Thesis

An Optimization of the Reorder Policy at Turff

BSc Industrial Engineering and Management

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PREFACE

Dear reader,

You are about to start reading my thesis on: 'an optimization of the reorder policy of Turff'. Within this thesis, we focused on the inventory management of Turff and especially the reorder process of the products offered through the delivery service of Turff's warehouse located in Delft. In the period between the end of September 2022 until the transition week from January to February 2023, I performed my internship at the company.

I would like to thank everyone who supported me during the setup period of the research, the research period itself, and the period of writing this thesis. In particular, my first supervisor Dennis Prak who supported me throughout this thesis and helped me to finish the thesis by the end of the first semester. During the meetings we always discussed in detail the topics included in this thesis and he always provided his considerations on my work in a very constructive way. Critical, but most importantly useful feedback was always provided. In addition, his door was always open where I could address my questions. Again, thank you very much for your support. Secondly, I would like to thank Wouter van Heeswijk for being my second supervisor and for providing a crucial evaluation during the last phase of the thesis, in addition to the feedback I had received by Dennis Prak. The feedback provided by you both brought my thesis to this final version.

Finally, a big thank you to Luke Marijnissen, Head of Deliveries at Turff. He was always supportive, highly interested in the results, and he believed in my research. Through Luke I met the company and its employees and always felt welcome at the office. When I needed something from Turff, for example the sales data or a description of the reorder policy, Luke helped me out. Additionally, he was always very open-minded about implementing the findings of this research into the company.

I genuinely hope you enjoy reading my thesis, where I wish you gain knowledge on the research approach, the research itself, and its results. Furthermore, I hope to inspire you to possibly implement my approach in practice.

Yours sincerely,

Yonah Bergsma

Enschede, February 2023

MANAGEMENT SUMMARY

Turff is a Dutch start-up run by students, providing a service of financial insight in the form of a tablet keeping track of consumption within a community. In addition to this service, Turff offers a delivery service of multiple products consisting of beer crates, seltzers, and sodas. A problem Turff is facing since they have included the delivery service is, on the one hand too many stockouts on a yearly basis, and on the other hand too large inventory levels resulting in stationary cash flows. This problem is caused by the execution of a poor reorder policy. Therefore, the core problem which is aimed to be tackled within this research is formulated as follows:

"Turff is managing their inventories based on a poor reorder policy, which is caused by too many oversupply and undersupply occurrences."

Hence, the aim of this research is to provide a new reorder policy that reduces the number of oversupplies and undersupplies for the 6 different observation objects (*Pils A, Pils B, Seltzer A, Seltzer B, Seltzer C,* and *Frisdranken*). Since the current reorder policy of Turff is only based on historical data in combination with experience of the Inventory Manager employee, demand forecasting considering explanatory variables (Exam, Holiday, Introduction, and Party Weekday) is used to obtain a new policy. From this perspective, the research was started, where first the performance of Turff was determined in the form of the *Cycle Service Level (CSL)*, where a normal distribution of demand was assumed. This *CSL* is an inventory performance theory which indicates the probability of no stockout in a replenishment cycle. To measure the *CSL,* all products were separated into different observation objects which were analyzed and for which calculations were performed throughout the thesis. For each observation object the current performance was calculated, where the *CSL* for *Pils A* equals 48.86%, *Pils B* 75.44%, and the remaining observation objects equal approximately 97.50%. Based on these findings, the required norms were set per observation object in the form of a *CSL* again and were equal to 90.00% for *Pils A,* and *Pils B* and 99.00% for the remaining observation objects. The specified norms state the goal we aim to reach when testing the new reorder policy.

Once the norms are set, the demand forecasting phase of the research was performed. Within the demand forecast, the explanatory variables (Exam, Holiday, Introduction, and Party Weekday) must be included. Therefore, literature review was performed to obtain suitable demand forecasting model and select the most applicable one. The model used to forecast the demand is known as the Autoregressive Distributed Lags (ADL) model, which is a linear regression model allowing the inclusion of explanatory variables.

After applying the forecasts per observation object, we found that the Holiday Weekday had a negative effect on the demand for all observation objects, except for *Frisdranken* which was positively influenced at a significance level of 90%. For *Pils A, Seltzer A,* and *Seltzer C*, we found that the Introduction Weekday had a significant positive effect whereas for *Pils A*, and *Seltzer C* the Exam Weekday had a significant negative effect. None of the observation objects was affected significantly by the Party Weekday explanatory variable.

Furthermore, from combining the demand forecasting phase with the inventory performance theory we created a new reorder policy. This policy considers the demand forecast, required *CSL*, and the fluctuation between the actual demand and the forecasted demand. From testing this reorder policy for each observation object, we found that the new policy resulted in a lower *CSL* than required for *Pils B, Seltzer C,* and *Frisdranken,* whereas for *Pils A, Seltzer A,* and *Seltzer B* the opposite result was obtained.

CONTENTS

ABBREVIATIONS

Abbreviations	
Symbol	**Description**
CSL	Cycle Service Level
ROP	Reorder Point
$\boldsymbol{D_L}$	Average Lead Time Demand
$\boldsymbol{\sigma_L}$	Standard Deviation of Lead Time Demand
D	Average Daily Demand per Week
$\boldsymbol{D_n}$	Actual Daily Demand on Day *n*
σ	Standard Deviation of Demand
L	Lead Time
$\boldsymbol{D_w}$	Actual Weekly Demand in Week *w*
$\boldsymbol{D_t}$	Forecasted Daily Demand on Day *t*
ss	Safety Stock
MSE	Mean Squared Error

1. PROBLEM SELECTION

For the starting phase of the research, it is important to acquire knowledge on the company. We provide a brief description of Turff, in which we elaborate on the product and services provided by the company and describe the operating locations of the company. One should keep in mind that within start-up companies such as Turff there are often multiple problems to issue, but not all of them are always influenceable. Therefore, we need to review possible problems at Turff and narrow them down to a more restricted range. By linking these problems an overview of the problems is created and a core problem, which is influenceable by Turff itself, can be selected for the purpose of this research. Within this section, each of the mentioned topics is discussed and the selected problem is quantified, so it is measurable throughout the entire research.

1.1 INTRODUCTION OF TURFF

Turff is a fast-growing start-up founded by a group of students of the TU Delft. This group of students was searching for a solution to the old-fashioned way of keeping track of multiple products used within student houses and, therefore, developed a tool, that could be used as a tablet application, to tackle this problem. Currently, Turff tablets are used in over 1.900 student houses, that equals to 18.000 active users. Users are mainly students and are distributed over the following 15 Dutch university cities: Delft, Leiden, Rotterdam, Amsterdam, Utrecht, Nijmegen, Wageningen, Eindhoven, Tilburg, Enschede, Groningen, Den Haag, Breda, Maastricht, and Leeuwarden.

In general, the tablet provides financial insight to the users. Within student houses there are multiple products for general use (think of beers, soft drinks, coffee, etc.). To keep track on how much every consumer of a certain group has used from the shared products, one should update their tally once a product has been consumed. Automatically, the personal balance of the one of which tally went up is updated as well. Thus, a financial overview over users of a certain group/household is created. Signing up for the Turff tablet is free of charge, however, an initial deposit of €60 as well as €20 for installation of the tablet on the wall is being charged. Besides these costs, the use of the tablet is for free. Moreover, the tablet remains on 24/7 and as it is not continuously in use, it displays advertisements as a screensaver. This represents the main part of the business model of Turff.

In addition to the tablet, Turff has developed a mobile application (available in App Store and Google Play). As mentioned before, users being linked to the same tablet can tally products when these are consumed. This tallying system can be performed directly on the tablet itself or can be executed on one's phone via the mobile application. Furthermore, the mobile application has an 'eetlijst' feature. On the 'eetlijst' feature, each user of the same tablet can indicate whether he will participate at the diner that evening. Next to this option, there are two additional options which can be selected in the 'eetlijst' feature of the mobile application. These refer to whether the user will cook or not and whether he will do the groceries or not. This useful tool enables an easy insight in the dining situation in a household on a daily basis.

The Turff tablet ensures that all users can keep track of the balances, expenses, and inventories. All these topics are displayed on the dashboard. Balances and inventories can be updated within this feature. This ensures that real-time updates and therefore, insights can be obtained at any moment. The user is able to easily export the data from this dashboard to Microsoft Excel, which might be useful for accounting purposes.

Over time Turff has expanded and implemented a delivery service consisting of products such as beers, specialty beers, and soft drinks. Currently, Turff is delivering orders in Delft, Leiden, Rotterdam, Utrecht, and Enschede on a daily basis. Furthermore, the company is delivering orders in Tilburg, Eindhoven, and Amsterdam on a weekly basis. The largest warehouse and the office of the company are both located in Delft. This warehouse is responsible for all the orders from Rotterdam, Leiden, and Delft itself. In the future Turff is focusing on expanding their delivery service to more cities. Users of the app or webshop of Turff, can easily place orders.

Since Turff recently started with a delivery service their inventory management is not optimized and there is room for improvement. The main hub of Turff is in Delft, from where they run the delivery service in Delft, Rotterdam, and Leiden. This is also the largest warehouse of Turff and therefore the most interesting one to focus on. Within the following section we will elaborate on a way to improve an inventory management process related to the warehouse in Delft.

1.2 MANAGEMENT PROBLEM

Every month, many new consumers start using the services of Turff, including the delivery service of Turff. Regarding this delivery service, Turff encounters multiple issues which must be considered in the inventory management of the company. Currently Turff is facing too many stockouts on a yearly basis for products such as beer crates. These stockouts cause stressful situations at Turff since orders cannot be delivered on time. In that situation, the delivery staff of the company must purchase the products by themselves at the supplier, to ensure that a part of the orders can be delivered. Furthermore, in case of a stockout, the customers are not able to order the products at Turff during that period. This causes missed cashflow for the company.

On an annual basis there are multiple weeks where sales are expected to be higher or lower than average and therefore have a higher probability of stockouts, since stock levels fluctuate over the year. Think of holidays, exam periods, and introduction periods (at (Applied) Universities). However, these are currently not considered within the demand forecasting and reorder policy of the company.

The motivation for this research is directly related to the multiple times Turff has faced a situation in which products were out of stock in the Delft warehouse. We investigated the main cause of this problem, in order to evaluate from which perspective the problem can be optimally approached.

1.3 PROBLEM IDENTIFICATION

Turff is facing multiple issues regarding inventory management causing stockouts, as mentioned in the previous section. The is the basis for the identification phase of the management problem (Heerkens & Van Winden, 2017). Therefore, within this section we will list the problems and elaborate on these briefly. All these problems can be categorized in a predictable as well as in an unpredictable group.

The unpredictable group consists of problems that are difficult to be solved by the Turff staff due to lack of data. These problems are mainly influenced by external factors. The first factor that causes problems in the inventory of Turff is the reliability of the supplier. Situations may occur where the supplier either delivers an incorrect number of products to the warehouse or is not able to deliver the products to the warehouse. Additionally, the expiration date of products should be considered as well, that might be a result of oversupply. These products are kept in the warehouse for an extensive period of time, and therefore their expiration date exceeds. In this situation all these products will be inevitably discarded. Since there is no overview of the expired products at Turff, incorrections in the inventory are caused.

Lastly, no registration occurs for products that are damaged upon delivery at Turff and therefore, no overview of such products is available. When loading and unloading a van or truck, it might be the case that a product gets dropped accidentally leading to a damaged, and therefore, to an unmarketable product. Since this is not registered, the inventory is not correct. Because of these incorrections, it is also not clear if products get stolen from the warehouse by the staff. However, if products are stolen from the warehouse, the incorrectness of the stock levels is even larger.

Next to the unpredictable factors for which data is unavailable, there are also predictable factors which can be influenced by Turff. From the predictable perspective, problems causing oversupply and undersupply can be found. These issues are caused by the current reorder policy of Turff. The variables mainly influencing the reorder process are the reorder point and the reorder size, which we expect to be affected by predictable factors such as holiday periods, exam periods, and introduction periods. Currently, stockouts occur too often and therefore the reorder policy deserves improvement.

All the issues mentioned before are causes for the effects of an incorrect inventory and undersupply causing stockouts. Combining these issues, the basis for the management problem is formed and the management problem is stated as:

Management problem: *The inventory management processes of Turff are not optimized, which causes stockouts and excessive inventory.*

1.4 PROBLEM CLUSTER

When foccusing on the causes of this management problem, multiple issues can be considered. Due to their categorization in an unpredictable and predictable group, the selection process of the core problem becomes easier. As it has been previously suggested, non-influenceable problems should not be selected as a core problem (Heerkens & Van Winden, 2017). Therefore, the scope of this research should be clarified.

1.4.1 SCOPE OF RESEARCH

From the problem identification, multiple issues have been obtained. Therefore, the number of issues should be narrowed down in order to focus on one specific core problem.

Since the problems have been categorized in a predictable and unpredictable group, the boundaries were set easily. Unpredictable issues such as the reliability of the supplier, expiration date of products and damaged products upon delivery, were considered out of the scope for this research, because Turff did not possess any data on these factors. We could still anticipate on them by making assumptions, however, for simplicity reasons, we considered them beyond the scope of the research. Therefore, the scope of this research would be concentrated on the issues within the predictable category, consisting of the reorder point and the reorder size. Due to time limitations, however, the reorder size was considered beyond the scope of this research, and we only focussed on the reorder point.

The current reorder point of Turff can be expressed by multiple variables such as cycle service level *(CSL)* and fill rate *(FR)*. Currently, during an out-of-stock period, Turff applies an emergency solution where they send each van to the wholesaler to buy the products over there and still deliver the orders on time. This implies that the usage of a *CSL* is applicable, since the company does not have a strict procedure at the moment which should be followed in case of a stock out. Furthermore, with some pre-knowledge on reorder points and reorder sizes, we knew that the reorder size did not represent essential information when focusing on the *CSL* and trying to find the reorder point. This was obtained from the following equation:

$$CSL = F_S\left(\frac{ROP - D_L}{\sigma_L}\right)$$

Obviously, the *CSL* is dependent on the reorder point (ROP), average demand during lead time (D_L), and the standard deviation of lead time demand (σ_L). According to Chopra & Meindl (2004), the lot size (Q) is not influencing the reorder point (*ROP*). Therefore, focusing on the reorder point by ignoring the order size was applicable for this research. Regarding the reorder point, factors such as holiday weeks, exam periods, and introduction periods should be considered in this research. As the scope within this research has been further clarified now, the core problem was defined as follows:

Core problem: *Turff is managing their inventories based on a poor reorder policy, which causes too many oversupply and undersupply occurrences.*

To clarify the cause-effect relations between the different problems, we provided a problem cluster as illustrated in Figure 1.

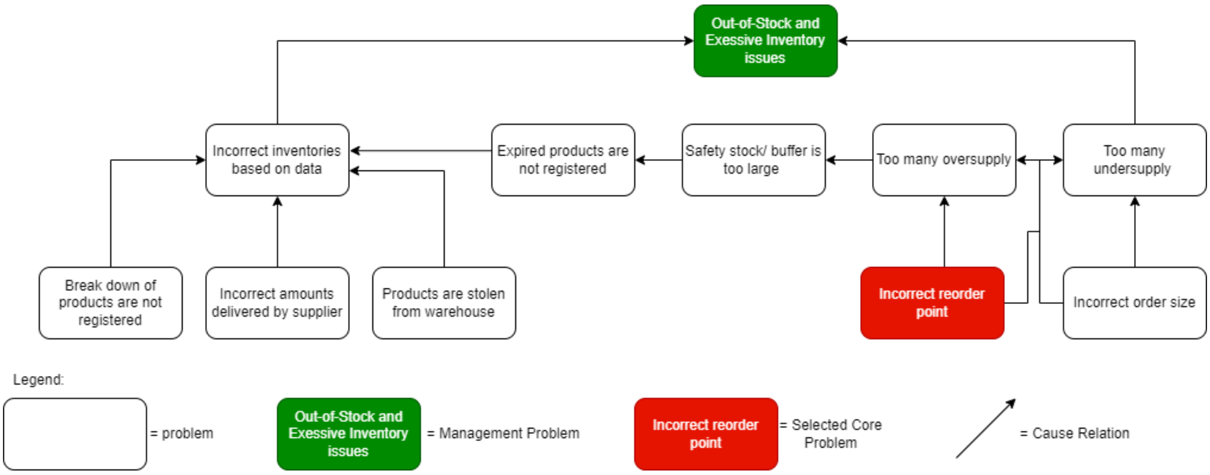

Figure 1- Problem Cluster

The selected core problem should be made quantifiable in order to be measurable. Therefore, the core problem has been quantified in the next section.

1.5 QUANTIFY THE CORE PROBLEM

To quantify the core problem, a variable has been selected to measure the reorder policy performance of Turff. After having selected this variable, it's norm and reality was defined. The expectation was that the gap between the set norm and the reality should clarify the core problem (Heerkens & Van Winden, 2017).

Currently, in case of stockouts, Turff uses an emergency solution. Since the orders placed by the customers should always be delivered on time, the company sends the delivery staff with the vans to the supplier to purchase the products, ensuring the order can be fulfilled. As we have indicated in 1.4, the *CSL* is the variable to make the defined core problem measurable. In the current situation, Turff is performing on a certain cycle service level (*CSL*) for each product, which was investigated in the following sections. In this way the reality of the problem statement was described. The value of this cycle service level (*CSL*) was assessed during the first phase of the research. Additionally, the norm of the company was to perform on improved cycle service levels (*CSL*) which was stated after the current *CSL*s were assessed. This has been realized by considering a new reorder policy. In the following sections, a new reorder policy was investigated which has also been evaluated and compared to the performance of the current reorder policy.

At that moment, only the current reorder policy of Turff was known. Given this reorder policy, the required *CSL* describing the reality could be found. Therefore, the following formula was required:

$$CSL = F_s\left(\frac{ROP - D_L}{\sigma_L}\right)$$

Where the cumulative distribution function is a normal distribution (Chopra & Meindl, 2004). One might notice that the D_L and σ_L represented the unknown variables. Where D_L is the average lead time demand per day during a certain week and σ_L is the standard deviation of lead time demand during a certain week. These have been first calculated to be able to finally estimate the *CSL*. Using the data sets provided by Turff, the average demand D and σ standard deviation of demand could be calculated using the following formulas:

$$D = \frac{\sum_{n=1}^{N} D_n}{N}$$

$$\sigma = \sqrt{\frac{\sum_{n=1}^{N} (D_n - D)^2}{N}}$$

Since these formulas provided the average demand and standard deviation of the demand, where the average lead time demand and standard deviation of lead time demand were required, two additional calculations have been performed (Chopra & Meindl, 2004).

$$D_L = D * L$$

$$\sigma_L = \sqrt{L} * \sigma$$

Implementing the *ROP* of Turff and these two variables into the previous described equation on the *CSL*, the performance values have been determined. These values actually described the reality at Turff and have been assessed in the following section.

2. CURRENT PERFORMANCE OF TURFF

Turff is currently ordering products according to a certain reorder policy. This reorder policy causes stockouts more often than the company actually would like them to occur. Therefore, the management problem within this thesis has been stated as: "*There is room for improvement within the inventory management processes of Turff, which causes stockouts.*"

Within the first phase of this research, the business understanding phase has been performed. It has been of great importance to create a clear overview of the current performance of Turff and therefore we have evaluated the *CSL* displaying the reality of Turff's performance.

An evaluation of the current situation has been conducted which was used during the final state of the research for the comparison with the performance of the obtained solution. Categorizing the products of Turff has been the first step during this process. Each product was categorized based on its characteristics.

2.1 PRODUCT CATEGORIZATION

Since Turff has been using a different reorder policy for their various web shop products, all products were categorized in three categories, These categories consisted of *Pils* (Dutch for beer), *Seltzers,* and *Frisdranken* (Dutch for sodas) (Table 1). Based on the relevance of each product, distinction has been made between either creating a separate object of observation for a specific product or a collection object of observation for multiple low sales products.

Firstly, all the *Pils* categories were defined. There were multiple labels of beer crates offered by Turff, but since only two beer crate labels represented the main selling beer offered in the web shop of Turff, a *Pils A* and *Pils B* has been created. The additional category consisted of the *Seltzers*. Currently, Turff is offering 3 different labels of seltzers on the web shop. Therefore, three separate seltzer objects were created referred to as *Seltzer A*, *Seltzer B*, and *Seltzer C*. Additionally, the remaining products have been categorized as *Frisdranken* where the assumption has been introduced in this research that the customer did not have a preference for a specific sort of soda. This assumption was made since different sorts of sodas were regularly ordered at Turff in one batch. Additionally, although there were many different sodas offered by Turff, they represented relatively low sales records. Therefore, sodas were categorized as a collection object and *Frisdranken* refered to all the different sodas which could be ordered in the Turff web shop.

Products overview	
Category	**Observation object**
Pils	• *Pils A* • *Pils B*
Seltzers	• *Seltzer A* • *Seltzer B* • *Seltzer C*
Frisdranken	• *Frisdranken*

Table 1 - Product Categorization

To evaluate the current performance of Turff based on the categories defined here above (Table 1), the contemporary reorder policy of Turff has been clarified. The reorder policies of the three categories were found not equal in all cases and have been described in the following section.

2.2 CURRENT REORDER POLICY OF TURFF

At this time, Turff is applying different reorder policies for the three categories described in the previous section. These reorder policies of the three product categories could be classified into two types of policies, either a (*R,S*)-reorder policy or a (*s,Q*)-reorder policy. Per category the reorder policy has been analyzed and classified as (*R,S*)-policy or (*s,Q*)-policy.

The (*R,S*)-policy was only applied by Turff as a reorder policy for the *Pils* category. When using a (*R,S*)-policy the inventory was refilled up to a level *S* by placing an order after time *R*. At that time, Turff was ordering *Pils A and Pils B* according to this (*R,S*)-policy (Tempelmeier, A procedure for the approximation of the waiting time distribution in a discrete-time (r, S) inventory system, 2017). The Inventory Manager was specifying the level *S* based on the highest sales week over the previous two months (approximately 8 weeks, so 7*8=56 days). After a period *R* of one week an order was placed and there was ordered up to that level *S*, based on the weekly number of sales over the previous 2 months. Therefore, the reorder point has been stated as:

$$ROP = \max\left(D_{w-1}, \dots, D_{w-8}\right) - D_w$$

Additionally, the (*s,Q*)-policy was applied by Turff on the other two categories, consisting of *Seltzers* and *Frisdranken*. When using a (*s,Q*)-policy, the moment of replenishment depended on the size of the reorder point *s*, however the order size *Q* remained constant over time (Tempelmeier, Inventory-Management, 2018). The Inventory Manager kept track of the inventory of the products in the warehouse categorized in the *Seltzers* and *Frisdranken* group. Once the inventory reached a level below the reorder point *s*, a replenishment of *Q* was realized. The reorder point *s* was determined by searching for the number of products sold during the highest sales week and multiplying this by 2. The size *Q* of each replenishment remained constant, which for these products has been set to one pallet of products (converted equal to 90 units). Therefore, the reorder point for the products categorized in either the *Seltzer* or *Frisdranken* has been stated as:

$$ROP = \max(D_{w-1}, \ldots, D_1) * 2$$

These two types of reorder policies have been applied later in section 2.4 on the approach during the evaluation of the current performance of Turff.

2.3 DISTRIBUTION OF DEMANDS

As mentioned in section 1.4, the performance value of Turff has been expressed as the cycle service level *(CSL).* Since the parameter demand was assumed to be normally distributed, it has been tested whether this assumption has been valid and thus applicable in this research. Therefore, the distribution of demand for *Pils A* over a period of time in 2021-2022 (in weeks) is presented in Figure 2, where the number of Pils A product sold during a specific week has been demonstrated.

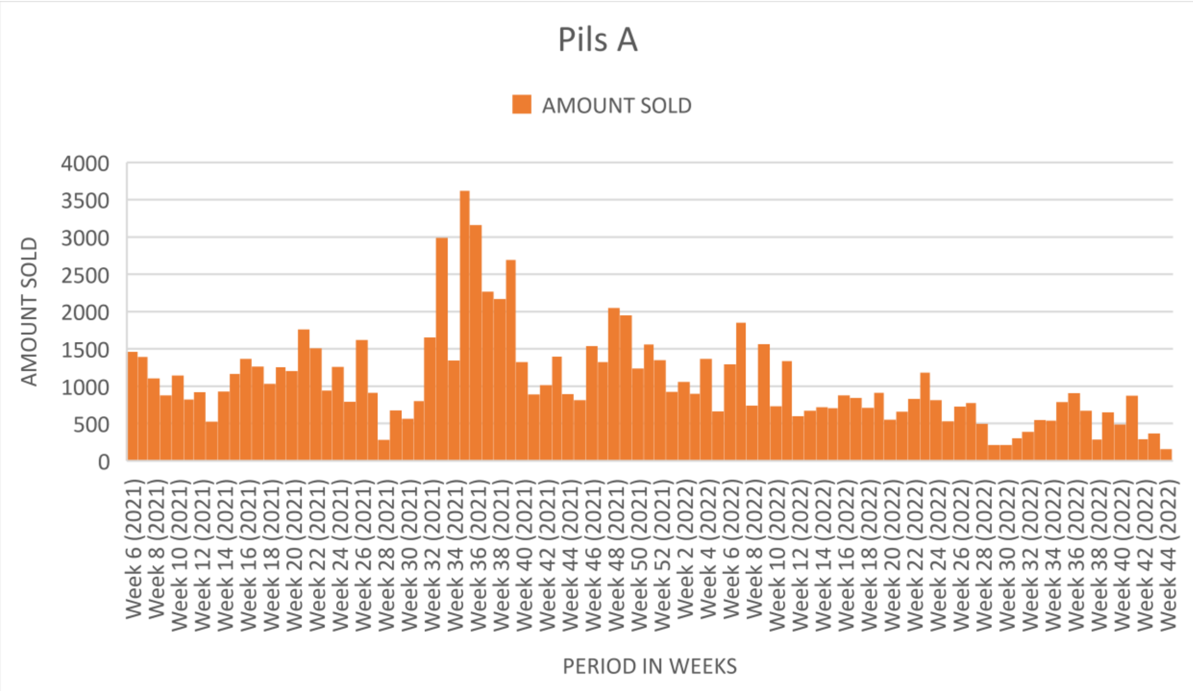

Figure 2 - Demand per Week of Pils A

Additionally, Figure 2 has been shown to be useful later during the research on the evaluation of the influence of the predictable factors as described in section 1.3.1.

Since we assumed that the parameter demand was following a normal distribution, two tests on normality were performed, to check if the null hypothesis of normal distribution in the populations could be rejected. These two tests consisted of both the Kolmogorov-Smirnov and Shapiro-Wilk tests. It is well demonstrated that the Shapiro-Wilk test quantifies the similarities between a normal distribution and the observations as a single number (Ghasemi & Zahediasl, 2012). Additionally, it is able to calculate the percentages which our sample overlaps with the normal curve. Similarly, the Kolmogorov-Smirnov test determines whether an expected distribution is suitable, and it calculates the percentage of cases which deviate from the expected distribution, in this case the normal curve (Savage, 1997). Based on the Kolmogorov-Smirnov and the Shapiro-Wilk tests the null hypothesis of a normal distribution in a population can be rejected if $p < 0.01$. Within the test on normality a significance level of $\alpha = 0.01$ has been selected. A small p-value indicates a large deviation from the normal distribution. From these tests the p-values and outcomes on the rejection of the null hypothesis have been summarized in the Table 2 below:

TEST $\mathbf{H_0}$ of Normal Distribution in Population				
	Kolmogorov-Smirnov		**Shapiro-Wilk**	
Observation Object	**P-Value**	**Normally Distributed**	**P-Value**	**Normally Distributed**
Pils A	<0.001	No	<0.001	No
Pils B	0.005	No	0.001	No
Seltzer A	<0.001	No	<0.001	No
Seltzer B	<0.001	No	<0.001	No
Seltzer C	<0.001	No	<0.001	No
Frisdranken	<0.001	No	<0.001	No

Table 2 - Null Hypothesis of Normal Distribution Tests

Based on the outcome of the Kolmogorov-Smirnov and Shapiro-Wilk tests presented in Table 2, the conclusion can be drawn that the assumption of normal distribution is not valid regarding the demand of all the observation objects. Similarly, when a histogram was created for each individual product, the conclusion could be drawn that the demand does not follow a normal distribution. For example, the histogram of *Pils A* can be found in the Figure 3 below.

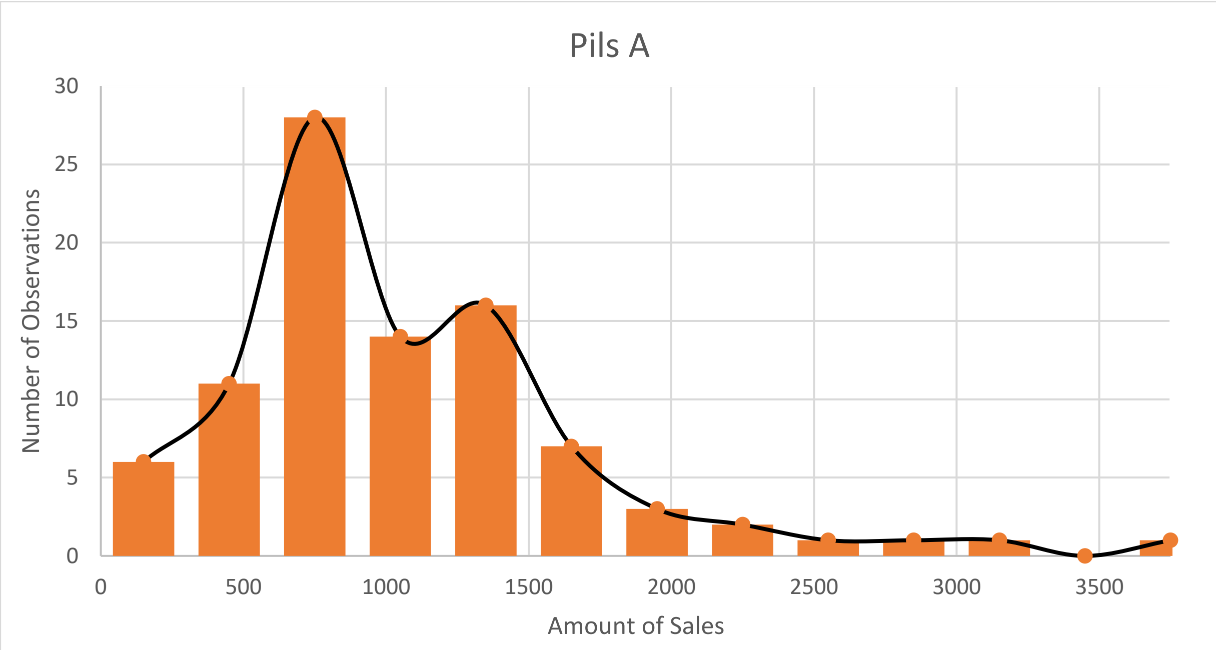

Figure 3 - Number of Observations per Number of Sales per Week

As observed in Figure 3 above, the distribution was found to be rather a gamma distribution than a normal distribution. However, for simplicity reasons the assumption of a normal distribution remained applicable in this thesis. Therefore, the calculations of the *CSL* where the cumulative distribution function is normal, has been applied in the following section.

2.4 THE APPROACH

When we computed the *CSL* of a certain observation object, there were multiple calculations which needed to be performed. A described overview of these formulas can be found in this section (2.4). For this phase of the research use of the following formula on the *CSL* has been made:

$$CSL = F_s\left(\frac{ROP - D_L}{\sigma_L}\right)$$

Where the cumulative distribution function follows a normal distribution. As one might obtain from the formula, the *CSL* is depending on three variables ROP, D_L, and σ_L. Using the reorder policy of Turff in section 3.2, the ROP of all the observation objects has been obtained from simulation. For *Pils A* and *Pils B* the highest sales week over the previous 8 weeks has been selected and subtracted by the number of sales in the first week. For example, in week 22 of 2022 Turff sold 2725.2 crates of beers of *Pils A* and sold 3232.8 crates during the highest sales week over the previous 8 weeks. For this week (22 in 2022):

$$ROP = 3232.8 - 2725.2 = 507.6$$

For *Seltzer A, B,* and *C,* and *Frisdranken,* the ROP was calculated easier. According to the reorder policies for these observation objects, the ROP was constant and equal to s. The two remaining variables D_L, and σ_L could only be obtained in case the lead times were known. Therefore, certain assumptions were made on the lead time to set an average lead time for each observation object and are described in the following section.

2.4.1 LEAD TIMES

From the formula on the *CSL* in the previous section, we could state that the lead time was required to calculate the average demand during lead time and standard deviation of lead time demand. Therefore, we have looked for the lead times per observation object. These lead times for each observation object were supplier dependent. For all the product categories of Turff, four types of suppliers existed and have been elaborated within this section.

After Turff placed the order for *Pils B* before a specific day, it reached the warehouse 4 days later. This indicated a lead time of 4 days (4/7 week). However, if the order was placed after a specific day, Turff should wait until that next specific day for the order to arrive, referring to a lead time of 7 days (7/7=1 week). Since most of the time orders were placed before this specific day, the average lead time for *Pils B* has been assumed to be 5 days (5/7 week). For *Pils A* the principle was the same. Since this situation was comparable to the case of *Pils B*, the same average lead time was assumed. Additionally, the supplier of *Seltzer A* used a lead time of 1 week approximately. Therefore, the average lead time for this observation object was assumed to be 7 days.

Finally, for the remaining observation objects the cycle time lasts longer. When these products were reordered, the products could reach the warehouse within 1 week but in some cases, it could take up to 3 weeks. After having taken an average of these two extreme values, a lead time of 2 weeks could be assumed. An overview of the lead times per observation object is presented in Table 3 below.

Lead Times per Observation Object		
Observation Object	**Lead Time (days)**	**Lead Times (weeks)**
Pils A	5	5/7
Pils B	5	5/7
Seltzer A	7	7/7
Seltzer B	14	14/7
Seltzer C	14	14/7
Frisdranken	14	14/7

Table 3 - Lead Times per Observation Object

Based on these lead times for each observation object, the average lead time demands, and standard deviations of lead time demand were calculated. In the following sections we elaborated on the calculations towards the *CSL,* after having our data cleaned up first.

2.4.2 AVERAGE LEAD TIME DEMAND

For the calculation of the *CSL* the average lead time demand D_L was needed, as we can conclude from the formula stated in section 3.4. For this purpose, we elaborated on the calculations on D_L in this section, using the provided daily sales data set by Turff.

For all the observation objects, the data on the number of sales per day has been viewed as the demand over the time. All daily demand D_n were summed to obtain the total amount of sales over the past week and was divided by the number of days *N* equal to 7, to determine the average demand per day during a certain week. This has been the general approach followed to obtain the average demand using the formula below.

$$D = \frac{\sum_{n=1}^{N} D_n}{N}$$

Currently the average demand per day during a certain week was obtained, but the average demand during lead time was required. Hence the following multiplication has been applied to the average demands per observation object:

$$D_L = D * L$$

The reorder points and average lead time demands were calculated at this stage of the *CSL* calculation process. As a last step, the standard deviations of lead time demand were required to finally calculate the *CSL* per observation object. Within the following section we discuss the approach followed to find these standard deviations.

2.4.3 STANDARD DEVIATIONS OF LEAD TIME DEMANDS

For the calculations of the standard deviation of lead time demands, the average lead time demands estimated in the previous section were required. For each observation on the demand, the average lead time demands were subtracted per week. By doing this, the deviation of each observation with the average was calculated and squared to prevent negative outcomes. Like with the calculation on the average lead time demands, the obtained value after summation was divided by the number of observations *N*. This was equal to the number of weeks that were observed. The outcome of this division was square rooted, and the standard deviation of the weekly demand was finally obtained. In general, the formula below has been applied.

$$\sigma = \sqrt{\frac{\sum_{n=1}^{N} (D_n - D)^2}{N}}$$

Since this formula was used to calculate the standard deviations of the demand per week, an additional calculation has been required to find the standard deviations of the demand during lead time. For this reason, the formula below was used.

$$\sigma_L = \sqrt{L} * \sigma$$

All the input variables required for the calculations of the *CSL* were obtained at this phase of the performance determination process. In the following section the findings on the variables were implemented in the formula of the *CSL* and the current performance of Turff became clear.

2.5 CYCLE SERVICE LEVELS

The approach to finally find the *CSL* for each observation object, was based on the *CSL* formula mentioned at the start of section 3.4. Like the process of calculating the average lead time demand and standard deviation during lead time demand, we calculated the *CSL*. Therefore, the assumption on a normal distributed demand was made and the function below has been used for the calculations:

$$CSL = F_s\left(\frac{ROP - D_L}{\sigma_L}\right)$$

The previously found ROP, D_L, and σ_L per week were implemented into the formula as input variables. According to the normal distribution, Microsoft Excel has been searching for the associated output variable that implies the *CSL*. By doing so, the *CSL* per week was obtained for each observation object. For example, the *CSL* per week over the previous period is presented in Figure 4 below.

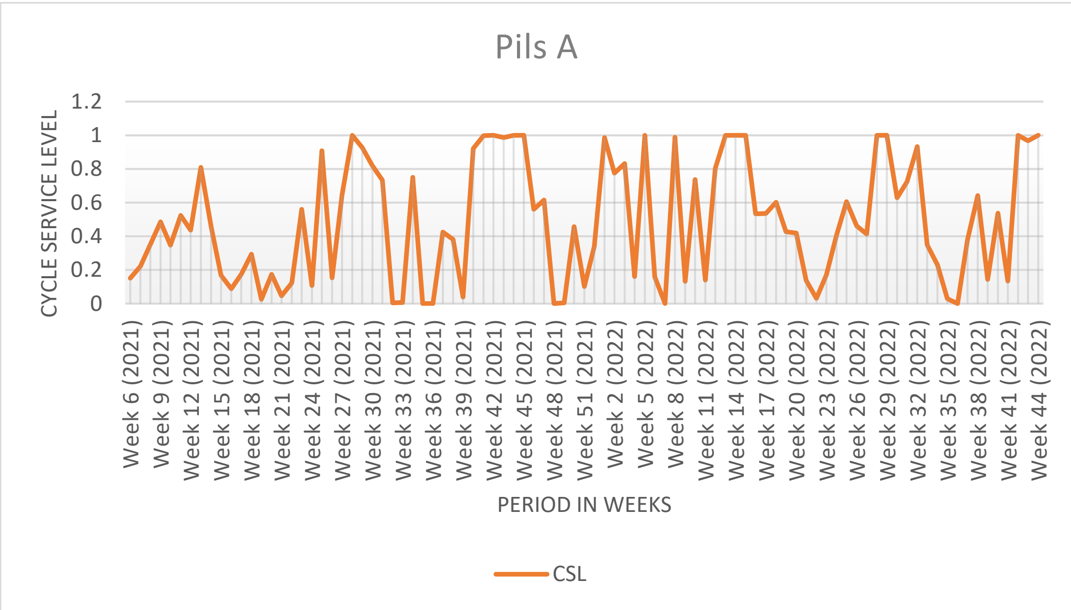

Figure 4 - Cycle Service Level over Time for Pils A

Strikingly, strong fluctuations in *CSLs* have been observed per week (Figure 4). During some weeks the *CSL* was approximately 0 or 1, which is remarkable when calculating a *CSL*. This, since a *CSL* of approximately 0 or 1 only occurs in case of 2 situations. When the *CSL* is approximately 0, the D_L is high and the σ_L is low. When the *CSL* is approximately 1, the D_L is lowl and the σ_L is high. From the formula mentioned earlier in this section we could conclude this, since the *z* value in the normality function becomes rather very small or large. A detail mathematical clarification has been stated below:

$$CSL = F_s(z) \quad \text{where } z = \frac{ROP - D_L}{\sigma_L}$$

Another explanation for these *CSL* values could be explained by the inventory in the warehouse on the day of ordering at the supplier. In case Turff was (almost) out of stock on *Pils A* and had placed an order at the supplier on a certain day, the company was actually unable to deliver the orders of the customers during lead time. This justified a drop of the *CSL* value in that week, which caould be noticed for multiple weeks (Figure 4).

Lastly, to be able to state one specific performance variable per observation object, the weekly *CSL value*s were averaged over the period. Hence, the obtained *CSL* of Turff per observation object have been summarized in Table 4 below. Each *CSL* depicted the reality and was considered when specifying the norm.

Cycle Service Level per Observation Object	
Observation Object	**Achieved *CSL***
Pils A	0.4885665 (48.86%)
Pils B	0.754406 (75.44%)
Seltzer A	0.972168 (97.22%)
Seltzer B	0.999889 (99.99%)
Seltzer C	0.946119 (94.61%)
Frisdranken	0.985169 (98.52%)

Table 4 - Cycle Service Level per Observation Object

These *CSL* values described the current performance of Turff which has been defined as the reality. For most of the observation objects the obtained *CSL* was in line with the experience of Turff itself, only the performance rate of *Pils A* indicated a lower *CSL* that the expected based on experience of the company. Since the purpose of this research was to improve the performance on the *CSL*, the norm must be stated per each observation object. For some objects, the *CSL* exceeded 95.00% which represented a well performance ratio which has been considered when identifying the norm.

2.6 SETTING THE NORM

When specifying the required *CSL* per observation object, a reasonable and feasible improvement percentage should be considered. For all observation objects on which Turff has been performing at ≤ 80.00% *CSL*, an improvement up to 90.00% *CSL* was required. These were the products with a short cycle time. For the remaining observation objects exceeding a performance rate of 80.00%, the required *CSL* has been selected to be 99.00%. An explanation for this high *CSL* referred to the low numbers of these product types. Turff aims to to be able to deliver any orders of these type of products. The norm for each observation object has been stated in Table 5 below.

Cycle Service Level per Observation Object	
Observation Object	**Required *CSL***
Pils A	90.00 %
Pils B	90.00%
Seltzer A	99.00%
Seltzer B	99.00%
Seltzer C	99.00%
Frisdranken	99.00%

Table 5 - Selected Norm per Observation Object

To achieve these selected norms, it was of great importance to select a proper demand forecasting approach. Multiple demand forecasting approaches were applicable, but for this specific research the selection of the demand forecasting model depended on the implementation of certain factors. In the following section we elaborated on these factors, and finally the most suitable demand forecasting model has been selected to perform the second phase of the research.

2.7 CHAPTER 2 SUMMARY

To distinguish the current performance values for the different observation objects of Turff as cycle service level (*CSL*), multiple calculations and assumptions were made. Within this section we reflect briefly on the results of the formulas used and assumptions made.

- *CSL* calculations and assumptions
  - A mathematically description of the current reorder policy of the different observation objects were:
    - *Pils*: $ROP = \max(D_{W-1}, \dots, D_{W-8}) - D_W$
    - *Seltzer and Frisdranken*: $ROP = Max(D_{W-1}, \dots, D_1) * 2$
  - For simplicity reasons in calculating the *CSL,* we assumed the demand to follow a normal distribution while from the Shapiro-Wilk and Kolmogorov-Smirnov test we concluded that the distribution of the demand is not normal.
  - The lead times for each observation object were determined as:
    - *Pils*: 5 days or 5/7 week
    - *Seltzer A*: 7 days or 7/7 week
    - *Seltzer B and C*: 14 days or 14/7 week
  - By applying the current reorder policy of Turff in combination with the *CSL* formula, the current performance or reality for each observation object resulted in:
    - *Pils A*: 48.86%
    - *Pils B*: 75.44%
    - *Seltzer A*: 97.22%
    - *Seltzer B*: 99.99%
    - *Seltzer C*: 94.61%
    - *Frisdranken*: 98.52%
  - For each observation object the outcome of the *CSL* formula was in line with what Turff observed, only for *Pils A* the *CSL* value was lower than expected.
  - Based on these findings, the *CSL* as norm was stated for each observation object:
    - *Pils*: 90.00%
    - *Seltzer and Frisdranken*: 99.00%

3. MODEL SELECTION

From the previous section, it has become clear how Turff is currently performing without any form of demand forecasting implemented in their reorder policy. The selection of the demand forecasting approach is of great importance when searching for a new reorder policy because we can base a reorder on the outcome of the demand forecast and improve the *CSL*s of Turff. Since the orders of Turff depend on multiple predictable factors, we considered these factors in our demand forecasting process and therefore elaborated on these factors in the following section. Additionally, the demand forecasting approaches which we reviewed were either double exponential smoothing or linear regression approaches. These approaches are discussed in more detain within the following sections.

3.1 INFLUENCING FACTORS

Since most of the customers using the services of Turff are students, the predictable factors which influence the demand of Turff were partially related to the yearly schedule of these students. The warehouse located in Delft is the hub supplying to all customers in Rotterdam, Leiden, and Delft itself. Therefore, the factors which have been considered during the demand forecasting process were the exam periods, introduction week, and holiday period. This information has been obtained from the websites from the Erasmus University, University of Leiden, and TU Delft.

It was expected that a correlation existed between the factors and the demand during a certain week. Since there has been less interest in the products of Turff during exam periods and holiday weeks in the last years, the correlation coefficient obtained was expected to be negative. On the other hand, during the introduction period of the university and the week after an exam period, a high number of students participating in various events and activities within each city have been monitored. Therefore, this factor was expected to have a positive correlation coefficient on the weekly demand.

To provide a reorder policy based on the demand forecast and ensuring improved *CSLs*, these four predictable factors (exam periods, holiday weeks, introduction period and the week after an exam period) havet been implemented in the demand forecasting model. Additionally, some unpredictable factors have been defined as well, that could influence the demand. These factors were considered during the prediction of the demand, that has been following the forecasting approaches discussed in the following section.

3.2 DEMAND FORECASTING APPROACHES

To finally select an applicable demand forecasting approach, qualitative data on these models was gathered. For this purpose, literature review has been performed from which four different demand forecasting models were obtained. To ensure selection of the most suitable model, elaboration of each of these models has been included in the following section. The first two models are based on a double seasonal exponential smoothing approach, whereas the last two on a linear regression approach.

3.2.1 DOUBLE SEASONALITY HOLT-WINTERS EXPONENTIAL SMOOTHING MODEL

The first approach there was elaborated was the Holt-Winters exponential smoothing model. To accommodate two seasonal cycles in a demand series the seasonal Holt-Winters method cwas adapted. The multiplicative formulation for the double seasonal Holt-Winters method is given the following expressions:

$$l_t = \alpha\left(\frac{D_t}{d_{t-s_1} w_{t-s_2}}\right) + (1-\alpha) l_{t-1}$$

$$d_t = \delta\left(\frac{D_t}{l_t w_{t-s_2}}\right) + (1-\delta) d_{t-s_1}$$

$$w_t = \omega\left(\frac{D_t}{l_t d_{t-s_1}}\right) + (1-\omega)w_{t-s_2}$$

$$\widehat{D}_t(k) = l_t d_{t-s_1+k} w_{t-s_2+k} + \phi^k(D_t - (l_{t-1} d_{t-s_1} w_{t-s_2}))$$

The variables used in each of the formula were:

- l_t: $smoothed\ level\ in\ time\ period\ t$
- $d_t\ and\ w_t$: $seasonal\ indices\ for\ the\ intraday\ and\ intraweek\ seasonal\ cycles\ in\ time\ period\ t$
- $\alpha, \delta, and\ \omega$: $smoothing\ parameters$
- $s_1, and\ s_2$: $the\ length\ of\ the\ intraday\ and\ intraweek\ cycles$
- $\widehat{D}_t(k)$: $is\ the\ k\ step - ahead\ forecast\ made\ from\ forecast\ origin\ t\ (were\ k \leq s_1)$
- ϕ: $simple\ adjustment\ for\ first - order\ autocorrelation$

There was no additional model specification required for the double seasonal Holt-Winters exponential smoothing approach. When reviewing other demand forecasting models, it was required to specify the number of lags for example with an ARIMA model that is discuss in section 4.2.3. With the double seasonal Holt-Winter exponential smoothing, the model was already completely specified. Therefore, simplicity and robustness strongly appealled to this method. By averaging the early observations, the initial smoothed values for level and seasonal components were estimated. By minimizing the sum of squared one-step-ahead in-sample errors, the parameters were estimated in a single procedure.. (Taylor & McSharry, 2007).

3.2.2 ALTERNATIVE DOUBLE SEASONALITY EXPONENTIAL SMOOTHING MODEL

The second approach was using the Holt-Winters model as a basis, this model is known as the alternative double seasonality exponential smoothing model by Gould et al. (2007). An assuming feature of the double seasonal Holt-Winters model presents the same intraday cycle for each day of a week.

The updates to the smoothed cycle were made at the same rate for all days of the week. Gould et al. (2007) has provided an alternative form of exponential smoothing for double seasonality. Different seasonal components represent the intraday cycle for different days, using the approach of Gould et al. (2007). For example, the week was divided into 3 types: weekdays, Saturdays, and Sundays. $c_{1t},\ c_{2t}, c_{3t}$ indicated the latest estimated value of the 3 distinct intraday cycles respectively. Therefore, the formulation required three corresponding dummy variables, $x_{1t},\ x_{2t},\ x_{3t}$, that were defined as follows:

$$x_{jt} = \begin{cases} 1, & if\ time\ period\ t\ occurs\ in\ a\ day\ of\ type\ j \\ 0, & otherwise \end{cases}$$

Gould et al. (2007) presented their approach in the form of a state space model:

$$D_t = l_{t-1} + \sum_{i=1}^{3} x_{it} c_{i,t-s_1} + \varepsilon_t$$

$$l_t = l_{t-1} + \alpha\varepsilon_t$$

$$c_{it} = c_{i,t-s1} + (\sum_{j=1}^{3} \gamma_{ij} x_{it})\varepsilon_t \qquad (i = 1,2,3)$$

The variables used in each of the formula were:

- $D_t = demand\ in\ time\ period\ t$
- l_t: $smoothed\ level\ in\ time\ period\ t$
- ε_t: $error\ term\ in\ time\ period\ t$

- γ_{ij} and α: $smoothing\ parameters$

The last two formulas could easily be rewritten as recursive expressions, which was the more widely used form for exponential smoothing methods. (Taylor & McSharry, 2007)

The two models described above were the double exponential smoothing approaches, both applying the rule of thumb where the past observations were weighted equally by a simple moving average. Additionally, the exponentially decreasing weights over time were assigned by exponential functions.

In the following two subsections, the two linear regression models are described. This approach has been used to predict values based on the values of other variables. There were independent and dependent variables, whereas for Turff the demand could be viewed as dependent variable and the factors described in section 4.1 were the independent variables.

3.2.3 AUTOREGRESSIVE INTEGRATED MOVING AVERAGE (ARIMA) MODEL

The first linear regression approach is known as the ARIMA model. This model is a demand forecasting model which integrates the autoregression model and moving average model. The model is usually denoted by ARIMA(*p,d,q*) and is based on a differenced series. The moving average (MA) in ARIMA indicates a technique of removing the non-stationary of series, which implies that datapoint have means, variances, and covariances that change over time. The model removes the non-constant trend, which means it only makes the mean stationary, but not the variance. (Zhang, 2021) Due to the integration of the autoregression model and a moving average model, the time series are transformed into a stationary series by differencing. By differencing a transformed series is created. This series consists of the differences between the lagged observations in the original timeseries. The parameter *d* refers to the required number of transformations for the series to become stationary. (Williams, 2001)

The parameters in an ARIMA model can be denoted as follows:

- p: $order\ of\ the\ autoregressive\ part$
- d: $degree\ of\ differencing$
- q: $order\ of\ the\ moving\ average\ part$

The ARIMA forecasting model can be denoted according to the following formula:

$$D_t = \alpha + \beta_1 y_{t-1} + \beta_2 y_{t-2} + .. + \beta_p D_{t-p} \varepsilon_t + \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2} + .. + \phi_q \varepsilon_{t-q}$$

The variables used in each of the formula were:

- α, β_t, ϕ_t : $constants$
- D_{t-p}: $demand\ lag\ of\ y\ during\ period\ t-p$
- ε_{t-q}: $forecast\ error\ lag\ during\ period\ t-p$

The ARIMA model formula can be stated in words. Predicted y_t = Constant + Linear combination lags of Y (upto p lags) + Linear combination of lagged forecast errors (upto q lags). (Prabhakaran, 2021)

3.2.4 AUTOREGRESSIVE DISTRIBUTED LAGS (ADL) MODEL

The second linear regression model selected during the literature review is the ADL model. The ADL model is an extension of autoregressive models with lags of explanatory variables. The model is therefore easily accessible when extra variables should be included in the forecasting process as well.

The ADL model can be calculated according to the following formula:

$$D_t = \delta_0 + \delta_1 t + .. + \delta_k t^k + \sum_{i=0}^{s-1} \gamma_i S_i + \sum_{p=1}^{P} \phi_p D_{t-p} + \sum_{k=1}^{M} \sum_{j=0}^{Q_k} \beta_{k,j} X_{k,t-j} + Z_t \Gamma + \varepsilon_t$$

The variables used in each of the formula can be described as:

- $\delta_0 + \delta_1 t + .. + \delta_k t^k$: *Constant and Trend*
  - δ_i: *constant and deterministic time regressors, set using trend*
- $\sum_{i=0}^{s-1} \gamma_i S_i$: *Seasonal*
  - S_i: *seasonal dummies which are included if there is seasonality*
- $\sum_{p=1}^{P} \phi_p D_{t-p}$: *Autoregressive*
- $\sum_{k=1}^{M} \sum_{j=0}^{Q_k} \beta_{k,j} X_{k,t-j}$: *Distributed Lag*
  - $X_{k,t-j}$: *exogenous regressors.*
- $Z_t \Gamma$: *Fixed*
  - Z_t: *any other fixed regressors that are not part of the distributed lag specification*
- $\{\varepsilon_t\}$: *assumed to be a White Noise* $\sim N(0, \sigma^2)$ *process*

This model is useful in case there are additional explanatory variables which must be considered in the demand forecasting. (Perktold, Skipper, & Taylor, 2022)

By combining the factors which were required to be considered, mentioned in section 4.1 and the described various demand forecasting approaches, a model has finally been selected.

3.3 SELECTION OF APPROACH

The main component during the demand forecasting phase for Turff was the inclusion of a number of predictable factors. These factors included the exam weekdays, holiday weekdays, introduction weekdays, and party weekdays. Since the demand was obviously depending on these factors, an approach has been selected that was able to include additional dependent variables. We discuss this point within this section.

In the framework of this research, the demand was the dependent variable, and the predictable factors were the independent variables. Our aim was to use the model which could forecast the demand based on multiple lags and the added predictable factors, such as exam, holiday, introduction, and party weekdays. As mentioned previously, the double seasonal exponential smoothing approaches were useful when the model did not require additional specification. Since this research required a model where we could specify the number of lags to be included and the number of explanatory variables to be added, a double exponential smoothing approach was not applicable, but a linear regression model was more suitable. Therefore, we have rejected the use of the double seasonality Holt-Winter exponential smoothing approach, and the alternative double seasonal exponential smoothing approach. This resulted in either using the ARIMA model or ADL model.

For both linear regression models, we can argue why we could use one or the other. On the one hand, the ARIMA model considers the past with the autoregressive part, where we could specify the number of lags to be used in the demand forecast, and it considers a moving average part where it adjusts for non-constant trends in the demand. On the other hand, the ADL model considers the past by using an autoregression of lags too, but more importantly, this model provides an easy way of extending the number of explanatory variables. Since this is the main property we are searching for in a model, it has been decided to use the ADL model instead of the ARIMA model. The ADL has been selected as a final model and has been implemented as follows:

$$D_t = \delta_0 + \sum_{p=1}^{P} \phi_p D_{t-7p} + \sum_{k=1}^{4} \beta_k X_k + \varepsilon_t$$

Where the variables can be described as follows:

- $\phi_p D_{t-7p}$: the influence of the demand at time t-p (lag p)
- $\beta_1 X_1$: the influence of the previous weekday being in an exam weekday
- $\beta_2 X_2$: the influence of the previous weekday being in a holiday weekday
- $\beta_3 X_3$: the influence of the previous weekday being in an introduction weekday
- $\beta_4 X_4$: the influence of the previous weekday being in a party weekday (day in the week after exam week)

As one might notice from the formula above, the trend and seasonality factors were removed from the original ADL model. The explanation for this is that we were unaware of the kind of trend and seasonality within the demand. Moreover, we were interested in the effect of the explanatory variables on the demand and not the trend and seasonality, so we did not aim to test these within the demand. In conclusion, we considered the inclusion of the trend and seasonality beyond the scope of our research for simplicity reasons.

For each observation object, the number of lags *p* has been distinguished according to an analyzation of the model. The final number of lags was based on the p-value of an added lag, but at least 1 lag was included. For example, when *Pils A* was analyzed and the p-value of lag 4 exceeds 0.01, only 3 lags were included in the forecast of *Pils A*.

These lags have been used as follows. For example, when the demand on a Monday must be forecasted, the first lag which was used was the demand of the first previous Monday. The number of demands *P*, consisting of past Mondays, was based on the model analyzation as mentioned above. Furthermore, in this formula the X_1, X_2, X_3, X_4 were dummy variables which described if a weekday referred to an Exam, Holiday, Introduction, and/or Party Weekday (weekday during the week after an exam week) respectively.

Using the formula described above, we have calculated the coefficients ϕ_p and β_k. This was done by fitting the model over the first 80% of the historical daily sales data. The outcome of this fit described the effect of each dependent variable on the independent variable and the significance of each effect. Once the coefficients were calculated according to the conditional maximum likelihood method, the effect of the predictable factors and past lags on the demand was described and the demand was forecasted over the 80% of the data. From this forecast, a new reorder policy was stated. Additionally, the demand was forecasted over the remaining 20% of the data to test the new created reorder policy. By comparing the *CSL*s obtained by the new reorder policy with the current reorder policy a conclusion and some recommendations were stated. A detailed description of the steps to obtain the new reorder policies have been provided in the following section.

3.4 CALCULATING THE REORDER POINT

To issue a reorder policy which exceeds the current *CSL*s for each observation object of Turff, we have performed multiple calculation steps. Within this calculation steps, the *CSL*s stated as norm from section 3.6 has been considered. Therefore, we shave performed these calculation steps separately for each observation object. Within this section we have elaborated on how we have obtained a reorder policy performing better than the current policy of Turff.

The first step towards a new reorder policy has been rebuilding the formula described in section 2.4. This formula stated how the *CSL* can be calculated in case the *ROP*, D_L, and σ_L were known. Since we aimed to set up a reorder policy now instead, we have rewritten this formula. This was done according to the formula below:

$$ROP = D_L + ss$$

$$ss = F_S^{-1}(CSL) * \sigma_L$$

From the formula above, we have noticed that the *ROP* iwa dependent of the D_L and the safety stock *ss.* To be able to apply the formula on the *ROP*, we first calculated the D_L, and σ_L. We first explained the approach to obtain the σ_L and later in this section we have elaborated on the calculations of the D_L. Furthermore, since the *CSL*s *we*re already known from section 2.4, we have implemented these directly in the cumulative normal distribution function to obtain the value according to the stated *CSL*s. This outcome has been multiplied with the σ_L to obtain the safety stock *ss*. Thereafter, we calculated the σ_L σ_L for the different observation objects according to the following formula:

$$\sigma_L = \sqrt{MSE} * \sqrt{L}$$

$$MSE = \frac{\sum_{n=1}^{N}(D_n - D_t)^2}{N}$$

According to this formula, the σ_L is dependent of the Mean Squared Error (*MSE*) and the lead time (*L*). We have already determined the lead times in section 2.4.1. Therefore, we have easily implemented them in the formula. However, to obtain the σ_L of the different observation object, we have calculated the *MSE*. This was performed according to the demand forecast over the first 80% of the daily sales data. The *MSE* basically calculates the error between the forecasted demand (D_t) and the actual demand (D_n) for *N* observations. In this case *N* equals the number of days for which we forecasted the demand.

For both the calculation of the *MSE* and the D_L we have used the demand forecasting formula stated in section 4.3. We have applied this formula by fitting the ADL model on the same 80% of the data as we have used for the demand forecast. The outcome of this fit provided us with the constant, and coefficients of the distributed lags and the dependent variables required for the demand forecast. By implementing these values into the formula in section 4.3, we have forecasted the demand over the time horizon of the first 80% of the daily data which again was implemented in the formula for the *MSE*. The unique value outcome from the *MSE* formula is square rooted and multiplied by the square root of the lead time, stated in section 2.4, for the certain observation object. This gives us the σ_L which we have used for the calculation of the *ss* and in a later phase when testing our new reorder policy. By combining the σ_L with the normal inverse cumulative distribution function of the stated *CSL* in section 3.6 we estimated the safety stock, which was constant for each observation object. To finally calculate the *ROP,* we additionally estimated the D_L.

The calculation of the *ROP* has been performed over the time horizon of the last 20% of the daily sales data. Therefore, we have first forecasted the demand using the formula in the previous section as mentioned before. The previously obtained coefficients were implemented in the demand forecasting formula and the daily demands were forecasted. All these daily demands were averaged per week using the following formula:

$$D = \frac{\sum_{t=1}^{7} D_t}{7}$$

The daily forecasted demands for the same week were summed and divided by the number of days in a week, equal to 7. In this way, the average daily demand during a certain week was calculated, but since the D_L was required according to the formula on the *ROP*, we have multiplied D as follows:

$$D_L = D * L$$

According to the formula above, the average daily demand *D* was multiplied with the lead time *L* in days, as stated in section 2.4.1. At this point we have obtained the D_L and *ss*, which were added to calculate the *ROP* according to the first mentioned formula within this section. These outcomes of the *ROP* per week for the certain observation provided the solution which performed according to the *CSL*s stated in section 2.4.1. However, to ensure this, we have tested the suggested *ROP* per week using the actual demand to see whether it met the required *CSL*. This has been tested according to the formula of Chopra & Meindl (2004) described below, which we previously used (section 3.5) to test the current performance of Turff:

$$CSL = F_s\left(\frac{ROP - D_L}{\sigma_L}\right)$$

Using the formula above, we have compared the *CSL* value achieved in our new solution with the *CSL* value in the current reorder policy, as discussed in section 3.2. The outcome of this comparison has provided conclusions and additional recommendations towards the company.

3.5 CHAPTER 3 SUMMARY

A detailed approach has been described in this chapter. The approach to obtain a solution and test it, required many calculations. A brief overview of the approach, including a summary on the formulas mentioned in chapter 4 has been provided.

- The new reorder policy was based on a demand forecasting model. Therefore, a demand forecasting model is selected.
    - The double seasonal Holt-Winter exponential smoothing, alternative double seasonal exponential smoothing, ARIMA, and ADL model were discussed in this chapter.
    - Since we search for a model which easily allows adding explanatory/ dependent variables we have selected the ADL forecasting model.
    - The ADL model for each observation object of Turff can be described as:

$$D_t = \delta_0 + \sum_{p=1}^{P} \phi_p D_{t-7p} + \sum_{k=1}^{4} \beta_k X_k + \varepsilon_t$$

    - The model has been fit over the first 80% of the historical daily sales data. This provided the constant, and coefficients of the lags and explanatory/ dependent variables on which the daily demand forecast has been based. The number of lags to be included was at least 1, otherwise it was the number of lags having a p-value below 0.01.
    - These demand forecasts were averaged per week and multiplied with the lead time to obtain the D_L:

$$D = \frac{\sum_{t=1}^{7} D_t}{7}$$

$$D_L = D * L$$

    - These D_L have been the input to calculate the *ROP*:

$$ROP = D_L + ss \text{ where } ss = F_s^{-1}(CSL) * \sigma_L$$

    - This safety stock *ss* was depending on the *CSL* stated in section 2.4.1 and the σ_L. Therefore, we calculated the σ_L, using the *MSE* approach over the first 80% of the historical daily sales data. This *MSE* formula was the following:

$$MSE = \frac{\sum_{n=1}^{N} (D_n - D_t)^2}{N}$$

    - The outcome of this formula was the input for the calculation of the σ_L:

$$\sigma_L = \sqrt{MSE} * \sqrt{L}$$

- Since the σ_L and $F_s^{-1}(CSL)$ were constant for each observation object, the *ss* for each observation object iwa constant as well.
- Lastly, we tested the obtained *ROP*s per week over the last 20% of the historical data according to the same approach described in section 1.5:

$$CSL = F_s\left(\frac{ROP - D_L}{\sigma_L}\right)$$

- The outcomes of the *CSL* per week of our solution has been compared with the ones obtained from Turff within the next section.

4. APPLICATION OF THE ADL MODEL

Within this section the model selected in section 3.3 has been applied on the historical data set provided by Turff. For each observation object we applied the ADL model. We fitted the model on the historical daily data and provided a summary, which includes an overview of the constant, and coefficients of each lag and explanatory variable. These coefficients described the effect of each variable on the dependent variable being the demand. Additionally, the summary of the model indicated the p-value for each lag and explanatory variable. Based on these p-values the reliability of the coefficients was estimated. To start with performing the demand forecast, we elaborated on the required input data from the historical dataset provided by Turff in this section.

4.1 INPUT DATA

The historical dataset of Turff consisted of the daily sales records covering all the cities where Turff is active. Each order whether it was paid or unpaid has been registered in the dataset (Google Data Studio). We selected a filter to filter all the orders from the cities Leiden, Delft and Rotterdam. This because the Delft warehouse is responsible for the delivery of orders in these three cities. Additionally, we set a filter on the status of an order. Only the paid orders were considered as demand in the ADL model and forecast. And finally, we filtered on the name of each observation object. For example, to obtain all the useful data for *Pils A*, data were filtered on the name of *Pils A*. In this way, we created separate data frames for each observation object, which we have used in the demand forecasting process. By summing all the sales on a certain date, we converted the data frame in a frame containing the number of sales of a certain observation object per day. Additionally, we determined for each sales record if the certain day was an Exam Weekday, Holiday Weekday, Introduction Weekday, and Party Weekday, which we have labeled as the explanatory variables. The information for this was obtained from the academic plannings of the universities in Delft, Leiden, and Rotterdam. These variables were indicated by 0's if not applicable and 1's if applicable within 4 separate columns in the data frame. For example, in case a day was an Exam Weekday, but not a Holiday Weekday, Introduction Weekday, and Party Weekday, we labeled a 1 in the Exam Weekday column and 0's in the Holiday Weekday, Introduction Weekday, and Party Weekday columns. In this way we created the data frames for each observation object separately.

Afterwards, we split each data frame into two separate frames, one frame consisting of the first 80 percent of the historical daily sales data and the other frame consisting of the last 20 percent of the historical daily sales data. The purpose of this was to create a training set for the ADL model over which we could determine the constants, coefficients of the lags and explanatory variable, and the σ_L as described in section 3.4, and a set to test our solution on. Both frames represented input for the demand forecasting phase and *ROP* determination. The data within these frames can be viewed as the autoregressive part ($\phi_p Y_{t-p}$) of the formula stated in section 3.3. Furthermore, the 4 columns consisting of dummy variables named Exam Weekday, Holiday Weekday, Introduction Weekday, and Party Weekday can be viewed as the distributed lags for the ADL model.

For the forecasting part, the frame containing the first 80 percent of the historical data was split into two frames again. The purpose of this was to create one frame which provided the start input for the demand forecast, and the other frame over which time horizon the demand forecast was performed to compare the actual demand D_n with the forecasted demand D_t, so we could obtain the *MSE* and therefore the σ_L as described in section 3.4. The length of the frame used as start input for the forecast, was determined by the number of lags which we included in the forecast. For example, when 3 lags were included, 3 weeks of data was required to start the forecast and therefore the length of the frame was equal to all the sales during the days in these weeks.

Finally, a frame containing the *ROP*s and a frame containing the *CSL*s for each week over the last 20 percent of the data was provided as input. The purpose of this file was to finally compare the new *ROP*s and *CSL*s per week, which were based on the forecasting results, to the current *ROP*s and *CSL*s, and plot these. To clarify the overview of input data, we provided a list of all the data frames in Table 6 below:

Input Data for ADL Model and Demand Forecast	
Dataset	**Purpose**
First 80% of the historical daily data	Fit the ADL model to obtain the parameters
Last 20% of the historical daily data	Forecast the average lead time demand per week using ADL
First X weeks of data from 80% of the historical daily data	Provides the starting point for the demand forecast
Remaining data from 80% of the historical daily data	Input for the mean squared error calculation
ROPs per week for last 20% of the historical data	Input for the comparison with the forecasted *ROP*s
CSLs per week for last 20% of the historical data	Input for the comparison with the forecasted *CSL*s

Table 6 - Input Data Purposes

Using the datasets obtained from the historical sales data, the models for each observation object were created and the demand forecast was performed. Within the following sections we have elaborated on the application of the ADL model and the outcome of the demand forecasts per observation object.

4.2 CREATING THE ADL MODEL

From the previous section, it is known that the historical data was split up in the first 80 percent of the daily sales data and the last 20 percent of the daily sales data. Two separate data frames contained the first 80 percent of the daily sales data and the last 20 percent of the daily sales data respectively. Both frames were required as input for the ADL model. In this section we created the ADL model and searched for the constant, and coefficients of the lags and explanatory variables for each observation object.

Using the data frame containing of the first 80 percent of the historical daily sales data, the ADL model was created. We created the model by fitting it over the training set which was the first 80 percent data frame mentioned. By fitting the model on the training set and indicating the number of lags and explanatory variables, it searched for the correct constant and, coefficients for the number of lags and explanatory variables. Additionally, it provided a p-value for each constant and coefficient, which indicated the level of significance for which the model ensured these constant and coefficients were the strongest. In this way, we determined the number of lags we included in the model, since we have included the number of lags which had a p-value below 0, however we included at least 1 lag in case no lag has a p-value below 0.01. According to this method above we created a separate ADL model for each observation object, which was described linear regressively as follows:

$$D_t = \delta_0 + \sum_{p=1}^{P} \phi_p D_{t-7p} + \sum_{k=1}^{4} \beta_k X_k + \varepsilon_t$$

For each observation object we analyzed what number of lags have a p-value below 0.01. In the example for *Pils A* this number *P* was equal to 4. Therefore, the number of lags used to distinguish the demand for a certain day was based on the demands of that specific day up to 4 weeks ago. Therefore, for *Pils A*, the ADL model was described as follows:

$$D_t = \delta_0 + \phi_1 D_{t-7} + \phi_2 D_{t-14} + \phi_3 D_{t-21} + \phi_4 D_{t-28} + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \varepsilon_t$$

For the example of *Pils A*, we provided a summary of the outcomes of the constant, and coefficients of the lags and explanatory variables. The explanatory variables consisted of the Exam Weekday, Holiday Weekday, Introduction Weekday, and Party Weekday, described in more detail in section 3.3. To clarify, *Lag 7* is 1 week ago, *Lag 14* is 2 weeks ago, etc. *For Pils A*, the following parameters were obtained from the model summary:

Effect of Variables Pils A			
Variable	**Coefficient**	**P-Value**	**95% CI**
Constant ($\boldsymbol{\delta_0}$)	73.7107	0.000	46.655 – 100.766
Lag 7 ($\boldsymbol{\phi_1 D_{t-7}}$)	0.2380	0.000	0.153 – 0.323
Lag 14 ($\boldsymbol{\phi_2 D_{t-14}}$)	0.1255	0.004	0.040 – 0.211
Lag 21 ($\boldsymbol{\phi_3 D_{t-21}}$)	0.1675	0.000	0.082 – 0.253
Lag 28 ($\boldsymbol{\phi_4 D_{t-28}}$)	0.1190	0.005	0.035 – 0.203
Exam Weekday ($\boldsymbol{\beta_1 X_1}$)	-50.7737	0.002	-82.474 – -19.073
Holiday Weekday ($\boldsymbol{\beta_2 X_2}$)	-28.5956	0.090	-61.699 – 4.507
Introduction Weekday ($\boldsymbol{\beta_3 X_3}$)	51.8582	0.063	-2.923 – 106.640
Party Weekday ($\boldsymbol{\beta_4 X_4}$)	1.0125	0.949	-30.220 – 32.245

Table 7 - Effect of Variables Pils A

From Table 4 above some notification on the demand can be made. The constant stated the bases for the demand of *Pils A* per day. Additionally, a correlation was found between the demand and the demand of that same specific day over the past four weeks. The coefficients related to lags 7, 14, 21, and 28 were the coefficients which influenced the demand. To have a better interpretation of the effect, the coefficient referred to as low when it is ± 0.1, as medium when it is ± 0.3 , and as high when it is ± 0.5 (Hemphill, 2003). Therefore, the effect of all lags was low where lag 7 approached a medium effect on the demand. Since the p-values for each lag did not exceed 0.01, there can be stated that the effect of each lag on the demand was found to be significantly reliable.

Furthermore, the coefficients related to the independent variables showed an important effect on the demand as well. From the p-values related to the independent variables, we concluded that the *Exam Weekday* effect was the strongest. The p-value for this variable did not exceed 0.01 and therefore it is significant to state that the demand decreased by 50.7737 on average when a certain day was an *Exam Weekday*. Additionally, the effect of a day being a *Holiday Weekday, or Introduction Weekday* was important as well. These effects were less significant than the effect of an *Exam Weekday*, however the p-values for these two variables did not exceed 0.1. Therefore, we stated at a 90% level of significance that a day being a *Holiday Weekday* or *Introduction Weekday* affected the demand by -28.5956 or 51.8582 respectively.

We demonstrated that the p-value of the Party Weekday is very high (Table 7). This indicated that the effect of a weekday being a Party Weekday on the demand was not strong and moreover the effect was extremely low. Since Turff has been applying two different reorder policies, described in section 2.2, to their products, we aimed to analyze the outcomes for an observation object following another reorder policy than *Pils A*. Therefore, we have also reviewed the model summary of *Seltzer A*. The summary is provided in Table 8.

Effect of Variables Seltzer A			
Variable	**Coefficient**	**P-Value**	**95% CI**
Constant ($\boldsymbol{\delta_0}$)	18.0084	0.000	9.900 – 26.117

Lag 7 ($\boldsymbol{\phi_1 D_{t-7}}$)	0.0935	0.135	-0.029 – 0.217
Exam Weekday ($\boldsymbol{\beta_1 X_1}$)	2.6708	0.645	-8.728 – 14.069
Holiday Weekday ($\boldsymbol{\beta_2 X_2}$)	-10.6739	0.052	-21.454 – 0.106
Introduction Weekday ($\boldsymbol{\beta_3 X_3}$)	19.3316	0.045	-0.461 – 38.203
Party Weekday ($\boldsymbol{\beta_4 X_4}$)	0.1244	0.982	-10.951 – 11.199

Table 8 - Effect of Variables Seltzer A

From the summary above, we noticed that the number of lags for this observation object was equal to 1 and the p-value of this certain lag exceeded 0.01, which we standardized as rejection value. However, we stated that in case the p-values of all lags exceeded 0.01 we would include 1 lag in the creation of the ADL model. Since the coefficient of the lag was below 0.1, the effect of the lag on the demand has been considered as low (Hemphill, 2003).

Regarding the four explanatory variables, we saw that for Holiday Weekday and Introduction Weekday the p-values resulted in a value around 0.050. This indicated a relatively strong effect, for which we conclude that the effect of the Holiday Weekday and Introduction Weekday explanatory variable were -10.6739 and 19.3316 respectively. For the demand of *Seltzer A*, this was an important effect, since we knew that the constant was equal to 18.0084. Therefore, the demand during an Introduction Weekday was double relative to the constant, which indicated the basis average value on which the demand was forecasted. Likewise, the effect on the demand during a Holiday Weekday was important as well, because as we saw the demand during such a day was halved due to the Holiday Weekday.

Additionally, we saw that the effect of the Exam Weekday and Party Weekday had a p-value equal to 0.645 and 0.982 respectively. These values indicated that the effect stated as coefficient in the summary was not very reliable and therefore it caused more inaccuracies in the demand forecasting. However, the coefficients of the Exam Weekday and the Party Weekday were 2.6708 and 0.1244 respectively, which were relatively low values. Therefore, the demand forecast was not greatly influenced by the effect of these two explanatory variables. The effect of each variable on the other observation objects can be found in Appendix A.

Once the coefficients were known, the demand forecasting phase was executed to obtain the average lead time demand, standard deviation of lead time demand, and finally the ROP. We have elaborated on the details of the forecasting phase in the following section.

4.3 DEMAND FORECAST USING ADL

For the demand forecasting approach, we have used the ADL model. Over both the first 80 percent data timeframe and the last 20 percent data timeframe, the demand was forecasted. Each forecast with another purpose.

Firstly, the demand over the first 80 percent of the data set was forecasted. Since the number of lags included for *Pils A* was equal to 4, there were 4 weeks of data separated from the first 80 percent data set as mentioned in section 4.1. Over the remaining period of the first 80 percent data frame, the demand was forecasted. The purpose of this was to obtain a constant mean squared error, to finally calculate a constant standard deviation of lead time demand. This σ_L was distinguished within section 4.4.

In addition to the forecast described above, a second forecast was executed over the last 20 percent of the data. The purpose of this forecast was to test the reorder policy described in section 4.7. From this demand forecast, the weekly D_L, and weekly *ROPs* were distinguished in section 4.5 and 4.6 respectively. In combination with the σ_L, the *CSL* was obtained and compared to the *CSL* stated as norm, and the *CSL* Turff obtained using their current reorder policy. For the forecast over the first 80 percent data timeframe and the forecast over the last 20 percent data timeframe of *Pils A*, we used the formula below:

$$D_t = \delta_0 + \phi_1 D_{t-7} + \phi_2 D_{t-14} + \phi_3 D_{t-21} + \phi_4 D_{t-28} + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \varepsilon_t$$

As one might notice, the formula starts using a constant δ_0. This constant is based on the average demand over the entire period. Additionally, for *Pils A* we included four distributed lags which effect the demand. The number of distributed lags was tested based on the p-value below 0.01 as we described in section 4.2. By including these distributed lags, the demands of the same day over the past four weeks were included in the forecast. For example, when we forecasted the demand for coming Monday, we considered the demands of the last four Mondays and have added this effect to the constants to accurate the demand forecast. Furthermore, the exogeneous regressors or explanatory variables were added, these consist of the Exam Weekdays, Holiday Weekdays, Introduction Weekdays, and Party Weekdays. We expected the forecast to be more precise by including these explanatory variables, since the demand was depending on these factors. Especially the Exam Weekdays affected the demand strongly, as we found in section 4.2. Using the constant and coefficients found in Table 7 and implement these in the formula, the formula for *Pils A* was as follows:

$$D_t = 73.7107 + 0.2380 * D_{t-7} + 0.1255 * D_{t-14} + 0.1675 * D_{t-21} + 0.1190 * D_{t-28} - 50.7737 * X_1 - 28.5956 * X_2 + 51.8582 * X_3 + 1.0125 * X_4 + \varepsilon_t$$

In the formula above, the Y_{t-7p} is indicating the demand of the day during previous week *p*, where X_k refers to the dummy variable that indicates whether the day for which we forecast is an Exam Weekday, Holiday Weekdays, Introduction Weekdays, and Party Weekday. Besides *Pils A* we pointed out the formula for *Seltzer A*, which only included one lag due to all lags having p-values exceeding 0.01 as discussed in section 4.2:

$$D_t = \delta_0 + \phi_1 D_{t-7} + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \varepsilon_t$$

Also, for this *Seltzer A*, the constant was the basis for the daily demand forecast. To this constant, the single included distributed lag was included, which indicated the effect on the forecasted demand of the demand on the same day during the previous week. Additionally, the explanatory variables were included for *Seltzer A* as well. Therefore, after implementing the constant and coefficients of Table 8, the formula for *Seltzer A was* equal to:

$$D_t = 18.0084 + 0.0935 * D_{t-7} + 2.6708 * X_1 - 10.6739 * X_2 + 19.3316 * X_3 + 0.1244 * X_4 + \varepsilon_t$$

Using the formula for *Pils A* and *Seltzer A*, the demand per day was forecasted over both the first 80 percent of the data timeframe and the last 20 percent of the data timeframe. From the forecast over the timeframe of the first 80 percent of the data, the mean squared error and standard deviation of lead time demand were obtained. We discuss this in the next section.

4.4 STANDARD DEVIATION OF LEAD TIME DEMAND

From the findings on the forecasted demand per day over the first 80 percent data time horizon, we estimated the standard deviation of the lead time demand. For this purpose, the mean squared error of the actual daily demand was compared with the daily forecasted demand. Therefore, an average mean squared error for each day during this period has been obtained using the formula below:

$$MSE = \frac{\sum_{n=1}^{N}(D_n - D_t)^2}{N}$$

For *Pils A*, the demand was forecasted for 566 days on a one-day ahead basis. Each demand observation was subtracted by the forecasted demand. By squaring the outcome, negative outcome values were prevented. All these outcome values were summed and divided by N, where N was equal to the 538 days. In this way, the average *MSE* per day was calculated. In this example for *Pils A*, the outcome of the *MSE* was equal to 110983.73, which was needed as input for the calculation of the σ_L. The result on the *MSE* was reasonably high, which indicated that the model was not a very good fit for our data set. However, the model was still very useful for testing the effect of the explanatory variables on the demand.

Since the σ_L was needed to finally calculate the reorder point per week, the *MSE* was initially square rooted. This makes sense since we are familiar with the fact that the standard deviation σ is equal to the square root of the variances σ^2. Where the variance implies how much the observations vary around the mean, the *MSE* implies how much the observations vary around our forecast. The similarities become clearer when we review the formula of the variance and compare it with the formula of the *MSE* stated above:

$$\sigma^2 = \frac{\sum_{n=1}^{N}(D_n - D)^2}{N}$$

The formula for the variance was almost the same as the formula for the *MSE*, the only difference was, as we mentioned before, when using the variance formula we searched for the variation around the mean, where we were searching for the variation around the forecast when using the *MSE*. Therefore, since the standard deviation equals the square root of the variances, it is logic that the standard deviation for the forecast equals the square root of the *MSE*.

We took the square root of the *MSE*, which provided us with the standard deviation of the demand. However, since the standard deviation of lead time demand was needed, the outcome was multiplied by the square root of the lead time in days. We applied the formula on the σ_L stated in section 3.4. For instance, for *Pils A*, the lead time in days was equal to 5 days, we multiplied the square root of the value found for the *MSE* by the square root of 5. This resulted in a σ_L equal to 333.14, which we used to calculate the safety stock and *ROP* later and helped for the indication of the accuracy of our forecast. Furthermore, we concluded that the result of σ_L was relatively high. Especially when we reflected on the values *D* and D_n and compared these to σ_L. This implied that our forecasts for D_n for *Pils A* were on average not very accurate. However, this did not indicate instant trouble since a safety stock *ss* was considered as well within the reorder policy. We elaborated on this safety stock in a later section.

In addition to the standard deviation of lead time demands, we calculated the average demand during lead time which was based on the demand forecasts over the time horizon of the last 20 percent of the daily data. In the following section we elaborated on the calculations and results of the average demand during lead time.

4.5 AVERAGE LEAD TIME DEMAND

Once the demand forecast over the period of the last 20 percent of the dataset was calculated, the average lead time demand was determined. The purpose of this was to be able to compare our forecast with the actual demand and finally obtain the *ROP* and *CSL* per week. To obtain the average lead time demand from the forecasted daily demand, it was important to first convert the daily forecasted demand into weekly demand. This daily forecasted demand for *Pils A* was calculated according to the formula mentioned in section 5.3.

Once the daily demand has been forecasted, each demand was summed to a weekly demand. Each weekly demand consisted of 7 daily demands. We did this according to the formula for *D* discussed in section 3.4.The outcome of these values was multiplied with the lead time in weeks afterwards. Therefore, for *Pils A* the forecasted daily demands converted to weekly demands were multiplied by 5/7, according to the formula on D_L described in section 3.4 as well.

For *Pils A* the last 20 percent of the dataset consisted of 10 weeks of data. In the Table below, the average lead time demands based on the forecast and the actual average lead time demands are described per week.

Average Lead Time Demand Pils A		
Week number	**Average Lead Time Demand (forecast)**	**Average Lead Time Demand (actual)**
Week 35 (2022)	305.17	565.14
Week 36 (2022)	373.14	648.07
Week 37 (2022)	427.74	482.21
Week 38 (2022)	427.77	205.79
Week 39 (2022)	376.23	466.86
Week 40 (2022)	391.19	350.14
Week 41 (2022)	329.80	626.57
Week 42 (2022)	132.85	208.86
Week 43 (2022)	338.56	264.14
Week 44 (2022)	457.28	219.30

Table 9 - Average Lead Time Demand Pils A

For some of the weeks, the demand forecast seemed inaccurate. However, when we reflected on the obtained σ_L over the first 80% of the historical daily sales data, the forecasts were in line with that. Since the forecasts over the first 80% data set were relatively inaccurate, the inaccuracy of the forecasts over the last 20% data was according to what we expected. This inaccuracy was explained by the coefficients of each lag and explanatory variable, and their p-values. Some p-values implied that the described coefficient in Table 7 was unreliable. We have reviewed the average forecasted lead time demand in more detail. As example, we reviewed *Week 36 (2022)* and *Week 42 (2022)*.

By comparing the forecasted D_L with the actual D_L in *Week 36 (2022)*, we found a large inaccuracy in the demand forecast. When reviewing the type of this week it was concluded that this week was a regular week. It did not consist of *Exam, Holiday, Introduction, and Party Weekdays*. Therefore, the demands for the days within this week were forecasted according to the formula below:

$$D_t = \delta_0 + \phi_1 D_{t-7} + \phi_2 D_{t-14} + \phi_3 D_{t-21} + \phi_4 D_{t-28} + \varepsilon_t$$

$$= 73.7107 + 0.2380 * D_{t-7} + 0.1255 * D_{t-14} + 0.1675 * D_{t-21} + 0.1190 * D_{t-28} + \varepsilon_t$$

Once the demands for all the 7 days were forecasted over a certain week, we summed all forecasts to obtain *D.* This weekly demand was multiplied with 5/7days which implied the lead time, and for week 36, 373.14 was found.

The influence of the demand on the same day over the past 4 weeks was relatively small as we concluded from the coefficients implemented for ϕ_p. Therefore, the ADL model forecasted a demand which was significantly lower than the actual demand. A declaration for this inaccuracy could be external factors which were unknown to the model. For example, in case a certain student house organized a party during this specific week. It was unknown to the model; however, it would largely affect the demand during that week. Due to the lack of knowledge of the model, it was not possible to anticipate for such an unpredictable influence. This inaccuracy could cause a lower outcome in the calculation of the *ROP,* which might result in a lower *CSL* than required during this week.

Secondly, we reviewed and clarified the forecasted demand in *Week 42 (2022)*, which was significantly lower than the other 9 forecasted demands. When reviewing what type of week this was, it was concluded that it was a week consisting of *Exam Weekdays*. Therefore, the demand forecast of this week was calculated according to the following formula:

$$D_t = \delta_0 + \phi_1 D_{t-7} + \phi_2 D_{t-14} + \phi_3 D_{t-21} + \phi_4 D_{t-28} + \beta_1 X_1 + \varepsilon_t$$

$$= 73.7107 + 0.2380 * D_{t-7} + 0.1255 * D_{t-14} + 0.1675 * D_{t-21} + 0.1190 * D_{t-28} - 50.7737 * X_1 + \varepsilon_t$$

As we notice form the formula, for the calculation of the demand for each day within the week, 50.7737 was subtracted every time. Since X_1 was a dummy variable, equal to 1 during this week because all days in *Week 42 (2022)* were *Exam Weekdays*. By summing the daily demand forecasts during this week and multiply by 7/7 we found the weekly demand during lead time, that was equal to 132.85 where the actual demand was equal to 208.86. This inaccuracy caused a lower outcome in the calculation of the *ROP,* which resulted in a lower *CSL* than required during this week again.

The weekly forecasted average lead time demands tabled with the actual average lead time demands of all the other observation objects can be found in Appendix B. Using the forecasted average lead time demands and the standard deviation during lead time demand, we obtained the *ROP* for each week. Within the following section we elaborated on the approach and result of the reorder point per week.

4.6 REORDER POINT

To be able to come up with a solution in the form of a new reorder policy for Turff, we calculated the *ROP* per week. The *ROP* is depending on the D_L and the σ_L we have calculated in the previous two sections. Additionally, we needed the *CSL* as stated in section 2.6. In this section we present the calculations of the *ROP* to finally state a new reorder policy.

Similarly, to section 2.3, the demand was assumed to follow a normal distribution for simplicity reasons. Therefore, using the cumulative distribution function of a normal distribution inversely, the safety stock was obtained by implementing the stated *CSL* and multiplying it by the σ_L. For the statistical description, we refer to the formula on the *ss* in section 3.4.

For the example of *Pils A,* the norm of the *CSL* has been set at 90.00%. Therefore, for *Pils A,* $F_S^{-1}(CSL)$ was approximately equal to1.285. This value was multiplied by the σ_L (equal to 333.14), clarified in section 4.4. From this we obtained a constant safety stock for each week for *Pils A* that was equal to 426.93. Due to a high σ_L, the *ss* resulted in a high value as well. The purpose for this was to prevent out of stock issues and to ensure the required *CSL*. Once these calculations were performed, the weekly *ROP* was obtained by summing the outcome of each *ss* with the D_L of the certain week, as discussed in section 3.4.

The *ROP* per week was obtained from the formula described in that section (3.4) and is stated per week in the Table 10 below. As one might notice, the values of the *ROP* in Table 10 fluctuated over the entire period. The maximum value for the *ROP* was found to be during *Week 44 (2022)*, where the lowest value was during *Week 42 (2022).*

Reorder Point Based on Forecast Pils A	
Week number	**Reorder Point**
Week 35 (2022)	732.11

Week 36 (2022)	800.08
Week 37 (2022)	854.68
Week 38 (2022)	854.71
Week 39 (2022)	803.17
Week 40 (2022)	818.13
Week 41 (2022)	756.74
Week 42 (2022)	559.78
Week 43 (2022)	765.50
Week 44 (2022)	884.22

Table 10 ROP on Forecast Pils A

The fluctuation was clarified by the *CSL* we aimed to achieve per observation object. In this example for *Pils A*, the aim was a *CSL* of at least 90.00%. In some weeks, the expected demand during lead time was lower than in other weeks. Therefore, the fluctuation in *ROP* followed the same pattern as the fluctuation in D_L provided in Table 9. For the other observation objects, the table on *ROP* can be found in Appendix D. The values on the *ROP* provided in Table 10, have been plotted against the *ROP* set by Turff during the same week. By doing this we gained insight in the differences on the *ROP*, where the aim of a 90.00% *CSL* was considered. Figure 5 below clearly illustrates the differences in *ROP* obtained.

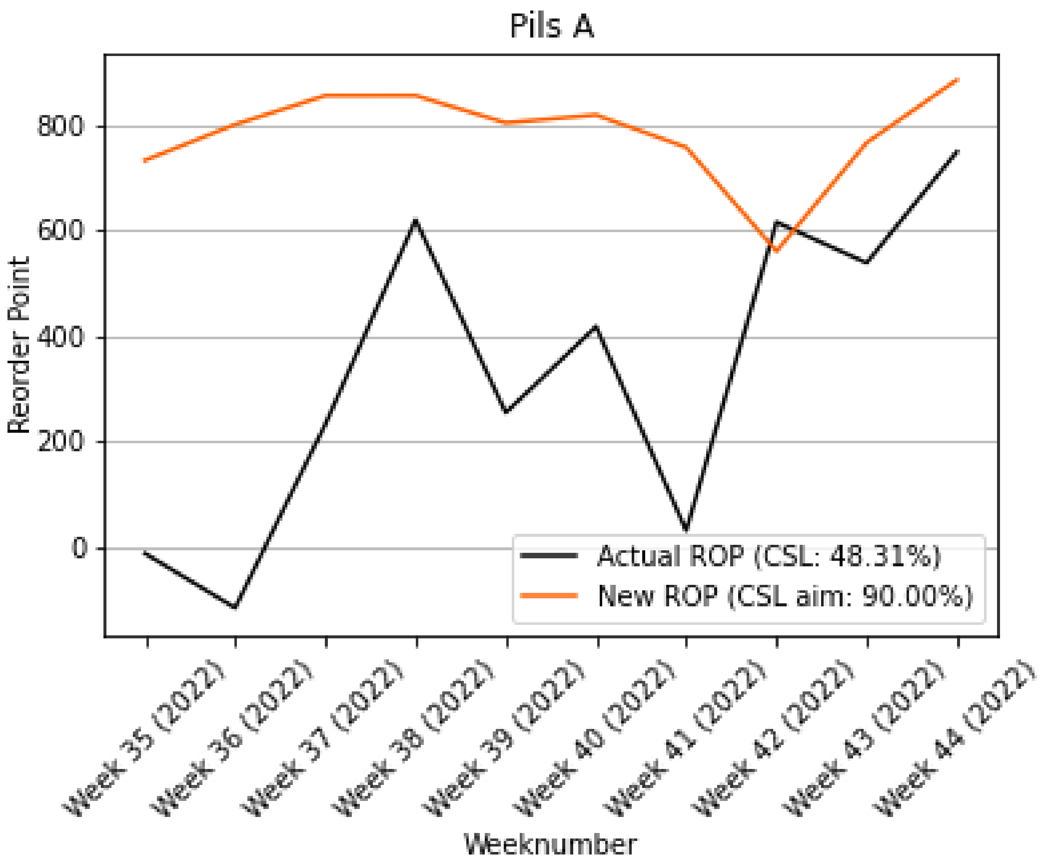

Figure 5 - Difference in ROP Pils A

As one might notice, during the majority of the weeks, the *ROP,* which is based on the demand forecast, turned out significantly higher than the *ROP* set by Turff according to their current reorder policy. Only during

Week 42 (2022), the actual *ROP* slightly exceeded the *ROP* based on the forecast. In addition to *Pils A*, we reflected on the *ROP* for *Seltzer A* to review some noticeable results:

Reorder Point Based on Forecast Seltzer A	
Week number	**Reorder Point**
Week 35 (2022)	362.28
Week 36 (2022)	367.02
Week 37 (2022)	362.71
Week 38 (2022)	363.58
Week 39 (2022)	361.42
Week 40 (2022)	515.87
Week 41 (2022)	362.29
Week 42 (2022)	382.27
Week 43 (2022)	365.74
Week 44 (2022)	361.42

Table 11 - ROP on Forecast Seltzer A

For *Seltzer A* the highest *ROP* was observed during *Week 40 (2022)* and the lowest *ROP* during *Week 39 (2022)* and *Week 44 (2022)*. This was remarkable since the model forecasted the same *ROP* during *Week 39 (2022)* as during *Week 44 (2022)*. However, this was easily explained since both weeks did not consist of Exam, Holiday, Introduction, or Party weekdays. Furthermore, in the forecast for *Seltzer A* only one lag was included, indicating that only the demand of the previous week (*Week 38 (2022)* and *Week 43 (2022)*) should be reviewed. When we reviewed Table 8, we noticed that the actual demand during these two weeks were equal to 0.0 implying no sales were made during this week. Therefore, the lead time demand forecasts for both weeks were equal and the result on the *ROP* was the same as well. Like for *Pils A*, we have plotted the actual *ROP* against the forecasted *ROP* (Figure 6):

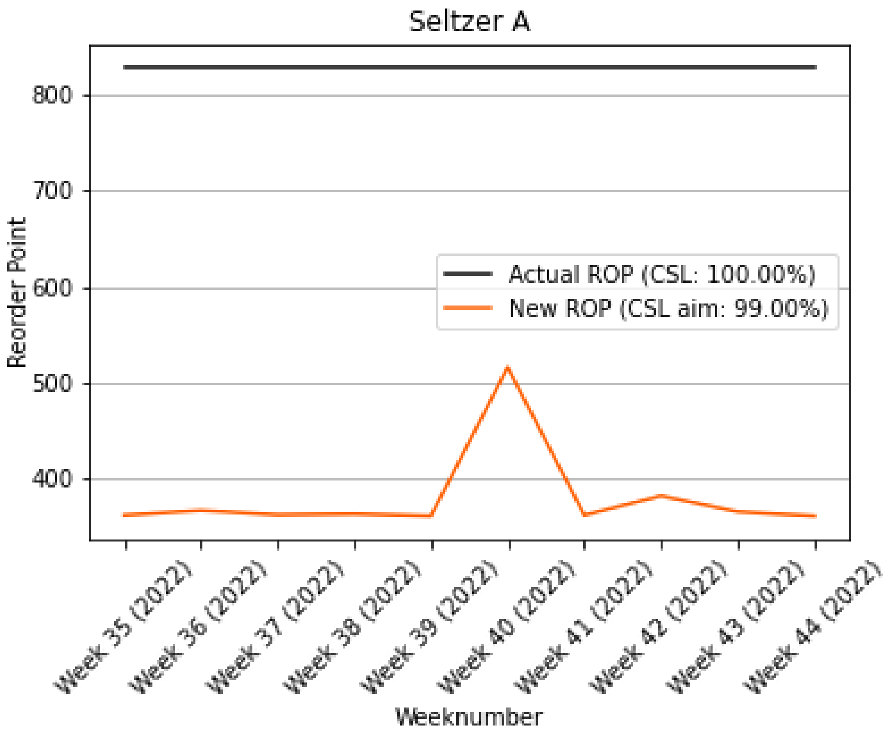

Figure 6 - Difference in ROP Seltzer A

In Figure 6, we noticed that the actual *ROP* ensured a *CSL* of 100%. This was a very high-performance percentage. However, since the *Seltzer A* observation object mostly presents a low cycle time, Turff does not want to be out of stock on this observation object. Therefore, the *ROP* was set very high. With our new policy, the goal was to reduce the stock levels, but still to be able to perform at a 99% *CSL*. To understand these *ROP*s, we elaborated on the reorder policies within the next section.

4.7 NEW REORDER POLICY

To understand the values of the *ROP* set by Turff over the time horizon from *Week 35 (2022)* up till *Week 44 (2022)*, we recalled the current reorder policy of Turff described in section 2.2. For the example of *Pils A*, Turff uses the reorder policy according to the formula below:

$$Actual\ ROP = \max\,(D_{w-1}, \dots, D_{w-8}) - D_w$$

The reorder point was set by measuring the week with the largest number of sales over the past 8 weeks. That number of sales was referred to as the order up to level *S.* From this amount, the number of sales during the week itself was subtracted and the *ROP* was obtained. When reviewing the *ROP* of *Week 42 (2022)*, it appeared that the point when a reorder was made, was equal to 614.9. Since the maximum number of sales over the past 8 weeks was the number of sales during *Week 36 (2022)*, equal to 907.3, this was subtracted by the number of sales during *Week 42 (2022).* The number of sales during this week was equal to 292.4 and therefore the *ROP* resulted in 907.3 – 292.4 = 614.9. For this example, it approximates the *ROP* we obtained when the new reorder policy was applied. The new reorder policy determined the *ROP* according to another formula stated below:

$$New\ ROP = ss + D_L = F_s^{-1}(CSL) * \sigma_L + L * \sum_{t=1}^{7} D_t = F_s^{-1}(CSL) * \sqrt{L} * \sqrt{\frac{\sum_{n=1}^{N}(D_n - D_t)^2}{N}} + L * \sum_{t=1}^{7} D_t$$

In this formula, the safety stock was summed with the average lead time demand, both based on the forecast. The ADL model forecasted an average lead time demand of 132.8 during *Week 42 (2022)*. By adding the safety stock of 426.93, which was calculated previously in section 4.6, we found a reorder point of 559.73 as depicted in Figure 5. Comparing this with the reorder point of Turff during the same week, our policy calculated a lower *ROP*. In case the *CSL,* which was obtained during this week with this new policy, was equal to the required 90% for *Pils A*, we concluded that our solution was good during this week. We have tested this in the next chapter. For the other weeks, the difference in reorder point was significantly higher. This was clarified by the expected demand calculated by the ADL model. Within the current reorder policy of Turff, a forecast of the demand has not been considered. Only the past was used to distinguish the reorder point, while the new reorder policy forecasts the demand over a future horizon. Although, the forecast referred to a future horizon but used the past as input data.

Besides the reorder policy stated earlier in this section for *Pils A*, Turff uses another reorder policy for *Seltzer A*. Since we also described a new reorder policy for this reorder policy of Turff, we recalled this policy stated in section 2.4 as well. For the example of *Seltzer A*, Turff uses the policy described below:

$$Actual\ ROP = Max(D_{w-1}, \dots, D_1) * 2$$

For example, if Turff was already selling the product for 50 weeks, *z* equals 50. This reorder policy can be viewed as an (*s*,*Q*)-policy where a replenishment of order size *Q* was made when the stock level was below the level *s*. This order size *Q* is equal to two times the maximum number of sales made over the past weeks. In this way, Turff ensures that there is a sufficient stock to prevent out of stock issues ensuring a high *CSL*. The new reorder policy aimed to remain these high *CSL* but reduced the stock levels. Also, for *Seltzer A* we tested this new policy in the next section. The reorder policy of *Seltzer A* can be described according to the same formula as *Pils A*, stated before.

As we were aiming to obtain a performance value as *CSL* of 90.00% for *Pils A* and 99% for *Seltzer A*, the application of the new reorder policy was tested over the last 20 percent of the data to review whether the policy ensured this performance rate. Hence, within the following section we elaborated on the test of the new reorder policy and compared the results with the current reorder policy.

4.8 TESTING THE NEW POLICY

To test the new reorder policy, we applied the new policy over the time horizon of the last 20 percent of the historical data of *Pils A,* by a What-If analysis (Borenstein, Hedges, Higgins, & Rothstein, 2009). We tested the results in case Turff would have applied our reorder policy. Therefore, we applied the new policy and the *CSL*s were measured for each week of the time horizon. From the *CSL* results on the test of our new reorder policy stated in section 4.7, we performed a comparison to validate the outcomes. We compared the obtained *CSL* of our own policy with the policy of Turff for each week over the last 20% of the historical daily sales data and plotted these for visualization purposes. Based on this comparison we could conclude whether the new policy exceeded the performance of Turff's current policy. In addition, we averaged the *CSL* per observation object and, in this way, an average *CSL* per observation object was found. This averaged *CSL was* compared to the norm described in section 2.6 to validate whether our solution fulfilled the requirements set per observation object. In this section, we describe all testing procedure steps and review on the results.

The procedure to obtain each weekly *CSL* remained the same as described in section 2.4. To apply this formula, the *ROP*, D_L, and σ_L were required again. We recalled the formula stated in section 2.4 on the *CSL*. Within this formula, the *ROP* was based on the forecast. For each week this *ROP* has been stated in Table 10 (section 4.6). By subtracting the actual lead time demand during a certain week from the *ROP* and dividing it by the actual standard deviation of the lead time demand, the *z* value was calculated. The D_L can be found in Table 9 (section 4.5), but the σ_L was calculated over the time horizon of the last 20 percent of the data. For this purpose, we calculated the weekly standard deviation of the demand using the following formula:

$$\sigma = \sqrt{\frac{\sum_{n=1}^{N}(D_n - D)^2}{N}}$$

Since the standard deviation of lead time demand was required, the multiplication with the square root of the lead time L was required. By implementing the *ROP*, D_L, and σ_L in the formula stated in section 2.4 for determining the *CSL,* the performance rate for each week was calculated and the effect of the new reorder policy was tested. In this way, the *CSL* of the new reorder policy per week was compared to the actual obtained *CSL* according to Turff's current reorder policy. To visualize this, a bar chart is provided (Figure 6). For each week the orange bars display the *CSL* in a certain week using the new policy and the black bars measures the *CSL* obtained using the current policy. One can view the difference in performance rate in Figure 6, however, should keep in mind that these are theoretical *CSL*s:

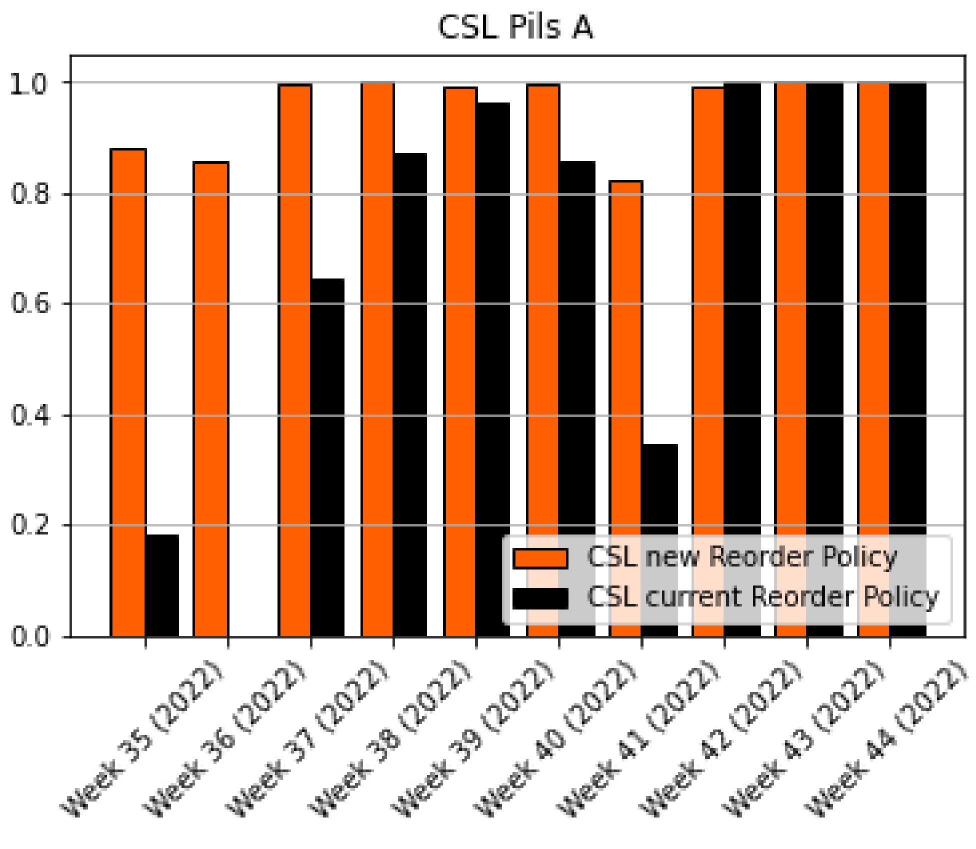

Figure 6 *CSL* Obtained According to the Current Policy against the New Policy for Pils A

As one might notice from the chart, during some weeks, for example *Week 36 (2022)*, it seemed that the *CSL* of the current reorder policy was missing. However, the *CSL* during this week was approximately zero and therefore the bar was very small. Over the entire period there can be stated that the new reorder policy ensured a higher performance rate on average. Only during *Week 42 (2022)* the current policy resulted in a higher *CSL*. An explanation for this was inaccuracies in the demand forecast. The applied ADL model forecasted the demand too low to obtain a *CSL* of 1.0 (= 100%) due to the parameters we implemented in the model. This consequently resulted in an *ROP* lower than the *ROP* according to the current reorder policy of Turff, and additionally a lower *CSL*. Therefore, one might think the policy of Turff performed better than the new policy.

However, we aimed to fulfil a required 90.00% *CSL* instead of a 100.00% *CSL,* and therefore concluded that the new policy performed well during this week as well.

Since the comparison with the current policy was one of the reasons for performing the test, we have checked whether the *CSL* of the new reorder policy exceeded the required *CSL* of 90.00%. Hence, the *CSL* per week were summed and divided by the number of observations to average the *CSL* over the entire period. In this example, a *CSL* of 95.43% was obtained for *Pils A* by averaging the *CSLs* over the entire period for the new policy, against a *CSL* of 48.31% for the current policy. The only weeks during which the model performed worse than required were *Week 35 (2022)*, *Week 36 (2022),* and *Week 40 (2022)*. During these weeks the *CSL* exceeded 80.00% but failed to fulfil the 90.00% *CSL* requirement. The demand forecast during this week was too inaccurate to ensure a 90.00% *CSL* in combination with the *ss*. Furthermore, the 95.43% *CSL* was higher than the required 90.00%, which indicated that *ROP*s were set too high, because of too large demand forecasts. Overall, the new policy performed better than Turff's current reorder policy and exceeded the required norm when averaging the performance rate over the entire time horizon of the last 20% of the daily sales data. Therefore, we conclude that our new policy is applicable for *Pils A*, and in practice has performed better than the current policy.

In addition to *Pils A*, we pointed out the case of *Seltzer A* as well. For this observation object the calculation steps to obtain the weekly *CSL* were equal to the case of *Pils A*. We discuss the outcomes for *Seltzer A* based on Figure 7 provided below:

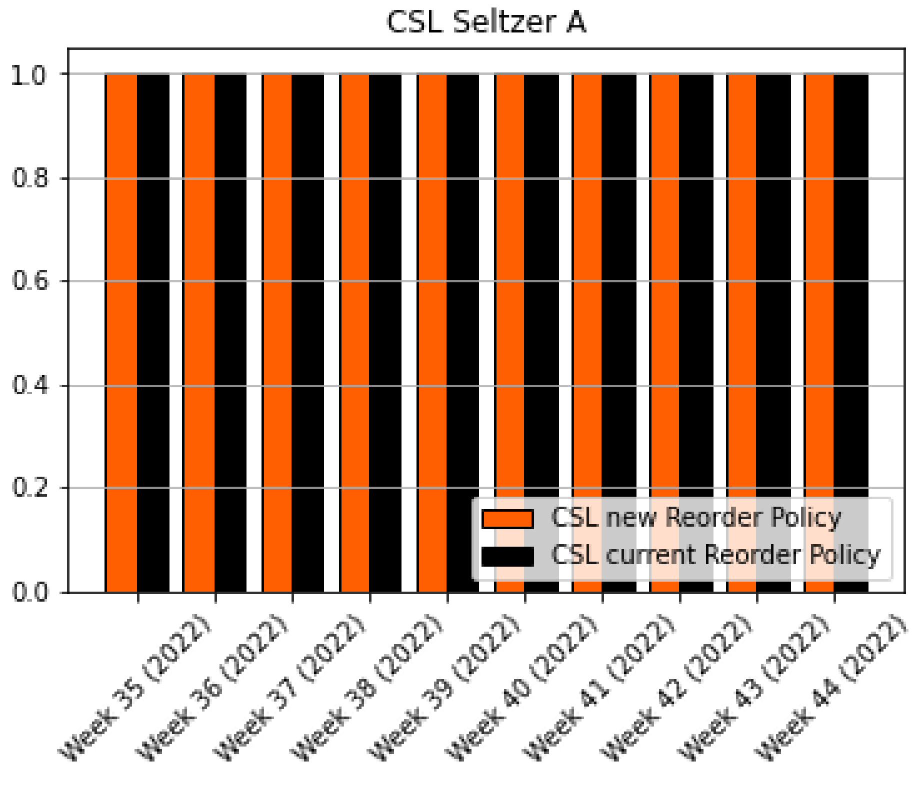

Figure 7 - *CSL* Obtained According to the Current Policy against the New Policy for Seltzer A

From the first look, it looks if the new policy and the current policy performed equally well, both policies ensured a *CSL* of 100.00% for each week. However, when recalling Figure 6 (section 4.6) on the weekly *ROP* for *Seltzer A*, we noticed that the *ROP* for each week was significantly lower for our policy than for the current policy, while performing equally each week as we concluded from Figure 7 above. These lower *ROP*s, indicated lower stock levels in the inventory, which was very favorable for start-up companies with limited cash flows such as Turff. Therefore, we state that our policy is better than the current policy of Turff.

Furthermore, one major notification should be made. The norm set for *Seltzer A* was equal to a *CSL* of 99.00%, while the application of the new reorder policy over the time horizon of the last 20% of the historical daily sales data ensured a *CSL* of 100%. This was a relatively extreme occurrence, since this implied that the *ROP* for each week could be reduced, and the norm would still be met. However, there is a risk that, when reducing the *ROP* too much, the *CSL* for each week will drop below the required 99.00% and the policy will perform poor accordingly. An explanation for the *CSL* of 100.00% for each week was found when comparing the actual demands during the 80% historical daily sales training dataset with the 20% historical daily sales test dataset. According to the obtained parameters from fitting the ADL model on the training dataset, we expected the daily demand over the test dataset to be higher. Consequently, the weekly demand forecasts over the test dataset were significantly higher than the actual weekly demand for Seltzer A (Appendix B). Additionally, the safety stock was higher than required as well for Seltzer A, resulting in a too large *ROP* and a higher *CSL* than required.

For the two examples presented, the new reorder policy performed better than required based on the test. However, this was not the case for all observation objects. Therefore, we provide Table 12 indicating the results for each observation object. For detailed visual information on the remaining observation objects, we refer to Appendix D and E to review the figures on the weekly *ROP* and *CSL* respectively.

Test Result per Observation Object				
Observation Object	**Required *CSL***	**Obtained *CSL* New Policy**	**Obtained *CSL* Current Policy**	**Better performing Policy Based on Test?**
Pils A	90.00%	95.43%	48.31%	New Policy
Pils B	90.00%	73.55%	75.46%	Current Policy
Seltzer A	99.00%	100.00%	100.00%	New Policy
Seltzer B	99.00%	99.83%	100.00%	New Policy
Seltzer C	99.00%	61.23%	100.00%	Current Policy
Frisdranken	99.00%	49.58	100.00%	Current Policy

Table 12 – Better Performing Policy per Observation Object

The results presented in the last column are based on the comparison between the performance of the current policy with the new policy, and the comparison between the current policy with the *CSL* required as norm. Based on these criteria we concluded whether our new policy or the current policy was performing better. As one might notice, our policy ensured an improvement for three of the observation objects but performed poorer than the current policy for the remaining three observation objects. Therefore, our policy was only partly useful, however, the ADL model used in this research provided important insights in the demand which were very useful for Turff. In chapter 5 we created an overview of the most important findings of the ADL model, and we provided recommendations and future research possibilities.

4.9 CHAPTER 4 SUMMARY

In this chapter, the main part of the research was performed, including many calculations, analyzation, and evaluations. We reviewed all the steps executed in this part of the research. Therefore, we briefly recall the steps mentioned in this chapter.

- Within this part of the research, we performed the demand forecasting part using the ADL model, for the example of *Pils A* and partly *Seltzer A*. Based on these forecasts we created a new reorder policy and tested the policy which resulted in the following:
    - We have split the provided data in an 80% and 20% data frame. Where the 80% data frame is used as training set for the ADL model and the 20% data frame is used for testing the new policy.

- For each observation object the ADL model was fitted on the 80% data set. In this way we obtained the constant, and coefficients of the distributed lags and explanatory variables and the related p-values. These were provided in a summary Table.
- We implemented these into the formula to forecast demand:

$$D_t = \delta_0 + \sum_{p=1}^{P} \phi_p D_{t-7p} + \sum_{k=1}^{4} \beta_k X_k + \varepsilon_t$$

- Using the *MSE* goodness-of-fit indicator we found that the forecasts over the 80% data frame for *Pils A* were inaccurate since the *MSE* resulted in a large value equal to 110983.73.
- Due to this large *MSE* we obtained large deviations between the forecasted demand and actual demand for *Pils A*.
- Also, the *ss* resulted in a high value for *Pils A*. Consequently, the *ROP* per week for *Pils A* resulted in higher values than these were using the current reorder policy of Turff.
- For *Seltzer A* the *ROP* per week resulted in significantly lower values than they were using the current reorder policy of Turff.
- Using all these findings, we stated a new reorder policy, which is universal for each observation object:

$$New\ ROP = ss + D_L = F_s^{-1}(CSL) * \sigma_L + L * \sum_{t=1}^{7} D_t$$

$$= F_s^{-1}(CSL) * \sqrt{L} * \sqrt{\frac{\sum_{n=1}^{N}(D_n - D_t)^2}{N}} + L * \sum_{t=1}^{7} D_t$$

  - The policy consists of the safety stock *ss* and the lead time demand D_L

- We tested the theoretical performance of the new policy using an What-If analysis and compare it to the required norm and performance of the current policy of Turff. We found that our policy performs better than the current policy of Turff and meets the norm for *Pils A, Seltzer A*, and *Seltzer B*. However, for *Pils B, Seltzer C,* and *Frisdranken* the current policy of Turff seems to perform better.

5. CONCLUSION

For our research the motivation is the experience of Turff of having too many out-of-stock issues on a yearly basis for some of their products as well as a too large inventory for some of their products. These products can be categorized into a *Pils, Seltzer,* and *Frisdranken* category. Each of these categories were subdivided into observation objects consisting of *Pils A*, *Pils B, Seltzer A, Seltzer B, Seltzer C,* and *Frisdranken*. Within our research we tried to increase the performance for the observation objects subdivided from the *Pils* category using the inventory service theory known as the cycle service level (*CSL*)*.* For the other observation objects, subdivided from the *Seltzer* and *Frisdranken* category, we tried to increase the *CSL* for the *Seltzer* and *Frisdranken* observation object by lowering the stock levels. By implementing a linear regressive demand forecast model, known as the Autoregressive Distribution Lags (ADL) model, we tried to forecast the demand to accurately set the reorder point (*ROP*) per week. We transformed these weekly set *ROP*s into a universal reorder policy for all observation objects and tested the performance of the reorder policy for each observation object in the form of the *CSL* and compared it to the performance of the current reorder policies of Turff. In this section, we briefly report the main findings, limitations, discussion, and recommendations of the research and we suggest what future research could be executed.

5.1 MAIN FINDINGS

From the conducted research, we can mention many important findings. These findings are regarding the current performance and the performance of the new reorder policies which we tested, but also about the factors influencing the demand which we obtained through fitting the ADL model on the 80% data training set. In this section, we discuss the main findings of our research that are relevant and noticeable.

Most of the findings on all the observation objects can be found in the Appendices, except for *Pils A* and *Seltzer A.* These two observation objects have been used as examples to describe the research steps. We demonstrated that when Turff uses its current reorder policy it scored the lowest *CSL* for *Pils A* among all observation objects, this was equal to 48.86%. For all the *Seltzers* and *Frisdranken* Turff ensures a *CSL* of approximately 99.00% each, however the stock levels of these observation objects are very high. Since the company's norm is a *CSL* of 99.00% for these observation objects, we investigated if we could create a new reorder policy which ensured this *CSL* but could simultaneously reduce the stock levels. For *Seltzer A* and *Seltzer B* we managed to do so, since the new reorder policy score exceeded the required 99.00%, but for *Seltzer C* and *Frisdranken* the policy resulted in a *CSL* of 61.23% and 49.58%, respectively, after testing (Appendix E). Therefore, we can conclude that our solution is suitable for *Seltzer A* and *Seltzer B*, since after testing our solution exceeded the required *CSL*. However, for *Seltzer C* and *Frisdranken* our solution is rather poor, since after testing we obtained scores far below the required *CSL*. An explanation for this could be the unexpected higher demand which we found in the last 20% of the historical daily sales data frame, which we used for testing. Based on the analysis of the first 80% of the historical daily sales data, we expected the demand to be lower during the last 20% of the historical sales data, than they actually were. An explanation for this might be a shift of preference from *Seltzer A* and *Seltzer B* to *Seltzer C* from the customer. The demand of *Setzer A* and *Seltzer B* over the last 20% of the daily sales data was lower than expected while the demand of *Seltzer C* was higher than expected based on the data frames. This higher demand of Seltzer C resulted in *ROP*s which were less than needed to ensure the required *CSL*, as an effect of the *ss* being too low. This *ss* was based on the σ_L which we calculated over the first 80% of the historical daily sales data and used during the testing phase over the last 20% of the daily sales data, to set the *ss*. Additionally, the forecasted demands per day were too low, since the constant and coefficients of the lags and explanatory variables were obtained from fitting the model over the first 80% of the daily sales data, which consisted of lower daily demands than the last 20% daily sales data frame. Therefore, both the D_L and σ_L were lower than they had to be, in order to ensure the required 99.00% for *Seltzer C* and *Frisdranken.* Furthermore, for *Pils B* we obtained the same findings after testing the new policy. However, for *Pils B* the obtained *CSL* equalled 73.55% where Turff required 90.00%. This was due to the same reasons as described for *Seltzer C* and *Frisdranken*.

In conclusion, we can say that the new reorder policy would have performed as required for *Pils A*, *Seltzer A*, and *Seltzer B* over the time horizon of the last 20% of the daily sales data. However, our solution of a new policy would have performed worse than required for *Pils B*, *Seltzer C*, and *Frisdranken*.

Besides the findings on our solution in the form of a new reorder policy, we have some important findings on the effects of the demand which are very interesting for Turff. These finding are about the effect of the explanatory variables on the demand for each observation object, consisting of the Exam Weekday, Holiday Weekday, Introduction Weekday, and Party Weekday. For some of the observation objects we can state the effect of one of these explanatory variables with a strong p-value.

We discussed in section 4.2, the results of fitting the ADL model on the 80% historical daily sales data training set for *Pils A* and *Seltzer A* according to Table 7 and 8 respectively. From these tables, not all results were very strong as we concluded from the included p-values. However, for both *Pils A* and *Seltzer A*, we recall some remarkable values which can be stated to influence the daily demand strongly.

Firstly, for *Pils A* we obtained that during an Exam Weekday, the demand decreases by 50.7737 on average with a p-value of 0.002. This strong indicates that a lower demand during such days. Additionally, during Holiday Weekdays the demand decreases as well by 28.5956 on average, with a p-value of 0.090. This p-value is significantly larger than the p-value of the result on Exam Weekday but is still worth to include as important finding because a strong decrease in demand is indicated by this value. Lastly, for *Pils A* we found that the demand increased during an Introduction Weekday the demand largely increases by 51.8582, with a p-value of 0.063. Like for Holiday Weekdays, the p-value of Introduction Weekdays is significantly larger than the p-value of Exam Weekdays, however the effect on the demand of the Introduction Weekday is still worth mentioning since the result implies a large increase in daily demand.

In addition to *Pils A*, we can recall a few important findings from section 4.2 on *Seltzer A* as well. Since the demand of Turff regarding *Seltzer A* is significantly lower than the demand of *Pils A*, the results of the effect on the demand are significantly smaller as well. From the fitting the ADL model on the 80% historical daily sales data training set, we obtained that the effect of a Holiday Weekday equals -10.6739 and an Introduction Weekday equals 19.3316, with p-values 0.052 and 0.045 respectively. For both explanatory variables we notice that the null hypothesis of the effect on the demand not being -10.6739 for Holiday Weekday and 19.3316 for Introduction Weekday would have been rejected at a significance level of 90% for which α equals 0.1.

For the remaining observation objects, we obtained important findings on the effect on the daily demand of the explanatory variables as well. To clarify these findings, we provide Table 13 including all the noticeable findings on the effect on the daily demand. From Table 13, one should notice that for some observation object more explanatory variables are included than for others, which is based on the p-values. We only included the explanatory variables having a p-value below 0.1, since for these we can state the effect at a significance level of 90%. This results in the explanatory variables stated in Table 13:

Main Findings			
Observation Object	**Explanatory Variable**	**Coefficient**	**p-value**
Pils A	Exam Weekday	-50.7737	0.002
	Holiday Weekday	-28.5956	0.090
	Introduction Weekday	51.8582	0.063
Pils B	Holiday Weekday	-72.3820	0.046

Seltzer A	Holiday Weekday	-10.6739	0.052
	Introduction Weekday	19.3316	0.045
Seltzer B	Holiday Weekday	-3.0483	0.004
Seltzer C	Exam Weekday	-3.9082	0.088
	Introduction Weekday	10.7911	0.002
Frisdranken	Holiday Weekday	4.6507	0.034

Table 13 - Effect of Explanatory Variables on Demand

From Table 13 above, one should notice that for no observation object the Party Weekday (weekday after an Exam Week) shows significant effect based on the p-values. Furthermore, the Holiday Weekday influences the demand for all observation object, except for *Seltzer C*. Noticeable is that the effect on the demand for *Frisdranken* is positive while for the other observation objects the effect on the demand is negative. A reason for the negative effect might be that students are not at their student homes during most of the Holiday Weekdays, so there are less parties where alcoholic beverages are consumed (*Pils* and *Seltzer*). However, when students are at home during a Holiday Weekday, they rather consume *Frisdranken*. The opposite holds for Introduction Weekdays, during which student attend a lot of parties and consume a higher number of alcoholic beverages. Therefore, for most of the *Pils* and *Seltzer* category products, a significant positive effect on the demand is found. Only for *Pils B* and *Seltzer B* no effect with a p-value below 0.1 is obtained. Although, for *Pils B* the found effect of an Introduction Weekday on the demand is still positive. For *Seltzer B* it is negative, but due to the p-value of the effect of an Introduction Weekday for *Seltzer B* we can conclude that the probability of this effect being correct is very low.

As described in this section, we found a lot of important factors which influence the daily demand and we concluded for which observation objects our new reorder policy would have done well in practice and for which it would have performed poorly. Since the research has been performed with the available data, we can conclude that we are satisfied with the results. However, due to limitations within the research there is room to potential additional research if these limitations would not exist. Therefore, we describe the limitations to our research in the following section.

5.2 LIMITATIONS

During our research at Turff we have not faced any major obstructions. Although, due to minor limitations the research could have been extended. Since for multiple phases of the research assumptions are made, the results can in practice vary of the theoretical approach applied in this thesis. Therefore, we elaborate on the limitations we faced in this thesis.

A major limitation in this thesis is the exclusion of the reorder quantity (*Q**). The reorder quantity for each observation object were beyond the scope of this research. Within this research we only included the calculation of the reorder point. When using a reorder point approach, the focus lays on minimizing the costs by considering the stock levels, while minimizing stockouts by forecasting the demand. Therefore, the new reorder policy provided in our thesis aims to ensure this. However, when including both the reorder point and reorder quantity within the research, the aim is to minimize stockouts and in case of a stockout provide backorders or split shipment, minimize cost-efficiency, and simplify inventory. Basically, by including the reorder quantity we could have provided Turff with additional recommendations to prevent stockouts, while minimizing costs. We are aware of the approach of finding the reorder quantity (or optimal lot size), using the economic order quantity (*EOQ*) approach denoted by *Q** of Chopra & Meindl (2004):

$$\text{Optimal lot size, } Q^* = \sqrt{\frac{2DS}{hC}}$$

In addition to the exclusion of the reorder quantity, we excluded the research to the optimal ordering frequency (*n**). However, these are accompanied due to the reliability of the optimal order frequency on the reorder quantity. The approach to obtain the optimal ordering frequency is given by (Chopra & Meindl, 2004):

$$n^* = \frac{D}{Q^*} = \sqrt{\frac{2DS}{hC}}$$

Due to the limitation of the exclusion of the reorder quantity and reorder frequency, potentials for future research are there. By including the formulas stated above in future research, useful recommendation could be provided to Turff about the reorder sizes and reorder frequency for each observation object.

Furthermore, the inclusion of the backorders could have been useful. However, Turff does not keep track of their backorders it was not applicable to select an inventory performance theory which considers backorders. This motivated our choice of using the *CSL* approach, although, to be more accurate with the description of the current performance of the company, backorders are required. By including the backorders, we could calculate the percentage of demand which is backordered. This provides options for future research as well, since Turff can specify a norm in the form of the maximum percentage of demand being backordered allowed by the company. In this future research there can be searched for a reorder policy which considers this stated norm.

Additionally, we assumed the demand to be equally divided over Leiden, Delft, and Rotterdam, but another division could be applicable. For example, it might be the case that 50% of the demand is from Delft, and the remaining 50% of demand is from Leiden and Rotterdam together. In that case the provided findings on the significant explanatory variables stated in section 5.1 are unlikely to be equal for all the three cities.

Lastly, we assumed the demand to follow a normal distribution for simplicity reasons within the calculations part of the research. After we tested this assumption, we concluded that the demand did not follow a normal distribution, and therefore the outcome of the *CSL* calculations might deviate. We are not aware of the best fitted distribution of the demand, but in case we are, the *CSL* calculations could be executed according to this distribution. In addition to the deviation of the actual *CSL* due to the assumption of normal distribution, we have made another assumption which influences the *CSL* outcomes as well. We refer to the assumption of the lead times, which we averaged to calculate with one lead time per observation object, stated in section 2.4.2. Due to averaging of the lead times, the D_L and σ_L are influenced because the actual lead times might differ from the averaged value. Since the *CSL* formula is depending on the D_L and σ_L as input values, the outcome of this formula might deviate from the practice. This limits the accuracy of the outcomes of the test on the current reorder policy of Turff and the test of our new created policy.

5.3 DISCUSSION

Within this thesis, we aimed at an improved reorder policy based on demand forecasting. During the test phase, in which we tested the *CSL* of the reorder policy per observation object, not all results were as required according to the norm. Due to multiple assumptions the *CSL* values for the observation objects *Pils B*, *Seltzer C*, and *Frisdranken* were lower than required. However, we found important insights regarding the effect several explanatory variables have on the daily demand through the application of the ADL model as mentioned in section 5.1.

The main contribution of this thesis refers to the insights acquired on the effect of the explanatory variables on the daily demand. These insights were obtained by fitting the ADL model on the first 80% daily sales data training set. This training set consisted of multiple records. The accuracy of the model has been improved when the number of records in the training set was increased. We used data frames over the time horizon from the moment Turff started the sale of observation objects until the moment this research was initiated. Therefore, these data frames were predefined during the thesis and real life data synchronization was not included in the research. However, real life data synchronization would probably be a useful improvement in the future, which could be implemented by Turff itself to keep constant insight in their demand. The only requirement for the company is to keep track of the explanatory variables in their data frame, otherwise the ADL model is not able to be fitted on the data set. These explanatory variables should consist of the Exam Weekdays, Holiday Weekdays, and Introduction Weekday. For each sales record these explanatory variables are indicated by a 0 or 1 depending on whether the explanatory variable was false or true respectively for the specific sale. For example, when a sale is made and it was during a Holiday Weekday, but not during an Exam Weekday or Introduction Weekday, Turff should indicate the Holiday Weekday variable by a 1 and the remaining variables by 0's. Over time the number of records in the data frame will extend, leading to a more accurate result of the model's analysis (Jiawei, Micheline, & Jian, 2012).

Furthermore, we should be aware that the results on the *CSL* values are theoretical and therefore hard to validate. The *CSL* values obtained when the current reorder policy of Turff per observation object was used, are validated by the company. They indicated whether these results were in line with their experience for each observation object. This was the case for almost all observation objects, except for *Pils A*. However, the validation of the results on the *CSL* values obtained by applying our new reorder policy is rather difficult. For this purpose, a simulation should be performed using the new reorder policy. A brief detailed description of this simulation is provided in section 5.6 on future research. The results of this simulation should be compared with the findings on the theoretical *CSL* obtained by the new policy, to validate these.

Based on the findings in section 5.1, the limitations in section 5.2 and the discussed topic in this section, we can provide Turff with multiple recommendations to improve their current workflow. As a starting company there is space for improvement, and therefore we provide the recommendations to Turff in the following section.

5.4 RECOMMENDATIONS

This research constitutes the first research that was focussing on the warehouse and inventories of the Turff company. Based on the results obtained during this thesis, recommendations are made to Turff in this section.

Firstly, we recall the discussed findings from section 5.1. Testing our new reorder policy solution has revealed that this reorder policy was not sufficiently reliable to be directly implemented in the company's system. As this reorder policy has been based on many assumptions, its accuracy is found to be highly influenced by these assumptions, for example the assumption of the demand following a normal distribution and other assumptions discussed in section 5.2. However, the new reorder policy clearly exhibited potential for a better reorder policy than the one currently used by Turff. This because the current reorder policy of Turff performed poorly under the same assumptions, as we showed in section 2.5. As mentioned in the previous section, to validate the performance of the new reorder policy, the simulation described in the next section should be executed. By implementing our new reorder policy partially and finetuning this policy in practice, Turff can improve their reorder policy. The parts of our research that are recommended for implementation by Turff are reflected in Table 12 and refer to the explanatory variables. This table shows great insights on the effect of the explanatory variables on the demand, as they are important for the company to consider when placing reorders. Therefore, we recommend Turff to keep track of the Exam Weekdays, Holiday Weekdays, and Introduction Weekdays since these variables significantly affect the demand of the observation object as we conclude from the findings in Table 12. The Party Weekday variable can be ignored by Turff, since this variable showed no significant effect for any of the observation objects. If the company implements the explanatory variables on a proper way in their database, where they track all orders, they can easily export a data frame from the database and fit an ADL model on this data frame. In this way, the company can keep track of the effect of the explanatory variables on the demand continuously. We recommend doing this monthly, since it is important to include the new sale records every month. In this way the company gains knowledge on potential differences the explanatory variables could cause.

The second recommendation is to keep track of the backorders and the number of times the emergency solution is applied. Within this research, we were unable to include the backorders since Turff does not keep any records of these. Therefore, the outcome of the current performance of Turff described in section 2.5 represents a worse performance than the experiences shared by Turff. The analysis of the current performance in this research was based on the paid sales at Turff. We obtained the paid sales for multiple weeks during which the company experienced stockouts. The example of *Pils A* has been visualized and can be found in Figure 4. However, Turff executes an emergency solution in case a stockout occurs. The delivery staff drives to the wholesaler and purchases the products by themselves, in order to be able to deliver the orders at the customer. All these purchases and deliveries are not initialized or registered in the database, so that no records of backorders and emergency solutions are kept. A recommendation for Turff, which will be very helpful for the company, is to track these. In this case, Turff gains important insight in their performance too. Currently, they are unaware of the number of stockouts and backorders. Registering them, will assist the company to obtain significant knowledge that can be used to improve their reorder policy too.

Finally, consistent reorder moments are very important to prevent stockouts. As mentioned throughout the thesis, as well as in section 2.4.2 regarding the lead times, the moment of delivery of the suppliers for observation objects depends on the moment Turff places a reorder. Therefore, we averaged the lead times for the purpose of this research, however it would be more accurate if Turff had constant lead times. In that case, the moment during which orders are delivered by the supplier at Turff will be equal every week. Obviously Turff can ensure this by themselves, but we therefore advise them to make clear agreements with the Inventory Manager on these reorder moments.

5.5 SCIENTIFIC CONTRIBUTION

Within the research the theoretical ADL model was applied on a case study, where the exogenous regressors were added and number of lags were indicated to the model (Perktold, Skipper, & Taylor, 2022). Furthermore, the inventory service theory in the form of the cycle service levels (*CSL*) assuming normal distributed demand was applied in the case study, and results were obtained (Chopra & Meindl, 2004). In conclusion, the combination of this demand forecasting model (ADL model) with the inventory service theory (*CSL*) is the contribution of our research to literature.

5.6 FUTURE RESEARCH

Since Turff is a relatively new company, this research represents the first external analysis that has been executed on the inventory management and reorder process. This research aimed to provide an improved reorder policy based on demand forecasting. However, the research is based on some major influencing assumptions. Hence, there is potential for future research when reflecting on the limitations of this research and in case Turff implements the provided recommendations of section 5.4, which we discussed within this section.

The most important future research refers to the simulation study in order to validate the outcomes of the new reorder policy described in our thesis. Within this simulation study there should be evaluated when a reorder is placed by Turff according to our new reorder policy. For each reorder there should be analyzed if during the lead time a stockout occurs. Thereafter, the number of stockout occurrences should be divided by the number of reorders. This result indicates the *CSL* based on the simulation, which can be compared to the theoretically *CSL* found in our thesis. In case these *CSL*s are approximately equal, our research has a strong validation. This procedure should be executed for each observation object.

As mentioned in the section 5.2 on the limitations of the research, we assumed the demand to follow a normal distribution. From the results of the Shapiro-Wilk and Kolmogorov-Smirnov tests, we concluded that the demand did not follow a normal distribution. Therefore, there is room for future research to the distribution of the demand. Based on the findings on the distribution of the demand, the *CSL* can be obtained according to the cumulative distribution formula of the concerned distribution. This is a different approach than what has been used within this thesis. For future research to the distribution of the demand and how to act accordingly, we refer to the book Inventory Control by Axsäter (2006). In addition, the effect of the normal distribution of demand assumption can be tested, where, for some cases, the result might indicate that the effect is negligible.

Furthermore, the inclusion of the reorder sizes for each observation object was beyond the scope for our research. However, this provides potential for future research to obtain the reorder size. As we already stated in section 5.2 on limitations, a useful approach for this is provided by Chopra & Meindl (2004). Obviously, there are multiple approaches to investigate the reorder sizes of each observation object. Although, when researching this topic, we suggest the researcher to review our thesis as well to create a headstart to their research because we already provide a detailed description and analysis of the reorder policies of Turff.

Additionally, another forecasting model than the ADL model can be selected to forecast the demand. We limited ourselves by selecting the most applicable model of the four models we obtained from the literature review. This was the ADL model. Using the mean squared error (*MSE*) approach as goodness-of-fit test, which implies the variation of the observations around the forecasts, we found a relatively large variation for all the observation objects. This indicates that the ADL model might not be the best fitting model for our research. Therefore, another model can be applied for forecasting, during future research. However, this model should have the ability of including multiple explanatory variables. Therefore, the suggested model is the ARIMAX model described in the paper Evaluation of ARIMAX Modeling by Williams (2001). This model is an extension of the ARIMA model described in section 3.2.3. This model allows the inclusion of multiple external variables, like the ADL model does but additionally considers the integrated autoregressive and moving average parts.

The last potential topic for future research, refers to the factors influencing the demand. In this thesis, we have included 4 explanatory variables (Exam, Holiday, Introduction, and Party Weekdays), a specified number of lags (demand from the past influencing current demand), no trend, and no seasonality, since we expected the demand to be affected accordingly to these factors. From testing and analyzing the results of the explanatory variables and number of included distributed lags, we found that three of the explanatory variables affected the demand for some observation objects and the number of lags included differed per observation object. For future research, there might be variables, trends, and/or seasonality unknown to us which might influence the demand as well. Research to these factors is very useful for additional work on forecasting the demand. In this way, the accuracy of the demand forecast can be improved over time.

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APPENDIX A – EFFECT OF INDEPENDENT VARIABLES ON THE DEMAND

PILS B

Effect of Variables Pils B			
Variable	**Coefficient**	**P-Value**	**95% CI**
Constant $(\boldsymbol{\delta_0})$	185.7571	0.000	121.617 – 249.897
Lag 7 $(\boldsymbol{\phi_1 D_{t-7}})$	0.1937	0.001	0.078 – 0.310
Lag 21 $(\boldsymbol{\phi_3 D_{t-21}})$	0.2720	0.000	0.149 – 0.395
Exam Weekday $(\boldsymbol{\beta_1 X_1})$	16.0289	0.635	-50.404 – 82.461
Holiday Weekday $(\boldsymbol{\beta_2 X_2})$	-72.3820	0.046	-143.487 – -1.277
Introduction Weekday $(\boldsymbol{\beta_3 X_3})$	54.0481	0.447	-85.646 – 193.742
Party Weekday $(\boldsymbol{\beta_4 X_4})$	-23.5310	0.488	-90.206 – 43.144

Table 14 - Effect of Variables Pils B

SELTZER A

Effect of Variables Seltzer A			
Variable	**Coefficient**	**P-Value**	**95% CI**
Constant $(\boldsymbol{\delta_0})$	18.0084	0.000	9.900 – 26.117
Lag 7 $(\boldsymbol{\phi_1 D_{t-7}})$	0.0935	0.135	-0.029 – 0.217
Exam Weekday $(\boldsymbol{\beta_1 X_1})$	2.6708	0.645	-8.728 – 14.069
Holiday Weekday $(\boldsymbol{\beta_2 X_2})$	-10.6739	0.052	-21.454 – 0.106
Introduction Weekday $(\boldsymbol{\beta_3 X_3})$	19.3316	0.045	-0.461 – 38.203
Party Weekday $(\boldsymbol{\beta_4 X_4})$	0.1244	0.982	-10.951 – 11.199

Table 15 - Effect of Variables Seltzer A

SELTZER B

Effect of Variables Seltzer B			
Variable	**Coefficient**	**P-Value**	**95% CI**
Constant $(\boldsymbol{\delta_0})$	3.5005	0.000	2.087 – 4.915
Lag 7 $(\boldsymbol{\phi_1 D_{t-7}})$	0.0212	0.724	-0.097 – 0.139
Exam Weekday $(\boldsymbol{\beta_1 X_1})$	-0.0914	0.935	-2.281 – 2.098
Holiday Weekday $(\boldsymbol{\beta_2 X_2})$	-3.0483	0.004	-5.126 – -0.971
Introduction Weekday $(\boldsymbol{\beta_3 X_3})$	-0.3383	0.858	-4.046 – 3.369
Party Weekday $(\boldsymbol{\beta_4 X_4})$	0.1849	0.867	-1.987 – 2.357

Table 16 - Effect of Variables Seltzer B

SELTZER C

Effect of Variables Seltzer C			
Variable	**Coefficient**	**P-Value**	**95% CI**
Constant $(\boldsymbol{\delta_0})$	6.4051	0.000	3.498 – 9.313
Lag 7 $(\boldsymbol{\phi_1 D_{t-7}})$	0.1942	0.000	0.104 – 0.284
Lag 21 $(\boldsymbol{\phi_3 D_{t-21}})$	0.2508	0.000	0.153 – 0.349
Exam Weekday $(\boldsymbol{\beta_1 X_1})$	-3.9082	0.088	-8.402 – 0.585
Holiday Weekday $(\boldsymbol{\beta_2 X_2})$	-0.9036	0.666	-5.021 – 3.213
Introduction Weekday $(\boldsymbol{\beta_3 X_3})$	10.7911	0.002	4.133 – 17.449
Party Weekday $(\boldsymbol{\beta_4 X_4})$	0.1227	0.957	-4.323 – 4.569

Table 17 - Effect of Variables Seltzer C

FRISDRANKEN

Effect of Variables Frisdranken			
Variable	**Coefficient**	**P-Value**	**95% CI**
Constant $(\boldsymbol{\delta_0})$	8.2392	0.000	5.439 – 11.039
Lag 7 $(\boldsymbol{\phi_1 D_{t-7}})$	0.1528	0.002	-0.054 – 0.251
Exam Weekday $(\boldsymbol{\beta_1 X_1})$	-1.6005	0.470	-5.948 – 2.747
Holiday Weekday $(\boldsymbol{\beta_2 X_2})$	4.6507	0.034	0.364 – 8.937
Introduction Weekday $(\boldsymbol{\beta_3 X_3})$	-0.9790	0.748	-6.955 – 4.997
Party Weekday $(\boldsymbol{\beta_4 X_4})$	-2.0134	0.355	-6.287 – 2.260

Table 18 - Effect of Variables Frisdranken

APPENDIX B – AVERAGE LEAD TIME DEMAND

PILS B

Average Lead Time Demands Pils B		
Week number	**Average Lead Time Demand (forecast)**	**Average Lead Time Demand (actual)**
Week 35 (2022)	2571.62	2203.71
Week 36 (2022)	3103.14	4106.57
Week 37 (2022)	2892.05	4037.14
Week 38 (2022)	2803.52	2802.86
Week 39 (2022)	3082.02	3489.43
Week 40 (2022)	3546.54	2646.00
Week 41 (2022)	2579.33	2226.86
Week 42 (2022)	2882.69	1699.71
Week 43 (2022)	2353.32	2687.14
Week 44 (2022)	3567.57	2401.20

Table 19 - Average Lead Time Demand Pils B

SELTZER A

Average Lead Time Demands Seltzer A		
Week number	**Average Lead Time Demand (forecast)**	**Average Lead Time Demand (actual)**
Week 35 (2022)	126.92	59.8
Week 36 (2022)	131.65	13.8
Week 37 (2022)	127.35	23.0
Week 38 (2022)	128.21	0.0
Week 39 (2022)	126.06	4.6
Week 40 (2022)	280.51	0.0
Week 41 (2022)	126.93	23.0
Week 42 (2022)	146.91	36.8
Week 43 (2022)	130.37	0.0
Week 44 (2022)	126.06	101.2

Table 20 - Average Lead Time Demand Seltzer A

SELTZER B

Average Lead Time Demands Seltzer B		
Week number	**Average Lead Time Demand (forecast)**	**Average Lead Time Demand (actual)**
Week 35 (2022)	49.14	6.4
Week 36 (2022)	49.14	12.8
Week 37 (2022)	49.28	25.6
Week 38 (2022)	49.55	12.8
Week 39 (2022)	49.28	44.8
Week 40 (2022)	43.94	0.0
Week 41 (2022)	51.60	12.8
Week 42 (2022)	48.00	0.0
Week 43 (2022)	51.60	44.8
Week 44 (2022)	24.98	6.4

Table 21 - Average Lead Time Demand Seltzer B

SELTZER C

Average Lead Time Demands Seltzer C		
Week number	**Average Lead Time Demand (forecast)**	**Average Lead Time Demand (actual)**
Week 36 (2022)	382.58	343.0
Week 37 (2022)	242.31	411.6
Week 38 (2022)	287.58	323.4
Week 39 (2022)	238.50	735.0
Week 40 (2022)	431.99	254.8
Week 41 (2022)	221.98	499.8
Week 42 (2022)	316.36	58.8
Week 43 (2022)	166.72	98.0
Week 44 (2022)	234.07	450.8
Week 45 (2022)	95.98	151.9

Table 22 - Average Lead Time Demand Seltzer C

Average Lead Time Demands Frisdranken		
Week number	**Average Lead Time Demand (forecast)**	**Average Lead Time Demand (actual)**
Week 36 (2022)	151.35	258.4
Week 37 (2022)	154.83	653.6
Week 38 (2022)	215.22	83.6
Week 39 (2022)	128.12	478.8
Week 40 (2022)	152.39	243.2
Week 41 (2022)	124.32	129.2
Week 42 (2022)	112.68	106.4
Week 43 (2022)	103.42	729.6
Week 44 (2022)	226.83	83.6
Week 45 (2022)	64.06	319.2

Table 23 - Average Lead Time Demand Frisdranken

APPENDIX C – FORECASTED REORDER POINT

PILS B

Reorder Point Based on Forecast Pils B	
Week number	**Reorder Point**
Week 35 (2022)	3223.88
Week 36 (2022)	3523.76
Week 37 (2022)	3274.07
Week 38 (2022)	3455.78
Week 39 (2022)	3734.28
Week 40 (2022)	4198.79
Week 41 (2022)	3231.58
Week 42 (2022)	3534.94
Week 43 (2022)	3005.57
Week 44 (2022)	4219.82

Table 24 - ROP on Forecast Pils B

SELTZER B

Reorder Point Based on Forecast Seltzer B	
Week number	**Reorder Point**
Week 35 (2022)	97.79
Week 36 (2022)	97.79
Week 37 (2022)	97.93
Week 38 (2022)	98.20
Week 39 (2022)	97.93
Week 40 (2022)	92.59
Week 41 (2022)	100.24
Week 42 (2022)	96.65
Week 43 (2022)	100.24
Week 44 (2022)	73.63

Table 25 - ROP on Forecast Seltzer B

SELTZER C

Reorder Point Based on Forecast Seltzer C	
Week number	**Reorder Point**
Week 36 (2022)	548.51
Week 37 (2022)	408.23
Week 38 (2022)	453.51
Week 39 (2022)	404.43
Week 40 (2022)	597.92
Week 41 (2022)	387.91
Week 42 (2022)	482.29
Week 43 (2022)	332.65
Week 44 (2022)	400.00
Week 45 (2022)	261.90

Table 26 - ROP on Forecast Seltzer C

FRISDRANKEN

Reorder Point Based on Forecast Frisdranken	
Week number	**Reorder Point**
Week 36 (2022)	300.78
Week 37 (2022)	304.27
Week 38 (2022)	364.65
Week 39 (2022)	277.56
Week 40 (2022)	301.83
Week 41 (2022)	273.76
Week 42 (2022)	262.12
Week 43 (2022)	252.85
Week 44 (2022)	376.26
Week 45 (2022)	213.50

Table 27 - ROP on Forecast Frisdranken

APPENDIX D – DIFFERENCE IN REORDER POINT

PILS B

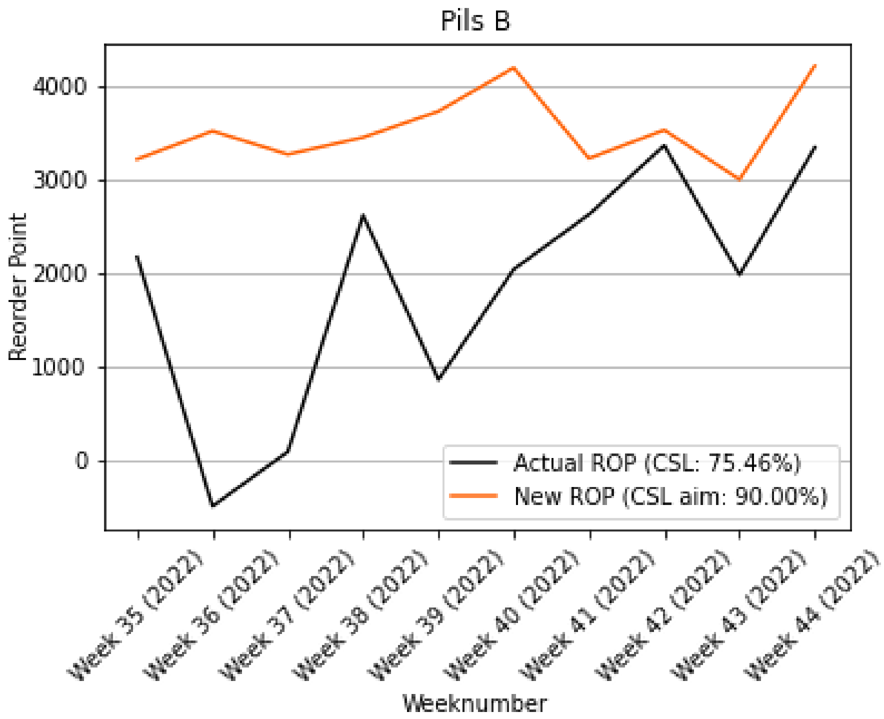

Figure 8 - Obtained ROP According to Current Policy Against the New Policy Pils B

SELTZER B

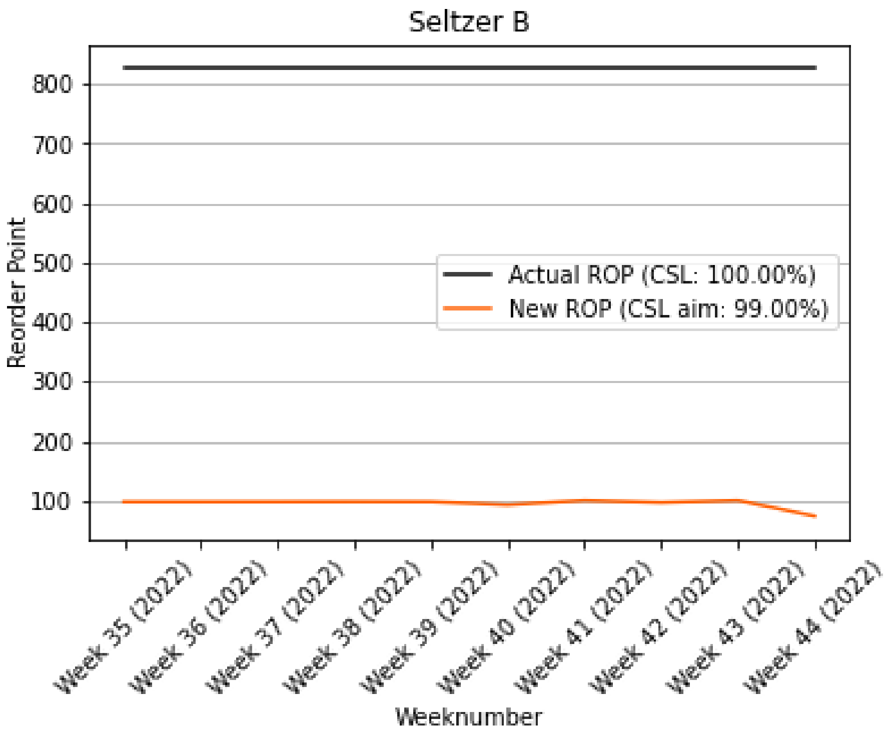

Figure 9 - Obtained ROP According to Current Policy Against the New Policy Seltzer B

SELTZER C

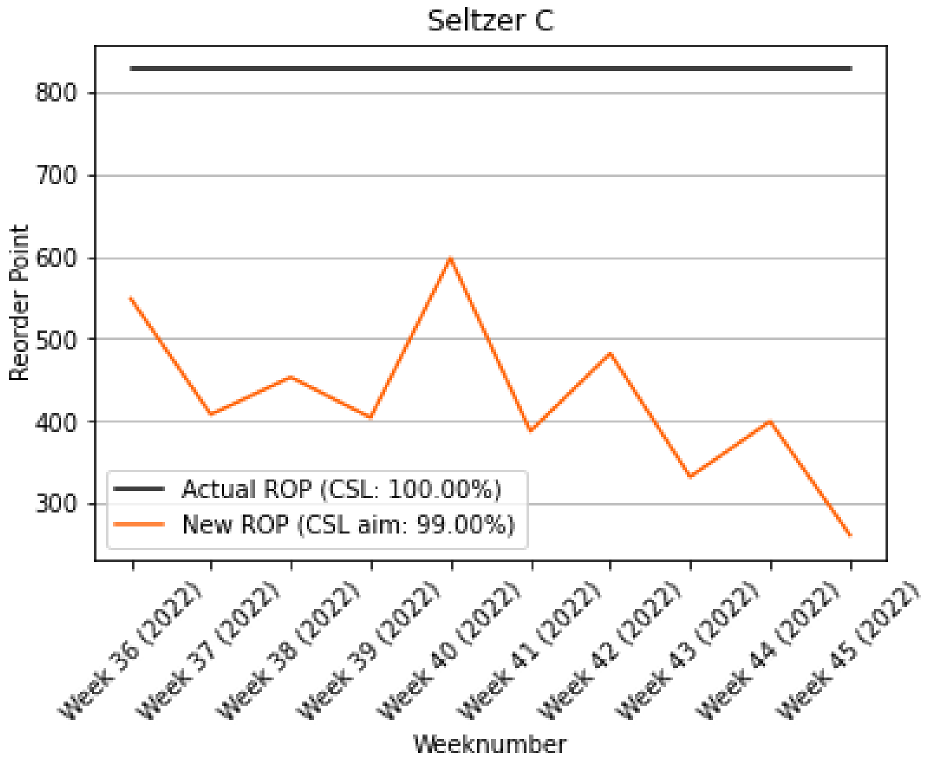

Figure 10 - Obtained ROP According to Current Policy Against the New Policy Seltzer C

FRISDRANKEN

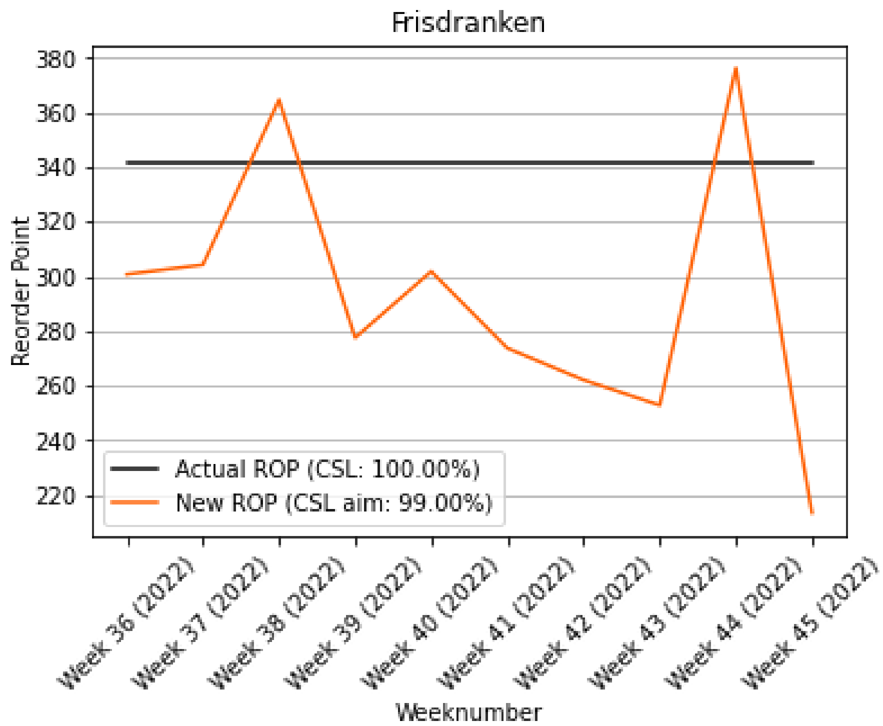

Figure 11 - Obtained ROP According to Current Policy Against the New Policy Frisdranken

APPENDIX E – REORDER POLICIES OBTAINED *CSL* COMPARISON

PILS B

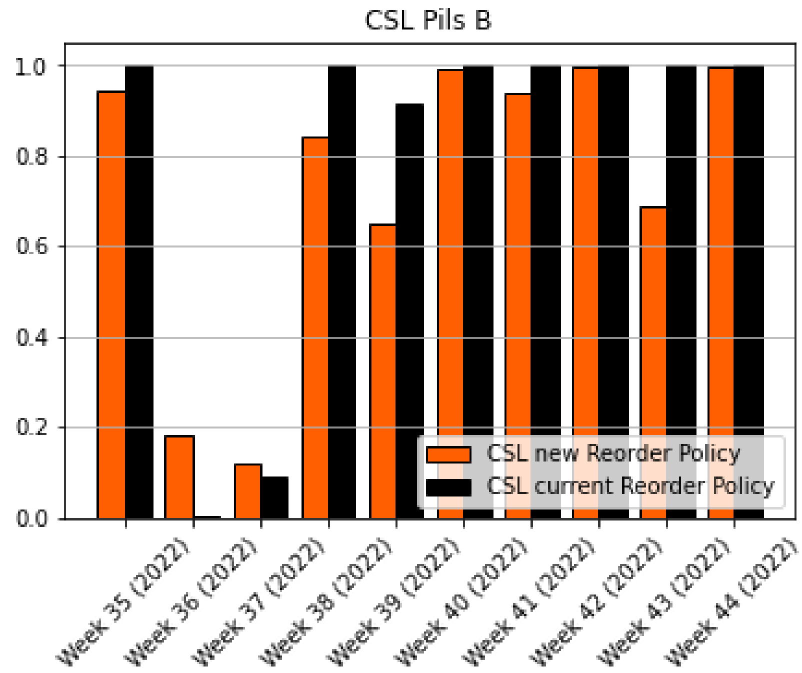

Figure 12 - *CSL* Obtained According to the Current Policy against the New Policy for Pils B

New *CSL*: 73.55% (required 90.00%) - Current *CSL*: 75.46%

SELTZER B

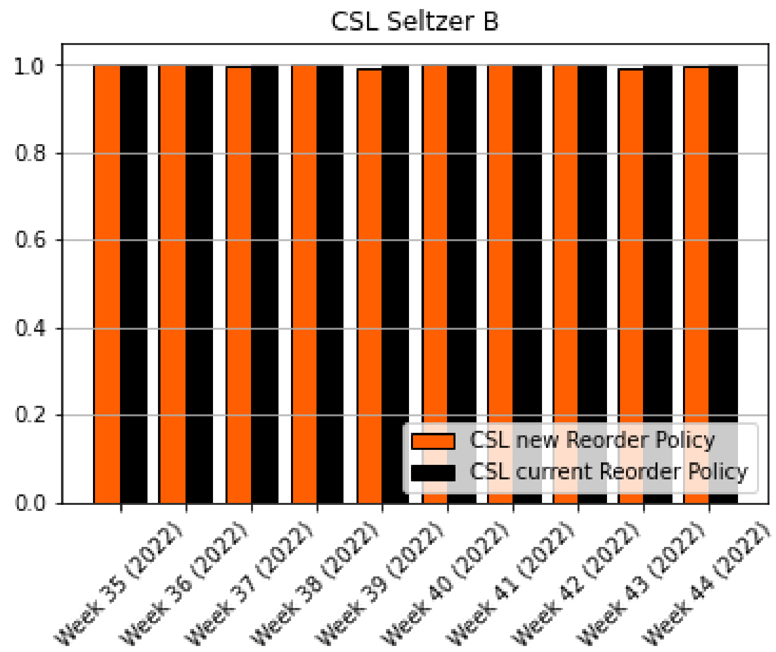

Figure 13 - *CSL* Obtained According to the Current Policy against the New Policy for Seltzer B

New *CSL*: 99.83% (required 99.00%) - Current *CSL*: 100.00%

SELTZER C

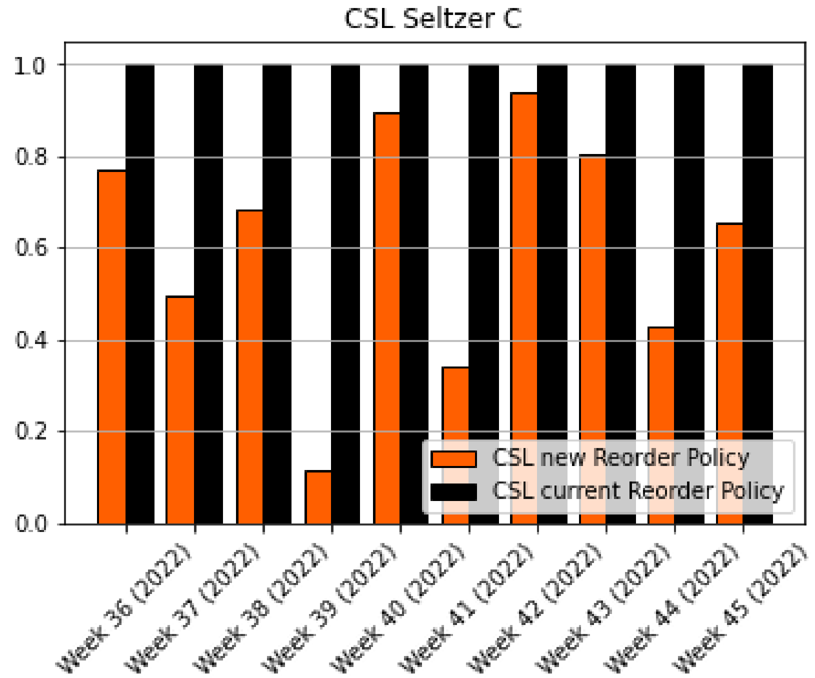

Figure 14 - *CSL* Obtained According to the Current Policy against the New Policy for Seltzer C

New *CSL*: 61.23 (required 99.00%) - Old *CSL*: 100.00%

FRISDRANKEN

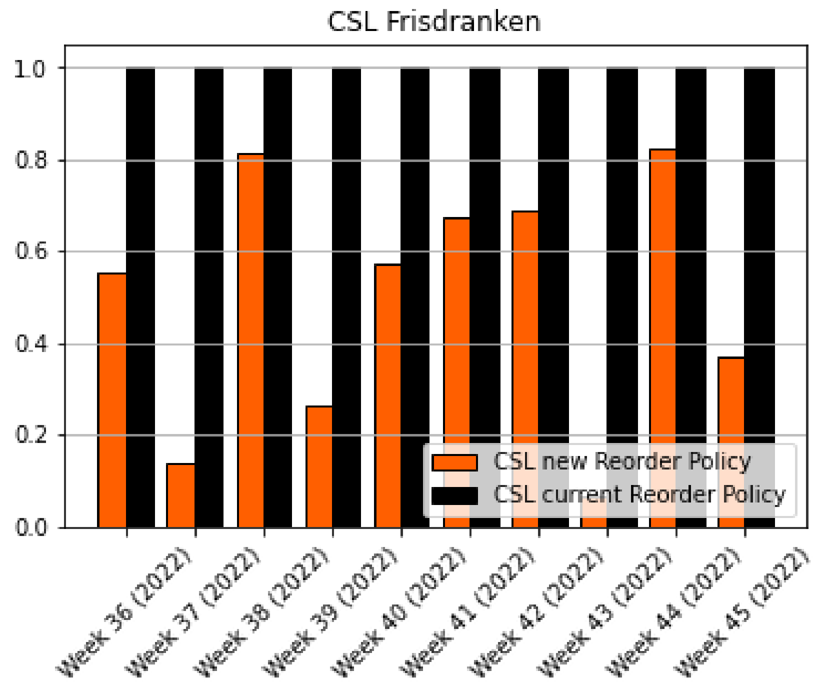

Figure 15 - *CSL* Obtained According to the Current Policy against the New Policy for Frisdranken

New *CSL*: 49.58% (required 99.00%) - Old *CSL*: 100.00%