X	X
Total batch size (hL)		X		X
Total early disposal (hL)		X		X
Total early disposal costs		*€ X*		*€ X*
Expected overstocking costs	*€ X*	*€ X*	*€ X*	*€ X*
Total costs		***€ X***		***€ X***
Expected understocking (hL)	X	X	X	X

Table 33 Results before and after batch size optimization - products 92376 and 92378 with shared brew stream at decision week 32

Products 92239 & 92089 from same matured- and filtrated beer stream

Product 92239 encountered 2 production moments during the year 2019 that had a final delivery date within that same year, at weeks 16 and 20. Product 92089 encountered 2 production moments during the year 2019 that had a final delivery date within that same year, at weeks 18 and 21. Both products belong to the same brew- and filtrated beer stream and production was shared for both of their production moments (took place at the earliest moment, so weeks 14 and 18), what means that postponement of packaging took place since packaging did not take place simultaneously. MinBrew batch size: X hectolitres.

Decision moment - week 14	Old model		Optimization model	
Product	**92239**	**92089**	**92239**	**92089**
Batch size (hL)	X	X	X	X
Total batch size (hL)		X		X
Total early disposal (hL)		X		X
Total early disposal costs		*€ X*		*€ X*
Expected overstocking costs	*€ X*	*€ X*	*€ X*	*€ X*
Total costs		***€ X***		***€ X***
Expected understocking (hL)	X	X	X	X

Table 34 Results before and after batch size optimization - products 92239 and 92089 with shared brew stream at decision week 14

Decision moment - week 18	Old model		Optimization model	
Product	**92239**	**92089**	**92239**	**92089**
Batch size (hL)	X	X	X	X
Total batch size (hL)		X		X
Total early disposal (hL)		X		X
Total early disposal costs		*€ X*		*€ X*
Expected overstocking costs	*€ X*	*€ X*	*€ X*	*€ X*
Total costs		***€ X***		***€ X***
Expected understocking (hL)	X	X	X	X

Table 35 Results before and after batch size optimization - products 92239 and 92089 with shared brew stream at decision week 18

Products 92298 & 92306 from same matured- and filtrated beer stream

Product 92298 encountered 2 production moments during the year 2019 that had a final delivery date within that same year, at weeks 5 and 28. Product 92306 encountered 2 production moments during the year 2019 that had a final delivery date within that same year, at weeks 9 and 28. Both products belong to the same brew- and filtrated beer stream. According to the packaging data of 2019, it is assumed that production of both products was shared at week 28, and together they met the minimum brewing volume at this production moment. Since there are 4 weeks between the remaining first production moments of both products, and since the products do not share their beer with any other products, it is assumed that at these production moments the products did not share their beer with each other or other products. It can be noticed from the packaging data that product 92298 complied with the minimum brewing volume at week 5, and so it can be assumed no early disposal took place for this production moment. However, when diving into the sales forecast data, it can be noticed that there is no sales forecast available for product 92306 during a period of 4 weeks before and 2 weeks after the production moment of week 9. This is quite strange since it is a question why the amount of 120 hectolitres is produced at week 9. Besides this, unfortunately, our model does not work without sales forecast data. For this reason it is decided to leave this production moment aside during this research. However, it needs to be kept in mind that probably even some more obsolescence could have been avoided, by applying optimization at this production moment.

Decision moment - week 3	Old model	Optimization model
Batch size (hL)	X	X
Early disposal (hL)	X	X
Early disposal costs	*€ X*	*€ X*
Expected overstocking costs	*€ X*	*€ X*
Total costs	***€ X***	***€ X***
Expected understocking (hL)	X	X

Table 36 Results before and after batch size optimization - product 92298 decision week 3

Decision moment - week 26	Old model		Optimization model	
Product	**92298**	**92306**	**92298**	**92306**
Batch size (hL)	X	X	X	X
Total batch size (hL)		X		X
Total early disposal (hL)		X		X
Total early disposal costs		*€ X*		*€ X*
Expected overstocking costs	*€ X*	*€ X*	*€ X*	*€ X*
Total costs		***€ X***		***€ X***
Expected understocking (hL)	X	X	X	X

Table 37 Results before and after batch size optimization - products 92298 and 92306 with shared brew stream at decision week 26

Appendix VIII: Extra set up costs due to optimization

In order to give an indication about the impact of optimization on the increased chance of running out of stock, for the 8 optimized production moments mentioned in Table 9 of Chapter 4.4 - where early disposal and/or a redivision of beer took place in order to save costs – in this appendix the extra set up costs due to optimization is estimated. As already discussed in Chapter 4.4, this will be done per production moment of a product. This means that every time an optimized batch size of a production moment is taken into account, the batch sizes of the other production moments of that same product are kept constant (remain their actual value) since we look at every production moment separately.

Per optimized production moment the total yearly production volume of that particular product for the year 2019 (after optimization of only 1 particular production batch size and keeping constant the actual batch sizes of the other production moments) is subtracted from the actual yearly demand (sales) of that particular product for the year 2019. In this way, per optimization of 1 production moment of a product, and assuming all other production moments stayed the same, the remaining production volume of a product that would have been necessary for the year 2019 can be calculated.

As one can imagine, sometimes the actual demand during the year 2019 appears to be higher than the total production volume that year, even when taking into account an optimized production moment. In these cases the remaining necessary production volume equals zero and no extra set up costs have to be charged for that particular production moment (€ 0).

With help of earlier determined remaining necessary production volumes and the minimum brewing volumes of products, the amount of extra reproduction moments can be calculated. However, not al extra set up costs for those reproduction moments are charged for the year 2019, but they are divided pro rata over the year 2019 and the following year. This means that only part of the set up costs belonging to the part of the extra produced volume that is needed during the year 2019 (remaining necessary volume/ MinBrew) is taken into account, and is multiplied with the average set up time and costs per hour of the production line. Ultimately, this results in the estimated extra set up costs for a product for the year 2019, after the optimization of 1 production moment of that product. These extra set up costs are then subtracted from the earlier determined cost savings due to optimization of that particular production moment, resulting in the final cost savings.

Note: often for only one product of the product pair the batch volume has been decreased during optimization. If this was the case, only this product is mentioned in between brackets after the week number in the table, and only for this product extra set up costs have been calculated. Here after these extra costs are subtracted from the pairs' earlier calculated cost savings due to optimization. If the batch volumes of both products of a product pair had been decreased during optimization, the extra needed production volumes are calculated for both products separately, where after the amount of extra production moments and its corresponding set up costs are calculated for both products together (assuming that they will be produced together), and are subtracted from the pairs' earlier calculated cost savings due to optimization.

SKU 92301 – prod. line 2	Wk. 3	Wk. 15
Actual demand '19	X hL	X hL
Production '19 after optimization	X + X = X hL	X + X = X hL
Remaining necessary volume	X hL	X hL
MinBrew	X hL	X hL
# extra reproduction moments	0	0
Average set up time of line	X min.	X min.
Set up costs per hour of line	€ X/ h	€ X/ h
Average set up costs of line	€ X	€ X
Estimated extra set up costs	(X/ X) * € X= € X	(X/ X) * € X= € X
Cost savings due to optimization	€ X	€ X
Final cost savings/ losses	*€ X - € X = € X*	*€ X - € X = € X*

Table 38 Estimation of extra set up costs per production moment due to optimization - SKU 92301 wk. 3 & wk. 15

SKU 92356 & 92318 - prod. line 7	Wk. 20 (92356)
Actual demand '19	X hL
Production '19 after optimization	X hL
Remaining necessary volume	X hL
MinBrew	X hL
# extra reproduction moments	1
Average set up time of line	X min.
Set up costs per hour of line	€ X/ h
Average set up costs of line	€ X
Estimated extra set up costs	(X/X) * € X = € X
Cost savings due to optimization	€ X
Final cost savings/ losses	*€ X - € X = - € X (loss)*

Table 39 Estimation of extra set up costs per production moment due to optimization - SKUs 92356 & 92318 wk. 20

SKU 92318 – prod. line 4	Wk. 5
Actual demand '19	X hL
Production '19 after optimization	X hL
Remaining necessary volume	X hL
MinBrew	X hL
# extra reproduction moments	2
Average set up time of line	X min.
Set up costs per hour of line	€ X/ h
Average set up costs of line	€ X
Estimated extra set up costs	(X/X) * € X = € X
Cost savings due to optimization	€ X
Final cost savings/ losses	*€ X - € X = € X*

Table 40 Estimation of extra set up costs per production moment due to optimization - SKU 92318 wk. 5, 24 and 28

SKUs 92376 & 92378 - prod. line 4	Wk. 20 (92378)
Actual demand '19	X hL
Production '19 after optimization	X + X = X hL
Remaining necessary volume	X hL
MinBrew	X hL
# extra reproduction moments	0
Average set up time of line	X min.
Set up costs per hour of line	€ X/ h
Average set up costs of line	€ X
Estimated extra set up costs	(X/ X) * € X= € X
Cost savings due to optimization	€ X
Final cost savings/ losses	*€ X - € X = € X*

Table 41 Estimation of extra set up costs per production moment due to optimization - SKUs 92376 & 92378 wk. 20

SKUs 92239 & 92089 – prod. line 2	Wk. 14 (92239)	Wk. 18 (92089)
Actual demand '19	X hL	X hL
Production '19 after optimization	X hL	X hL
Remaining necessary volume	X hL	X hL
MinBrew	X hL	X hL
# extra reproduction moments	1	1
Average set up time of line	X min.	X min.
Set up costs per hour of line	€ X/ h	€ X/ h
Average set up costs of line	€ X	€ X
Estimated extra set up costs	(X/X) * € X = € X	(X/X) * € X = € X
Cost savings due to optimization	€ X	€ X
Final cost savings/ losses	*€ X - € X = - € X (loss)*	*€ X - € X = € X*

Table 42 Estimation of extra set up costs per production moment due to optimization - SKUs 92239 & 92089 wk. 14 & wk. 18

SKUs 92298– prod. line 2	Wk. 3
Actual demand '19	X hL
Production '19 after optimization	X hL
Remaining necessary volume	X hL
MinBrew	X hL
# extra reproduction moments	0
Average set up time of line	X min.
Set up costs per hour of line	€ X/ h
Average set up costs of line	€ X
Estimated extra set up costs	(X/X) * € X = € X
Cost savings due to optimization	€ X
Final cost savings/ losses	*€ X - € X = € X*

Table 43 Estimation of extra set up costs per production moment due to optimization - SKU 92298 wk. 3

<table>
<tr><th>SKUs 92298 & 92306
– prod. line 2</th><th>Wk. 26 (92298)</th><th>Wk. 26 (92306)</th></tr>
<tr><td>Actual demand ‘19</td><td>X hL</td><td>X hL</td></tr>
<tr><td>Production ’19 after optimization</td><td>X + X = X hL</td><td>X hL</td></tr>
<tr><td>Remaining necessary volume</td><td colspan="2">X + X = X hL</td></tr>
<tr><td>MinBrew</td><td colspan="2">X hL</td></tr>
<tr><td># extra reproduction moments</td><td colspan="2">1</td></tr>
<tr><td>Average set up time of line</td><td colspan="2">X min.</td></tr>
<tr><td>Set up costs per hour of line</td><td colspan="2">€ X/ h</td></tr>
<tr><td>Average set up costs of line</td><td colspan="2">€ X</td></tr>
<tr><td>Estimated extra set up costs</td><td colspan="2">(X/X) * € X = € X</td></tr>
<tr><td>Cost savings due to optimization</td><td colspan="2">€ X</td></tr>
<tr><td>Final cost savings/ losses</td><td colspan="2">€ X - € X = € X</td></tr>
</table>

Table 44 Estimation of extra set up costs per production moment due to optimization - SKUs 92298 & 92306 wk. 3 & wk. 26