MASTER

Analysis of forecast-based inventory control policies under a target service level
a case study at Bonduelle Northern Europe

Lardee, D.

Award date:
2020

Analysis of forecast-based inventory control policies under a target service level

A case study at Bonduelle Northern Europe

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In partial fulfillment of the requirements for the degree of:

Master of Science in Operations Management and Logistics

Eindhoven, May 25, 2020

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Series Master Thesis Operations Management and Logistics

Keywords: Inventory Control, Demand Distributions, Demand Forecasting, Customer Service Level, Non-Stationary Demand.

Preface

This master thesis report is the final step in the fulfillmentt of my Master's Degree in Operations Management and Logistics at Eindhoven University of Technology (TU/e). This project has been supervised by Dr. S. Poormoaied and Prof. Dr. A.G. de Kok from the TU/e and by H. Van Herpen from Bonduelle Northern Europe.

First of all, I would like to thank my first supervisor from the TU/e Saeed Poormoaied. I highly appreciate the guidance and help during the project from the beginning until the end. I appreciate all discussions we had about the project and it helped me to see things differently. Furthermore, I would like to thank my second supervisor from the TU/e Ton de Kok. His experience in many fields and critical view helped to improve the project. Also, I want to thank Zümbül Atan for being the third assessor.

From Bonduelle, I would like to thank Heidi van Herpen for giving me the opportunity of doing this project at her department within the company. The conversations we had about the project and many other interesting topics have made the result significantly better. Moreover, I want to thank the other colleagues at Bonduelle, and special thanks to Wieger, Richard, and Marijke for helping me with everything within the project.

Finally, I would like to thank my friends and family for all their support during this project.

Don Lardee,
May 2020

Abstract

Increasing supply chain costs, competitiveness, and high customer requirements challenge companies to raise their supply chain processes to a higher level. Reducing supply chain costs by satisfying high customer service levels has become more important these years to remain competitively advantaged. The goal of this study is to implement and test an inventory control system that satisfies a specific customer service level for a company operating in the Fast Moving Consumer Goods (FMCG) market.

In this research, an inventory control policy (R, s, nQ) is designed and implemented. Two main approaches are compared: A stationary inventory model and a non-stationary inventory model based on demand forecasting. For both the models, the best-fit Normal and Gamma distributions are based on sales data. It is highlighted that the Gamma distribution is a better distribution to simulate demand in most cases. Both models have been implemented to compare results and eventually, a final model has been designed, which is a combination of the stationary and the non-stationary model. Also, the algorithms can automatically order Full Truck Loads to reduce transportation costs. It has been proven that a non-stationary model based on demand forecasts can outperform a stationary inventory model, and the relevance of improving demand forecasts has been highlighted.

Management Summary

Introduction
This research is conducted at Bonduelle Northern Europe, which is a company that produces, stocks, and sells vegetables for both the Retail and the Foodservice market. In this study, the focus is on the supply chain of frozen Stock Keeping Units (SKUs) sold in the Benelux. The problem is a single warehouse, multi SKU problem with fixed review periods R and a case pack pf size Q per SKU, specified as (R, s, nQ) policy. In the current situation at Bonduelle, the target service level of 98.5% is not always met and holding costs must be reduced. The main goal of the model, therefore, is to minimize inventory costs by satisfying a target customer service level, measured by the Fill Rate.

Currently, the company makes demand forecasts based on both the standard, well-known forecasting models, and manual adjustments. These forecasts take price discounts, seasonality patterns, and for example marketing actions at retailers into account. In this research, the possibility of using these forecasts to control the inventory at the warehouse is investigated. To do so, both a stationary model and a non-stationary model have been designed. The models are compared with the current situation and relevant differences are highlighted.

Following the foregoing discussion, we present the main goal of the research as follows:

> "*Develop and compare inventory control models based on historical demand as well as on demand forecasts with an SKU-specific target service level that minimize the inventory holding costs.*"

Research Design
To address the research questions, some models have been designed and implemented to test the costs and service level performance. All model parameters were determined based on 2017 and 2018 sales data and tested on 2019 sales data. In the project, three main methods are used:

1. Method 1
Method 1 indicates the stationary model, which is denoted by the *Historical Demand Based Model*. The model is based on fitting demand distributions on the sales data, using the maximum likelihood function. By doing this, the best-fit parameters for the demand distributions are found, dependent on the demand pattern of an SKU. Both the Gamma distribution and the Normal distribution have been investigated in this research. The optimal values of the reorder level (s) in this method have been found by calculating the fill rate for every value of s and find the minimum value that satisfies the target fill rate for every SKU. These values of s are implemented and tested on actual sales data.

2. Method 2
Method 2 indicates the non-stationary model, which is denoted by the *Forecast Based Model*. The model is based on the forecast and average forecast error instead of on historical demand and demand fluctuation. Similar to Method 1, the Gamma and the Normal distribution have been investigated for this method as well. The main difference with Method 1 is the dynamic reorder levels instead of the fixed reorder levels s per SKU. Dynamic reorder level means the model calculates the optimal reorder level again every review moment, dependent on the demand forecast for the coming $L + R$ periods (lead time plus review period).

3. Truck loading
In addition to the stationary and the non-stationary models, Bonduelle has Full Truck Loading as a model restriction. After testing all models without truck loading to investigate their performance

independent of truck loading, the model is modified by implementing a truck loading heuristic algorithm. Since the transportation costs are defined independent of the truck utilization, transporting full truckloads is more cost-efficient. The algorithm that has been designed in this research calculates which pallets need to be added to the truck in addition to the initial order to fill up the truck. The determination of which pallets to be added is based on minimizing the additional holding costs of adding these pallets by choosing the pallets that are expected to be on stock as short as possible.

Final Model

Finally, the three methods that are explained (Method 1, Method 2, and Truck Loading) have been implemented on actual sales data and analyzed. The final model that is found in this research is a combination of the *Historical Demand Based Model* for some SKUs and the *Forecast Based Model* for some SKUs. The decision of which model fits the best for which SKU in the case study is based on choosing the higher Fill Rate with minimal costs. The combination of the right model for every SKU forms the final model. This final model was implemented on 2019 sales data and compared to the current situation. Furthermore, this final model could help the company to investigate the effect of changing target service levels for every single SKU.

Implementation and Results

All models have been tested on real sales data to analyze the performance in a real situation. Firstly, Table 1 shows the effect of the Full Truck Loading algorithm that is implemented in this research on 2019 data. The results in Table 1 are based on the *Historical Demand Based Model* to illustrate the difference between Full Truck Loads and Less than Truck Load. Less than truck load is denoted by LTL and full truck loading is denoted by FTL. Furthermore, Foodservice is denoted by FS and the Fill Rate is denoted by FR. Holding costs are denoted by C_H and transportation costs are denoted by C_T.

Table 1: Full truck Loading Results

Approach	Target FR	FR '19	C_H '19	C_T '19	Costs Total '19
LTL FS	**98%**	97.36%	€ 49.645	€ 402.970	€ 452.615
FTL FS	**98%**	97.89%	€ 65.332	€ 151.995	€ 217.327
LTL Retail	**98%**	98.14%	€ 45.934	€ 83.625	€ 129.559
FTL Retail	**98%**	98.67%	€ 47.455	€ 73.500	€ 120.955

As can be derived from Table 1, the total costs with Full Truck Loading significantly decreased. The major difference can be observed for FS. This difference makes sense because FS SKUs are supplied from different factories with relatively higher transportation costs. For retail, we conclude that full truck loading makes sense because the increase in holding costs is significantly lower than the decrease in transportation costs.

The results of the final model, are shown in Table 2 and Table 3. Table 2 illustrates the results of Foodservice and Table 3 illustrates the results of Retail. Holding costs are denoted by C_H and transportation costs are denoted by C_T.

Table 2: Foodservice Results

	Target FR	FR '19	C_H '19	C_T '19
Current Bonduelle Situation	**98.5%**	95.8%	€ 64.108	€ 151.995
Model Output FTL	**98%**	98.65%	€ 59.934	€ 151.995
Difference	**-**	+ 2.85%	- 6.51%	-

Table 3: Retail Results

	Target FR	FR '19	C_H '19	C_T '19
Current Bonduelle Situation	**98.5%**	97.0%	€ 59.725	€ 73.500
Model Output FTL	**98%**	98.77%	€ 47.030	€ 73.500
Difference	**-**	+ 1.77%	- 21.2%	-

As can be derived from Table 2 and Table 3, the model that is designed in this research realizes cost savings together with higher customer service levels (FR). The transportation costs are assumed to be the same as in the current situation because already only FTL was transported. For FS, especially the fill rate increases, while for retail especially the costs decrease. Moreover, the model automatically decides what and how much to order and how to fill up the truck to FTL. These decisions reduce the human workload, and probably therewith the impact of human mistakes.

Conclusions and Recommendations

Concluding, this research resulted in major cost savings when the model would have been implemented at the company. It can be concluded that the *Forecast Based Model* can outperform the *Historical Demand Based Model* when forecast errors are not too high and not biased.

Based on this conclusion, some recommendations can be done for the company. Firstly, the company is recommended to implement the proposed model. This implementation will result in lower inventory costs combined with higher customer service levels. Furthermore, the model outperforms the current situation, because it is an algorithm that automatically calculates the order quantities and automatically decides on how to load the trucks. These automatic decisions lead to a reduction of negative manual influence and therefore human error.

Furthermore, the research has proven that the *Forecast Based Model* could outperform the *Historical Demand Based Model* for more SKUs when the forecast would be more accurate. To improve this forecast accuracy, it is recommended to do thorough analyses of the expected sales. Improving forecast accuracy will result in better performance of the *Forecast Based Model*, which could bring further cost savings.

Lastly, we found that the total costs for some SKUs are relatively high, caused by transporting FTL. Because a model constraint in this research was transporting Full Truck Loads, SKUs that need to be transported from certain factories have relatively high costs. Investigating what the actual costs of transporting less than Truck Loads could be beneficial, especially for some FS SKUs from certain factories. The methods presented in this research make this SKU specific analysis possible.

Limitations and Future Research

Several directions for future research have been provided in this report. This research has been conducted at a company and the results of the forecast based model can be widely used and further investigated in different settings. Possibly some market-specific characteristics have impacted the demand patterns on which the study is based. Moreover, forecasts generated by the company have been used to test the models. Further research with different forecasting methods at more different companies in several markets can be interesting.

Besides, some future research on the assumptions that have been made in this research might be interesting. For example, the assumption that the factories can always supply without uncertainty is an assumption that could differ from the real-world situation. Although it is extensively explained why this assumption is plausible, further analysis of the actual delivery performance of all factories could impact the results slightly.

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List of Abbreviations

D_t Demand during t,

$FMCG$ Fast Moving Consumer Goods,

FTL Full Truck Load,

FS Foodservice,

FR Fill Rate,

KPI Key Performance Indicator

L Leadtime,

LTL Less than (full) Truck Load,

Q Case Pack Size (pallet),

RT Retail,

R Review period,

SKU Stock Keeping Unit,

ss Safety Stock.

1. Introduction

This section aims to provide insight into the main problem of this research faced by Bonduelle Northern Europe. Firstly, the company is introduced and the relevant supply chain aspects are discussed. Furthermore, the problem of the research is defined and the corresponding research questions are given and explained. Sequentially, the project scope and the methodology are briefly addressed.

1.1 Bonduelle Northern Europe

1.1.1 Company Introduction

Bonduelle is a French company specialized in producing vegetables and is, therefore, operating in the market of Fast Moving Consumer Goods (FMCG). The main goal of the Bonduelle Group as a whole is: “To be the world referent in well-living through vegetables”. Currently, Bonduelle is a market leader in ready to use plant-based products. The total turnover of the financial year 2018/2019 was 2.7 billion of which 5% comes from Bonduelle Northern Europe. The ready-to-use plant-based products that are produced by Bonduelle can be divided into three types: Ambient, frozen, refrigerated fresh. The Bonduelle Group is strategically present in three main areas over the world: Western-Europe, Eastern-Europe, and the American Continent. As shown in Figure 1.1 the Bonduelle group has been divided into five business units. This Master Thesis is performed at the headquarters of Northern Europe, located in Eindhoven, which is part of the Bonduelle Europe Long Life (BELL) business unit.

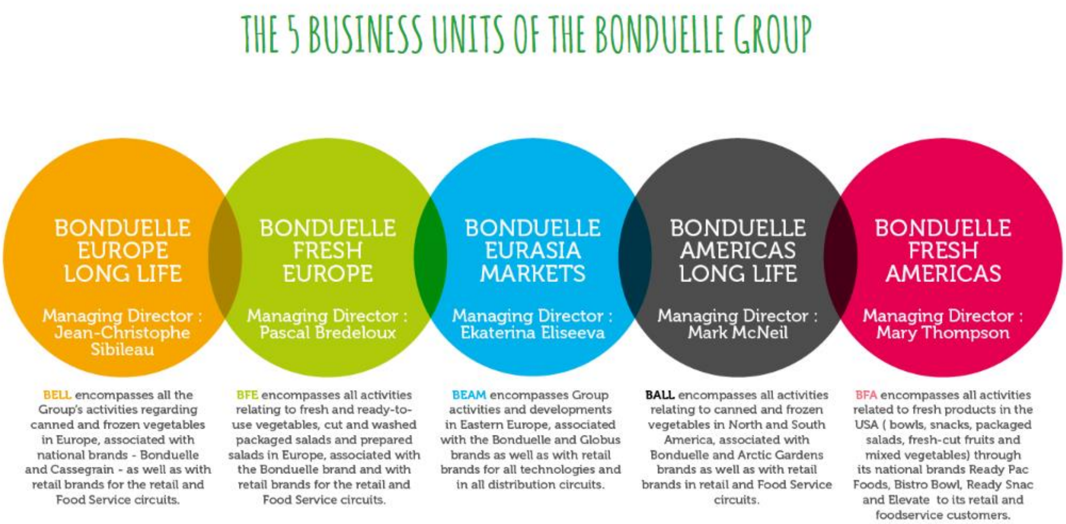

Figure 1.1: The Five Business Units of the Bonduelle Group.

Figure 1.2 also illustrates a geographical distinction between the Nordics and the Benelux. This distinction can be explained by both the geographical location and the market needs. The Benelux consists of Belgium, the Netherlands, and Luxembourg. The Nordic countries consist of Norway, Sweden, Finland, and Denmark.

These markets can be further divided into two main departments: Retail and Foodservice. The Retail and the Foodservice market can also be split up into ambient and frozen vegetables. Figure 1.2 shows the division of departments and products of the Bonduelle Northern Europe group.

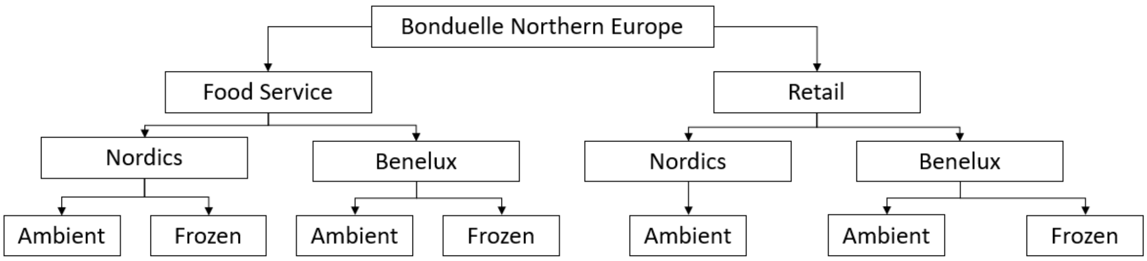

Figure 1.2: Departments Bonduelle Northern Europe.

As can be seen in Figure 1.2 the first distinction is the difference between Foodservice and Retail. Retail is the market in which Bonduelle delivers the products, especially to supermarkets. The products for the Retail market can be brand products as well as private labels. Foodservice, however, is the market in which Bonduelle delivers the products to restaurants, hotels, and wholesalers instead of supermarkets. This market differs from the Retail market because customers have other needs and the products and product packaging differ from the Retail market. Therefore, demand patterns and marketing strategies are different.

Finally, the distinction between ambient and frozen food can be made. This distinction can be explained by the fact that the supply chain of frozen products differs from the supply chain of ambient products. Both species are stored in different kinds of warehouses, have different transportations and other different supply characteristics.

1.1.2 Current Supply Chain Bonduelle Northern Europe

As stated in the previous section, the company has been divided into different markets and different product types. To get insight into the relevant supply chain, the differences between the markets and products are addressed in this section.

The three warehouses that matter for the markets explained in previous sections are one in the Netherlands, one in Belgium, and one in Denmark Furthermore, the two main factories that deliver most of the products to these warehouses are located in France and some products are delivered from smaller factories all over Europe. For the basic explanation of the supply chain, the distinction between Benelux and Nordics has been made.

The products to Norway, Sweden, and Finland are all delivered directly from one factory to customers or external distributors. For Denmark, the supply of frozen food for the Retail market and all products from the Foodservice market are also directly delivered and controlled, from the factory in France. Ambient products for the Retail market, however, are distributed from a Bonduelle Warehouse in Copenhagen. In this thesis, the analysis is not based on the Nordic supply chain, because the focus is on frozen products of the Benelux market. However, recommendations that come from this research can also be implemented for the warehouse in Copenhagen.

The supply chain of the Benelux market is divided into the chain of ambient and frozen products. Ambient products are distributed from the Kortemark warehouse to all customers in the Benelux. The control and management of Kortemark, however, is done from the headquarters in France, which is a reason to keep this group of products out of the scope of this research.

Frozen products are distributed from a warehouse in the Netherlands (Frigolanda). The inventory control of this warehouse is done from the office in Eindhoven, and this department is also responsible for the holding- and transportation costs of this warehouse. Retail products for the warehouse are all supplied from the factory in Estrées. Furthermore, most of the Food-Service products are supplied from Estrées, but some also from 4 other factories (Milagro, Santarém, Benimodo, and Gniewkowo). All these factories are also illustrated in Figure 1.3, where L represents the lead time and R represent the review periods of product flows. The aim of this research is on the inventory control and performance of this warehouse because Bonduelle Northern Europe is responsible for the inventory control as well as all costs associated with this warehouse. Figure 1.3 is a general overview of the flow of products for Foodservice and Figure 1.4 is a general overview of the product flow for Retail.

About 60% of the total sold volume is Retail and the other 40% on the Foodservice market. The Foodservice market of frozen products consists of 132 Stock Keeping Units (SKUs) and the Retail market of only 28 SKUs. Therefore, it can be concluded that the market for Foodservice products has some SKUs with much lower sales volumes than the Retail market. For the Foodservice market, as shown in Figure 1.3, approximately 83% of the total volume is delivered from Estrées instead of the other 5 factories, which means that most Foodservice products have a lead time of one week.

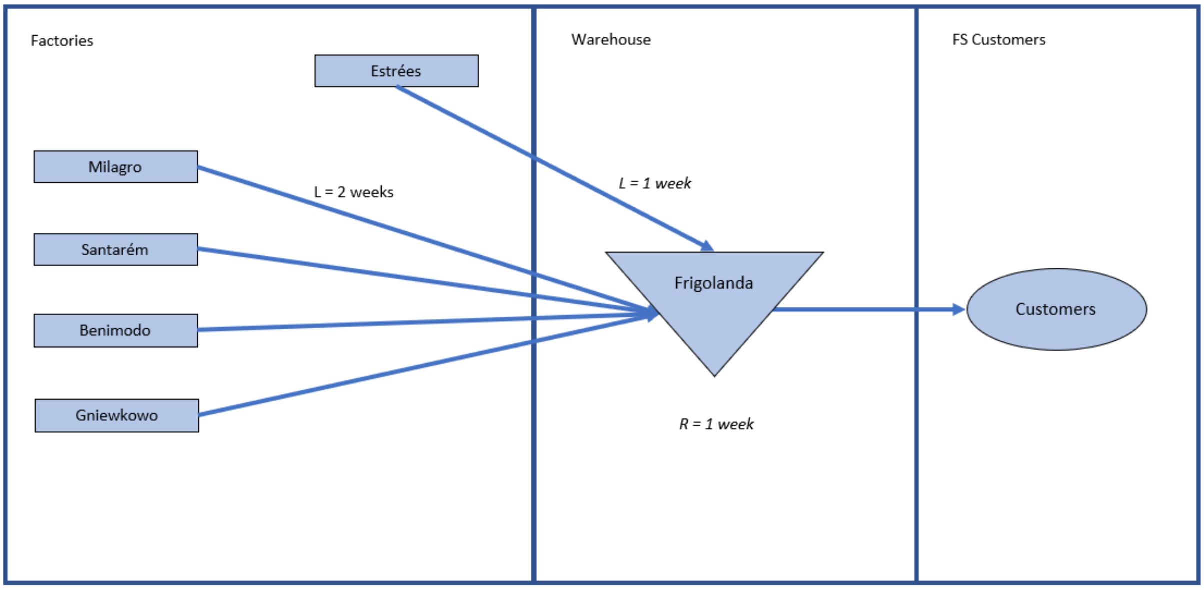

Figure 1.3: Supply Chain of Foodservice.

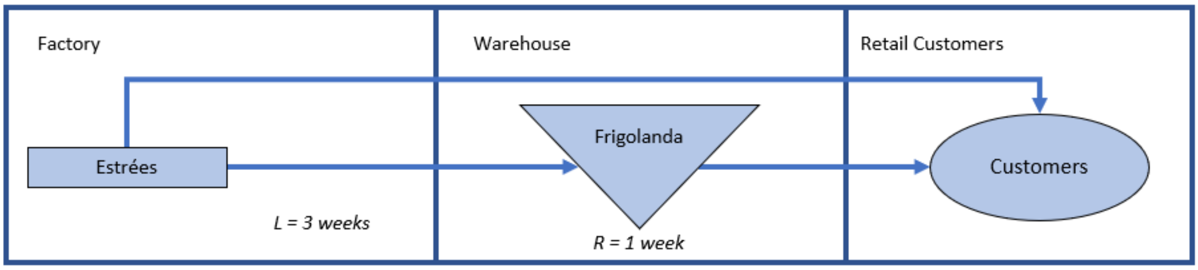

Figure 1.4: Supply Chain of Retail.

As can be seen in Figure 1.4, some products are delivered directly from Estrées to customers. Direct delivery from the factory to customers happens in periods of promotion and high volumes. Periods of promotions mean that the sales department offers price discounts for a certain customer on selected products in a fixed period. The situation that products are not delivered via Frigolanda should be taken into account because the inventory model for the warehouse should not be affected by the direct supplies. The direct delivery supply chain is only for a couple of (known) customers and was approximately 29% of the total volume of frozen products for the Benelux in 2018.

Figure 1.3 and Figure 1.4 also show the Lead times (L) and Review periods (R) of the product flows.

1.1.3 Demand Forecasting

The demand forecast for Bonduelle Northern Europe can be split up into short-term and long-term forecasts. Since Bonduelle sells plant-based food, the long-term forecast is important. This relevance comes from the yearly harvest of vegetables that need to be forecasted as good as possible, to prevent overstock or out-of-stocks at the plants. From the beginning of the year, the total expected sales need to be produced to serve the demand for the rest of the year. To make long-term demand forecasts, different departments like sales and supply chain, work together according to the Sales & Operations Planning process (S&OP process). This S&OP process is a way of working together and therefore share responsibility. For the demand forecast, the collaboration between the sales department and the supply chain is important. Input from the sales department about expected trends, promotions, new customers, and new products in the market can result in manual adjustments of forecasts. Every month there is an S&OP meeting with the different departments together to review the forecasts for the last period as well as to compare the actual sales with the budget and plan. The short term demand forecast, in general, is reviewed and this review input is translated into SKU specific forecasts.

Next to the long-term forecast that helps to make budgets and to forecast the harvest, the short-term SKU-specific forecasts are also relevant for Bonduelle. As explained later in the report, Bonduelle is responsible for the inventory control of different warehouses. Since the demand is stochastic, a demand forecast is needed to be able to supply the warehouses with the right amounts. The demand forecast is the input for the inventory model.

Currently, the demand forecast is done with a demand planning tool. This tool uses different general forecasting methods, like exponential smoothing and the Hold-Winters method (Axsater, 2006). The system chooses a forecasting method per SKU based on historical demand data, trends, and seasonality and also determines the parameters per SKU. Together with the sales department, the forecasts that are output from the system are adjusted by hand. For example, when the sales department expects certain products to have increased sales in the coming year, the forecast is adjusted. Also when new customers are expected in the market, the demand forecast can be increased by a certain percentage. These manual adjustments together with the forecasts that come out of the models form the final demand forecast. Literature has proven that the degree of precision of the forecast (forecast accuracy) influences the inventory control policy performance (Ali, Boylan, & Syntetos, 2012; Ahmadi, Atan, de Kok, & Adan, 201s9). The impact of the forecast accuracy on the inventory control performance and final inventory holding costs is relevant for this project.

In addition to the demand forecast (denoted by baseline demand), promotions are added to the usual demand forecast. These promotions are price discounts at certain customers that are known beforehand. The sales department negotiates price discounts, especially for the Retail market, on a weekly bases, that impacts the total weekly sales (Promotion + Baseline). The expectation of the extra sales due to a promotion is forecasted and then added to the baseline forecast.

1.1.4 Inventory Control Policy

The inventory control at the warehouse is currently done by a system that works with safety stocks and a reorder point. When the inventory position drops below the reorder point, a multiple of a fixed amount Q is ordered to bring the inventory position back on or above the order-up-to point. From the literature, it can be concluded that the current supply policy is a (R, s, nQ) system, which has a review period (R), reorder point (s), and orders are placed based on a multiple of Q units. The value of Q is different per SKU and is fixed by the number of boxes that can be placed on one pallet. The review period is also fixed and is one week for all SKUs since the warehouse has weekly truck loading time slots. The current determination of the safety stock levels and the reorder point, however, is not supported by statistical analysis or a demand distribution.

Furthermore, the expected demand for the coming periods is based on historical data, instead of using the demand forecast to develop an order strategy. The main goal of inventory control is always to reach a high customer service level with low inventory costs. Because demand is stochastic and fluctuating, certain safety stock is needed to deal with unexpected demand fluctuations. In the current situation at Bonduelle, the demand fluctuation and demand forecast accuracy are not taken into account when determining the safety stock levels; and the amount of safety stock is currently determined based on the mean period demand multiplied by a certain SKU specific value, which is probably not optimal (Inderfurth & Vogelgesang, 2013). When, for example, some stock-outs have occurred for a certain SKU, the safety stock is raised by hand. Although this might be a working heuristic, in this research more data-driven inventory control policies are addressed.

As stated in the previous section, promotions and price discounts influence the total demand. Currently, the sales that come from promotions and price discounts are not taken into account for the inventory policy. The baseline historical mean demand is used to determine whether to order and how much and also the safety stocks are based on the baseline demand. Besides, the promotional forecasted amount is added to the order. The reason for this distinction is based on the purchase agreements of the sales departments with customers. In this way, no separate safety stock is added for the promotional expected sales.

1.2 Problem Definition

In this section, the problem definition is addressed. The motivation of the problem is provided and the problem statement is explained. Furthermore, the project scope research questions are given.

1.2.1 Research Motivation

The problem in this research is motivated by the actual situation faced at Bonduelle Northern Europe. Currently, the inventory system at Bonduelle works as follows: the inventory position is reviewed every week and an order of size Q is done whenever the inventory position drops below the determined fixed reorder level s. Later in this report, the inventory policy is explained in more detail.

The current way of controlling the inventory is not based on statistical analyses. As explained before every SKU at the warehouse has some safety stock, but this safety stock is not determined based on the analysis of data or fitted demand distributions. From literature, it can be concluded that setting fixed safety stocks, independent of the sales or forecast patterns of SKUs, is mostly far from optimal (Inderfurth & Vogelgesang, 2013). This non-optimal way of controlling the warehouse probably causes unnecessary inventory costs and relatively low customer service level. Currently, the target service level at Bonduelle is not always met. In this research, sales from the past are analyzed to determine statistically substantiated stock levels, which could probably result in cost savings or improvement of customer service level (Dubelaar, Chow, & Larson, 2001; Inderfurth & Vogelgesang, 2013).

Furthermore, the current inventory control policy is based on the mean sales of the past couple of weeks, while the demand forecasts take promotions, seasonality, and other influential matters into account. It might be more cost-efficient to consider this demand forecast as the basis of the inventory policy instead of using the mean historical demand without trends and seasonality. In scientific literature, most of the papers assume some demand distribution to optimize inventory models or focus on demand distribution gained from the historical data with a certain mean and standard deviation (Forsberg, 1997; Iglehart, 1964). However, taking the demand forecast and its error as a model parameter might be interesting and more beneficial in some cases (Beutel & Minner, 2012). Taking the forecast as a basis for inventory control makes the inventory control a non-stationary model because optimal stock levels are determined again every review moment, dependent on the demand forecast at that moment in time. An example of a situation in which a non-stationary forecast-based model might work better is a deterministic situation with seasonality in the demand pattern. A non-stationary model would assume high variation in demand and therefore (unnecessarily) high safety stocks, while the model based on forecast would exactly use the right values because a deterministic situation means the forecast is equal to the actual demand. The approach is not much addressed in the literature, which makes this topic scientifically interesting. This research is conducted based on 143 frozen SKUs stored in a single warehouse. From the literature study, we see that the supply chain of frozen products always has to deal with relatively high transportation and inventory costs, which makes reducing inventory levels for these products even more beneficial for the company (Zanoni & Zavanella, 2012).

In this research, the difference between a model based on historical demand and based on demand forecasts and forecast errors is analyzed to get insight into the performance of both models. Furthermore, both models are compared with the current situation to get insight into the improvement of using data-driven decisions in inventory control. The first approach is based on a demand distribution fitted on historical sales data and the second approach is based on demand distributions based on the demand forecast and forecast error. For the company, it is expected that both models could results in major cost savings since both models are based on data analysis instead of the current manually set safety stocks. Available literature helps to find a more efficient model for the company to provide inventory cost savings and also maintain the service level constraint. Furthermore, order up to levels can differ per period, because the forecast for a certain period is sometimes higher than for another period, which makes the expected demand during the lead time non-stationary. Because the expected demand during the lead time differs per period, the optimal reorder levels s differs per period (s_t). Because of this dynamic s_t, we can state it is a non-stationary or dynamic model.

As a result, this research can help the company to save inventory costs while maintaining the current customer service level. The results are based on a selection of SKUs, but the model itself can be applied to other warehouses and could, therefore, cause major cost savings for the organization as a whole. Furthermore, the research might also contribute to the currently available scientific literature on demand distributions and inventory control.

1.2.2 Research Objectives and Research Questions

The current problem faced at the company is an inventory control problem. As described before, the current way of ordering is not based on customer service level as a constraint. Furthermore, the trends and seasonality patterns that are included in the demand forecast models, are not applied to the inventory control policy. When the wrong demand is used to determine the demand during the lead time, the non-optimal amounts are ordered for the warehouse. This can result in either too high inventory levels or too low customer service levels. From the literature review, we conclude that the demand distribution that is assumed to simulate the demand during the lead time has a relevant impact on both the inventory policy and the customer service level (Gérard Cachon & Terwiesch, 2006).

In this research, the goal is to find better ways of controlling the inventory and minimize the inventory holding cost by meeting the fill rate requirements. The problem is a single echelon inventory control problem with stochastic demand, periodic review, and fixed replenishment lead times. The target service levels are set per SKU. This service level forms the basis for a new and closer to the optimal system with revised stock levels.

In this section, the main goal and corresponding research questions are given and explained. Based on the project description and the available information from the company and scientific literature, the aim of this project is:

> "*Develop and compare inventory control models based on historical demand as well as demand forecasts with an SKU-specific target service level that minimize the inventory holding costs."*

This aim results in the following research question:

> *"How does an inventory policy based on the demand forecast perform compared to an inventory policy based on historical demand?"*

To answer this research question, some sub-questions have been addressed:

1. How are the current inventory model, service level constraints, and demand forecasts designed?
This question gives insight into the current situation. The way the demand is forecasted, the inventory policy and the service level determination and measurement are described. The current situation gives insights into the current problems and also forms the basis for the model development and model assumptions.

2. How is an inventory policy based on historical demand data designed?
Based on a previously deducted literature review, an inventory model is designed. Data is used to fit distributions on the demand patterns.

3. How is an inventory policy based on the demand forecast and forecast errors designed?
Based on a previously deducted literature review, an inventory model is designed. Data is used to fit distributions on the demand patterns.

4. What is the performance of an inventory policy based on historical demand compared to the current inventory model?
The performance can be compared to the current situation. Performance is measured by the customer service level and inventory costs.

5. What is the performance of an inventory policy based on demand forecast and forecast errors compared to the current policy and a policy based on historical demand?

The performance of the two models is compared. This comparison is discussed and interpreted. Based on these comparisons, recommendations for the company can be given.

6. What are the advantages and disadvantages of using an inventory policy based on demand forecast and based on historical demand?
Finally, the results and interpretations of the models are discussed in this sub-question.

To address these research questions, data from the company is obtained and filtered in a way that the analyses can be done. In Section 3, the exact way of finding solutions is addressed.

1.3 Problem Definition

The project is being executed at Bonduelle Northern Europe, with a specific focus on the Benelux market of frozen products. This point of focus has been chosen because an external warehouse is controlled by Bonduelle Northern Europe.

As described before, the results of the research should help to reconsider the other markets that are controlled by Bonduelle Northern Europe as well. Furthermore, only the supply chain of the frozen SKUs is considered in this research, because the supply chain of ambient products is not controlled by Bonduelle Northern Europe, but controlled by the central headquarters in France. Within the scope of this research, the distinction between sales data and demand forecasts, and therefore the distinction between stationary and non-stationary models is taken into account and reviewed.

1.4 Methodology

In this section, a description of the research methodology is provided. In this research, the first three steps in the problem-solving cycle of Van Aken et al (2012) were executed to conduct the research (Aken, J., Berends, H., & Bij, 2012). The cycle they propose is illustrated in Figure 1.5.

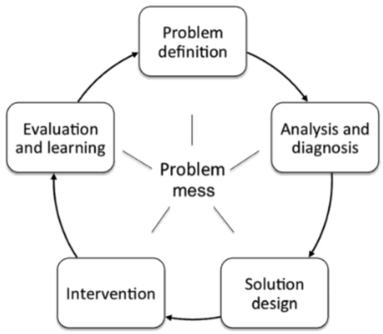

Figure 1.5: Problem Solving Cycle (Aken, J., Berends, H., & Bij, 2012).

As can be derived from Figure 1.5, the first three steps consist of the problem definition, the analysis and diagnosis, and the solution design. Firstly, the problem definition is provided in the previous section. The problem definition has been done in the form of a research proposal based on internal documents from the company and an analysis of the current supply chain. The current situation is described and can be used as a basis for the analysis and solution design.

After the definition of the problem, the current inventory model has been analyzed, and together with the literature review, different inventory control systems have been considered. Furthermore, an analysis of the demand patterns and forecast accuracy has been done to get insight into the possible demand models. The current model has been compared to different new inventory models and the results are analyzed. This comparison can be done by testing the models with real historical data of the case study. The analyses of the results are based on costs as well as the performance of the model.

After the analyses had been done, the solution for the specific case was designed. Recommendations were done based on the costs- and performance results. Arguments for and against the different models and approaches together form the solutions for the inventory problem.

1.5 Outline of Report

Firstly, the literature review is given about inventory control and demand forecasting. Thereafter, all methods are explained with the necessary calculations. After an explanation of the methods, the model is validated and also implemented on the situation at Bonduelle. Lastly, conclusions are elaborated based on the analyses and in the final section all results are discussed directions for future research are provided.

2. Literature Review

In the literature review, an overview of the existing models and theories on inventory control and demand forecasting is provided.

2.1 Inventory Control

In this section, the basics of inventory control management are discussed. According to Axsater (2016), the total investment for companies in inventories is enormous, which makes the optimization of inventory control necessary to keep a competitive advantage. Dependent on the products and parameters, different models can be distinguished. The main goal of an inventory model is usually to balance conflicting goals. Most commonly, the objective is to minimize the cost (inventory holding costs) with conflicting requirements like capacity constraints or service level constraints (Axsater, 2006). In this section, some relevant different inventory models are discussed. Different costs and constraints, inventory policies, and economic order quantity are addressed.

2.1.1 Costs and Constraints

For different optimizations, especially at the supply chain department, different costs influence all decisions. In this section, the relevant costs to consider are discussed. By Axsater (2006) different costs that impact the inventory are discussed.

To deal with uncertainty and to make sure customers are served within a certain period, holding inventory is necessary. Keep inventory is always associated with holding costs (h). The most important part of the holding costs is the cost of storing place (Axsater, 2006). When a warehouse is owned or hired, these costs are usually well defined and therefore easy to determine. Usually, the holding cost of an item per period is determined as a percentage of the value of the Stock Keeping Unit (SKU). In some cases, the unit holding cost for SKU is just a fixed amount per time unit.

Holding costs are dependent on the size of a product, but also the type of products. Bozorgi, Pazour, & Nazzal (2014) state that especially the supply chain of frozen and temperature-controlled items extra costs are associated. The extra costs with these kinds of products are caused by refrigerated trucks, cold warehouses, packaging, and other supply chain components that differ from usual products (Bozorgi et al., 2014). Cost warehouses are warehouses in which the temperature is always within a certain range that fits the product requirements. The unit holding costs in these kinds of warehouses are always higher than the unit cost in other warehouses, which makes it interesting for companies to reduce inventory levels. Furthermore, the supply chain of frozen and temperature-controlled products also has an emission footprint. Because currently, the reduction of emissions is some of most companies' goals, the emission footprint could be added as a constraint in different models (Bozorgi et al., 2014).

On top of the holding cost per SKU per time unit also the fixed order cost should be taken into account when making an inventory- or order policy. The fixed ordering cost (K) is independent of the batch size and determined depending on different parameters (Axsater, 2006). According to Axsater (2006), the most important factors that determine the fixed order costs are administrative costs and handling costs of an order. The fixed ordering costs influence inventory models, because the optimal order quantity is lower when the fixed order costs are high, and vice versa.

Although the goal of an inventory model in most of the cases is to obtain a target service level, the model always has to deal with out-of-stock and overstock. Overstock can be expressed in either outdating or high stock levels. High stock levels result in high inventory costs and outdating results in costs of waste. The trade-off between higher stocks and service levels can be determined by using the Newsvendor policy (Benzion, Cohen, & Shavit, 2010). According to Benzion et al. the optimal quantity to order (Q^*) can be determined by comparing the cost of underage (Cu) and the cost of overage (Co). The following equation is used by Benzion et al. to determine the optimal quantity to order:

$$F(Q^*) = \left(\frac{\mathrm{Cu}}{\mathrm{Cu+Co}}\right) \tag{1}$$

As can be derived from Equation (1) the fraction of the cost of underage and the cost of overage determines an optimal order quantity based on demand distributions. High costs of underage in comparison to the cost of overage would result in high order quantities because out of stocks are more expensive than overstocks in that situation. In Equation (1) the cost of underage is based on a penalty cost together with the lost amount of margin. The cost of overage is based on the buying price of the SKU minus, if there is any, the salvage value of the SKU. The explained newsvendor equation is a good way to determine the optimal quantity, but in some cases determining the penalty cost, for example, can be challenging (Benzion et al., 2010), Axsater, 2006). Because determining these penalty costs and therefore the cost of underage is challenging, the equation is sometimes replaced by a target service level as a constraint for the system. Determining the target service level and possible ways of doing this is discussed later in the report.

2.1.2 Inventory Control Policies

To optimize the amount of inventory and the order quantities per period, different models can be explained. In this section, some well-known models from the scientific literature are highlighted. According to Van Donselaar & Broekmeulen (2013), the literature about inventory control policies can be distinguished into four categories. The first split is whether the system is periodically reviewed or continuously reviewed. The second categorization is made based on a fixed- or variable order size.

Systems with continuous reviewing are referred to as (s, nQ) and (s, S) policies, which are fixed order size and variable order size, respectively. Systems with periodic review moments are referred to as (R, s, nQ) and (R, s, S), which are systems with fixed order quantity and variable order quantity, respectively. Table 2.1 summarizes the four categories.

Table 2.1: Four Categories of Inventory Policies.

	Periodic Review (R)	Continuous Review
Fixed Order Quantity (Q)	*(R,s,nQ)*	*(s,Q)*
Variable Order Quantity	*(R,s,S) or (R,S)*	*(s,S)*

As can be derived from Table 2.1, five different policies can be distinguished based on four different situations. The parameters stated in this table have the following meaning:

- (s, Q): Whenever the inventory position drops to below the reorder level s, order the order quantity Q.
- (s, S): Whenever the inventory position drops below s, place an order up to the order up to level S.
- (R, s, S): Review the inventory position every period with length R. Whenever the inventory position drops below s, place an order up to S units.
- (R, S): Review the inventory position every period with length R and bring the inventory position up to level S.

- (R, s, nQ): Review the inventory position every period with length R. Whenever the inventory position drops below s, order nQ units to bring the inventory position to ≥ s

Systems with periodic review have a fixed review moment every R time units. Usually, this moment of reviewing is the moment that whether to order and how much to order has to be decided. Systems with continuous reviews are reviewed all the time, which means a replenishment action can be taken at every moment. The system with continuous review usually results in higher costs because of unpredictable loads, but better customer service (Purnomo, Wee, & Praharsi, 2012). Dependent on the situation one policy results in lower total costs, but Purnomo et al. (2012) state that continuous review systems usually are more cost-efficient because on-hand holding costs usually have more impact on the total cost than other costs. Furthermore, de Kok (2018a) has proven that (s, S) performs slightly better than (s, Q) results, but also proven that optimal values for Q can be found (De Kok, 2018a).

(s,Q) – and (s,S) Policy

As stated before the (s, Q) and the (s, S) policies are policies based on a continuous review. In every moment in time, the inventory on hand and inventory position is reviewed, which means the decision to order new units and how much can be made at every moment in time.

The advantage of the (s, S) policy in comparison to the (s, Q) policy is that the optimal s and S can be determined, which probably reduces inventory costs. On the other hand, with a fixed order quantity Q, the order quantity is predictable which can make the handling cost lower.

(R,s,S) – , (R,S) – and (R,s,nQ) Policy

As stated before the periodic review models are: (R, s, S), (R, S), and (R, s, nQ). Figure 2.1 depicts a sample path of the (R, s, nQ) model with $n = 1$. Under a (R, s, nQ) policy, the inventory position is reviewed every R periods. When the inventory position on a review moment drops below s, an amount Q is ordered. The R in Figure 2.1 is the reorder level (s) and the T is the review period (R).

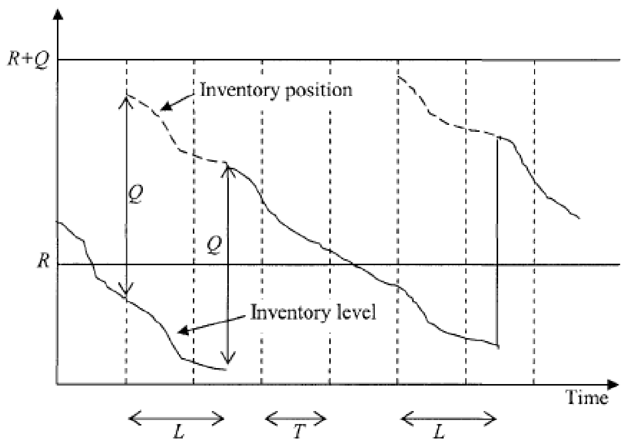

Figure 2.1: (R,s,nQ) Model (Axsater, 2006).

As can be seen in Figure 2.1, an order of size Q is placed when the inventory position is under a certain level on a review moment. In research, the main focus is on the (R, s, nQ) policy because this policy fits the best with the problem faced by Bonduelle.

2.2 Performance Measurements

Companies use performance measures to assess their success and keep their competitive advantage in changing environments (Ghalayini, Noble, & Crowe, 1997). Measuring performance can be done in many different ways for different goals. Ghalayini et al. (1997) state that an integrated performance measurement system is needed to control the current changing environment. However, still many traditional performance measures are used in companies. Performance measurements can also be used as Key Performance Indicators (KPI's) to assess and compare the performance of different departments and employees in a company. Furthermore, performance measures (KPI's) are used as constraints in models, because using conflicting KPIs as constraints and model objectives can help to find optimal outcomes (Lockamy & Spencer, 1998). An example of using KPIs in an optimization model is minimizing certain costs subject to a service level or capacity constraint. The performance measures that are relevant for this thesis are further elaborated in this section.

2.2.1 Service Levels

Which inventory policies are applied and what value is chosen for all decision variables (for example reorder point) depends on the kind of model that is chosen in combination with all the associated costs. Furthermore, the requirements of the model, like service levels or capacity constraints, have an impact on the output of the inventory model.

As stated before the fill rate can be a KPI for a company to measure performance and is even the most used service level measure for companies (Teunter, Syntetos, & Babai, 2017). The fill rate can be measured in different ways to measure the performance of a company or a part of a company. The fill rate of a system can be defined by: "The percentage of demands satisfied directly from stock-on-hand" (Teunter et al., 2017). An alternative less applied measure of service level is the ready rate. The ready rate can be defined as: "The fraction of time during which the stock-on-hand is positive" (Teunter et al., 2017). In this project, the focus is set on the fill rate as a measure of service.

For every warehouse that has to deliver products at a certain service level under the condition of cost minimization an inventory control policy could help to optimize the ordering process. Slightly decreasing the desired service level constraints could for example already significantly save costs (Greis, 1994). Furthermore, the lead time of an SKU significantly influences the fill rate (Tan, Paul, Deng, & Wei, 2017).

In the field of inventory control, service level constraints play a relevant role. Greis (1994) states that the relationship between demand variability and target service level strongly influences the optimal inventory- or production policy. Reviewing the best target service levels, therefore, could help to define a better inventory control model (Greis, 1994).

Van Donselaar & Broekmeulen (2013) discuss the difference between a system that allows backorders and a system that assumes loss sales. Backordering means that when demand cannot be met directly from stock, a backorder is placed and therefore the demand is added to the order quantity of the next period (Van der Heide, Van Foreest, & Roodbergen, 2018). Van der Heide et al. (2018) state that also partial back-ordering is possible, which is a combination of a back ordering system and a loss sales system.

Van Donselaar & Broekmeulen (2013) state that most of the literature is based on systems with backorders, because these are easier to analyze, while in reality, also some of the customers decide to buy something else when a product is out of stock, which corresponds to a loss sales system. They propose three kinds of approximations to approximate the service level (Fill Rate) of a loss sales system with the service level of a loss sales system.

For the approximations, an (R, s, nQ) system with discrete demand is the base of the equations. The first approximation is the approximation that $FR^{BO} = FR^{LS}$. This first approximation of the fill rate of a back ordering system being equal to the fill rate of a loss sales system is reasonable for high customer service levels (Silver, E., Pyke, D., & Peterson, 1998). Also, two ways of recalculating the back order fill rate into a loss sales fill rate are addressed, but that part is kept out of the scope of this research. Finally, Van Donselaar and Broekmeulen (2013) state that the ratio between the demand rate and the minimum order quantity (in (R, s, nQ) environment) is relevant when determining the number of outstanding orders and therefore the inventory position and other parameters.

2.2.2 *Aggregate Fill Rate*

As mentioned before, the service level (fill rate) can be used as a performance measure as well as a model constraint. Furthermore, the service level per product can be distinguished from the total system aggregate service level (Kat & Avșar, 2011). Kat & Avsar (2011) suggest calculations and comparisons of the SKU fill rate and the aggregate fill rate as a model constraint. According to Kat & Avsar (2011), the total fill rate can be calculated by a weighted average:

$$FR(\pi) = \sum_{i=1}^{I} w_i * FR_i(\pi) \tag{2}$$

Where:

$FR(\pi)$ = System aggregate Fill Rate under policy π

$FR_i(\pi)$ = Fill Rate of SKU i

w_i = weight of SKU i with $\sum_{i=1}^{I} w_i = 1$

The choice of the weight factor is proposed to be calculated by the fraction SKU of the total demand of all SKUs I (Kat & Avșar, 2011). The weight per SKU can be calculated by:

$$w_i = \frac{\lambda_i}{\sum_{i=1}^{I} \lambda_j} \quad \text{, where } \lambda_i \text{ = demand rate of SKU } i \tag{3}$$

Taking Equation (2) and (3) Together, the total aggregate Fill Rate FR(π) becomes:

$$FR(\pi) = \frac{\sum_{i=1}^{I} \lambda_i * FR_i(\pi)}{\sum_{i=1}^{I} \lambda_i} \tag{4}$$

The aggregate service level calculation proposed by Kat & Avsar (2011) can be used to measure the performance of a system. The disadvantage of this approach is that only the demand rate is taken into account. Furthermore, when looking at the aggregate fill rate, the fill rate of some SKUs can be significantly lower than the target, because products with high demand rates can compensate for these products (Tan et al., 2017). In this case, some customers may be experiencing a very low service level, while the target aggregate service level constraint of the supplier is still met. To assure every single SKU meets the service level target, a service level constraint should be set for all SKUs.

When the aggregate service level can be calculated, the base stock levels of all SKUs can be optimized using a greedy algorithm (Park & Klabjan, 2015). The greedy algorithm is explained by Park & Klabjan (2015) and is based on an iterative way of increasing the base stock level of a single item until the moment that the system target is achieved.

2.2.3 SKU Specific Service Level

As mentioned before, the service level can be determined for the system as a whole or separate SKUs (Teunter et al., 2017). The disadvantages that are mentioned about only taking the aggregate fill rate into account are addressed by Kat & Avsar (2011) as well. To deal with these disadvantages, the SKU specific target fill rate could also be determined (Teunter et al., 2017). To determine the SKU specific service level, different strategies can be applied. To measure the total system fill rate a weighted average of all SKU fill rates can be calculated (Teunter et al., 2017; Kat & Avșar, 2011). According to Closs, Nyaga, & Voss (2010), however, the fill rate could also be determined based on the percentage of orders that are fulfilled completely of the total amount of orders, which is called the order fill rate. This approach is more general and is not based on the SKU specific target.

By Greis (1994) the task of finding the optimal balance between high service levels and high return on investment is discussed. Greis states that the determination of the target service level depends on management decision and market characteristics. In highly competitive markets, where customer satisfaction is an important factor, higher target service levels are needed to keep a competitive advantage (Greis, 1994). The trade-off between service level and costs is called the reliability curve. The shape of the reliability curve depends on the type of product that the company produces or sells and the inventory costs and -capacity.

The results of this article indicate that the trade-off between costs and service level can be graphically shown and the management decision of determining the target service level can be optimized in some cases. The exact shape of the curve is strongly dependent on company-specific factors like unit holding cost and demand variability (Greis, 1994). Furthermore, Greis (1994) has shown that management's influence on determining the service level targets is important because different market impacts are relevant.

In contrast to Greis (1994), Teunter, R. H. , Babai, M. Z. , & Syntetos (2010) explain the classification of SKUs in the assortment of a company into three classes. The classification that is explained is called the ABC classification and means: "A group of items in decreasing order of annual dollar volume or other criteria" (Teunter, R. H. , Babai, M. Z. , & Syntetos, 2010). Comparing the results of Greis (1994) and Teunter et al. (2010), it can be concluded that cost factors, like holding costs, as well as managerial factors, like market opportunities, should influence the target service level of all SKUs (Silver, E., Pyke, D., & Peterson, 1998).

Although, some literature states that the classification model is a good way of determining target service levels, Teunter et al. (2017) explain the disadvantages of classifying SKUs in different service level categories. They explain that service level targets influence the inventory policies that should be used and also the responsiveness of the company to the market. Classification of target service levels is not optimal according to Teunter et al. (2017), but determining the service level target per single SKU sometimes is not realistic. Furthermore, the model that this article proposed is based on penalty- or backordering costs, which are usually hard to determine.

2.3 Demand Forecasting

The expected demand in the future is an important factor in Supply Chain Management (Trapero, Fildes, & Davydenko, 2011). Because demand is fluctuating and stochastic in most cases, demand should be forecasted. As stated before the service level to customers has become more important to maintain a competitively advantaged position in the market (Greis, 1994). Furthermore, the demand forecast accuracy has a major impact on the inventory control policy (Trapero et al., 2011). Also, demand forecast accuracy can impact the financial results of a company (Kahn B. Kenneth, 2003).

In this section, the topic of demand forecasting and demand models is discussed.

2.3.1 Demand Model

To make an inventory model, the demand always has to be estimated by a demand distribution. When this demand distribution is determined, many calculations can be done, like expected demand during lead time, stockout probability, etc.

In the literature, a lot of researches about inventory control is based on the assumption that the demand has a simple distribution, like the Normal distribution or poison distribution (Burgin, 1975). The article also states that finding the right demand distribution for an item is important in inventory control. The Gamma distribution might perform better than the Normal distribution because the Normal distribution is not non-negative and also always symmetric. Non-negativity is a common characteristic of product demand distributions (Wales & Woodland, 1983), and not every product demand distribution fits best with symmetry (Burgin, 1975; Wales & Woodland, 1983). Furthermore, the negative exponential distribution is argued to be not tenable for fast-moving items. Burgin (1975) therefore argues that the Gamma distribution should be taken as a general distribution in inventory control models.

More general, for using demand distributions in inventory control policies, the expected demand and standard deviation of the demand are important. The mean and standard deviation of the demand can usually be calculated quite easily, but the conversion into the right period is relevant as well (Gérard Cachon & Terwiesch, 2006). Cachon & Terwiesch (2006) explain a general way of the conversion to different periods, and especially to the duration of the lead time plus the review period.

The demand distribution of one period (for example one month) can be computed by taking the mean monthly demand and the standard deviation of this mean demand. When the expected mean demand ($E[D]$) and standard deviation (σ) has to be converted into a shorter period, conversions to the more period parameters can be done.

In addition to these general expressions of time conversions, Burgin (1975) explains the conversion of the Gamma distribution and its parameters for the demand during the lead time. When the demand per period is Gamma distributed with parameters α and b, the demand during the lead time can be assumed to be Gamma distributed with parameter $L * \alpha$ and b (Burgin, 1975). As demonstrated by Burgin (1975) and proven by Weatherburn (1949), the Gamma-distributed demand during the lead time can, therefore, be calculated by using the converted parameters.

With these conversions, we can determine the distribution of the lead time demand when the demand is stationary. In addition to the equations of converting expected demand and standard deviations to another time unit, also non-stationary demand can be taken into account. Non-stationary demand means that the demand rate in period t can be different from the demand rate in period $t + 1$ for different reasons, for example, manual demand forecast adjustments.

Both Tarim & Kingsman (2006) and Bookbinder & Tan (1988) state that the coefficient of variation (CV) is constant and independent of the period. The CV means the relative standard deviation, which is calculated by dividing σ over μ (Stępniak, 2011). However, as stated before, the expected demand per period can be different depending on the demand forecast. Tarim & Kingsman (2006) show that the demand in period t can be assumed to be normally distributed with the forecast as the mean (μ_t) and standard deviation $\sigma_t = \mathrm{CV} * \tilde{d}_t$ in which $\tilde{d}_t$ is the expected demand in period t. Using this calculation, σ_t and μ_t can ben determined and therewith a demand distribution for the period t can be defined.

In addition to the way of determining the standard deviation of Tarim & Kingsman (2006), Axsater (2006) explains a way of calculating the expected demand and standard deviation by taking the forecast and forecast accuracy into account. Axsater (2006) proposes calculating the standard deviation of the demand to be as stated in Equation (11) and (12). Using this calculation also the CV can be determined.

As mentioned before, usually the demand during the lead time (and review period) is relevant when making demand distribution for inventory control. The parameters can be converted into demand during the lead time. The demand during the lead time (μ) and matching standard deviation (σ') just after the forecast update is computed with the following equations:

$$\mu' = \frac{\hat{a}_t}{t_F} L \tag{5}$$

$$\sigma' = \left(\frac{L}{t_F}\right)^c \sqrt{\frac{\pi}{2}} MAD_t \tag{6}$$

Where parameter c in Equation (6) is always in the interval (0.5; 1) and assumed to be 0.5 when the forecast errors in different periods are independent (Axsater, 2006). Further, t_F is the forecasted period and $\hat{a}_t$ the estimated demand over that period.

Axsater (2016) also addresses that usually the demand during the lead time, knowing the mean and standard deviation, is assumed to be normally distributed. Chen (2019) also uses the forecast and forecast accuracy as an input of the inventory control model.

Tunc, Kilic, Tarim & Eksioglu (2011) investigated the use of both stationary and non-stationary demand models in non-stationary demand environments and suggest that in some situations (especially with high demand uncertainty) using a stationary demand model is closer to optimal than using non-stationary models with forecasts. However, in some cases, when the demand can be forecasted relatively well, non-stationary models perform better (Tunc et al., 2011).

As stated before, the demand forecast can be used as the expected demand and the forecast error (either positive or negative) can be added as a stochastic variable. Instead of assuming a distribution to the demand data, a distribution should be designed for the forecast error. Also, this distribution should be transformed into the distribution for the lead time. The approach for determining the demand distribution in this research is addressed in Section 3.

2.3.2 Forecasting Methods

Different forecasting methods can be used to forecast the demand in a stochastic environment as accurately as possible. First of all, the simplest forecasting model is the constant model. The constant model takes the mean demand plus or minus an independent random variable with mean zero.

This forecasting model is mostly common for products with very low variation and usually in the mature stage of the product life cycle. For products that do not have this constant demand, exponential smoothing could be used. The main point of exponential smoothing is that not only the actual demand from the last periods is taken into account, but also the last forecast (Taylor, 2003). Exponential smoothing results in the following equation:

$$F_t = \alpha * D_{t-1} + (1 - \alpha) * F_{t-1} \tag{7}$$

The determination of α is dependent on how reactive the forecasting model should be. When α is large, the system responds quickly to environmental changes, which might result in variations for period to period. In Equation (7) D_{t-1} and F_{t-1} are the demand and forecast, respectively, of the previous period. In general, $F_{t,t+k}$ is the forecast made in period t for k periods ahead. Later in this report, the accuracy of determining $F_{t,t+k}$ is discussed.

In addition to the standard exponential smoothing method proposed by Taylor (2003), it is also stated that some SKUs can have a seasonal pattern of a trend that can be analyzed and taken into account when making demand forecasts. To explain the methods of trends and seasonality forecasting, Taylor (2003) shows the double seasonal Holt-Winters, exponential smoothing model. This method distinguished the level, the trend, and the seasonality. Furthermore, the seasonal (s-period) index is estimated. Taking these parameters together, an equation for the forecast is designed (Taylor, 2003):

$$F_{t,t+k} = (S_t + k * T_t) * I_{t-s+k} \tag{8}$$

In this equation, S_t T_t and I_{t-s+k} are parameters that are determined for the level, trend, and seasonality. The determination of the smoothing parameters determines what the actual forecast using these equations will be. Furthermore, every SKU of the assortment of a company probably has different optimal parameters.

2.3.3 Manual Forecasts

In addition to the many ways of forecasting the mean demand for a certain period, some cases require manual modifications to the demand forecasting models. The demand forecast that comes from a forecasting tool combined with the manual modifications together forms the total forecast of an SKU for a certain period (Axsater, 2006; Singh, Olasky, Cluff, & William F. Welch, 2001). Relevant examples of situations in which manual forecasting is sometimes required are Sales Promotions, Price Changes, Innovations, Market Changes. These environmental changes cause flexibility in the process, which is why sometimes human influence on forecasts can be beneficial (De Kok, 2018b).

All of these examples are based on the fact that there is no, or limited, historical data that can be used to form the basis of a model. For example, innovations, which are usually products that have never been sold before, make using statistical models challenging. Although manual forecasting or manual modification of forecasts are sometimes necessary due to the lack of data on the need for managerial knowledge, Trapero et al. (2011) state that managerial impact on the forecast could also negatively influence the forecast accuracy. These managerial errors are mostly due to optimistic thinking, which may result in higher demand forecasts than actual demand (Davydenko & Fildes, 2013; Trapero et al., 2011). Markovitch et at. (2015) also state that this optimistic way of thinking is very common and caused by overconfidence: “excessive belief in one’s abilities to generate superior performance” (Markovitch et al., 2015).

2.3.4 Demand Forecast Updating

As stated before, the demand forecast can serve as an input for the replenishment policy. Boulaksil (2016) proposes a way of updating the demand forecast. Forecasts are made for a certain planning horizon T periods. The forecast can be denoted as a vector: $\vec{f_{\mathrm{t}}} = (f_{t,t+1}, f_{t,t+2}, \dots, f_{t,t+T})$, in which $\vec{f_{\mathrm{t}}}$ denotes the forecast in period t for the next T periods. After a period t, the actual demand is known and the forecast can be updated, by using the latest demand data. The demand for period t is denoted by D_t and can be written as: $D_{t+1} = f_{t,t+1} \pm \varepsilon$ in which ε is a possible forecast error.

Compared to the situation of stationary demand, in this case, the value of ε becomes a stochastic variable with a probability density function.

Demand updating is important to keep a competitive advantage in some markets, for example, the food Retail market (Mazzoleni, Formentin, Previdi, & Savaresi, 2017). Mazzoleni et. al (2017) also state that usually, the main reason for the need for forecast updating is promotional events at customers. Promotional events in the Retail market can be predicted by the sales department, and together with the sales department, the demand forecast can be determined. For a market in which promotional events are relevant, updating the demand forecast is usually also needed (Mazzoleni et al., 2017). The known information of promotional events in a certain period together with the updated actual historical demand information and the last forecast form the latest updated demand forecast for the next period (Mazzoleni et al., 2017; Boulaksil, 2016).

2.3.5 Forecast Errors

As stated before, different forecasting models can be used to forecast as accurately as possible. However, the forecast is most of the times not the same as the real demand, which is why the forecast errors should always be taken into account and analyzed. The accuracy of the forecast is a relevant factor when determining the safety stock levels and it is therefore important to measure the forecast error properly (Davydenko & Fildes, 2013). In this section different ways of calculating and interpreting forecast errors are discussed.

First of all, the most common way of measuring variation is to determine the standard deviation (σ) and the variance (σ^2). The standard deviation is calculating with the following equation:

$$\sigma = \sqrt{\sigma^2} = \sqrt{E(X - \mu)^2} \tag{9}$$

Where:

X = Stochastic variable with mean $\mu = E(X)$

Usually, an easier way to determine the error is used, namely the Mean Absolute Deviation (MAD). The following equation is used to calculate the MAD:

$$MAD = E|X - m| \tag{10}$$

To calculate the standard deviation with the MAD, Axsater (2006) proposes the following equation:

$$\sigma = \sqrt{\frac{\pi}{2}} * MAD \approx 1.25 * MAD \tag{11}$$

When the forecast has to be reviewed further in the future, usually the forecast is less accurate. To take into account the fact that longer-term forecasts are usually less accurate than shorter-term forecasts, the following equation can be used to determine the standard deviation over L periods ($\sigma(L)$):

$$\sigma(\mathrm{L}) = \sigma_t * \sqrt{L} \tag{12}$$

In addition to this statement, Tarim & Kingsman (2006) explain a way of determining the standard deviation of a demand model with non-stationary demand.

2.4 Determination of Stock Levels

The mean demand, demand forecasts, forecast error, service level constraints, and different cost parameters together contribute to the design of an inventory model. A general inventory model is a model that minimizes costs. The standard trade-off between holding costs, ordering costs, and backordering costs together form the optimal inventory model.

An alternative, as earlier described, is the inventory model that aims to have the lowest base stock levels, while serving a certain target service level. In this case, the expected demand can be either be a mean expected demand, or a periodic demand that is updated every review period. In this last situation, the base stock levels should be determined again every period, based on the expected demand (and standard deviation) in that specific period. Literature has proven that sometimes the service level based model, rather than the cost-based model, is more accurate, because of inaccurate cost determinations (Ouyang & Chuang, 2000; Kat & Avșar, 2011). Furthermore, the service level based model is more customer-focused, which is also more accurate for most of the companies in competitive markets (Lockamy & Spencer, 1998).

In this section, the two types of optimization problems by Kat & Avșar (2011) are presented.

2.4.1 Costs and Service Level

The first model is, as earlier explained, the model that finds the optimal trade-off between the holding cost per SKU (C^H) and the back ordering cost per SKU (C^{BO}). The expected inventory on hand ($E[IOH_i]$) and the expected amount of backorders ($E[BO_i]$) are taking into account. Kat & Avsar (2011) describe the cost optimization model with the following equation:

$$Minimize \{ \sum_{i=1}^{I} (C^H * E[IOH_i](\pi) + C^{BO} * E[BO_i](\pi)) | \, \pi \in \Pi \} \tag{13}$$

Here, π denotes the chosen inventory policy. In this optimization problem the best inventory policy π of all policies, Π is chosen to minimize the total cost. The policies in Π are decisions on base stock levels that influence the total holding cost and backordering cost. In the basic formula, therefore, the decision variable is π, which means choosing from a selection of policies. In most of the cases in the literature, however, finding the optimal value for the base stock level (S) is the decision variable.

In addition to the trade-off between the holding cost and backordering cost, the holding cost could also be minimized subject to a service level constraint. Kat & Avșar (2011) show the service level constrained model with the following model equation:

$$Minimize \left\{ \sum_{i=1}^{I} C^H * \; E[IOH_i] \, \middle| \, FR(\pi) \geq TFR, \; \pi \in \Pi \right\} \tag{14}$$

Also in this equation, the best policy (π) out of all policies (Π) is chosen to optimize the problem. In this equation, meeting the target fill rate (TFR) is the relevant model constraint. The determination of the optimal base stock level is again the decision variable here. Furthermore, Woerner, Laumanns, & Wagner (2018) address that the determination of the base stock levels significantly influences the service levels and corresponding holding costs. As described before, in the sections about service levels, the target fill rate can also be SKU specific instead of an average total fill rate.

2.4.2 Updating Stock Levels

As explained before, the demand forecast (expected demand) can be determined in many different ways with different parameters. When the forecast is adjusted by hand with the influence of the management, the safety stock, and base stock levels can be adjusted per period as well (Davydenko & Fildes, 2013).

When the demand forecast per period determines the demand distribution of that period, the expected demand is probably non-stationary. Updating the stock levels every period means that the order-up-to level of period t (S_t) is determined at the start of period t, and influences the stockout probability $L + R$ periods later. The value of the base stock level (S_t) at moment t influences the probability of a stock-out (FR) $L + R$ periods later. To determine this base stock level, therefore, the demand distribution of the periods lead time plus review period ($L + R$) is relevant.

As stated before in an earlier section, and also in Feng, Gallego, Sethi, Yan, & Zhang (2005), the demand distribution in period t is an important factor. The way of determining this demand distribution, and also the choice of whether to make this a stationary distribution or a non-stationary period dependent distribution influences the base stock level.

When this base stock level is determined, the decision on whether to order and if so, which amount to order can be made. The order placed in period t (supplied in period $t + L$) is dependent on the inventory position (IP_t). For an (R, s, nQ) policy, as we use in this research: When the inventory position at review moment t drops below the value of S_t, an order is of size $n * Q$ is placed.

3. Research Method

In this section, the research design is described. The assumptions of the model are provided and the models that have been used to solve the problem are explained. Firstly, the basic model calculations are shown and explained. Secondly, the methods of both the *Historical Demand Based Model* and the *Forecast Based Model* are explained. Lastly, heuristics for Full Truck Loading are presented, and also the relevant total cost calculation is shown. Section 3.1, 3.2, and 3.3 show all methods without considering truck loading and transportation costs and after that the consideration of transportation costs is added to all analyses and explained in Section 3.4.

3.1 Replenishment Policy

First of all, the literature review has been done to find and compare different models for inventory control. By comprehensive reviews of the literature, we found models to solve the problems faced by Bonduelle. We consider an extensive literature on inventory models and found that the problem is an inventory model with a fixed review period and fixed case pack size Q, well known as an (R, s, nQ) policy.

The principle of the (R, s, nQ) policy is that the inventory position (IP_t) is reviewed every period R. If the inventory position at this review moment drops below the reorder level s, an order of size $n * Q$ is placed, where n the minimum integer that is needed to bring the inventory back or above the reorder level s. The main goal of the model is to meet the service level constraint per SKU with minimal costs. To minimize the costs by satisfying the service level constraint, the decision variables are the reorder level s, the review period R, and the order size Q. In this research, the order size Q was fixed, because it is the case pack size (one pallet) on an SKU. Furthermore, the review R was set at one week since every week the warehouse can be supplied on fixed time slots. The decision on the value of s, therefore, influences the total holding costs and also the fill rate of the system. In this section, the main formulas are provided and explained.

The basic formula that has been used for the model is de stock-out probability for an (R, s, nQ) policy (Van Donselaar & Broekmeulen, 2014). The value of n at review moment t (every R periods) is determined using the following equation, where subscript i denotes SKU i:

$$n_{t,i} = \left\lceil \frac{(s_{t,i} - IP_{t,i})^+}{Q_i} \right\rceil \tag{15}$$

$IP_{t,i}$ is determined by taking the actual inventory on hand ($IOH_{t,i}$) minus backorders ($BO_{t,i}$) plus the in-transit stock ($IT_{t,i}$) that has already been ordered. The in-transit stock is stock that has already been ordered at another moment but has not arrived at the warehouse yet. Equation (16) is a calculation for the Inventory Position at moment t of SKU i. Moment t can be any moment in time, but usually $IP_{t,i}$ is calculated at a review moment because the decision of how much to order depends on $IP_{t,i}$.

$$IP_{t,i} = IT_{t,i} + IOH_{t,i} - BO_{t,i} \tag{16}$$

Since we have a system with a fixed review period, the measurement of the expected inventory on hand is relevant at both the beginning and the end of the arbitrary review period (Van Donselaar & Broekmeulen, 2014). The inventory on hand at the beginning of the review period (just after potential delivery) is denoted by $I^{OH}(\tau + L)$ and the inventory on hand at the end of the review period by $I^{OH}(\tau + L + R)$. Van Donselaar & Broekmeulen (2014) mention that in systems with fixed review periods, the average of the expectance of the two measures of inventory on hand is a proper approximation of the average inventory on hand of the system. The general expression for the expected inventory on hand is given in Equation (17). In this general equation, τ denotes the review moment at the beginning of a review cycle and t can be any moment in time, however, the relevant values for t are L and $L + R$, respectively. The expected backorders over period $\tau + t$ is denoted by $E[BO(\tau + t)]$. Further explanation about the derivation of $E[BO(\tau + t)]$ is explained later in this section.

$$E[I^{OH}(\tau + t)] = s + \frac{Q}{2} - E[D_t] + E[BO(\tau + t)] \tag{17}$$

As can be derived from Equation (17), the expected inventory on hand increases when s increases. The goal of the mathematical model in this research is therefore to find the minimum value for s that satisfies the fill rate constraint. The Fill Rate (FR) is defined as the long term fraction of demand immediately delivered from the on-hand stock. This fill rate is the main KPI to measure the customer service level at Bonduelle.

In general, the fill rate is calculated by taking the fraction of demand delivered immediately from stock, which means $1 - FR^{BO}$ is equal to the demand that is backordered. According to Van Donselaar & Broekmeulen (2014) the stockout probability (FR) can be calculated given by Equation (18):

$$FR^{BO} = 1 - \frac{E[BO]}{E[D(\tau + L, \tau + R + L)]} = 1 - \frac{E[BO(\tau + R + L)] - E[BO(\tau + L)]}{E[D(\tau + L, \tau + R + L)]}$$

$$= 1 - \frac{E[\{D(\tau, \tau + R + L) - IP(\tau)\}^{+}] - E[\{D(\tau, \tau + L) - IP(\tau)\}^{+}]}{E[D(\tau + L, \tau + R + L)]} \tag{18}$$

As can be derived from Equation (18), the fill rate was calculated by subtracting the number of backorders divided by the expected demand from 1. Because we consider a delivery cycle, the relevant backorders and demand to take into account are the 'extra back orders' and the demand in the interval $(\tau + L, \tau + R + L)$, which is the interval from a potential delivery until the next review moment. As can be seen in Equation (18), this relevant $E[BO]$ over the time interval is calculated by subtracting the expected backorders on moment $\tau + L$ from the expected backorders at moment $\tau + R + L$.

To calculate the fill rate given above, the expression for the expected backorders is needed. Equation (19) shows the expected backorders for the period $\tau + t$, in which τ again denotes the review moment at the beginning of the review cycle (Van Donselaar & Broekmeulen, 2014).

$$E[BO(\tau + t)] = \frac{1}{Q}\int_{s}^{s+Q} \frac{1}{2}(x - s)^2 f_t(x)dx + \int_{s+Q}^{\infty} x f_t(x)dx - (s + \frac{Q}{2})\int_{s+Q}^{\infty} f_t(x)dx \tag{19}$$

Combining Equation (18) and (19) gives the fill rate of the SKU, depending on the value of the reorder level s, the SKU specific value for Q (Q_i), and the demand distribution of SKU i $f_t(x)^i$. Filling in the right values for t (L and $L + R$) gives the fill rate. The full derivation of Equation (19) is presented and explained in Appendix A.

The optimal value for the reorder level s for every SKU i needed to be found in this research. The optimal value for s was chosen by calculating the minimal value of s that satisfies the fill rate constraint. The optimal s that satisfies $FR \geq TFR$ is the value that needed to be found in this research.

As can be derived from Equations (18) and (19), the demand distribution $f_t(x)$ is of major importance for the outcome of the fill rate calculation and therefore for the determination of the reorder levels. When we change $f_t(x)$, the outcome of all integrals in Equation (19) also changes, which impacts the expected backorders. When the expected backorders are impacted, the fill rate is also impacted.

In this research, two kinds of demand distributions ($f_t(x)$) have been used: The Gamma distribution and the Normal distribution. The probability density functions of the Gamma distribution are given by combining Equations (20) and (21). The probability density function of the Normal distribution is given in Equation (22).

$$PDF_{gamma} = f_t(x|a,b) = \frac{1}{b^a\,\Gamma(a)} x^{a-1} e^{\frac{-x}{b}} \tag{20}$$

$$\Gamma(a) = \int_0^\infty x^{a-1} e^{-x}\, dx \tag{21}$$

$$PDF_{normal} = f_t(x|\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} \tag{22}$$

For the Gamma Distribution yields $x \in [0, \infty)$ and for the Normal Distribution yields $x \in \mathbb{R}$.

As can be derived from the probability density functions, the values for the parameters a, b, μ, and σ determine the outcome of the fill rate specific reorder level s. The parameters for the Gamma distribution that were used, are a and b, which are the shape and scale parameters, respectively. The parameters of the Normal distribution that are used are the mean (μ) and standard deviation (σ). Since the parameters are calculated separately for every single SKU i, the parameters are denoted by a_i, b_i, μ_i, and σ_i.

The equations that are explained in this section together form the basic replenishment policy of this research. In the following two sections, two different models are explained: The *Historical Demand Model* and the *Forecast Based Model*.

The first model is denoted by the *Historical Demand Based Model*. This model is based on demand distribution fitting on historical sales data and is a stationary inventory model with stationery demands. The second model is denoted by the *Forecast Based Model*. This second model is a non-stationary inventory model that calculates the reorder level s at every review moment t for every SKU i ($s_{t,i}$).

For both these two models, different approaches are addressed in Section 3.2 and 3.3.

3.2 Historical Demand Based Model

A model based on fitting distributions on the historical demand and demand fluctuation (*Historical Demand Model*) has been designed. To build the model, the weekly sales data of 2017 and 2018 has been used (104 weeks). Of these years the sales data was available. The sales data of 2017 and 2018 have been chosen, because is it more reliable to have two years of data instead of one (more data points). Furthermore, the sales data of these 104 weeks were used to build the models, and the sales data of 2019 (52 weeks) were used to test the models.

On the sales data, demand distributions have been fitted. On all data, the Normal distribution, as well as the Gamma distribution, were fitted. As explained earlier in the literature review, the Normal distribution is widely used in inventory control systems, however, it has the disadvantage of always being symmetric, and also the negativity probability is not realistic for a demand distribution. For both distributions, two different approaches have been used to fit distributions. Firstly, the procedure of fitting distributions on the demand is explained. Secondly, the two different approaches to determine the parameters are explained.

The two different approaches differ from each other in the way of fitting a distribution on data. The first approach is the *Parameter Calculating Approach*, where parameters are fitted on single period demands and calculated into more period demands. The second approach is the *Parameter Fitting Approach*, where parameters are directly fitted on the relevant period data. Both approaches are explained in more detail in Section 3.2.3.

3.2.1 Distribution Fitting Procedure

To fit distributions on the demand data, the maximum likelihood estimation has been used to estimate the parameters of the demand distribution. The likelihood function is maximized, which gives the parameters of the demand distribution that is most likely on the observed data (Myung, 2003). By maximizing the likelihood function as proposed in Myung (2003), the best-fit parameters are found. As a result of the maximum likelihood method, Figure 3.1 illustrates two example histograms of SKUs on which the Gamma and the Normal distribution are fitted. Figure 3.1 depicts a histogram of the weekly demand over 2017 and 2018 for two different SKUs together with the fitted Gamma- and Normal distributions, using the likelihood function.

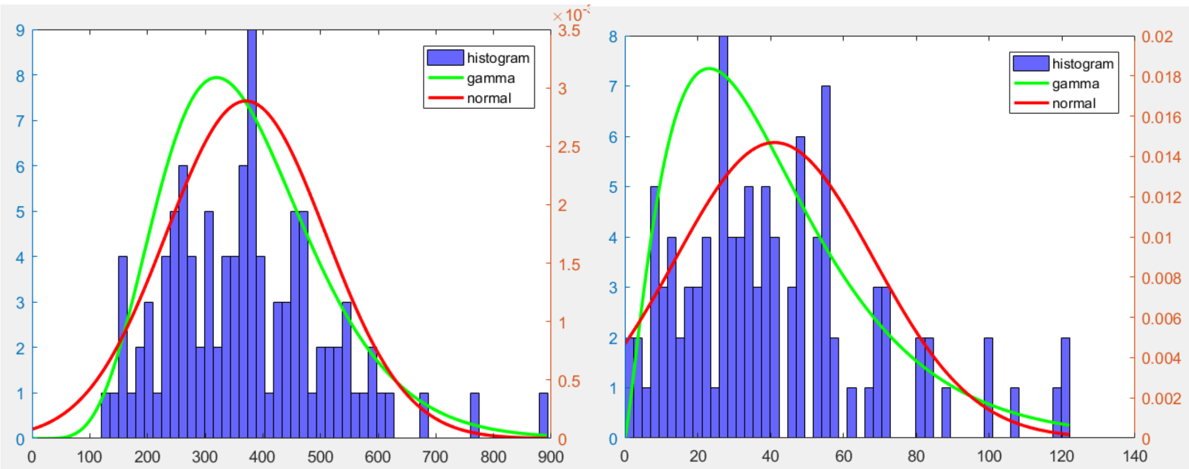

Figure 3.1: Gamma and Normal Distribution Fitted on Data with Maximum Likelihood.

As can be derived from Figure 3.1, the Normal distribution is symmetric and also has a negativity probability, which can be a disadvantage of the application of the Normal distribution. Although the Normal distribution is the most commonly used in inventory management, the Gamma distribution might be better (Gleason, 1982). Especially for SKUs with relatively low demand rates (shown on the right hand-side of Figure 3.1), the Normal distribution is not expected to be a good distribution to use because of the relatively high negativity probability.

After fitting distributions on the demand, chi-square ($\chi 2$) goodness of fit tests can be done to test whether the distributions with the found parameters fit on the actual data. The null hypothesis in this test is that there is no significant difference between the observed data and the expected value

(Morgan, Banks, & Carson, 1984). As stated in many papers, the $\chi2$ - test is a good test to investigate whether a certain distribution reflects how the data is distributed (Morgan et al., 1984; Cai, Song, & Chen, 2017; Thun, Drüke, & Grubner, 2010). An exact explanation of this $\chi2$ - test is provided in Appendix B.

3.2.2 Discrete Distribution Fitting

In addition to the main fitting procedure of Gamma and Normal Distribution that have been used for all analyses in this research, also two discrete distributions have been fitted on the data to see the effect. The Poisson and Negative Binomial distributions were fitted the same way as explained in the previous section. By analyzing the $\chi2$ - tests also on these fittings, it can be concluded that the Poisson distribution did not fit well on almost all SKUs. This result can be explained by the fact that the Poisson distribution only has one parameter, which makes it less general than the other distributions. Because of this bad fits, the Poisson distribution has not been used for further analysis in this research.

As stated, also the Negative Binomial distribution had been fitted on the data. This distribution appeared to fit, in most cases, as good as or worse than the Gamma distribution. Because the general result of the Gamma distribution was better than the result of the Negative Binomial distribution, the Gamma distribution has been used for further analysis in this research. Especially for fast-moving SKUs, which are most of the SKUs in this study since it is executed at an FMCG company, the gamma distribution fitted better. For a few SKUs, however, especially slow-moving SKUs, the Negative Binomial distribution fitted better. In Appendix C, examples to illustrate the comparison of the Gamma distribution and the Negative Binomial distribution are shown.

For the reasons that are explained in this section, the Poisson distribution and the Negative Binomial distribution have not been analyzed and implemented further in this research. However, further research on the implementation of Negative Binomial distribution might be interesting.

3.2.3 Fitting Approaches

As mentioned before, two different approaches have been investigated to find the distribution of the demand during the lead time plus review period ($L + R$ periods).

For the first approach (*Parameter Calculating Approach*) the demand distributions are fitted on the weekly sales data. Using the maximum likelihood estimation method the parameters (a_i, b_i, μ_i, and σ_i) fit the best on the data that has been calculated for every SKU i. Although from this approach the parameters for the weekly demand were found, we need to have the relevant parameters for the demand during Leadtime (L) and the demand during lead time plus review period ($L + R$). L and $L + R$ are the relevant periods, because these periods are used to calculate backorders and fill rates (explained in Section 3.1). As stated by Burgin (1975) and Axsater (2006) the demand distribution can be converted to more (n) periods. When the period demand is Gamma distributed with parameter a_i and b_i, the demand over n periods is Gamma distributed with parameters $n * a_i$ and b_i (Burgin, 1975; Weatherburn, 1949). When demand is normally distributed with parameters μ_i and σ_i, the demand of n periods is normally distributed with parameters $n * \mu_i$ and $\sqrt{n} * \sigma_i$, respectively (Axsater, 2006).

As can be seen in the above explanation, the parameters for the Normal distribution (μ and σ) and the parameters for the Gamma distribution (a and b) can be converted to parameters for more period ($L + R$).

For the second approach (*Parameter Fitting Approach)* more periods of sales data have been collected. Per SKU the fitting procedure has been done as discussed in Section 3.2.1, but instead of transforming the single period parameters into more period parameters, the sales data of more weeks sales has been used to fit the n-weeks parameters on. In this way, the parameters for the demand during $L + R$ are directly determined by taking the demand of $L + R$ periods.

The *Parameter Calculating Approach* assumes that the transformation from single period parameters to more period parameters can be done as stated in the equations. The advantage of this approach is that we only need the period demand, independent of the SKU lead time to calculate the parameters for the demand distributions. This approach is generic, and can easily be applied to different situations. Furthermore, a changing environment, like changing lead times, can easily be adopted by calculating new parameters. Since we considered a real sales environment, however, fitting demand on the more weeks sales data (*Parameter Fitting Approach)* might result in different stock out probabilities and could, therefore, perform differently. The *Parameter Calculating Approach* is widely used and generic, however, the *Parameter Fitting Approach* is also investigated in this research.

3.3 Forecast Based Model

Sometimes demand is not stationary, because of promotional events, environmental changes, seasonality, or trends. In this case, demand forecasting might be a more cost-efficient way of controlling the warehouse. Instead of demand fluctuation, the forecast error is the main factor of uncertainty. In this case, the size of the forecast error rather than the fluctuation of the demand itself is the relevant factor for determining the standard deviation of the expected demand. In this section, the two approaches for using the forecast error as input for inventory control are explained.

For the model based on forecasts and forecast errors, some things are similar to the stationary model. To determine the fill rate, which is still the most important constraint and performance measure of the model, again Equation (18) and (19) of Van Donselaar & Broekmeulen (2014) have been used. The main difference with the *Historical Demand Model* is that the reorder level (s_t) is determined every review moment t, dependent on the demand forecast at that moment ($F_{t,t+L+R}$), which makes the model a non-stationary model. Furthermore, as stated before, the input parameters for the demand distribution of the demand during $L + R$ are based on demand forecasting errors, instead of only the variation in historical demand data.

Every review moment t the parameters for the demand distribution are determined. Similar to the other model, the Normal distribution, as well as the Gamma distribution, have been used. As addressed by Tarim & Kingsman (2006), the expected demand ($\mu_{t,i}$) is the demand forecast during the relevant period ($F_{t,i}$). Tarim & Kingsman (2006) state that the demand for a single SKU i in period t can be assumed to be normally distributed with the forecast as the mean ($\mu_{t,i}$) and standard deviation $\sigma_{t,i} = \mathrm{CV}_i * F_{t,i}$, where $F_{t,i}$ is the expected demand of SKU i over period t and CV_i is the Coefficient of Variation of SKU i. As can be derived from this explanation, a value for CV_i is needed to calculate this $\sigma_{t,i}$ every period. In general, the CV is calculated by dividing the standard deviation by the mean. In this case, the standard deviation that is used to determine CV_i, is denoted by $\hat{\sigma}_i$, and is calculated by using the Mean Absolute Deviation of the forecast of SKU i *(MAD_i)*.

To determine this $\hat{\sigma}_i$, the Mean Absolute Deviation of the forecast *(MAD_i)* is used. The MAD_i is calculated by using Equation (10) in Section 2.3.5. Using this MAD_i, the value of $\hat{\sigma}_i$ has been calculated by Equation (23).

$$\hat{\sigma}_i = \sqrt{\frac{\pi}{2}} * MAD_i \tag{23}$$

The $\hat{\sigma}_i$ that is found here, was calculated over one year (52 weeks). Just as in all analyses, also here, the calculations of the parameters have been done based on the 2017 and 2018 data and are tested on 2019 data. To calculate CV_i, we have to divide $\hat{\sigma}_i$ by the average forecast. The calculation of CV_i is shown in Equation (24), where T denoted the time horizon of 1 year (52 weeks).

$$\mathrm{CV}_i = \frac{\hat{\sigma}_i}{\sum_{t=1}^{T} \frac{F_{t,i}}{T}} \tag{24}$$

Here, $\sum_{t=1}^{T} \frac{F_{t,i}}{T}$ denotes the average forecast over T periods. The CV_i that is found here, is assumed to be the measure for the relative forecast error in this research. Now we have found the CV_i, the parameters for the relevant demand distribution can be calculated. Every review moment t, $\mu_{t,i}$ and $\sigma_{t,i}$ were calculated using Equation (25) and (26), respectively.

$$\mu_{t,i} = F_{t,i} \tag{25}$$

$$\sigma_{t,i} = \mathrm{CV}_i * F_{t,i} \tag{26}$$

For every SKU i the forecast that was set at moment t for the period $T + L$ is denoted by $F_{t,t+L}$. At review moment t, at least the forecasts $F_{t,t+1}, F_{t,t+2}, \dots, F_{t,t+L}, F_{t,t+L+R}$ are known. In this model $\mu_{t,i}$ and $\sigma_{t,i}$ were calculated for the Normal distribution and the parameters for the Gamma distribution are obtained from these values. Equation (27) and Equation (28) explain the conversion from $\mu_{t,i}$ and $\sigma_{t,i}$ to $a_{t,i}$, and $b_{t,i}$ (Gomes, Combes, & Dussauchoy, 2008).

$$a_{t,i} = \frac{(\sigma_{t,i})^2}{(\mu_{t,i})^2} \tag{27}$$

$$b_{t,i} = \frac{(\sigma_{t,i})^2}{\mu_{t,i}} \tag{28}$$

As can be derived from Equation (27) and (28), the parameters needed for the Gamma demand distribution can be calculated when we have the parameters of the Normal distribution.

Similar to the approaches of the *Historical Demand Based* Model, also two approaches have been investigated for the *Forecast Based Model.* The first approach is the *Parameter Calculating Approach* and is based on determining CV_i based on the of the forecasts of single period demand, using Equation (24), and then convert this CV_i into the relevant CV_i for more periods. Similarly, the relevant CV_i $(L + R)$ is calculated by $\mathrm{CV}_{i,L+R} = \frac{\mathrm{CV}_{i,1\,period}}{\sqrt{L+R}}$. When the relevant CV_i is determined for every SKU, $\sigma_{t,i}$ can be calculated, and therewith all other relevant parameters.

The *Parameter Fitting Approach* calculates the Coefficient of Variation by analyzing the forecast and actual sales over the relevant period $(L + R)$. This Coefficient of Variation is used to calculate the parameters at every review moment t.

As stated before, the methods that have been explained so far are not considering transportation costs and the constraint of full truck loading. Therefore a truck loading policy has been designed to fill up trucks. This policy is explained in Section 3.4 and has also been used for all analyses in this research.

3.4 Truck Loading Policy

As explained before, the replenishment system at Bonduelle is a periodic review system. Every review period, orders are placed for different SKUs from different factories. In this research, every truck has a finite capacity C, and has a fixed transportation cost K per delivery, independent of the truck utilization. This fixed cost of a truck means that low truck utilization always implies higher transportation costs per SKU. It is never cost-optimal to ship empty trucks, but filling up trucks to have 'Full Truck Loading' also brings additional costs, especially holding costs (Gerard Cachon, 2001). When fixed transportation costs are high, high utilization of trucks is economically beneficial (Kiesmüller, 2009). Furthermore, ordering full truckloads is a constraint for the case study at Bonduelle. Both the policies of the *Forecast Based Model* and the *Historical Demand Model* are implemented without considering truck loading (LTL) as well as with full truckloads (FTL), to compare inventory costs and analyze performance independent of truck loads. However, in reality, the models should be implemented with Full Truck Loading (FTL). In this section, the heuristic that is designed and implemented for this research is elaborated. The goal of this heuristic to have a workable way of filling up trucks, considering that the increase in holding costs should be as little as possible.

Since the transportation costs are relatively high compared to the holding costs of holding 1 pallet of stock, a policy has been designed to fill up trucks to FTL. As stated in Gerard Cachon (2001) a policy needs to be designed that realizes full truckloads, by adding the cheapest pallets to the trucks. The disadvantage of filling a truck is that the system then orders more pallets than the model advises to order, however, in this way the service level constraint is still met when the FTL policy is implemented. The relevant cost factor of adding pallets in this study is the additional inventory holding cost of adding an extra pallet. The steps of the policy that has been designed are explained here.

Full truck loading procedure:

1. *Determine initial LTL order:*
   At every periodic review moment, the inventory position is checked and an order is placed according to the (R, s, nQ) policy, without considering truck loading. The (R, s, nQ) policy without considering truck loading is denoted by LTL policy from now on. Let I denote the total number of SKUs where $I \in \mathbb{N}$. The number of pallets that needs to be ordered according to the LTL policy is denoted by n_i with $\mathrm{n}_i \in \mathbb{N} \cup \{0\}$. The total number of pallets that needs to be ordered at review moment t according to the LTL policy, therefore, is $N_t = \sum_{i=1}^{I} \mathrm{n}_{t,i}$.
2. *Calculate needed truck and pallets:*
   When the total minimum amount of needed pallets has been calculated, the amount of trucks that are needed to supply these pallets is calculated (either full or not-full trucks). The total number of trucks needed to be dispatched to complete the order is denoted by M_t and calculated as $M_t = \lceil N_t/C \rceil$, which is a rounded-up integer value. The optimal amount of pallets to have a full truckload order is denoted by $\widehat{N}_t$ and calculated as $\widehat{N}_t = C * M_t$. The initial amount of pallets that need to be added to the initial order is therefore $\widehat{N}_t - N_t$. If $\widehat{N}_t - N_t = 0$, the trucks are fully loaded, which means the order is finished. If $\widehat{N}_t - N_t > 0$, the following steps are executed.
3. *Set added pallets to 0:*
   When pallets are added, caused by the truck loading policy, the total amount of pallets for SKU i becomes higher. The amount of 'extra' pallets that is added to the initial order is denoted by $N'_t = \sum_{i=1}^{I} n'_{t,i}$. The initial value before adding any pallets therefore is $n'_{t,i} = 0 \ \forall \ i \in I$.

4. *Calculate the cheapest pallet:*
   To calculate the cheapest pallet to be added, two ways of calculating the starting point has been investigated.

$$\tau 1_{t,i} = \frac{IP_{t,i} + n_{t,i} * Q_i + n'_{t,i} * Q_i}{\mu_i} \quad (29)$$

$$\tau 2_{t,i} = \frac{IP_{t,i} - s_{t,i} + n_{t,i} * Q_i + n'_{t,i} * Q_i}{\mu_i} \quad (30)$$

   In these equations, $n'_{t,i}$ denotes the pallets that are added because of the FTL heuristic already. Furthermore, inventory turnover T_i per SKU is calculated for all SKUs by $T_i = Q_i/\mu_i$, which means the expected time an extra pallet will be on hand stock when a pallet is added. Using Equation (29) and (30) the 'cheapest' pallet to add is calculated by taking the smallest value of $\tau_{t,i} + T_i$, because adding that pallet will probably result in the smallest increase in holding costs.
5. *Add the cheapest pallet:*
   The pallet of SKU i that has been chosen to be the cheapest in *Step 4* has to be added to the truck. For this chosen SKU, $n'_{t,i}$ becomes $n'_{t,i} + 1$ for that SKU. The new value for N'_t is calculated by taking the new value of $n'_{t,i}$ $\forall$ $i \in I$.
6. *Check FTL:*
   The amount of pallets still to add is calculated by $\widehat{N}_t - N_t - N'_t$. If $\widehat{N}_t - N_t - N'_t > 0$, the procedure is repeated from *Step 4.* If $\widehat{N}_t - N_t - N'_t = 0$, the trucks are fully loaded and the procedure is stopped.

As can be seen in *Step 4* of the procedure, two different ways of calculating the value for $\tau_{i,t}$ have been explained. The difference between the two approaches is whether the reorder level $s_{t,i}$ should be taken into account or not. The advantage of including $s_{t,i}$ could be that demand fluctuation is taken into account when filling up a truck. The reorder level $s_{t,i}$ is, in fact, the desired stock level of an SKU. Subtracting $s_{t,i}$ from the inventory position in the calculation of the inventory turnover, therefore, could result in a higher total fill rate of the system. Concluding, *Approach 1* (FTL1) takes into account how many periods of demand are on stock, and *Approach 2* (FTL2) takes into account how many periods of demand are extra in stock above the reorder level. Both approaches 1 and 2 are investigated in this research.

3.5 Relevant Costs

All models that are explained so far have been implemented on the real situation to observe the performance and investigate what models perform the best on what ground. The most relevant performance measures are the customer service level (calculated by FR) and the total inventory- and transportation costs. In this section, the relevant cost functions are given.

The total costs are built up from inventory costs together with transportation costs. The models try to find the lowest values for the reorder levels ($s_{t,i}$) to meet the service level requirement. When the stock levels have been calculated by the model, the actual costs can be determined. Equation (31) shows the calculation of the total costs over time horizon T (for example one year) for all SKUs I delivered from factories $j \in J$ to the warehouse. In Equation (31) $IOH_{t,i}$ is the inventory on hand at time t of SKU i, $C_{H,i}$ the holding costs, $M_{t,j}$ the number of needed trucks at time t from factory j, and $C_{T,j}$ the transportation cost from factory j.

$$Total\ costs = \sum_{t=1}^{T} \sum_{i=1}^{I} \left\lceil \frac{IOH_{t,i}}{Q^i} \right\rceil * C_{H,i} + \sum_{t=1}^{T} \sum_{j=1}^{J} M_{t,j} * C_{T,j} \quad (31)$$

As can be derived from the cost function, the inventory on hand is rounded up to full pallets. This is done because the holding costs are calculated by full pallet (e.g. 1.3 pallet has the same holding cost as 1.9 pallets). The total costs are calculated as the sum of all periods ($t \in \mathrm{T}$), all SKUs ($i \in \mathrm{I}$), and all factories ($j \in \mathrm{J}$).

4. Model Validation

The models that are described in Section 3 were all implemented to be tested for the case study at Bonduelle, but before implementation, the calculation of the out of stock probability was validated by simulated demand instead of actual sales. By simulating the demand, we can see whether the model works as expected. In this section, the results of the model on demand simulation are shown.

As explained before, the main formula is the calculation of the stock out probability based on the demand function $f(x)$ that has been chosen. The *Historical Demand Based Model* is a stationary model based on the best-fitted parameters of the Gamma distribution and the Normal distribution and the *Forecast Based Model* is a non-stationary model that has a different demand function every period. The main goal of the model is to have as little as possible inventory by satisfying the target service level. The stationary model can be used to validate the stockout calculations. The parameters that are derived from the periodic fitting procedure (*Calculating Parameters Approach)* as explained in Section 3.2.1 were used to generate demand and validate whether the model works. Random demand has been generated to validate that the model fill rate calculation is accurate. To validate the model, the truck loading constraint was not taken into account, because filling up full trucks may influence the fill rate. Firstly, the number of periods to simulate was determined. The demand has been generated 50 times for a single SKU to see how many periods of demand needed to be generated to have convergence in the fill rate outcome. Figure 4.1 shows the result of these 50 replications of demand simulation. The target fill rate for this test has been set to 95%.

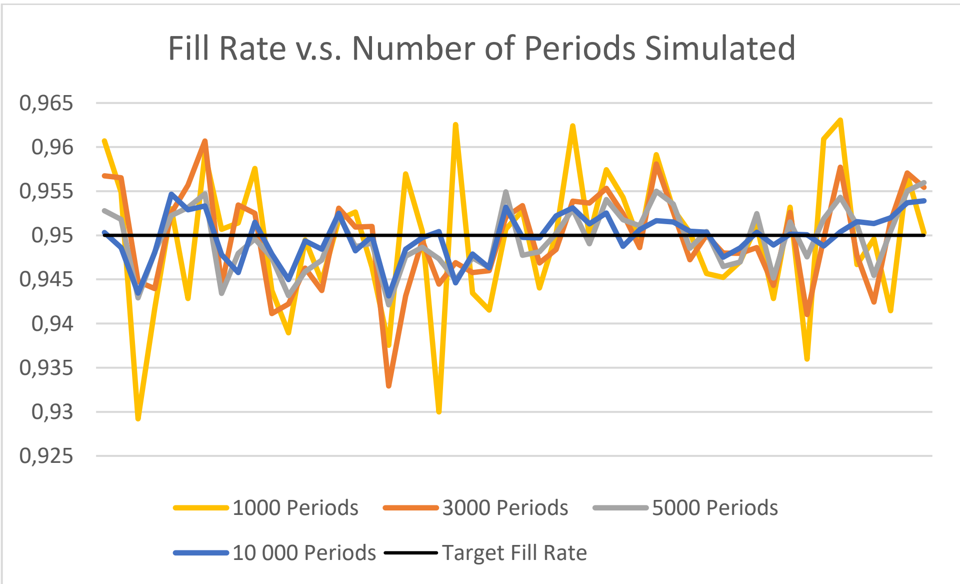

Figure 4.1: Fill Rate v.s. Number of Periods Simulated.

As can be derived from Figure 4.1, simulating not enough periods does not give a convergent fill rate as an output. The lines of 1000 and 3000 periods of simulation fluctuate more than the other ones. Since the line of 10 000 periods is not much more convergent than the line of 5000 periods, 5000 periods of demand have been generated to test the behavior of the model.

To see whether the calculations of the fill rate as well as the calculation of the expected inventory on hand (IOH) make sense, all SKUs have been analyzed. The results of two different SKUs are reviewed. One SKU (SKU 1) has relatively low demand fluctuation ($CV \approx 0.35$), while another SKU (SKU 2) has a relatively fluctuating demand pattern ($CV \approx 0.93$). The parameters for the Gamma distribution as well as the Normal distribution for the period demand are given in Table 4.1.

Table 4.1: Input Parameters.

	α	β	μ	σ
SKU 1	5.86	24.67	144.72	49.87
SKU 2	1.15	128.91	147.97	138.11

To have a reliable validation of the model, the average results of 5 simulation runs over 5000 time periods are given. The results of the analysis are displayed in Table 4.2 and Table 4.3. Table 4.2 shows the results of the Gamma distribution and Table 4.3 shows the results of the Normal distribution

Table 4.2: Simulation Output Gamma Distribution.

	Target FR	Actual FR	Expected Mean IOH	Actual Mean IOH
SKU 1	**91%**	91.09%	144.5	145.4
	95%	95.08%	175.6	175.5
	99%	98.99%	256.6	256.8
SKU 2	**91%**	91.64%	352.0	354.6
	95%	95.35%	443.9	444.7
	99%	99.03%	692.9	693.2

Table 4.3: Simulation Output Normal Distribution.

	Target FR	Actual FR	Expected Mean IOH	Actual Mean IOH
SKU 1	**91%**	91.03%	122.3	122.2
	95%	95.15%	144.5	144.8
	99%	99.08%	197.6	197.9
SKU 2	**91%**	91.33%	296.9	308.6
	95%	95.47%	349.8	362.6
	99%	99.12%	476.8	492.1

As can be derived from Table 4.2 and Table 4.3, the model outcome is the FR as expected. The only remarkable thing is the outcome of the Normal distribution of SKU 2. The values for the FR and average inventory on hand are slightly higher than expected. This finding can be explained by the negativity probability of the Normal distribution. Negative demands in the simulation occur, and these negative demands might positively influence the inventory on hand. To see that the calculation is right, we see that for SKU 1 the Normal distribution is working properly because the low Coefficient of Variation results in a negative demand probability of approximately zero. In reality, negative demands will not occur. Furthermore, the relationship between FR and inventory costs can be seen. The increase in inventory costs for SKU 2 was higher when increasing the target FR than for SKU 1, which makes sense because this SKU has a more variating demand pattern. From this, we can already conclude that SKUs with high variation in demand are more expensive to have enough on stock that SKUs with a relatively constant demand pattern.

5. Model Implementation and Results

In this section, the results of the case study are provided and explained. The models that are described in Section 3 are all implemented on the actual sales data of 2017, 2018, and 2019. As explained before, all parameters are calculated based on the 2017 and 2018 data only. Finally, the model is tested on 2019 sales data and compared to the actual situation faced by Bonduelle.

To see how the models work on inventory costs and target fill rate, the models are firstly compared without considering transportation costs and full truck loading and later with the implementation of Full Truck Loading. Firstly, the results of the *Historical Demand Based Model* and the *Forecasting Based Model* are analyzed separately to see how the different approaches perform. Thereafter, the two models are compared. The sensitivity of the FR on the inventory cost is analyzed and also the impact of the forecast error on FR and inventory costs is elaborated. Finally, the impact of the full truck loading heuristics is highlighted and the comparison with the current situation at Bonduelle is made.

5.1 Historical Demand Based Model

In this section, the results of the *Historical Demand Based* model implemented on 2017, 2018, and 2019 demands are discussed. The results of 2017 and 2018 indicate how the model performs in general since the parameters are fitted on these data. The results of 2019 indicate how the model would have performed in 2019 by only using data from 2017 and 2018. The yearly holding costs (C_H) and the total fill rates (FR) are analyzed.

The results of both Retail and Foodservice (FS) are discussed. This distinction has to be made because customers in these markets behave differently and therefore sales patterns and the optimal inventory policies are also different. The four different approaches, as discussed in Section 3.2, are shown: the *Parameter Calculating Approach* and the *Parameter Fitting Approach* of both the Gamma and Normal distribution. Recall that the difference between these two approaches is whether to fit the parameters on more periods demand (*Parameter Fitting Approach*) or fit the parameters on single period demands and convert them into more periods demand (*Parameter Calculating Approach*). All results are presented without considering truck loading, to examine the actual result of the model on the FR and the holding costs.

Table 5.1 presents the result of all FS SKUs and Table 5.2 presents the result of all Retail SKUs. The Target Fill Rate (Target FR) is set on 95% and 98%. The FR of a specific year is denoted by FR ’19, for example, in which FR denotes ‘Fill Rate’ and ’19 denoted 2019.

Table 5.1: FS Historical Demand Based Model without Truck Loading.

Approach	Target FR	FR ‘17-‘18	Yearly C_H ‘17-‘18	FR ‘19	C_H ‘19
Gamma Parameters Calculated	95%	94.97%	€ 35.086	94.55%	€ 35.769
	98%	97.93%	€ 43.514	97.20%	€ 44.251
Normal Parameters Calculated	95%	92.56%	€ 31.129	92.08%	€ 31.576
	98%	95.87%	€ 36.258	94.99%	€ 36.858
Gamma Parameters Fitted	95%	95.74%	€ 39.249	94.71%	€ 39.814
	98%	98.31%	€ 48.890	97.36%	€ 49.645
Normal Parameters Fitted	95%	93.54%	€ 32.555	92.66%	€ 32.972
	98%	96.67%	€ 37.891	95.44%	€ 38.532

Table 5.2: Retail Historical Demand Based Model without Truck Loading.

Approach	Target FR	FR '17-'18	Yearly C_H '17-'18	FR '19	C_H '19
Gamma Parameters Calculated	**95%**	95.19%	€ 28.660	92.25%	€ 33.529
	98%	98.42%	€ 35.991	96.57%	€ 42.010
Normal Parameters Calculated	**95%**	93.86%	€ 26.199	91.08%	€ 30.360
	98%	97.14%	€ 31.280	94.86%	€ 36.084
Gamma Parameters Fitted	**95%**	96.89%	€ 30.586	94.32%	€ 36.236
	98%	99.09%	€ 38.818	98.14%	€ 45.934
Normal Parameters Fitted	**95%**	94.87%	€ 26.979	92.12%	€ 31.206
	98%	97.79%	€ 32.373	95.96%	€ 37.292

As can be derived from Table 5.1 and Table 5.2, using the Normal distribution results in too low system FR. Although many papers use the Normal as an assumption, because it is a general distribution to simulate demands, the Normal distribution does not seem to work properly in reality. Especially the FR of the FS SKUs is lower than the target when the Normal distribution is used. This result can be explained by the fact that Foodservice SKUs on average have a lower demand rate than Retail SKUs, which makes the negativity probability of the Normal distribution more relevant.

Furthermore, Table 5.1 and Table 5.2 indicate that the difference between the *Parameter Calculating Approach* and the *Parameter Fitting Approach* is not significant. This result means that the conversion from single period parameters to more period $(L + R)$ parameters can be done as explained in Section 3.2.3. The advantage of the *Parameter Calculating Approach* is that it is a general way of analyzing demand because only the period demand needs to be analyzed to fit a distribution on, and thereafter the relevant parameters can be determined, independent of the lead time and review period of the SKU. Although the difference between the two approaches is not significant in most cases, we see that the differences obtained in Table 5.2 are slightly bigger than the difference in Table 5.1. This difference makes sense because Retail SKUs have longer lead times. Because the parameters are calculated from a single period into $L + R$ periods, more difference might be obtained when into $L + R$ is bigger.

Also, some differences can be seen between the target fill rate and the actual measured fill rate. This can be explained by the fact that the model is tested on real sales data instead of on randomly generated demand. Although there is some difference between the target and the result fill rate, this difference is negligible.

At last, results show that the models (especially Gamma distribution) work well for the years 2017 and 2018 since the parameters are fitted on these years. The FR of 2019 is slightly lower compared to the fill rate of 2017/2018 because demand patterns could have been slightly changed. These changes can be caused by trends, but also for example by the acquisition of new customers that buy the products. The *Forecast Based Model* might be a solution to these changes in demand patterns because these changes are taken into account as good as possible when the demand is forecasted. The results of the *Forecast Based Model* are addressed in Section 5.2 and further analysis of the forecast error is presented in Section 5.3.

5.2 Forecast Based Model

In this section, the results of the *Forecast Based Model* implemented on 2017, 2018, and 2019 demands are discussed. The results for both FS and Retail are elaborated. The four different approaches, as discussed in Section 3.3, are shown: the *Parameter Calculating Approach* and the *Parameter Fitting Approach* of both Gamma- and the Normal distribution. All results are presented without considering truck loading, to see the actual effect of the model on the FR and holding costs. Just as in Section 5.1 the distinction between 2017/2018 and 2019 has been made, to see how the model performs on 2019 data with the parameters based on 2017/2018 data.

Table 5.3: FS Forecast Based Model without Truck Loading.

Approach	Target FR	FR '17-'18	Yearly C_H '17-'18	FR '19	C_H '19
Gamma Parameters Calculated	95%	95.53%	€ 36.735	93.46%	€ 34.489
	98%	97.97%	€ 45.477	96.89%	€ 43.000
Normal Parameters Calculated	95%	93.85%	€ 32.934	91.38%	€ 30.977
	98%	96.37%	€ 38.567	94.79%	€ 36.399
Gamma Parameters Fitted	95%	96.31%	€ 41.351	94.01%	€ 40.598
	98%	98.48%	€ 50.687	97.19%	€ 49.343
Normal Parameters Fitted	95%	94.46%	€ 35.186	92.24%	€ 34.132
	98%	97.02%	€ 41.172	95.42%	€ 39.955

Table 5.4: Retail Forecast Based Model without Truck Loading.

Approach	Target FR	FR '17-'18	Yearly C_H '17-'18	FR '19	C_H '19
Gamma Parameters Calculated	95%	97.79%	€ 62.371	84.36%	€ 35.655
	98%	98.76%	€ 75.847	87.59%	€ 45.133
Normal Parameters Calculated	95%	97.40%	€ 57.932	83.69%	€ 32.785
	98%	98.41%	€ 67.292	86.59%	€ 39.191
Gamma Parameters Fitted	95%	98.90%	€ 98.096	93.87%	€ 72.170
	98%	99.37%	€ 122.517	96.16%	€ 94.311
Normal Parameters Fitted	95%	98.67%	€ 81.320	92.65%	€ 55.560
	98%	99.05%	€ 94.683	94.92%	€ 66.729

Table 5.3 shows the results of FS. In total, the *Forecasting Based Model* does not differ a lot from the *Historical Demand Based Model*, which means that both models can work properly for the FS market. Furthermore, again the Normal distribution seems to result in lower fill rates than the target, as explained in the previous section. To investigate which SKUs work better with which of the two models, further analysis on the single SKU level is elaborated in Section 5.3. In that section, the effect of seasonality on the model outcome and the possible advantages of the *Forecast Based Model* are described as well.

The most remarkable result is the relatively high costs and high FR for the Retail market (Table 5.4) in 2017/2018, compared to the target. From this result, the impact of consistently forecasting too much can be derived. The *Forecast Based Model* is influenced by demand forecasts, which means forecasting too much, probably caused by manual adjustments and management impact, causes unnecessarily high holding costs. Structurally forecasting too much, is denoted by a positive forecast bias (Fildes, Ma, & Kolassa, 2019). The impact of this bias on the model performance is significant.

Also, the Normal distribution seems to work better for 2017/2018, which is also caused by the positive forecast bias. Using the Normal distribution usually results in lower reorder levels and therefore lower costs and FR, which is why it seems to give better results here, while this result is caused by the forecast bias. Further explanation of the effect of forecast errors of single SKUs on the model results is given in Section 5.3.

Furthermore, the difference between the *Parameter Fitting Approach* and the *Parameter Calculating Approach* can be derived from Table 5.3 and Table 5.4. Especially in Table 5.4, we obtain a significant difference between the two approaches. The *Parameter Fitting Approach* performs better, which makes sense, since this was expected to be a more accurate way of calculating the forecast error, especially with longer lead times. Also, the Gamma distribution performs better for the costs and FR of 2019.

5.3 Forecast Error Sensitivity

In this section, further analysis has been done on the effect of the forecast and forecast error on the FR and holding costs. To illustrate this effect, three different kinds of results are addressed. Firstly, a single FS SKU that has a better result with the *Forecast Based Model* than with the *Historical Demand Based Model* has been analyzed. Secondly, a Retail SKU is shown that has structurally been forecasted too high, which results in high inventory costs. Third and finally, demand is generated to highlight the *Forecast Based Model* can work when the forecast would have been improved.

5.3.1 Single FS SKU

To prove that inventory control of some SKUs performs better with the *Forecast Based Model* than with the *Historical Demand Based Model,* analysis of a single FS SKU with obvious seasonality demand pattern is presented. The SKU is an example of an SKU that has a higher coefficient of variation of demand than the coefficient of variation of the forecast error.

Firstly, Figure 5.1 illustrates the actual sales and forecasts of this single SKU with seasonal demand. To clearly show the seasonality, the monthly sales and forecasts of 24 months during 2017 and 2018 are depicted.

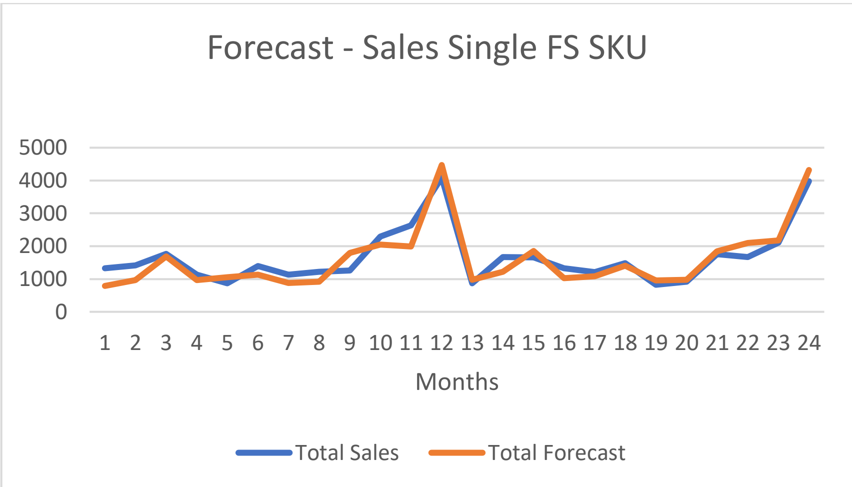

Figure 5.1: Forecast and Sales over 2017-2018 Single FS SKU.

As can be derived from Figure 5.1, sales during winter are significantly higher than during the summer. This difference is caused by (known) higher demand in winter. The fluctuation of demand is very high, which is why the stationary *Historical Demand Model* does not work well for this SKU. To show that the *Forecast Based Model* performs better for this kind of SKUs, Table 5.5 illustrates the results of this single SKU of both the *Forecast Based Model* and *Historical Demand Model* over 2017 and 2018. To compare both models, the *Calculated Parameters Approach* has been used for both models.

Table 5.5: Result 2017-2018 Single FS SKU.

Approach	Target FR	FR '17-'18	Yearly C_H '17-'18
Historical Demand Model	**95%**	87.18%	€ 1.238
	98%	90.47%	€ 1.547
Forecast Model	**95%**	96.98%	€ 997
	98%	99.17%	€ 1.288

As can be seen in Table 5.5 the costs of the *Forecast Based Model* are lower, and the service level is higher. With higher FR, the cost savings of using the *Forecast Based Model* for this SKU are 19.5% and 16.7% for the 95% and 98% target fill rate, respectively. This costs saving is combined with a significantly higher fill rate compared to the *Historical Demand Based Model*. This SKU is, therefore, an example of an SKU of which inventory control should be done by using the forecast and forecast error rather than the stationary demand and demand fluctuation.

5.3.2 Single Retail SKU

To explain the high holding costs obtained when using the *Forecast Based Model* for Retail over 2017 and 2018 (Section 5.2, Table 5.4), the actual sales and forecasts of a single Retail SKU that has been forecasted too high are displayed in Figure 5.2 as an example. The sales and forecasts of 104 weeks during 2017 and 2018 are shown.

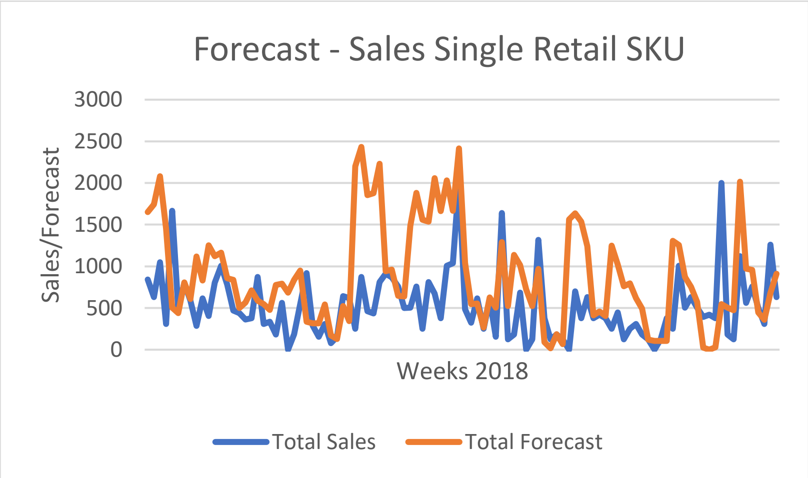

Figure 5.2: Forecast and Sales over 2017-2018 Single Retail SKU.

As can be seen in Figure 5.2, the forecasted demand is higher than the actual sales in almost every week. The average weekly sales over 2017/2018 were 532 boxes/week while the average forecast was 885 boxes/week.

To illustrate the effect of this bias better, Table 5.6 shows the results of this single SKU of both the *Forecast Based Model* and *Historical Demand Model* over 2018. To compare both models, the *Calculated Parameters Approach* has been used for both models.

Table 5.6: Result 2017-2018 Single Retail SKU.

Approach	Target FR	FR '17-18	Yearly C_H '17-18
Historical Demand Model	**95%**	96.41%	€ 1.396
	98%	98.07%	€ 1.750
Forecast Model	**95%**	100.00%	€ 4.058
	98%	100.00%	€ 4.923

As can be seen in Table 5.6, for this SKU, the costs of the *Forecast Based Model* are significantly higher, and the FR is unnecessarily high. This SKU is, therefore, an example of an SKU of which controlling inventory based on forecast results in higher costs, caused by forecasting too much. This SKU is, therefore, an explanation of the high inventory costs of the *Forecast Based Model* of the Retail market as explained in Section 5.2. Since this is a Retail SKU that has promotions with known peaks, the *Forecast Based Model* should work better when these peaks can be forecasted better. Forecasting structurally too much results in significantly higher costs. Concluding, to make the *Forecast Based Model* work better for this kind of SKUs, the demand forecast needs to be revised and improved. When the forecast is structurally too high, as given in Figure 5.2, the *Forecast Based Model* results in relatively high holding costs.

In Section 5.3.3, demand is generated around the forecast of this SKU to indicate how the forecasting model would perform when forecast bias would be eliminated and forecast accuracy would have been improved.

5.3.3 Simulation Non-Stationary Demand

As concluded from the 2017 and 2018 results presented in Table 5.5 in the previous section, in most cases the forecasting based model does not work properly on the Retail market. This problem is mostly caused by consistently high forecasting (positive forecast bias). To show that the model can work when demand is indeed distributed around the forecasted values, demand is generated around the forecast, to simulate an unbiased forecast. In this way, it can be highlighted that good forecasts of the Retail SKUs (especially promotions) can result in efficient inventory control. To make a good comparison, the results of the same SKU as in the previous section (Section 5.3.2) are shown, and also the forecasts for 2017 and 2018 are taken to evaluate results. As explained in Section 3.3, the magnitude of the forecast error of SKU i is expressed with CV^i. The demand is generated for the years 2017 and 2018, and the results in this section are based on the average result of 20 replications.

Firstly, the real CV^i, just as used in Section 5.3.2 has been used to generate demand and see the results, especially of meeting the target FR. Secondly, reorder levels for 2017 and 2018 have been calculated with lower forecast errors, to see the effect on the holding costs. With this second case, we simulate that the peaks that are shown in Figure 5.2 could have been forecasted better.

Table 5.7 presents the results of calculating new reorder levels over 2017 and 2018 and generating demand that corresponds to these forecast errors.

Table 5.7: Generated Demands Forecast Model Single SKU.

Input CV	Target FR	FR ‘17-‘18	Yearly C_H ‘17-‘18
CV_i	**95%**	94.95%	€ 2.524
	98%	97.78%	€ 3.120
$0.8 * CV_i$	**95%**	95.89%	€ 1.951
	98%	98.01%	€ 2.473
$0.6 * CV_i$	**95%**	94.93%	€ 1.412
	98%	98.07%	€ 1.790

From these results, we find that also for this Retail SKU (with peaks in the demand pattern), controlling inventory based on forecast could work. Structurally forecasting too much results in higher costs and unnecessarily high fill rates. Furthermore, forecasting more accurate (lower CV_i) results in a reduction of holding costs.

When we compare Table 5.6 and Table 5.7, it can be concluded that the *Forecast Based Model* does not perform better than the *Historical Demand Based Model* when the forecast error is too high. However, when forecast accuracy improves, the forecasting model performs better. We see that the situation in which the forecast accuracy is set on $0.6 * CV_i$ (Table 5.7) the costs are approximately equal to the cost of the *Historical Demand Based Model* (Table 5.6) while the average generated weekly demand here is 885 boxes/week instead of 532 boxes/week.

5.4 Fill Rate – Costs Relationship

In this section, the sensitivity of the inventory costs on the target fill rate is addressed. To show this relationship, the *Historical Demand Model* has been used. To have a good overview, only the results of the *Fitted Parameter Approach* of the Gamma Distribution is presented, because this is proven to be the best approach for the *Historical Demand Model* (Section 5.1). In Figure 5.3 the relationship between the FR and the Holding Costs over 2019 is demonstrated. Figure 5.3 shows the total of Retail and FS SKUs together, to have an overview of the total costs and performance.

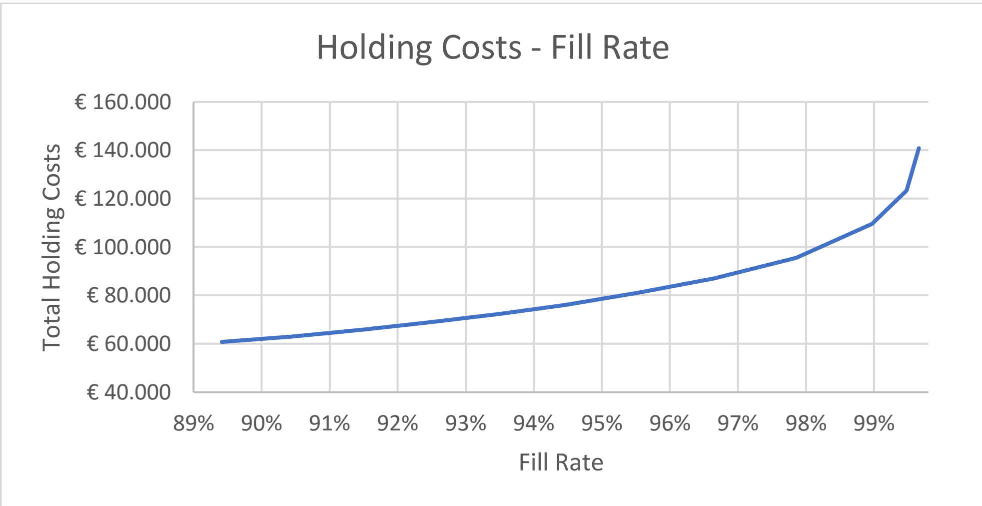

Figure 5.3: Fill Rate and Holding Costs Total 2019.

As can be derived from Figure 5.3, a higher fill rate results in higher costs. Figure 5.3 also shows that the relationship between the fill rate and the holding costs is not linear. The closer the total fill rate to 100%, the higher the increase in holding costs. This convexity means that for small FRs the function is not sensitive and for high FRs the function becomes relatively more cost-sensitive. The trade-off between the fill rate and holding costs can be used to determine what the target fill rate should be.

5.5 Full Truck Load

The previous sections are all implemented without considering full truck loading to show the actual relationship between inventory control policies, holding costs, and FR. In reality, transportation costs are also a relevant factor. To illustrate the effect of the designed truck loading heuristic, the results of implementing the heuristics as explained in Section 3.4 are shown in this section. The truck loading heuristics are implemented for all models that have been explained in previous sections, but to explain the effect of truck loading, like in the previous section, only the results of models with the Historical Demand Model are presented. To have a good overview, only the Fitted Parameter Approach of the Gamma distribution is used in this section.

Table 5.8 and Table 5.9 show the costs and performance of three situations: Without considering truck loading (LTL), Full Truck Loading Approach 1 (FTL1), and Full Truck Loading Approach 2 (FTL2). The transportation costs are calculated as explained in Section 3.5 with considering the transportation costs $C_{T,j}$ per factory $j \in J$ to the warehouse multiplied by the number of needed trucks. The results of FS are presented separately from the results of Retail, FS SKUs are supplied from different factories with higher transportation costs, which could result in different effects of Full Truck Loading. Table 5.8 represents the FS performance and Table 5.9 represents the Retail performance both of the year 2019.

Table 5.8: Truck Loading Results FS.

Approach	Target FR	FR ‘19	C_H ‘19	C_T ‘19	Costs Total ‘19
LTL	95%	94.71%	€ 39.814	€ 403.720	€ 443.534
	98%	97.36%	€ 49.645	€ 402.970	€ 452.615
FTL1	95%	96.31%	€ 66.679	€ 151.115	€ 217.794
	98%	98.08%	€ 80.277	€ 154.235	€ 234.512
FTL2	95%	96.06%	€ 55.492	€ 151.620	€ 207.112
	98%	97.89%	€ 65.332	€ 151.995	€ 217.327

Table 5.9: Truck Loading Results Retail.

Approach	Target FR	FR ‘19	C_H ‘19	C_T ‘19	Costs Total ‘19
LTL	95%	94.32%	€ 36.236	€ 84000	€ 120.236
	98%	98.14%	€ 45.934	€ 83.625	€ 129.559
FTL1	95%	95.19%	€ 37.933	€ 73.125	€ 111.058
	98%	98.60%	€ 48.232	€ 73.500	€ 121.732
FTL2	95%	96.05%	€ 37.787	€ 73.125	€ 110.912
	98%	98.67%	€ 47.455	€ 73.500	€ 120.955

As can be derived from both Tables, Full Truck Loading results in a substantial reduction of transportation costs, combined with a relatively small increase in holding costs, which results in a reduction of the total costs.

Furthermore, when the performance of *FTL1* and *FTL2* are compared, it can be concluded that the *FTL2 approach* performs better than the *FTL1 approach*. The goal of the truck loading heuristics is to fill truck till FTL under the least increase of holdings costs. As explained in Section 3.4, *FTL2* takes the reorder level into account when calculating which SKU needs to be added to the order.

Lastly, when Table 5.8 and Table 5.9 are compared, it can be seen that the difference between FTL and LTL in transportation costs for FS is significantly higher than for Retail. This can be explained by the fact that FS SKUs are delivered from different factories with higher transportation costs.

5.6 Final Model Analysis

Combining the results of the different models and approaches gives insight into which model(s) would suit the best in the situation at Bonduelle. In this section, every SKU is analyzed with the different models and a combination of the best models for all SKUs is analyzed and compared with the current performance and costs of Bonduelle. Firstly, the recommended final model is explained, and thereafter the comparison with the current Bonduelle performance is shown.

5.6.1 Recommended Model

It can be concluded from the previous section that some SKUs perform better with the *Historical Demand Based Model* and some SKUs perform better with the *Forecast Based Model*. In Section 5.3.1 and 5.3.2 examples are shown of both these types of SKUs. Furthermore, it can be concluded that the Gamma distribution performs better than the Normal distribution and in (almost) all models the *Fitting Parameters Approach out*performs the *Calculating Parameters Approach*. To make an optimal 'final model' every single SKU is compared using both the *Forecast Based Model* and the *Historical Demand Based Model* using the Gamma distribution and the *Fitting Parameter Approach.* The SKU specific analysis lead to an optimal combination of using both models. Since this analysis is about the actual implementation and recommendations, the implementation of 2019 data is used to determine which model performs the best for which SKU.

To determine which model fits the best, the holding costs, as well as the fill rates, are analyzed per SKU. Three steps have been taken to determine which model is the best. The tests are explained by calling the models 'Model 1' (*Historical Demand Model)* and 'Model 2' *(Forecast Based Model)*, so for example FR^1 is the Fill Rate of Model 1. Target Fill Rate is denoted by TFR. The analysis of choosing between the two models is as follows:

1. If $FR^1 > FR^2 \text{ and } {C_H}^1 < {C_H}^2$, choose Model 1.
   If $FR^2 > FR^1 \text{ and } {C_H}^2 < {C_H}^1$, choose Model 2.
   If both statements are not true, go to Step 2.

2. If $FR^1 > TFR \text{ and } {C_H}^1 < {C_H}^2$, choose Model 1.
   If $FR^2 > TFR \text{ and } {C_H}^2 < {C_H}^1$, choose Model 2.
   If both statements are not true, go to Step 3.

3. If $FR^1 > FR^2$, choose Model 1.
   If $FR^2 > FR^1$, choose Model 2.

The main idea behind this decision tree is to find the right model for the right SKUs in the current situation. Moreover, this decision tree could always be used to see which model performs the best for a single SKU. For example, when the demand forecast is improved in the future, and forecast accuracy is analyzed over a time horizon, it can be tested whether the *Forecast Based Model* works for this SKU. From this analysis over the year 2019, 96 SKUs perform the best with the *Historical Demand Based Model* and 47 SKUs perform better with the *Forecast Based Model*. Which SKU is chosen for which model can be found in Appendix D.

The output of the performance of this 'final' model is shown in Table 5.10.

Table 5.10: Final Model Output LTL and FTL.

	Target FR	FR '19	C_H '19	C_T '19
LTL Model Output FS	**98.0%**	98,20%	€ 44.861	€ 398.270
FTL Model Output FS	**98.0%**	98.65%	€ 59.934	€ 151.995
LTL Model Output Retail	**98.0%**	98,14%	€ 45.625	€ 84.000
FTL Model Output Retail	**98.0%**	98.77%	€ 47.030	€ 73.500

As can ben seen in Table 5.10, the target fill rate is always met for LTL as well as FTL, which means the final model performs how it should perform. The comparison with the current situation of Bonduelle is done in the next section (Section 5.6.2).

5.6.2 Comparison Current Situation Bonduelle

In this section, the implementation of the final model with truck loading on the real sales of 2019 is compared with the actual performance of Bonduelle in 2019 with the current inventory control policy. The target fill rate at Bonduelle is 98.5%. It is assumed that the transportation costs in the current situation are the same, because currently also only FTL is transported from the factories to the warehouse. Table 5.11: Final Model Comparison FS. Table 5.11 shows the results of FS and Table 5.12 shows the results of Retail. The actual target fill rate of the model is set to 98.0% because FTL results in a slightly higher fill rate than the target.

Table 5.11: Final Model Comparison FS.

	Target FR	FR '19	C_H '19	C_T '19
Current Bonduelle Situation	**98.5%**	95.8%	€ 64.108	€ 151.995
Model Output FTL	**98%**	98.65%	€ 59.934	€ 151.995
Difference	**-**	+ 2.85%	- 6.51%	-

Table 5.12: Final Model Comparison Retail.

	Target FR	FR '19	C_H '19	C_T '19
Current Bonduelle Situation	**98.5%**	97.0%	€ 59.725	€ 73.500
Model Output FTL	**98%**	98.77%	€ 47.030	€ 73.500
Difference	**-**	+ 1.77%	- 21.2%	-

Firstly, as can be derived from Table 5.11 and Table 5.12, the final model results in cost savings for both the Retail and the FS SKUs. The most remarkable result is that on the Retail market especially costs are saved, which means some SKUs are currently significantly too much on stock and for the FS market especially the service level increased when the final model would have been implemented. From the combination of lower fill rate and higher holdings costs at the current situation, it can be concluded that the distribution of the total stock over the SKUs is not optimal in the current situation. The high holding costs mean that some SKUs are kept more on stock than necessary to meet the target fill rate and the low total fill rate means that some SKUs do not have enough stock to meet the target fill rate.

Because the fill rate of the final model is higher, the costs can not be compared properly. To make a better comparison of the model costs and the costs of the actual situation, Table 5.13 and Table 5.14 represent the results when the target FR of the model is set the same as the actual realized fill rate. Again, FTL results are presented, so the transportation costs (C_T) do not change. Table 5.13 shows the FS results and Table 5.14 shows the Retail results.

Table 5.13: Low FR Final Model Comparison FS.

	FR '19	C_H '19
Current Bonduelle Situation	95.8%	€ 64.108
Model Output	95.58%	€ 47.406
Difference	-	- 26.1%

Table 5.14: Low FR Final Model Comparison Retail.

	FR '19	C_H '19
Current Bonduelle Situation	97.0%	€ 59.725
Model Output	97.0%	€ 40.203
Difference	-	- 32.7%

As can be seen in Table 5.13 and Table 5.14 above, the savings of holding costs are significant. When the fill rate is set approximately equal to the total fill rate of 2019, 26% of the holding costs will be saved for FS and 33% for Retail. In reality, the fill rate should be 98.5%.

In Section 6, conclusions are drawn based on all analyses that have been explained in Section 5. Furthermore, answers to the research questions are provided. After the conclusions, some recommendations for improvements are done and the limitations and directions for future research are elaborated.

6. Conclusions and Recommendations

In this section, conclusions for the research are drawn. Firstly, answers to the research questions are provided and explained based on the analyses. In addition, recommendations for the case study are given.

6.1 Sub Research Questions

Subquestion 1: How are the current inventory model, service level constraints, and demand forecasts designed?

Nowadays, the Supply Chain of frozen products of Bonduelle Northern Europe follows a (R, s, nQ) policy. A (R, s, nQ) policy means that every R periods the inventory position is reviewed, and whenever the inventory position drops below reorder level s, an order of size $n * Q$ is placed, in which n is the minimal integer value that brings the inventory position back to or above s. SKUs are shipped from different factories to the central warehouse and distributed from the warehouse to all customers. Only full truckloads are transported. The determination of the safety stock levels is done on intuition, and not based on statistical analyses. Also, truck loading until Full Truck Load is done with a very simple method.

Besides, demand forecasts are made to inform the factories about production and to control the central warehouse. These demand forecasts are partly based on standard forecasting methods, but also mostly adjusted by hand. These adjustments are based on, for example, price discounts, market changes, or marketing information.

Using the current methods of controlling the warehouse reveals non-optimal stock levels, and therefore lower customer service levels than the specified targets, and probably unnecessarily high holding costs.

Subquestion 2. How is an inventory policy based on historical demand data designed?

The inventory model based on historical demand is a stationary model with a fixed review period and case pack size, knows as a (R, s, nQ) model. Demand has been fitted on sales data in different ways and the Gamma distribution was proven to be the most appropriate demand distribution. Determining the parameters of the Gamma distribution has been done by using the *Maximum Likelihood Method.* The reorder levels s have been found by calculating the minimum value of s that still satisfies the fill rate constraint.

Every review period orders are placed at different factories and only full truckloads are transported to the warehouse. Filling up the trucks is done by adding pallets to the trucks that are expected to be on stock as short as possible.

Subquestion 3: How is an inventory policy based on the demand forecast and forecast errors designed?

The inventory model based on forecasts is a non-stationary model with fixed review periods and case pack size, known as (R, s_t, nQ) model with fluctuating values for s_t every R periods. The demand distribution that is used every review moment to determine the optimal stock level is built up from the forecast and the average forecast error. Truck loading has been done the same way as for the *Historical Demand Based Model.*

Subquestion 4: What is the performance of an inventory policy based on historical demand compared to the current inventory model?
The implementation of the *Historical Demand Based Model* results in cost savings and an increase in customer service compared to the current situation. Moreover, the model calculates the right amounts to order, and no manual adjustment is needed, which is also an advantage compared to the current system. The model can calculate the right stock levels for different target fill rates, which makes analysis of the cost of increasing customer service possible.

Subquestion 5: What is the performance of an inventory policy based on demand forecast and forecast errors compared to the current policy and a policy based on historical demand?
The *Forecast Based Model* outperforms the *Historical Demand Based Model* for some SKUs. An important requirement of the model is that the forecast is reliable. Cost savings can be realized when demand can be forecasted well, for example for SKUs with a know seasonality pattern or better forecasting of promotional sales. When forecast accuracy is relatively low (high average forecast error) or the forecast is biased, the *Forecast Based Model* results in unnecessarily high costs or either too high or too low service levels.

Subquestion 6: What are the advantages and disadvantages of using an inventory policy based on demand forecast and based on historical demand?
From this research, some advantages of using forecasting to control a warehouse can be concluded. In this research, both a stationary and a non-stationary model have been tested. The stationary model is referred to as the *Historical Demand Based Model* and the non-stationary model is referred to as the *Forecast Based Model*. We can conclude that for some SKUs the non-stationary model performs the best, and for some SKUs, the stationary model performs the best.

The overall advantage that has been found for the non-stationary model is the fact that it is non-stationary, which makes the model more suitable for changing environments, seasonality patterns, changing customer needs, and periods of promotion. Because the forecast based model uses the demand forecast as input, known changes are taken into account when controlling the warehouse.

The overall disadvantage, however, that has been found, is that the non-stationary model is dependent on the accuracy of the forecast. Especially in the case study that has been done, this disadvantage could give some problems when the forecast is not reliable. For some SKUs, the holding costs appeared to become too high because of the relatively high forecast error. When forecasting accurately for an SKU is proven to be difficult, for example, because no clear trend or seasonality pattern is present, probably the stationary *Historical Demand Based Model* performs better.

Main Research Question: How does an inventory policy based on the demand forecast perform compared to an inventory policy based on historical demand?
Taking the subquestions together, we can draw general conclusions from the research. First of all, in this research, it has been confirmed that in most cases using modeling and scientifically based methods results in closer to optimal solutions than setting safety stocks by hand. By implementing the model that is developed in this research, the company can save costs in the long term and the customer service level will probably be higher. For the Foodservice market, especially the fill rate increases by the implementation of the methods. For the Retail market especially holding costs are saved by implementation of the methods.

Furthermore, it has been proven that a model based on forecasts can outperform a stationary model. However, for the forecast model to perform good, accurate demand forecasts are needed. When forecasts are accurate (small error and not-biased), controlling the warehouse based on these forecasts is advantageous. In this way, market changes can be taken into account better. Moreover, for example, the effect of marketing activities at supermarkets or expected environmental changes can be taken into account for controlling the inventory at the warehouse. Therefore, although the model can work properly, improving forecast accuracy especially for Retail SKUs is needed. Improving this forecast can be done by a thorough analysis of promotional sales per customer, and also, for example, investigate the effect of promotions on baseline sales.

Taken everything together, this research resulted in significant cost savings when the model would have been implemented at the company. It can be concluded that the *Forecast Based Model* can outperform a *Historical Demand Based Model* when forecast errors are not too high and also not biased. Based on all results and conclusions, recommendations have been done. These recommendations are addressed in the next section.

6.2 Recommendations

Based on the conclusions that are drawn, recommendations are done for the problems faced by Bonduelle Northern Europe. In this section, these recommendations are discussed.

Firstly, the major recommendation for Bonduelle is to implement the final model as presented in this report. Implementing the model will result in a significant increase in customer service level combined with cost savings. Moreover, the model decides what and how much to order every review period. Implementing the model results in a reduction of manual influence and therefore possible wrong human judgments. Also, the model helps to automatically fill up trucks to Full Truck Loads in such a way that the increase in holding costs is slight.

Furthermore, the research has proven that an inventory model based on demand forecast can work properly, and sometimes even better than a stationary model. To make the system perform better, the forecast needs to be improved, and further research on how to reduce the forecast error and forecast error bias needs to be conducted. Especially for the retail market, which is characterized by non-stationary demand patterns, an improvement of the forecast accuracy can result in significant cost savings and higher customer service. To improve this forecast accuracy, further analysis of predicting the demand of baseline as well as promotions is needed. Forecast accuracy of promotions can possibly be improved by settling fixed promotion amounts together with customers, so that high unexpected demand fluctuations can be reduced, and thereby forecast accuracy can be increased.

Thirdly, it can be concluded that the total costs caused by Full Truck Loading of Foodservice are relatively high. These high costs are caused by some different factories from which some SKUs are supplied that have high transportation costs. The implemented model can calculate fill rates, transportation costs, and holding costs for all SKU separately to get insight into the actual cost of a single SKU. It is recommended to reconsider the total range of SKUs of Foodservice and to decide which SKUs are possibly not worth selling because of the relatively high costs. Using the model, more insight can be obtained about the actual margin of every single SKU, which helps with reconsidering all SKUs.

Lastly, it can be concluded that collecting data of sales, forecasts, forecast errors, and forecast adjustments is important. It is recommended to store all data from the weekly forecasts to be able to get better insight into the usefulness of manual adjustments of the forecasts and also on the effect of these adjustments on holding costs and service levels. Storing data is essential to make future research possible. Furthermore, storing these data makes further improvement and long term implementation of the model more efficient.

7. Limitations and Future Research

In this section, the limitations of the research and some directions for possible future research are addressed.

7.1 Limitations

The first possible limitation in this research might be that all results obtained from the research are based on a case study with specific model constraints and parameters. Possibly, some market-specific characteristics have impacted the demand patterns on which the study is based. It can be assumed that the results of the analysis are useful for other markets or other SKUs, but that has not been proven. Although the parameters and constraints are specific for the case study, the methods in this research can be used in many different cases.

Secondly, in this research, it is assumed that trucks always have to be Full Truck Load (FTL) when an order is placed at a factory because this is a basic rule that is followed by the company. In fact, the model might be closer to optimal when costs of different truck utilization would have been known. For some factories of Foodservice (FS), it might be more cost-efficient to transport less than Truck Load (LTL), especially for factories that supply just a few SKUs and have high transportation costs. When these cost information would have been available, the model of truck loading can be adjusted to this situation, and this might result in sometimes not transporting FTL trucks. Especially from trucks from factories with high transportation costs and a small number of SKUs it might be interesting to know the costs of transporting LTL. In the current situation, however, it has been shown that transporting full truckloads significantly saves transportation costs.

Thirdly, the assumption that the factories can always supply might be a limitation for the research. Because the case study is conducted on products that are yearly harvested, the assumption of always having enough stock is reasonable. However, sometimes, mostly close to the next harvest period, stockouts occur at the factories, which could result in stock-outs in the warehouse. Although it is extensively explained why this assumption is plausible, further analysis of the actual delivery performance of all factories could impact the results slightly.

Lastly, this research is based on the demand forecasts that are set by the company and is not combined with scientifically set demand forecasts that might be better. The research could have been improved when better forecasting methods would have been tested and implemented before this research about using the forecast would have been conducted. As can be derived from the conclusions, a more accurate demand forecast will probably improve the performance of the investigated models. Also, the forecasts have been made on a monthly basis, and are converted into weekly forecasts, which could affect the total forecast accuracy. When weekly forecast data would have been available, a better analysis of the forecast error over different time periods could have been done.

7.2 Future Research

From these limitations, some suggestions and directions for interesting possible future research are done.

First of all, expansion of the research that has been conducted can be valuable. Firstly, the research can be expanded by taking a larger part of the supply chain of Bonduelle, instead of the focus on only a specific part of the products and customers. Since this report highlights that cost savings can be realized when using the models, more research can be conducted on the possibility to implement the models on different markets within and outside the scope of Bonduelle. Since the research has proven the potential of the *Forecast Based* Model investigating in on a larger scale is interesting. Furthermore, the research can be expanded on the content. More analyses about how to improve the forecasting methods can help to make the models work more efficiently. Also, further analysis of the forecast evolution over time can be done, when data of the current forecasts are collected properly for a longer period of time.

In the current research project, insight has been provided about the effect of changing target service levels on the holding costs. Using these insights, decisions on setting target service levels for different SKUs can be supported by the effects on costs. However, both qualitative and quantitative analyses can be done in the future on the impact of changing customer service levels on customer- and consumer satisfaction and thereafter the effect of this satisfaction on many other KPIs. By doing these analyses, for example, costs of backordering can be defined, which could support decisions on setting target service levels better.

Since this research was based on 2017, 2018, and 2019 data, future research can also be done on the specific period situation in 2020. The current Corona crisis probably influences the performance of all methods and models investigated in this research. Because this crisis is an event that has not happened in the near history, data collection is challenging. This crisis probably impacts the buying behavior of all consumers and therefore the demand patterns of customers. Further research can be done on the short term effects of this crisis on inventory control policies and demand forecasting, but also on the long term impact on demand patterns. Conducting that research can give insight in which sales data can be used to properly simulate the future, and therefore which data can be used to analyze 2020 and find the right parameters.

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Appendix

A. Derivation of Expected Back Orders

Here, the total derivation of the equation to calculated the expected backorders of Van Donselaar & Broekmeulen (2014) are given.

To explain the formula, two relevant things are stated before calculating $E[BO(\tau + t)]$. Firstly, $IP(\tau) \sim u(s, s+Q)$ and secondly stochastic variable $\Delta = IP(\tau) - s$, so $\Delta \sim u(0, Q)$. Furthermore, the probability density functions that are used are ft, which is the PDF of demand during t (D_t), and g, which is the PDF for Δ.

The steps that are taken to come to Equation (19) in Section 3.1 are shown below:

$$E[BO(\tau + t)]$$

$$= E[\{D(\tau, \tau + t) - IP(\tau)\}^+] = E[(D_t - s - \Delta)^+]$$

$$= \int_{-\infty}^{\infty} \int_{0}^{Q} (x - s - \delta)^+ f_t(x) g(\delta) d\delta dx$$

$$= \int_{-\infty}^{\infty} \int_{0}^{Q} (x - s - \delta)^+ f_t(x) g(\delta) d\delta dx + \int_{s}^{s+Q} \int_{0}^{Q} (x - s - \delta)^+ f_t(x) g(\delta) d\delta dx$$
$$+ \int_{s+Q}^{\infty} \int_{0}^{Q} (x - s - \delta)^+ f_t(x) g(\delta) d\delta dx$$

$$= \int_{-\infty}^{\infty} \int_{0}^{Q} (x - s - \delta)^+ f_t(x) g(\delta) d\delta dx + \int_{s}^{s+Q} \int_{0}^{x-s} (x - s - \delta)^+ f_t(x) g(\delta) d\delta dx$$
$$+ \int_{s}^{s+Q} \int_{x-s}^{Q} (x - s - \delta)^+ f_t(x) g(\delta) d\delta dx + \int_{s+Q}^{\infty} \int_{0}^{Q} (x - s - \delta)^+ f_t(x) g(\delta) d\delta dx$$

* Note: -∞ is formally right, in reality demand cannot be negative.

Now, we see in the first and third integral $(x - s - \delta)^+ = 0$ because $x \leq s$ and $\delta \geq x - s$, respectively. In the second and fourth integral, $(x - s - \delta)^+$ is always positive, $(x - s - \delta)^+ = (x - s - \delta)$. Furthermore, we set $g(\delta) = \frac{1}{Q}$, because $\Delta \sim u(0, Q)$.

$$E[BO(\tau + t)]$$

$$= \frac{1}{Q} \int_{s}^{s+Q} \int_{0}^{x-s} (x - s - \delta) f_t(x) g d\delta dx + \frac{1}{Q} \int_{s+Q}^{\infty} \int_{0}^{Q} (x - s - \delta) f_t(x) g d\delta dx$$

We integrate over δ:

$$E[BO(\tau + t)]$$

$$= \frac{1}{Q} \int_{s}^{s+Q} [(x-s)\delta - \frac{1}{2}\delta^2]_{\delta=0}^{\delta=x-s} f_t(x)dx + \frac{1}{Q} \int_{s+Q}^{\infty} [(x-s)\delta - \frac{1}{2}\delta^2]_{\delta=0}^{\delta=Q} f_t(x)dx$$

$$= \frac{1}{Q} \int_{s}^{s+Q} \frac{1}{2}(x-s)^2 f_t(x)dx + \frac{1}{Q} \int_{s+Q}^{\infty} [(x-s)Q - \frac{1}{2}Q^2] f_t(x)dx$$

$$= \frac{1}{Q} \int_{s}^{s+Q} \frac{1}{2}(x-s)^2 f_t(x)dx + \int_{s+Q}^{\infty} x f_t(x)dx - (s + \frac{Q}{2}) \int_{s+Q}^{\infty} f_t(x)dx$$

The final equation is the equation that is given in Section 3.1 and is used for all calculations.

B. Chi-Squared Tests Gamma Normal

The significance level is set on 0.05, which is generally done in literature. This significance level means the “Probability of falsely rejecting H_0” (Morgan et al., 1984). According to Morgan et al., (1984) the hypotheses of the test are formulated as follows:

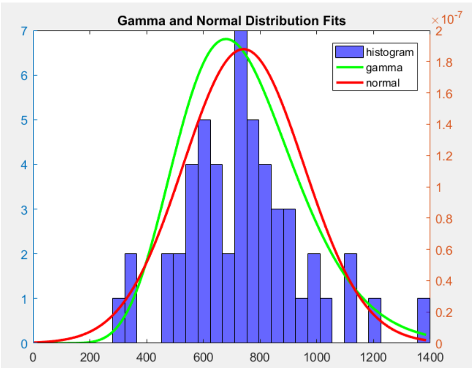
H_0 : “The random variable conforms to the distributional assumption”

H_1 : “The random variable does not conform to the distributional assumption”

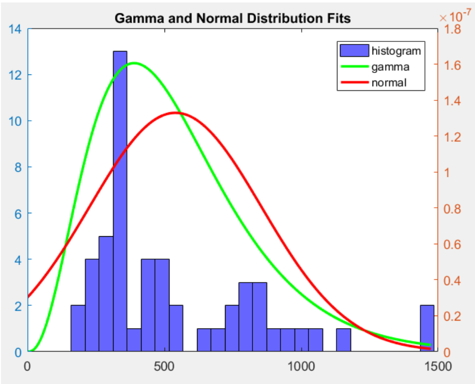
The chi-squared goodness of fit test tests whether H_0 can be rejected or not. The P-value is calculated. The higher the P-value, the better the fit. When the H_0 is rejected, the output of the test gives 1 instead of 0. According to the fitting tests, less than 2% of the total demand did not fit when distributions are fitted on the sales of $R + L$ periods.

Three examples of SKUs are given: one that fits both Gamma and Normal distribution, one that fits Gamma the best, and one that fits Normal the best, respectively:

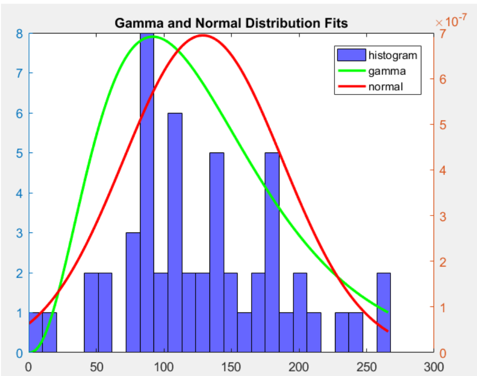
P Value Gamma	0,920125
P value Normal	0,844239
Hypothesis testing Gamma	0
Hypothesis testing Normal	0



P Value Gamma	0,179151
P value Normal	0,008213
Hypothesis testing Gamma	0
Hypothesis testing Normal	1



P Value Gamma	0,309166
P value Normal	0,58795
Hypothesis testing Gamma	0
Hypothesis testing Normal	0

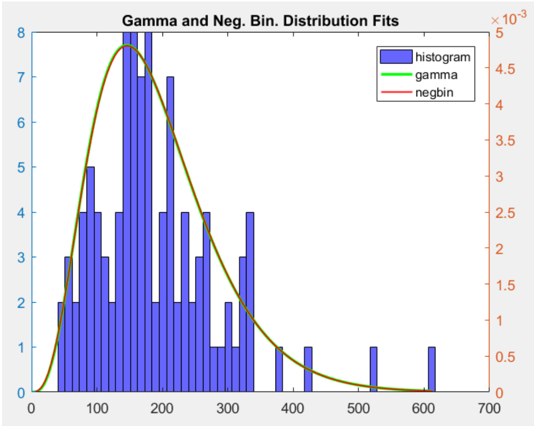


C. Chi-Squared Tests Discrete Distribution

Here, three examples of $\chi 2-$ tests are shown of both the Gamma distribution and the Negative Binomial distribution. The first example (Example 1) shows an SKU for which the difference between the two distribution is not significant. Example 2 is an example of an SKU of which the gamma distribution fitted better. Example 3 shows an SKU of which the Negative Binomial distribution fits (slightly) better. This third case is only the case for a very few number of SKUs and very small percentage of the total demand. Furthermore, we see that the difference of example 3 is very slight.

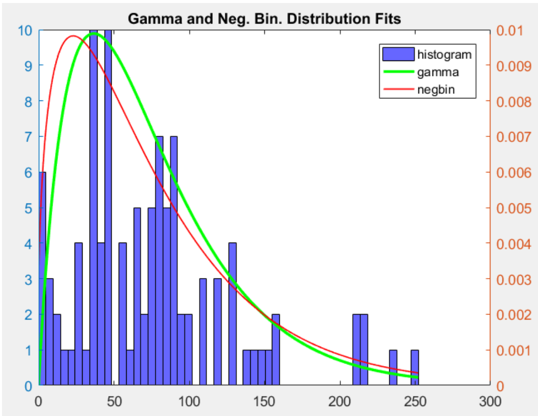
Example 1:

P Value Gamma	0,6099
P value Neg. Binomial	0,6110
Average period demand	270.23



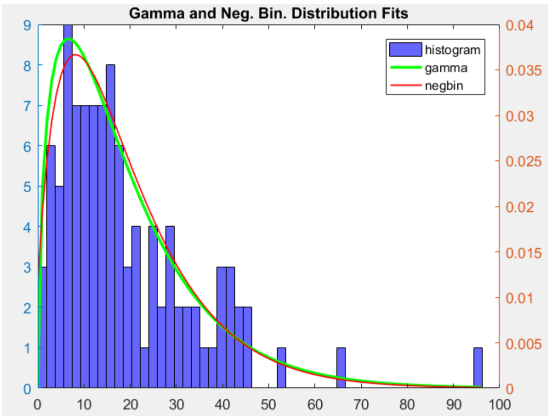
Example 2:

P Value Gamma	0,355
P value Neg. Binomial	0,041
Average period demand	270.23



Example 3:

P Value Gamma	0,102
P value Neg. Binomial	0,462
Average period demand	18.96



D. SKU Output Final Model

Output which model fits the best to which SKU.

*1 = *Historical Demand Based Model, 2 = Forecast Based Model*

*** The real company SKU numbers are not provided in this report for confidentiality reasons.*

SKU Nr	Company SKUNr**	Model*	SKU Nr	Company SKUNr**	Model*	SKU Nr	Company SKUNr**	Model*	SKU Nr	Company SKUNr**	Model*
1	[redacted]	1	37	[redacted]	1	73	[redacted]	1	109	[redacted]	2
2	[redacted]	1	38	[redacted]	1	74	[redacted]	1	110	[redacted]	2
3	[redacted]	2	39	[redacted]	1	75	[redacted]	1	111	[redacted]	1
4	[redacted]	1	40	[redacted]	1	76	[redacted]	2	112	[redacted]	1
5	[redacted]	2	41	[redacted]	1	77	[redacted]	1	113	[redacted]	2
6	[redacted]	1	42	[redacted]	1	78	[redacted]	2	114	[redacted]	2
7	[redacted]	2	43	[redacted]	2	79	[redacted]	2	115	[redacted]	2
8	[redacted]	1	44	[redacted]	2	80	[redacted]	1	116	[redacted]	1
9	[redacted]	1	45	[redacted]	2	81	[redacted]	2	117	[redacted]	1
10	[redacted]	1	46	[redacted]	1	82	[redacted]	2	118	[redacted]	1
11	[redacted]	2	47	[redacted]	1	83	[redacted]	2	119	[redacted]	1
12	[redacted]	1	48	[redacted]	1	84	[redacted]	1	120	[redacted]	1
13	[redacted]	1	49	[redacted]	1	85	[redacted]	1	121	[redacted]	1
14	[redacted]	1	50	[redacted]	2	86	[redacted]	1	122	[redacted]	1
15	[redacted]	2	51	[redacted]	2	87	[redacted]	1	123	[redacted]	1
16	[redacted]	1	52	[redacted]	1	88	[redacted]	1	124	[redacted]	1
17	[redacted]	1	53	[redacted]	2	89	[redacted]	1	125	[redacted]	1
18	[redacted]	1	54	[redacted]	1	90	[redacted]	1	126	[redacted]	1
19	[redacted]	2	55	[redacted]	1	91	[redacted]	2	127	[redacted]	1
20	[redacted]	2	56	[redacted]	2	92	[redacted]	1	128	[redacted]	2
21	[redacted]	1	57	[redacted]	1	93	[redacted]	2	129	[redacted]	1
22	[redacted]	2	58	[redacted]	2	94	[redacted]	1	130	[redacted]	1
23	[redacted]	1	59	[redacted]	1	95	[redacted]	2	131	[redacted]	1
24	[redacted]	1	60	[redacted]	1	96	[redacted]	2	132	[redacted]	1
25	[redacted]	1	61	[redacted]	2	97	[redacted]	1	133	[redacted]	1
26	[redacted]	2	62	[redacted]	1	98	[redacted]	2	134	[redacted]	1
27	[redacted]	1	63	[redacted]	2	99	[redacted]	1	135	[redacted]	1
28	[redacted]	1	64	[redacted]	1	100	[redacted]	1	136	[redacted]	1
29	[redacted]	2	65	[redacted]	2	101	[redacted]	1	137	[redacted]	1
30	[redacted]	2	66	[redacted]	2	102	[redacted]	1	138	[redacted]	1
31	[redacted]	2	67	[redacted]	2	103	[redacted]	1	139	[redacted]	1
32	[redacted]	2	68	[redacted]	2	104	[redacted]	1	140	[redacted]	1
33	[redacted]	1	69	[redacted]	1	105	[redacted]	1	141	[redacted]	1
34	[redacted]	2	70	[redacted]	1	106	[redacted]	1	142	[redacted]	1
35	[redacted]	2	71	[redacted]	1	107	[redacted]	1	143	[redacted]	1
36	[redacted]	1	72	[redacted]	1	108	[redacted]	2			