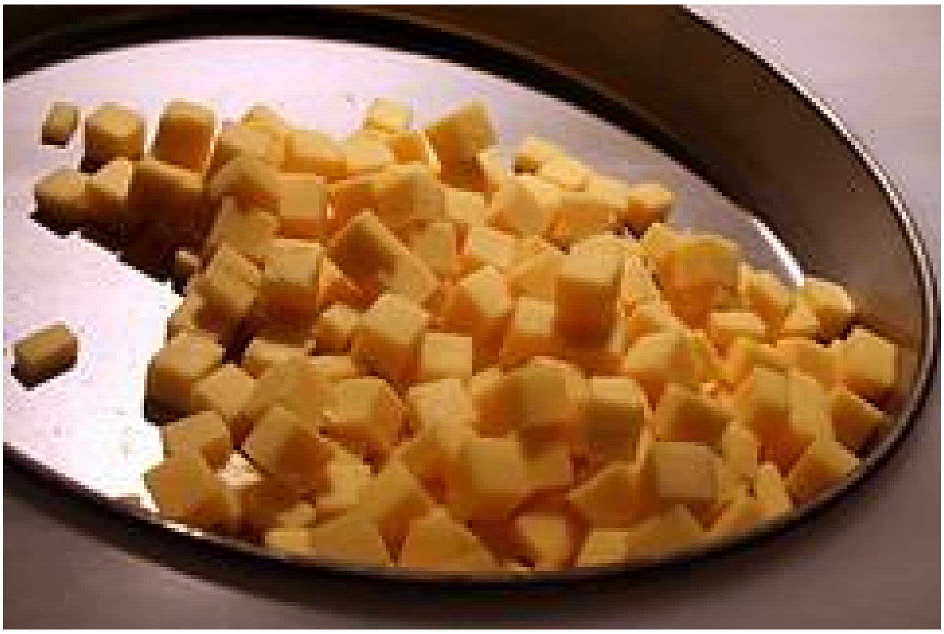
Improving forecast accuracy

Improving the baseline forecast for
cheese products
by use of statistical forecasting



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FrieslandCampina

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Project manager:	Freek van Sommeren	Discipline:	Supply chain

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ABSTRACT

This master thesis project was carried out at the supply chain department of FrieslandCampina Cheese. This research project, analyzes the applicability of statistical forecasting for cheese products. The project focuses on forecasts for baseline sales. Baseline sales are the sales that are left when promotion sales have been excluded. FrieslandCampina wants to use APO (a forecast module in SAP) to create statistical forecasts. In this research project, we explore the statistical models that are available in APO. Because APO cannot optimize the parameters for every statistical model, we create an advanced forecasting tool in Microsoft Excel to optimize the parameters per model. Our analysis indicates that implementation of statistical forecasting would benefit FrieslandCampina. Because of the great variety and amounts of products at FrieslandCampina, we select 80 products to analyze in our research. 72,5% of these products show an improvement in forecast performance.

PREFACE

This master thesis is the final result of my master study Production and Logistic Management at the University of Twente. This thesis is the result of six months of research at the supply chain department of FrieslandCampina Cheese in Amersfoort. It has been an enriching experience, which contributed extensively to my professional and personal development.

First of all, I would like to thank my first supervisor at the University of Twente, Leo van der Wegen. I thank Leo for his critical feedback over the course of the entire project. His precise guidance and feedback have contributed greatly to the quality of this research project.
Secondly, I would like to thank my second supervisor at the University of Twente, Peter Schuur. I thank Peter for sharing his knowledge and his feedback.

I enjoyed working at the supply chain department at FrieslandCampina. Colleagues at FrieslandCampina were very friendly and helped me whenever necessary. I would especially like to thank Francisca Knulst-Wouda for giving me feedback and the flexibility to conduct my research. Another special thanks to Jacob Kroes for providing me with information and helping me whenever it was needed.

Furthermore, I would like to thank my family and friends for their support and the pleasant time I had as student in Enschede. I would especially like to thank my parents for giving me the opportunity to finish this study.
Lastly, I would like to thank my girlfriend, for the support and inspiration she has given me.

Freek van Sommeren

MANAGEMENT SUMMARY

Problem

The supply chain department is charged with finding the right balance between operating costs and service and inventory levels. To create the right balance between the three factors, service level, inventory level, and operating costs, forecasts should be accurate. Underestimation of demand can result in lost sales, dissatisfied customers, or insufficient resources for production. Overestimation of demand can result in high operating costs and high inventory.
The supply chain and sales departments are dissatisfied with the current forecast method. FrieslandCampina presumes a more accurate forecast to be important for the increase of service levels and the decrease of inventory levels and operating costs. FrieslandCampina wants to improve the performance of Cheese & Cheese Specialties with regard to delivery to customers in balance with working capital. In order to achieve optimal performance from the working capital, the forecast accuracy needs to be improved.
FrieslandCampina wants to increase forecast accuracy by using statistical forecasting. However, it is unclear whether statistical forecasting is the appropriate method. Furthermore, it is unclear which statistical forecast models exist and which forecast models can be used.

Analysis

By interviewing sales planners and project managers, we identified various causes for the current forecast inaccuracy. The following causes were identified:

1. Inaccurate forecast procedure
2. Inaccurate use of performance evaluation
3. Insufficient use of system functionalities in APO

Our project focuses on the insufficient use of system functionalities. We want to increase forecast performance by using the statistical forecast functionality in APO. This master thesis project focuses on the applicability of statistical forecasting for the portfolio of FrieslandCampina.

Results

We created eight groups of articles, which cover all of FrieslandCampina's markets. We created three groups in the branded retail market, two groups in the non-branded retail market, and three groups divided over the B2B, IM, and indirect markets. Furthermore, the group division is based on sales volume per article, importance of customer, and variance in demand.
For each group, we analyzed whether or not statistical forecasting would improve the forecast performance. Results show that statistical forecasting is appropriate for all markets. On average, forecast accuracy for the branded retail market improves by 15,6% and bias performance over the baseline sales improves by 22,2%. Baseline sales are the sales that are left when promotions are excluded. Forecast accuracy for the non-branded retail market improves by 4,2% and forecast bias performance over baseline sales improves by 7%. Overall, statistical forecasting improves forecast accuracy by 11,4% over the baseline sales and the forecast bias performance by 14,4% over the baseline sales. 72,5% of the products we analyzed show an improvement in forecast

performance when statistical forecasting is used. Statistical forecasting decreases the forecast performance for products with strongly fluctuating sales patterns or products with an unpredictable intermittent sales pattern.

This master thesis project explores several statistical forecast models. The best model and parameters vary greatly per product. The damped trend model is the best statistical model for 26,3% of the products and the simple exponential smoothing model is the best statistical model for 20% of the products.

Recommendations

The implementation of statistical forecasting results in an improvement of the forecast performance. To implement statistical forecasting, we provide FrieslandCampina with several recommendations.

Model and parameter selection

The forecast module APO can automatically select the appropriate statistical forecast model and optimize its parameters. This function requires three years of data. At this point, one and a half years of data is available. Therefore, we cannot automatically select the optimal model.
In this project, we created an advanced forecast tool in Microsoft Excel to select the best model and its optimal parameters. FrieslandCampina can use this forecast tool to select the best model and its parameters for the complete portfolio of FrieslandCampina. This requires a lot of work. Therefore, we advise FrieslandCampina to use the simple or double exponential smoothing model in APO. The parameters for these two models can be optimized by APO. We discovered that there is a 1,4% decrease in forecast accuracy and a 3,27% decrease in forecast bias performance when we use the best of the simple or double exponential smoothing model instead of the overall best model. We advise FrieslandCampina to use the double exponential smoothing model when dealing with a (damped) trend in the sales pattern of the product, and to use the simple exponential smoothing model when there is no trend.
When three years of data are available, we advise FrieslandCampina to use the automatic model selection function in APO.

Aggregation levels

In Section 7.2, we analyze which aggregation level should be used in each case. We advise FrieslandCampina to forecast production on the basic material/age level (in case age is older than 10 weeks) and to forecast packaging on the commercial article level.

Outlier method

In Section 5.1, we describe the modified z-score method to statistically remove outliers from the sales pattern. We use the modified z-score method because the parameters used to calculate the modified z-score are minimally affected by outliers. APO does not contain the modified z-score method but does contain the median method. The median method calculates the median over the level-value and the median over the trend-value from past data. Based on these two median values, a tolerance lane is calculated. Values outside the tolerance lane are outliers.
Depending on the ambition level, we advise FrieslandCampina to use the median method to remove outliers. This method is available in APO. In case FrieslandCampina is dissatisfied with the results of this median method, we advise the company to build a macro to create the modified z-score method that is used in this project.

Forward buying effect

In this master thesis project we also analyzed the forward buying effect. The forward buying effect is the loss of sales after a promotion. Our analysis indicates that the forward buying effect takes place in the first two weeks after a promotion. We analyzed the quantity of the forward buying effect in the first two weeks. On average, there is a 30,5% decrease in sales in the first two weeks after a promotion.

The forward buying effect varies greatly between promotions. In some cases, the forward buying effect shows an 80% decrease in sales. In other cases, there is an increase in sales after a promotion. Therefore, it is difficult for FrieslandCampina to incorporate the forward buying effect.

We advise FrieslandCampina to do more research on the forward buying effect.

Tracking signal

The sales patterns of products can change over time. Therefore, it is possible for the statistical forecast model and parameters to no longer be appropriate. To control the model and parameters, we advise FrieslandCampina to use Trigg's tracking signal. This tracking signal indicates when a forecast is out of control and the parameters need to be updated. A tracking signal indicates if the forecast is consistently biased high or low. The tracking signal should be recomputed each period. The movement of the tracking signal is compared to the control limits; as long as the tracking signal is within these limits, the forecast is under control. Trigg's tracking signal is available in APO.

Demand forecasting versus sales forecasting

The data we use in our research is based on actual sales. When sales are lost due to incorrect forecasting or capacity problems, we do not fulfill the complete sales orders from customers. Therefore, the actual sales are not equal to the demand. When we make forecasts based on actual sales, we do not incorporate the complete demand and the forecasts will be incorrect.

Therefore, we advise basing forecasts on actual demand instead of actual sales.

Improved forecast process

We created an improved forecast process (see Figure 7.9 in Section 7.6). The forecast process incorporates all the steps that are required to statistical forecast products, including a new planning strategy per product and the forecast module APO to create statistical forecasts. We advise to use the improved forecast process.

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1. INTRODUCTION

In the framework of my master program Industrial Engineering and Management, I performed a master thesis project at the company, FrieslandCampina. This chapter describes the company at which my research took place. FrieslandCampina wants to increase their forecast accuracy by introducing statistical forecasting. In Chapter 2, the research problem, the research approach, and the structure of this report are described in more detail.

1.1 Company introduction

Royal FrieslandCampina is a multinational dairy company, fully owned by the dairy co-operative Zuivelcoöperatie FrieslandCampina, which is comprised of 15,326 dairy farms in the Netherlands, Germany, and Belgium. Daily FrieslandCampina provides food for hundreds of millions of people all over the world. Products are sold in more than one hundred countries, the key regions being Europe, Asia, and Africa. In 2010, sales amounted to nearly 8.2 billion Euros. FrieslandCampina employs over 20.000 employees, in 25 countries. See Figure 1.1 for more company facts.

Figure 1.1: Company facts (www.frieslandcampina.com, 2011)

FrieslandCampina is deeply rooted in the culture and commerce of the Netherlands, Germany, and Belgium. FrieslandCampina is a global company, but focuses on local communities and customers. The company is also deeply rooted in many countries outside Europe.

1.2 History

In late December 2008, the merger of Friesland Foods and Campina, two companies that developed along similar lines, results in the creation of FrieslandCampina.
It all started in the 1870s, when, all over the Netherlands, farmers joined forces in local co-operative dairy factories. They did this to safeguard the sales of their milk (without the benefit of modern refrigeration they had to work together) and to gain more power on the market.
FrieslandCampina began on local farms in the Netherlands, Germany, and Belgium in the late nineteenth century. Many of these farms are still in cooperation with FrieslandCampina today, and their farmers are just as firmly anchored to their regions and local communities as were their forebears. Over the years, these farmers have built an international dairy company that spans the world. Later, local dairy factories merged into regional dairy factories. These smaller co-operatives began joining together in the 1960s, creating the first big national brands. DOMO, for example, serves the provinces

Groningen and Drenthe, and Coberco covers Gelderland and Overijssel. In the west of the Netherlands, several co-operatives merged into Melkunie Holland in 1979. Melkunie Holland also acquired several privately owned dairy companies. 1979 is also the year that DMV Campina was established in the south. DMV Campina and Melkunie Holland merged into Campina Melkunie in 1989. In 1997 four major co-operatives in the north and east of the Netherlands merged to create Friesland Coberco, which later became Friesland Foods. In 2001, Campina merged with the Milchwerke Köln/Wuppertal co-operative from Cologne, Germany and the De Verbroedering co-operative from the Antwerp region of Belgium. This created the international Campina co-operative.
In December 2007, Friesland Foods and Campina announced their intentions to merge. One year later, in December 2008, they received the approval of the European competition authorities to become FrieslandCampina.

1.3 Strategy

FrieslandCampina's strategy is to increase their added value. At the same time, they want to ensure that all the milk produced by the cooperative's member dairy farmers reaches its full value. To this end, FrieslandCampina formulated route2020; a new strategy aimed at achieving accelerated growth in selected markets and product categories.
In developing and expanding their value, FrieslandCampina primarily focuses on growth, profitability, and milk valorization (adding value to milk). The route2020 strategy defines six value drivers to achieve value growth.

- Worldwide growth in dairy-based beverages by increasing the share in total consumption.
- Strengthening market positions in infant nutrition, both ingredients and end products, worldwide.
- Increased market share in branded cheese, by, for example, expanding the brand portfolio.
- Geographical growth in the above categories and improving the strong positions outside of these categories.
- Foodservice in Europe: strengthening and expanding existing strong positions in the eating-out category, partly through geographical expansion.
- Strengthening of basic products such as standard ingredients, industrial cheese, and private labels, in order to reduce the share of member milk that is processed into commodities.

1.4 Products and locations

FrieslandCampina processes over 10 billion kilograms of milk per year in consumer products such as dairy drinks, baby and infant food, cheese, butter, cream and desserts, and butter and cream products to professional customers. Aside from that, FrieslandCampina processes ingredients and components for the food and pharmaceutical sectors. These products are primarily sold in 25 countries, located mainly in Europe, Asia, North America, and Africa, while the ingredients are sold worldwide. FrieslandCampina carries leading brands, including Appelsientje, Best Cool, Chocomel, Campina Milner and Mona.
FrieslandCampina plays an important role in providing food for hundreds of millions of people all over the world on a daily basis. FrieslandCampina's products include dairy-

based beverages, infant and toddler nutrition, cheese, butter, cream, desserts and functional dairy-based ingredients.

FrieslandCampina has limited product presence in America, but the continent is still important to the company, especially to the operating companies which sell high quality dairy ingredients. FrieslandCampina DMV, FrieslandCampina Domo, and FrieslandCampina Creamy Creation all have sales offices in the United States.

FrieslandCampina can be found all over Europe, where 70% of its total turnover is generated. In Europe, there is a broad product range, extending from daily fresh liquid milk to cheese, butter, and fruit juice. FrieslandCampina's ingredients, which vary from milkshake mixes to caseinates, are used by professional and industrial food producers all over Europe to prepare their products. FrieslandCampina has its own sales outlets in many European countries. Aside from that, there are also production plants throughout Europe, mainly in the Netherlands, Germany, and Belgium. This is not surprising, since FrieslandCampina dairy cooperative member farmers are based in these three countries.

In many African and Middle Eastern countries, FrieslandCampina sells products that are tailored to local conditions. These include large amounts of condensed milk and milk powder, as well as cheese and butter. Peak and Rainbow are well-known FrieslandCampina brands that are sold in these countries.

FrieslandCampina is a key player in the dairy sector in Africa and the Middle East, which accounts for 10% of the company's total sales. There are also outlets in Nigeria and Saudi Arabia. Many of the products, which are sold in Africa and the Middle East, are based on milk supplied by FrieslandCampina's own member farmers in the Netherlands, Germany, and Belgium. FrieslandCampina Creamy Creation is also active on the African market, where it sells cream liqueur in sachets.

FrieslandCampina has a long history on the Asian market. The company has, for example, been selling dairy products in Vietnam and Indonesia for more than 80 years. This initially began with the sale of sweetened condensed milk and has since extended to a wide range of dairy products. Whether it is milk-based drinks, baby food, yoghurts, yoghurt drinks, or advanced dairy ingredients, FrieslandCampina's products can be found in many Asian countries. There are also sales offices and production plants across Asia. Asia accounts for 17% of the company's total turnover.

1.5 Organization

In order to be successful on the market, FrieslandCampina must have a keen eye for customer wishes and connect these to the potential uses of milk. This is what FrieslandCampina's operating companies do every day. These operating companies are active in specific product groups, and sometimes also in a specific country or region (see Figure 1.2).

Each of the four business groups stands for a certain product group;

• Consumer Products Europe (milk, dairy drinks, cream, coffee creamers, yoghurts and desserts in Western Europe);

• Consumer Products International (milk, milk powder, condensed milk, yoghurts and desserts in Eastern Europe, Asia and Africa);

• Cheese and Butter (cheese and butter, worldwide);

• Ingredients (ingredients for the food and pharmaceutical industry, worldwide).

The Corporate Center of FrieslandCampina is the head office, located in the central Dutch city of Amersfoort, where staff services and various operating companies are situated.

The departments of the Corporate Center are engaged in Business Group-overarching strategic issues. These include contact with the member dairy farmers.

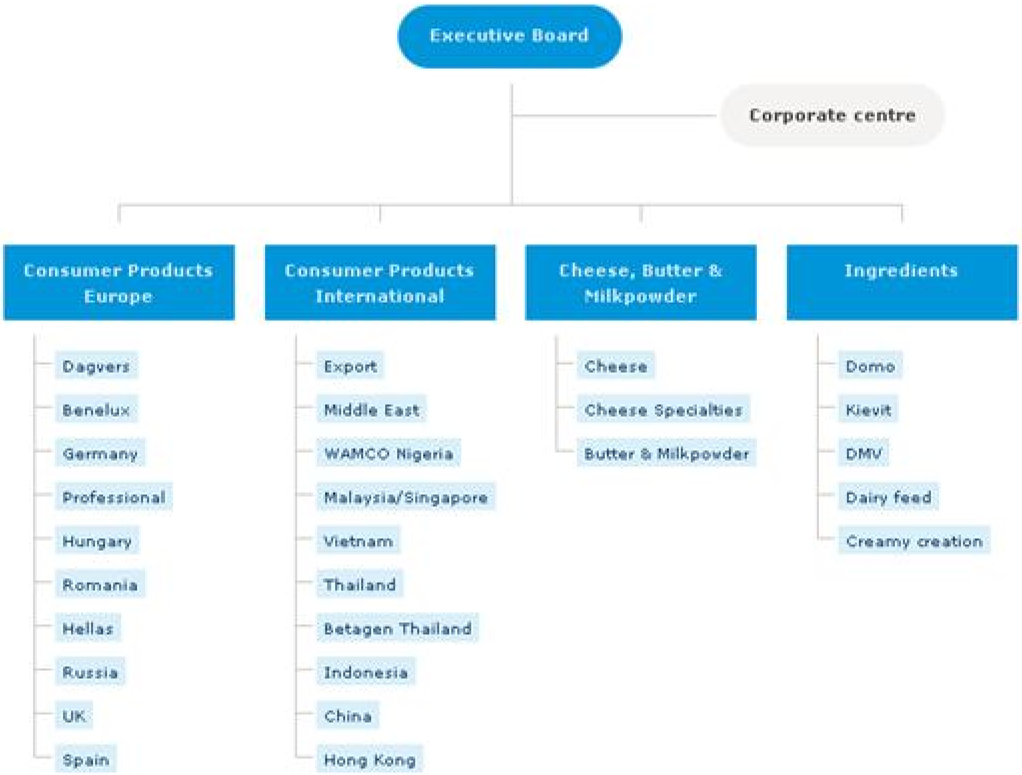

Figure 1.2: Organization of the company (www.frieslandcampina.com, 2011)

1.6 Business Group

Our project focuses on the Business Group Cheese, Butter & Milk Powder. The Business Group produces and sells a broad range of cheeses, butters, and milk powders. In Europe, FrieslandCampina's butter is sold under the familiar brands by other dairy producers such as Campina (Botergoud and Buttergold), Landliebe, and Milli. In countries outside Europe FrieslandCampina sells consumer-packaged butter and butter oil under brand names such as Campina and Frico.
The Business Group creates 26 percent of FrieslandCampina's total turnover and produces cheese from 4,5 billion kilos of milk every year. FrieslandCampina has classic cheeses, Gouda, Maasdammer, and Edam, which are hugely popular all over the world. Our project focuses on Cheese and Cheese Specialties. Cheese Specialties sells branded cheese to customers and Cheese sells non-branded cheese to customers.

2. RESEARCH APPROACH

This chapter introduces the project assignment. Based on the method of Heerkens et al. (2004), the core problem is identified. After the identification of the core problem, this chapter describes the research approach.

2.1 Problem identification

Before discussing our project, the core problem must be identified (Heerkens, 2004). The core problem is the main problem, which needs to be solved in this project. To identify our core problem, different managers of the Business Group Cheese, Butter, and Milk Powder were interviewed. During the interviews with these managers, who all work for the supply chain department or the sales department, we discovered cohesion between the problems that were mentioned.

The supply chain department is charged with finding the right balance between operating costs, service level, and inventory level. In order to create the right balance between the three factors, service level, inventory level, and operating costs, forecasts must be accurate (see Figure 2.1). Underestimating demand can result in lost sales, dissatisfied customers and insufficient resources. Overestimating demand can result in high operating costs and a high inventory.

Figure 2.1: Balancing factors (MT, 2010)

Planning decisions for Cheese & Cheese Specialties products are based on forecasts. According to Silver et al. (1998), planning decisions and inventory management could be steered by effective forecasting. Effective forecasting is essential to achieve service levels, to plan allocation of total inventory investment, to identify needs for additional production capacity, and to choose between alternative operating strategies. The problem is, however, that it is improbable for forecasts to be 100% correct. By choosing the right forecast method and achieving the most accurate forecast possible, the total expected relevant costs for decisions should be as low as possible.

The supply chain and sales departments are dissatisfied with the current forecast method. FrieslandCampina presumes a more accurate forecast is important to increase service levels, decrease inventory levels, and operating costs. Currently FrieslandCampina has difficulty achieving forecast accuracy[1] targets. In 2010, the forecast targets[2] were not achieved for most markets. The actual forecast accuracy deviates on average -5,5% compared to the forecast accuracy targets.

FrieslandCampina wants to improve the performance of Cheese & Cheese Specialties with regard to delivery performance to customers, in balance with working capital. To create optimal performance from working capital, the forecast accuracy needs to be improved.

Therefore, we identified the following core problem.

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[1] Forecast accuracy: 100% - MAPE (see Section 4.5)

[2] Forecast targets for the complete demand (baseline and promotions)

Core problem:

The current forecast method results in insufficient forecast accuracy.

2.2 Project objective

The management team of the supply chain department Cheese & Cheese Specialties wants to improve forecast accuracy. Currently, the forecast applies to complete demand[3]. We are going to analyze the usefulness of statistical forecasting for the baseline demand[4]. The overall forecast framework from Silver et al. (1998) suggests a forecasting system where statistical forecasting is involved. By means of statistical forecasting, we want to increase baseline forecast accuracy.

We are going to analyze the use of statistical forecasting per product per market. If statistical forecasting seems to be appropriate, different statistical forecast models will be analyzed concerning accuracy and bias.

FrieslandCampina intends to use the software tool APO (planning component of SAP) to generate forecasts. We are going to explore if the standard models in SAP are appropriate to forecast the products sold by FrieslandCampina.

Forecast error reduction is a main goal for this project. As stated earlier, the increase of forecast accuracy leads to decreasing inventory levels, operating costs, or increasing service levels. These factors are not performance measures for this project. The project focuses fully on increasing forecast accuracy.

2.3 Problem statement

The core problem concerns insufficient forecast accuracy. FrieslandCampina wants to increase forecast accuracy by using statistical forecasting. However, it is unclear whether statistical forecasting is the appropriate method. Furthermore, it is unclear which statistical forecast models exist and which forecast models would best fit to the demand patterns at FrieslandCampina.

The following ***problem statement*** captures the above described assignment:

Is statistical forecasting an appropriate method to forecast the baseline demand for Cheese and Cheese Specialties products and, if so, which statistical forecast models does FrieslandCampina need to use for cheese products to improve their baseline forecast accuracy?

2.4 Research questions

To solve the problem, research questions need to be defined. To execute this research, the scientific approach towards the design of a new forecasting process from DeLurgio (1998) is used (see Appendix B). This is an effective approach and provides attention to detail (DeLurgio, 1998). The first steps used in this scientific approach will be followed. Within the various steps, research questions need to be answered.

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[3] Complete demand: demand including promotions

[4] Baseline demand: demand that will be sold without support of any specific action (e.g. promotions)

Chapter 2: Research approach

Chapter 2 of this report contains the first step in the approach from DeLurgio. This section contains the identification, the objective, the problem statement, and the research approach of this project.

Chapter 3: Current situation

The Business Group FrieslandCampina Cheese, Butter, and Milk Powder has a broad range of products. This project focuses on cheese products. FrieslandCampina is present within a number of markets. Per product level, the different types of markets need to be analyzed, in order to identify the characteristics of each market. Interviews with project managers, sales planners and account managers will allow us to analyze the current situation and identify causes for the currently insufficient forecast accuracy.
Therefore, the following research questions are set up.

1. What are the characteristics per product per market at FrieslandCampina?
2. How are forecast processes organized and controlled in the current situation?
3. What are the causes for the low forecast performance?

Chapter 4: Literature research

The next step in DeLurgios approach is formulating statistical models. To create a starting point, literature, more accurately, literature on quantitative forecast models, will be researched in order to find statistical forecast models. To create statistical forecast models, FrieslandCampina needs to know how the performance of these models can be measured. In literature, we will search for methods to measure the accuracy of different models.

4. Which statistical forecast models are used in other (food) organizations?
5. How can the forecast performance be measured?

Chapter 5: Data cleaning and model selection method

After researching the literature, we will explore how the historical data needs to be cleaned to create an accurate baseline demand. All peaks caused by promotions and push orders will be removed from historic data. In this chapter, we will also design a model selection method to obtain the best forecast models for FrieslandCampina.

6. How should historical data be cleaned to create statistical baseline forecast models?
7. How should FrieslandCampina select the best appropriate statistical model to forecast each product?

Chapter 6: Performance evaluation

By using literature and baseline data, the most accurate forecast models will be set up for the baseline sales. After the creation of the statistical forecast models, they will be tested on bias and accuracy. In cooperation with FrieslandCampina a representative group of products will be chosen to be analyzed. Based on the performance of the statistical models in comparison with the current method, we will check, per product, if statistical forecasting is appropriate.

8. Which statistical forecast models would fit best to the demand patterns at FrieslandCampina?
9. Which products at FrieslandCampina are appropriate for using statistical forecasting?

Chapter 7: Implementation

At this point, we will explore how to implement statistical forecasting into APO. There are models present in APO, but not all parameters for each model can be optimized. We will analyze how to handle these difficulties. We will also advise FrieslandCampina on the management of the forecast per product and review the forecast process. Therefore, the following research questions are setup:

10. How can FrieslandCampina implement statistical forecasting?
11. How should FrieslandCampina manage the forecast of their products?
12. What should the new forecast process look like?

2.5 Scope of the project

FrieslandCampina's current forecast method develops two different types of forecasts: baseline forecast (sales under normal circumstances) and promotion forecast (extra sales due to promotions). According to FrieslandCampina, promotions cannot be forecasted statistically because promotions fluctuate heavily and are often ordered by customers. Therefore, we focus our research on the baseline forecast.
This master thesis project only focuses on baseline forecast for existing products. Hence, forecasts for product introductions are excluded. This project focuses on regular sales without dump sales or sales due to oversupply.
Furthermore, not all products from FrieslandCampina are taken into account. The project focuses on cheese products, all other products are excluded from analysis.
Not all cheeses will be analyzed. During project execution, a representative group of products will be chosen in cooperation with FrieslandCampina.
This project only explores quantitative forecast models, qualitative forecast models will be explored by FrieslandCampina.

2.6 Deliverables

We create an advisory report concerning the usefulness of statistical forecasting for the products sold by FrieslandCampina. This report contains:

- Analysis of current forecast method
- Description of useful statistical forecast models
- Description of useful forecast measures
- Advice about best fit statistical forecast models
- Advice on which markets are appropriate for using statistical forecasting
- Advice about the creation of the baseline demand
- Advice about the best forecast aggregation level
- Control mechanism for statistical models
- Advice about the management of the forecast per product type
- New improved forecast process

3. CURRENT SITUATION

In this chapter, we describe the current forecast process used by FrieslandCampina. Because each forecast process is different per market, we first describe product characteristics in Section 3.1 and market characteristics in Section 3.2. Secondly, we present overviews of production, planning and forecasting processes in the current situation in Section 3.3. Finally, in Section 3.4, we analyze causes for the insufficient forecast accuracy in the current situation.

3.1 Product characteristics

FrieslandCampina produces 130 different cheeses, currently using twelve factories, located throughout the Netherlands and Germany. They produce two types of products; nature cheese and rindless cheese. Nature cheese matures in the open air, where the quality of air is regulated. In the production of this type of cheese, a special coating for natural moistening is used, which is the original approach for producing cheese. The rindless cheese matures in closed plastic and does not get a coating. In most cases, rindless cheese is used for industrial purposes, while nature cheese is used for direct consumption. Popular nature cheeses are Gouda, Milner, Edam, and Maasdam.
Another characteristic of cheese is the age of the product. Cheese matures over time, maturation time depends on the cheese recipe. Nature cheese can be matured up to a year. Rindless cheese can be matured up to a few weeks. The third and fourth characteristics are weight and commercial product appearance.

3.1.1 Product aggregation levels

In Chapter 6, we test statistical forecasting for different aggregation levels. Therefore, we first identify the different levels. FrieslandCampina distinguishes seven product aggregation levels for cheese products. The aggregation levels are the following:

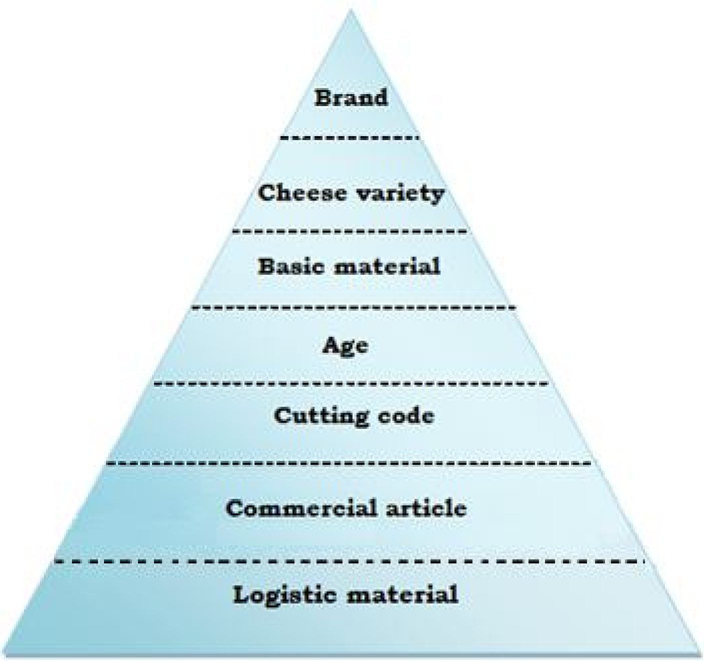

Figure 3.1: Product aggregation levels

Brand
Brand is the highest aggregation level of products. Every specific brand has its own characteristics that belong to their specific type of cheese. Typical brands produced by FrieslandCampina are: Milner, Frico, Old Dutch Master and Slankie.

Cheese variety
Cheese variety is a group of basic materials from the same brand, which have the same structure or weight. Cheese varieties from the Edam ball are: baby Edam, Edam ball 1,9 kg, Edam ball, and special Edam ball.

Basic material
Basic material is the aggregation level that shows which ingredients, model and size are used for a specific cheese. The basic material level is used by production planning to plan the production of cheeses. Basic materials from the special Edam ball are: Edam 1,9 kg NL Veg, Edam Tkr 1,9 kg NL, Edam Sambal 1,9 kg NL, Edam Rooksmaak 1,9 kg NL and Kaas 20+ 1,9 kg Bolvorm ELF DV.

Age
Aggregation level age is used to specify the maturation time of the cheese. The Goudse Wielen 12 kg can be matured for: 15 days, 4 weeks, 7 weeks, 11 weeks, 13 weeks or 17 weeks.

Cutting code
The cutting code specifies how the cheese is sliced into pieces. Example cutting codes are: 510 (wheels), 210 (wedges), 310 (flat pieces) or 410 (blocks).

Commercial article
The level below cutting code is the commercial article level. A customer places an order based on commercial article. The order desk translates this into the, at that moment, correct, valid logistic material, i.e., commercial article level and logistic material level are on same aggregation level, The difference being, that a logistic material contains more information.

Logistic material
All data is saved on the logistic material level. This level provides information about the customer (is connected with planning customer, see Section 3.3.2), the product appearance (bill of material), the age, the basic material, the cheese variety and the brand. This is the article planned upon and packed, transported and delivered to a customer.

All products below the basic material aggregation level could be moved to another type of product, e.g., in case there is a shortage in 11 week cheese for the Edam 1,9 kg, we could choose to mature a 7 week cheese for the Edam 1,9 kg a little longer and let it mature for 11 weeks.

3.2 Market characteristics

Aside from different product aggregation levels, we distinguish three types of cheese sectors (see Figure 3.2), namely, direct, indirect and export.

We start by explaining the direct sector. The direct channels can be divided into Business-to-Business (B2B), customers and retail customers. The B2B market is about selling rindless cheese to industry customers, such as grated cheese for Dr. Oetker. The retail channel is about direct marketing towards retail customers, such as Albert Heijn and Aldi. The retail market can be subdivided into two markets; branded and non-branded. Branded cheese is called the cheese specialties market and non-branded cheese is called the cheese market.
FrieslandCampina considers the production of cheese its core business. For some products, FrieslandCampina controls the entire process, from buying the raw materials, up to the sale of final products to customers. For other products, FrieslandCampina outsources different stages of the process. For example, FrieslandCampina outsources the maturation, packaging, and trade process of cheese. Processes can be outsourced to two types of customers from the indirect sector. First, customers that take over the maturation process and/or packaging process and trade process are called Value Added Resellers (VARs). Second, customers that only take over the trade process, which are called trade customers, and sell their products mainly to small shops and markets.
Aside from the indirect market, products are also exported. Exporting products signifies the sale of products to international markets (markets outside the EU). Export, therefore, is also referred to as the International Markets.

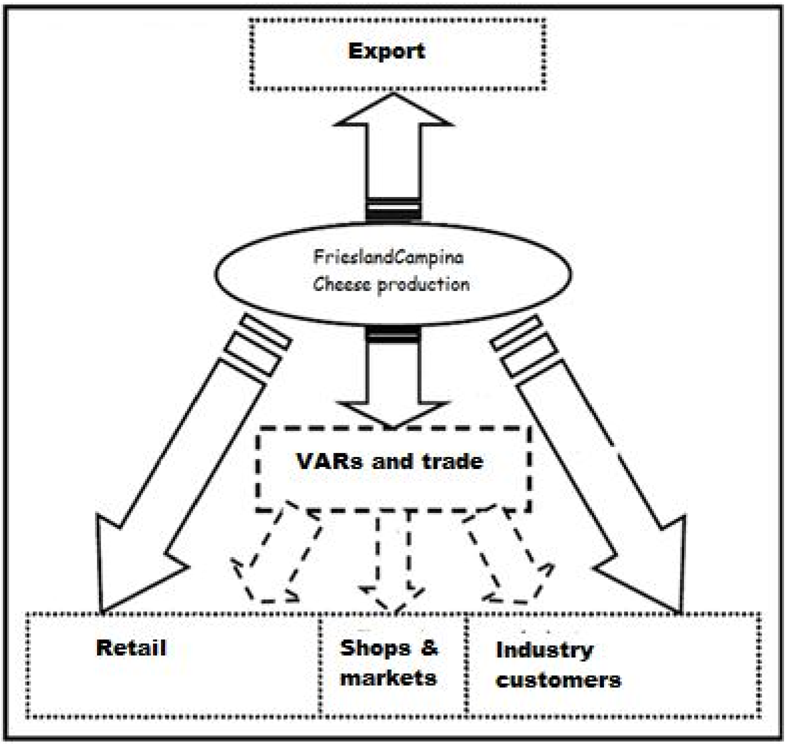

Figure 3.2: FrieslandCampina Cheese markets

3.2.1 Demand characteristics

Demand patterns differ per market type. They are influenced by FrieslandCampina's promotions, contracts and push actions. The branded retail market (cheese specialties) shows very irregular demand patterns (see Figure 3.3). An explanation for this, is that the demand within the branded cheese market is mainly characterized by its numerous promotions. This is called a promo-driven business. Promotions significantly influence the demand patterns for this market.

Within the non-branded retail market, demand is characterized by numerous contracts with customers. This is called a contract-driven business. New contracts are obtained through a bidding process called tendering. New tenders are usually confirmed approximately three months before the start of a contract. Several products in the indirect, B2B and International Markets are make-to-order products or packed-to-order products. Make-to-order products are produced on order. Packed-to-order products are produced on forecast and packed on order. The indirect, B2B, and international markets are also contract-driven businesses.
All markets are equally important to FrieslandCampina and will be included in the performance evaluation for statistical forecasting (Chapter 6).

3.2.2 Customer aggregation levels

Just as we analyze statistical forecasting on different product aggregation levels, we also analyze statistical forecasting on different customer aggregation levels. We distinguish three customer aggregation levels.

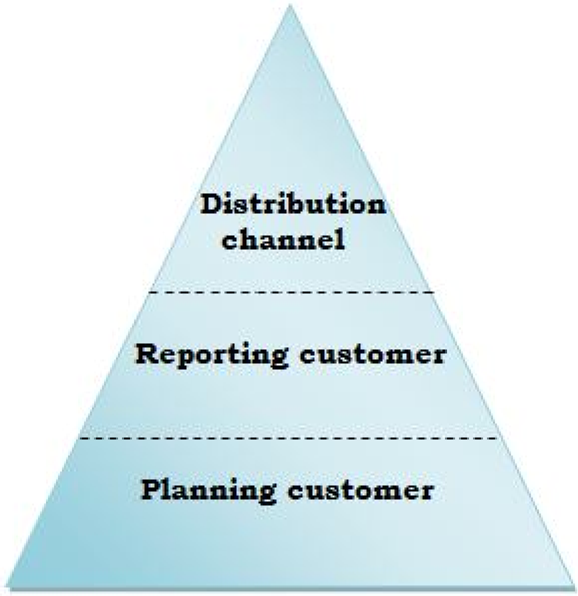

Figure 3.5: Customer aggregation levels

Distribution channel

The highest aggregation level is the distribution channel. This level describes the market to which the customers belong. The distribution channel can be subdivided into five different channels, namely, International Markets, Branded Retail Europe, Non-Branded Retail Europe, Business-to-Business, and Indirect.

Reporting customer

The reporting customer is a purchase organization for a number of planning customers. The purchase organization Bijeen, for example, purchases goods for Jumbo Group Holding and Schuitema.

Planning customer

The most detailed customer aggregation level for this research is the planning customer level. This level describes the customer to which the product should be delivered. Example planning customers are Albert Heijn and Super de Boer.

The planning customer can be subdivided into different distribution centers (DC's). Because promotions by customers are planned on planning customer level, description on DC level is not relevant to our research.

3.3 Supply chain department

This section provides an overview of the production and planning process and its relation to the forecast process.

FrieslandCampina has twelve production locations, which are all located in the Netherlands. The supply chain department is a bridge between the sales department and these production locations. Using forecasting and the limits of production capacities and the milk supply, the supply chain department decides on the quantity and allocation that are to be produced each week. Milk supply can be seen as an important constraint on cheese production. The milk quantity needed to produce cheese in a particular week has to be aligned by the milk supply for that specific week by the corporate department of Milk Valorization.

3.3.1 Production and planning overview

The production plants are managed by the planning department, centrally located in Amersfoort. Production planning and packaging planning depend on forecasting. The forecast process will be explained in the next section.

Production is scheduled every week, and one week after scheduling, basic materials are produced at production plants.

The produced products leave the chain at different stages (Figure 3.6). The first group of products leaves the chain immediately after production; these products are called exit-factory products (EF). The second group leaves after the maturation facility; these are the large-packaged items (LPI). The third group of articles is transported to a specialized packaging facility where it is packed into small-packaged items (SPI). The number of different articles increases and the volume of the entire flow decreases towards the end of the chain.

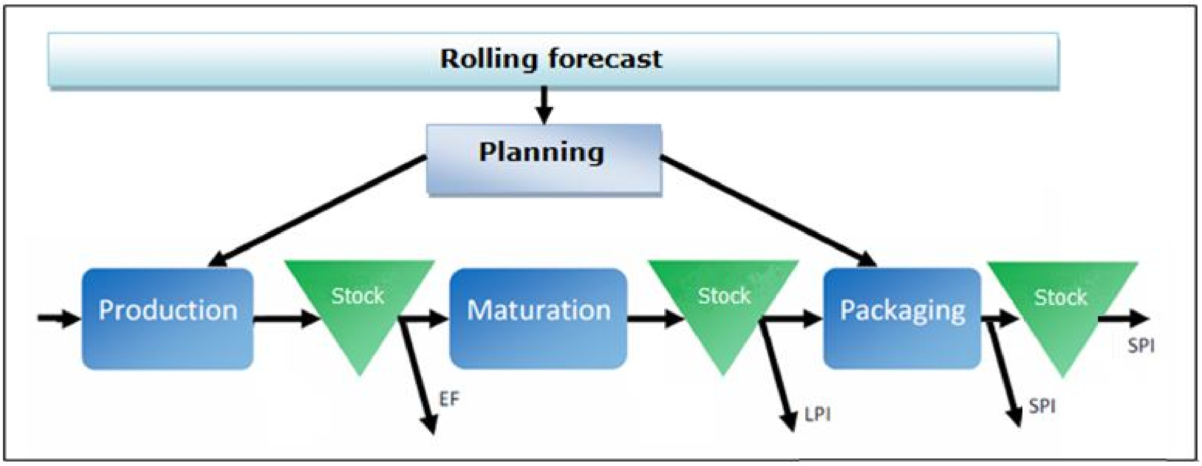

Figure 3.6: Production and planning overview

Production

At a production plant, milk is processed into cheese and whey. The cheese stays at the factory storage for fifteen days because the cheese is very vulnerable immediately after production. After this, the cheese is ready to be handled and part of it is sold to trade customers. These products are called the 'ex-factory' stream and account for roughly twenty percent of the total sales volume. In official terms, 'Ex-factory' is also referred to as 'Ex-works', a trade term requiring the seller to deliver goods at his or her own place of business. All other transportation costs and risks are assumed by the buyer.

Maturation

After fifteen days of storage at the production plants, the cheese is transported to a specialized maturation facility. At the maturation facility large volumes of cheese are stored until they are ready to be sold.

In a maturation facility the cheese is stored for two to sixty weeks, depending on the commercial age of the end product. The commercial age is the official ripening age, which is communicated to the customer.

Packaging

Two weeks before products are packed, the packaging forecast is determined. The packaging forecast is compared with the production forecast from a few weeks earlier. Oversupplies or shortages in the production forecast can be solved by using age tolerance. Age tolerance means that the ripening period of a specific cheese type can be used variably. For example, the norm for the Milner Licht Gerijpt is to ripe nine weeks. To solve oversupplies or shortages in cheese demand, the cheese could be packed in week eight (lower tolerance), or in week eleven (upper tolerance). Age tolerance is applied when there is not enough cheese available in the norm age.

If necessary, the cheese of week eleven could be cooled for a maximum of four weeks. Therefore, it has a maximum internal shelf life of four weeks. During cooling, the ripening process is severely slowed down. This can be used as a solution in case of very disappointing demands. This solution is only used in emergency cases.

Cheeses are packed, either in large or in small items. The LPIs are packed at a maturation facility. After the LPIs are packed, they leave the production chain and are transported to a distribution center or sold directly to a customer (Figure 3.6). The packaging type of the large packaged items is different, for example, a carton box, a plastic crate, cut in halves, coated with paraffin, etcetera. Not every facility can pack every type of packaging shape. The SPIs are packed at a specialized packaging facility elsewhere. A small part of the small packaging activities is outsourced to specialized packaging companies. After packaging, some products are sold directly to the customer (PTO[5]-products), while other products are sent to a warehousing and distribution center where customer orders are handled. These products are delivered on customer demand (PTS[6]-products).

3.3.2 Forecast overview

Production planning and packaging planning depend on forecasting. The forecast is determined by the sales planner and the sales team by creating a rolling sales forecast, starting eighteen months before production. The rolling forecast is updated weekly and is forecast on customer level and logistic material level. The same rolling forecast is used for the production planning and the packaging planning. Two weeks before the production of the cheese starts, the rolling forecast is frozen on the basis material/age

[5] PTO: Pack-to-Order

[6] PTS: Pack-to-Stock

level and is used to steer production planning. The production forecast is made on the basic material/age aggregation level (see Section 3.1.1). Figure 3.7 shows the forecast timeline for cheese that needs to ripen for nine weeks. If the cheese needs to ripen for nine weeks, the forecast horizon for production needs to be eleven weeks. If the cheese needs to ripen for 26 weeks, the forecast horizon for production needs to be 28 weeks.
After a number of weeks (which depends on the commercial age of the cheese), the rolling forecast is frozen on the commercial article level to steer packaging planning. The packaging forecast is made on the commercial article aggregation level (see Section 3.1.1). This rolling forecast is frozen two weeks before packaging.

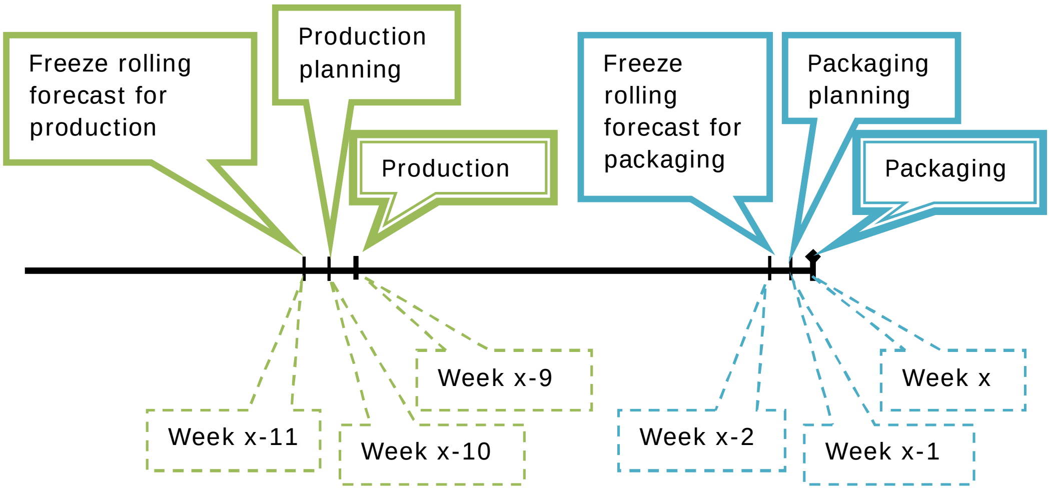

Figure 3.7: Forecast timeline for nine-week cheese

The forecast process is supported by the system APO (Advanced Planner and Optimizer). This is a forecast module from the ERP-system SAP. The forecast process starts with loading the actual sales from last year into APO. The sales planner makes manual adjustments in forecast after consulting the account manager. Account management is accountable for final forecast and has final control over the goods that will be produced.
FrieslandCampina distinguishes five types of markets, namely retail (branded and non-branded), indirect, B2B and international markets. Per market, there is difference in forecast method. The following three subsections give a description of forecast characteristics per market.

Retail

The retail market can be subdivided into two markets; branded market and non-branded market. The branded market is mainly a promo-driven business and the non-branded market is a contract-driven business.
The forecast for the non-branded market is based on the continuation of current contracts. Expectations for gaining new contracts through tendering are not taken into account. New tenders are not included in the forecast because of the uncertainty involved in obtaining the contract.
For the non-branded market, forecasts for promotions are only included on customer indication. There are no production reservations for optional promotions. The sales manager indicates what amounts are produced when, in case of promotions.
The rolling forecast is evaluated every two weeks. These evaluations are discussed by the sales team and, if necessary, the forecast is adapted.
Promotions play an important part in forecasts for the branded cheese market, and are followed in detail. The promotion forecast is steered by the sales team in consultation

with the customers. The baseline forecast is a process that runs parallel to the promotion forecast. The first step in creating the baseline forecast is uploading the actual sales from the previous year. Then, the sales planner, in consultation with the account manager, makes manual adjustments. Promotion forecast is then added to this baseline forecast. The account manager makes estimations for the promotion demand in consultation with some customers. Not all customers announce their promotions. Estimations for promotion demand are added to the baseline forecast. Promotion effects from history are stored in separate files, without a link to APO. These historic effects are used to estimate the effects of future promotions.

Indirect

Within the indirect market the sales planner creates a rolling forecast, starting 18 months before production. The rolling forecast is updated weekly and is forecast on customer level and item level. Fixed contracts are the most important information upon which the baseline forecast is based. Expected contracts are used for baseline adjustment. Long-term forecasting (18 months before production) is generated by assuming the extension of current contracts. The sales planner creates a forecast in cooperation with the sales manager by use of APO. The sales manager is responsible for expectations regarding future contracts.

In the indirect market sales orders are used for many products' short-term forecasts. When this is the case, no forecast is made since the forecast registered in APO will be overwritten by the customer orders.

Business-to-Business and International Markets

The forecast process for B2B and international markets is based mainly on the forecast process for the indirect market, but there are small differences. The contracts are the main information for sales forecast. The problem, however, is that this information is not always available to the sales planner. Although the contract information is the focus of the forecast process, the sales planner does not always have access to this information. For short-term forecasting, the forecast should be based on information on actual customer orders. Another difference in the forecast process for B2B, compared to the process within the indirect market, is that product orders are not always received in time and translated into SAP. Furthermore, the short-term forecast is not always overwritten by customer orders.

3.4 Analysis

FrieslandCampina has problems reaching forecast accuracy targets[7]. In 2010 the forecast targets were not achieved for most markets (see Appendix A). After interviewing sales planners and project managers, we have concluded that the current forecast method can be improved. We identified various causes for the current forecast inaccuracy. The following causes were identified:

1. Inaccurate forecast procedure
2. Inaccurate use of performance evaluation
3. Insufficient use of system functionalities

[7] Forecast targets for the complete demand (baseline and promotions)

The following three subsections provide more details about the causes of the current forecast inaccuracy.

3.4.1 Inaccurate forecast procedure

There is no distinction between forecast generation and forecast enrichment (i.e. forecast evaluation). Sales planners spend a lot of time creating new forecasts. Section 3.3 describes how sales planners load the actual sales from last year into the forecast system. The sales planner makes manual adjustments for all products every two weeks. These manual adjustments need to be discussed with the account manager. This process applies only to sales under normal circumstances. There are also promotions that need to be taken into account. These promotions must also be discussed with the account manager. This entire forecast process generates a lot of work, leaving no time to evaluate the forecast. In conclusion, the dominance of the administrative aspect of the sales planner's function does not allow him to use forecast enrichment. Every day, sales planners work with demand patterns for their product group and obtain market intelligence from these patterns. Because too much time is spent generating new forecasts, no time is left to add market intelligence.

Furthermore, forecast procedures lack standardization . Each market has its own sales planners and every sales planner has his own forecast procedure. Sales planner's roles and responsibilities are not standardized. Every sales planner has his own method for generating forecasts. Sales planners' responsibilities vary greatly from person to person, depending on his experience and the attitude of the account team.

3.4.2 Inaccurate use of performance evaluation

KPIs are calculated every week (periodic review) to measure forecast accuracy (e.g. the mean absolute percentage error). These KPIs only measure the short term forecast. There are no KPIs for mid- and long-term forecasts. The second problem is that the forecast bias performance is not properly used in periodic reviews. Yet another problem is that the KPIs used in short-term forecasts are interpreted in different ways. Furthermore, the weekly forecast performance is only reported in the total forecast, which includes promotion forecasting. This complicates the analysis of the baseline forecast performance.

The last problem is that the measured forecast performance is not followed up by actions. The forecast performance is measured each week, but the sales planner does not perform any actions based on these forecast performances or may not have time to do this.

3.4.3 Insufficient use of system functionalities

Sales planners make use of APO (Advanced Planner and Optimizer), which is a forecast module in SAP. APO can create a forecast using several methods. Appendix C shows the models that are available in APO. The sales manager uses the 'copy history' method in APO. This means that the historical sales data from the previous year is copied (i.e. naïve method). There are more appropriate statistical forecast methods available in APO. APO contains statistical forecasting methods like the Linear Regression Method and the Holt-Winters method. The sales planner does not use these methods. For more functionalities in APO, visit http://help.sap.com. Sales planners do not make use of statistical forecast methods and therefore do not use all APO's system functionalities.

In this chapter we answered research questions 1, 2 and 3. We identified several causes for the current low forecast performance. Our project focuses on the insufficient use of system functionalities. We want to use the statistical forecast functionality in APO and try to increase forecast performance by using statistical forecasting. In Chapter 4, we research literature on possible methods for statistical forecasting.

4. LITERATURE RESEARCH

In this chapter we research literature on sales pattern components (Section 4.1), statistical forecast models (Section 4.2, 4.3 and 4.4) and forecast measures (Section 4.5). We start by explaining the sales pattern components.

4.1 Sales pattern components

According to DeLurgio (1998), the most common methods of statistical forecasting make estimates of the future on the basis of past patterns. In this research we will explore univariate forecast methods. Univariate forecast methods are based on one variable, without using relations to other variables. Univariate forecast methods are based on demand patterns from history. All forecast methods described in this section are extrapolative. Extrapolative forecast methods are based on the assumption that a certain demand pattern from the past will persist in the future. Because of this assumption, extrapolative methods only use historical values as input for their forecast models.

Sales patterns can be divided into five components: level, trend, seasonal variations, cyclical movements and irregular random fluctuations (Silver et al., 1998). When there is only one level present in a sales pattern the series is constant through time. Trend specifies the rate of growth or decline of a pattern over time. Seasonal variations are periodic and recurrent patterns, which result from natural forces or arise from human decisions or customs. Cyclical variations are the result of the business cycles that are the result of economic activity. In time series analysis, irregular fluctuations are the residues that remain after the effects of the other four components have been identified and removed from the time series. These fluctuations are the result of unpredictable events.

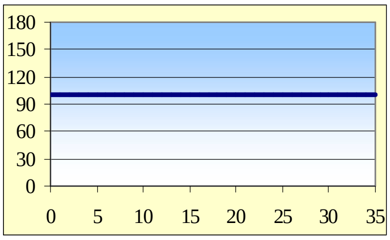

Figure 4.1: level pattern

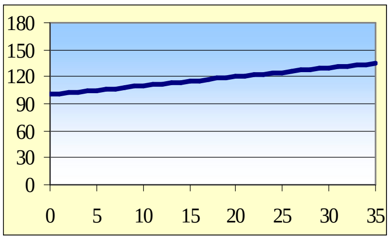

Figure 4.2: trend pattern

Using these concepts we can formulate the following model:

Demand in period t = (Level) + (Trend) + (Seasonal) + (Cyclic) + (Irregular)

This report concentrates on short- to medium-term forecasting and will therefore not incorporate cyclical effects (Silver et al., 1998).

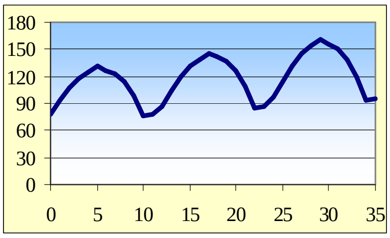

Figure 4.3: Seasonal pattern

We describe models that have the following patterns:

$x_t = a + \varepsilon_t$ (level pattern)

$x_t = a + bt + \varepsilon_t$ (trend pattern)

$x_t = (a + bt)F_t + \varepsilon_t$ (trend-seasonal pattern)

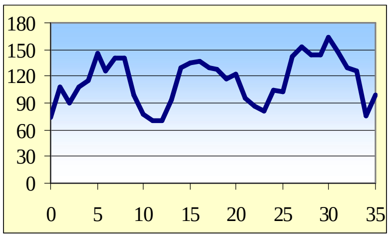

Figure 4.4: Cyclical pattern

where
x_t = demand in period t
a = level
b= trend
F_t = a seasonal coefficient appropriate for period t
ε_t = independent random variable with mean 0 and constant variance

4.2 Moving averages and smoothing methods

We will start by explaining moving average and smoothing forecasting models.

4.2.1 Simple moving average

According to Silver et al. (1998), the simple moving average is appropriate when demand displays only a level pattern.
The simple N-period moving average, at the end of period t, is given by;

$$\bar{x}_{t,N} = (x_t + x_{t-1} + x_{t-2} + .. + x_{t-N+1})/N \qquad [4.1]$$

In this case the letters x represent actual demand in the corresponding periods. The forecast for period $t+\tau$ $(=\hat{x}_{t,t+\tau})$ is then:

$$\hat{x}_{t,t+\tau} = \bar{x}_{t,N}$$

If there is a change in the parameter x_t , a small value of N is preferable because it gives more weight to recent data, and thus picks up changes more quickly. Typical N values that are used range from 3 to as high as 12.

4.2.2 Weighted moving averages

It is normally true that the immediate past is most relevant in forecasting the immediate future. For this reason, weighted moving averages place more weight on the most recent observations. The simple moving average uses equal weights for each observation, but a weighted moving average uses different weights for each observation. The only restriction on the weights is that their sum equals one. An advantage of the weighted moving average is that the weights placed on past demands can be varied. See the following formula for an example of a four-period weighted moving average;

$$\hat{x}_{t,t+\tau} = 0.1 * x_{t-4} + 0.2 * x_{t-3} + 0.3 * x_{t-2} + 0.4 * x_{t-1}) \qquad [4.2]$$

When using a moving average, it is difficult to determine the optimal number of periods to include in the average. However, this is not a problem for exponential smoothing.

4.2.3 Simple exponential smoothing

According to Silver et al. (1997) simple exponential smoothing is probably the most widely used statistical method for short-term forecasting. The basic underlying demand pattern assumes the level model.
To estimate the forecast at the end of period t, the following formula should be used to update the forecast:

$\hat{a}_t = \alpha x_t + (1-\alpha)\hat{a}_{t-1}$
$a = smoothing\ constant$
$\hat{a}_t = estimation\ of\ level\ value$ [4.3]
$\hat{x}_{t,t+\tau} = \hat{a}_t$
$\hat{x}_{t,t+\tau} = the\ forecast, made\ at\ the\ end\ of\ period\ t, of\ the\ demand\ in\ period\ t+\tau$

4.2.4 Exponential smoothing for a trend model

The model described in Subsection 4.2.3 is based on a model without a trend and is therefore inappropriate when the underlying demand pattern contains a significant trend. When this is the case, exponential smoothing for a trend model is needed. The basic underlying model is the trend model:

$x_t = a + bt + \varepsilon_t$

Holt (1957) suggests a procedure that is a natural extension of simple exponential smoothing:

$\hat{a}_t = \alpha_{HW} x_t + (1-\alpha_{HW})(\hat{a}_{t-1} + \hat{b}_{t-1})$ [4.4]
$\hat{b}_t = \beta_{HW}(\hat{a}_t - \hat{a}_{t-1}) + (1-\beta_{HW})\hat{b}_{t-1}$
$\hat{b}_t = estimation\ of\ trend\ value$

Where α_{HW} and β_{HW} are smoothing constants and, the difference $\hat{a}_t - \hat{a}_{t-1}$ is an estimate of the actual trend in period t.

$x_t = demand\ for\ an\ item\ at\ time\ t$

To estimate the forecast at end of period t the following formula should be used:

$\hat{x}_{t,t+\tau} = \hat{a}_t + \hat{b}_t\tau$
$\hat{x}_{t,t+\tau} = the\ forecast, made\ at\ the\ end\ of\ period\ t, of\ the\ demand\ in\ period\ t+\tau$

Double exponential smoothing

DeLurgio (1998) describes Brown's double exponential smoothing method to compute the difference between single and double smoothed values as a measure of trend. It adds this value to the single smoothed value together with adjustment for the current trend. It uses a single coefficient, alpha, for both smoothing operations.
Brown's model is implemented with the following equations (S'_t denotes a single smoothed and $S"_t$ denotes the double smoothed value):

$S'_t = ax_t + (1-a)S'_{t-1}$
$S"_t = aS'_t + (1-a)S"_{t-1}$
$\hat{a}_t = 2S'_t - S"_t$
$\hat{b}_t = \frac{a}{1-a}(S'_t - S"_t)$ [4.5]
$\hat{x}_{t,t+\tau} = \hat{a}_t + \hat{b}_t\tau$
$\hat{x}_{t,t+\tau} = the\ forecast, made\ at\ the\ end\ of\ period\ t, of\ the\ demand\ in\ period\ t+\tau$

Exponential smoothing with damped trend
Sometimes data is so noisy, or the trend so erratic, that a linear trend is not very accurate. Gardner & McKenzie (1985) introduced a damped trend procedure that works well in these situations.
They recommend using the following formulas:

$$\hat{a}_t = \alpha_{HW} x_t + (1 - \alpha_{HW})(\hat{a}_{t-1} + \phi \hat{b}_{t-1})$$
$$\hat{b}_t = \beta_{HW}(\hat{a}_t - \hat{a}_{t-1}) + (1 - \beta_{HW})\phi \hat{b}_{t-1} \qquad [4.6]$$
$$\hat{x}_{t,t+\tau} = \hat{a}_t + \sum_{i=1}^{\tau} \phi^i \hat{b}_t$$
$$\hat{x}_{t,t+\tau} = the\ forecast, made\ at\ the\ end\ of\ period\ t, of\ the\ demand\ in\ period\ t + \tau$$

where ϕ is a dampening parameter. If ϕ = 1, the trend is linear and identical to the normal exponential smoothing with trend model. If ϕ = 0 the method is identical to standard simple exponential smoothing. In case the dampening parameter is such that 0 < ϕ < 1, the trend is damped.

4.2.5 Exponential smoothing procedure for a seasonal model
There are a number of products in organizations that exhibit demand patterns that contain significant seasonality. Seasonal series result from events that are periodic and recurrent (e.g. monthly changes recurring each year). Common seasonal influences are climate, human habits, holidays, and so on. The underlying model in this case is:

$$x_t = (a + bt)F_t + \varepsilon_t$$

Winters (1960) suggest the following procedure, which is a natural extension of the Holt procedure described in Subsection 4.2.4. The parameters are updated according to the following three equations:

$$\hat{a}_t = \alpha_{HW}(\frac{x_t}{\hat{F}_{t-P}}) + (1 - \alpha_{HW})(\hat{a}_{t-1} + \hat{b}_{t-1})$$
$$\hat{b}_t = \beta_{HW}(\hat{a}_t - \hat{a}_{t-1}) + (1 - \beta_{HW})\hat{b}_{t-1} \qquad [4.7]$$
$$\hat{F}_t = \gamma_{HW}\left(\frac{x_t}{\hat{a}_t}\right) + (1 - \gamma_{HW})\hat{F}_{t-P}$$
$$\hat{F}_t = estimation\ of\ seasonal\ value$$
$$\hat{x}_{t,t+\tau} = (\hat{a}_t + \hat{b}_t\tau)\hat{F}_{t+\tau-P}$$
$$\hat{x}_{t,t+\tau} = the\ forecast, made\ at\ the\ end\ of\ period\ t, of\ the\ demand\ in\ period\ t + \tau$$

where α_{HW}, β_{HW} and γ_{HW} are smoothing constants lying between 0 and 1. Silver et al. (1998) suggests the use of a search experiment to establish reasonable values for the smoothing constants.

The limits for each smoothing constant are based on literature (Silver et al., (1998).

4.2.6 Evaluation

Makridakis et al. (1993) used 1001 time series to compare the accuracy of several methods. When data is deseasonalized and exponential smoothing methods are compared to sophisticated forecast procedures, in some cases, they perform the same. Furthermore, the research identified that when randomness in data increases, it is preferable to select simple forecast procedures.

Murdick and Georgoff (1986) present general characteristics of short-range through long-range forecasting methods. The effective horizon lengths of methods are longer as we move from univariate, to multivariate[8], to qualitative methods. Our research focuses on univariate methods. We can assert that, in general, short-horizon forecasts are typically more accurate than longer-horizon forecasts. The forecast accuracy of the simple exponential smoothing method is high[9] when the horizon length remains under one month (DeLurgio, 1998). The single exponential smoothing method performs worse as the forecast horizon increases because the method does not take trends into consideration. Forecast accuracy for more complex smoothing methods, like trend or seasonal models, is high[9] when the horizon length remains under three months. For complex smoothing methods, medium[9] forecast accuracy is obtained when the forecast horizon length is between three months and three years.

4.3 Other methods

The methods that have been described so far are moving average or smoothing methods. There are a number of other methods that could also be appropriate for the products sold by FrieslandCampina. The following methods could be appropriate:

4.3.1 Simple linear regression

The simple linear regression model assumes that demand is a linear function of time:

$$x_t = a + bt + \varepsilon_t$$

A least squares criterion is used to estimate values, denoted by $\hat{a}$ and $\hat{b}$, of the parameters a and b. The resulting modelled value of x_t, denoted $\hat{x}_t$, is then given by

$$\hat{x}_t = \hat{a} + \hat{b}t$$

If there are n historical observations, then the least squares criterion involves the selection of $\hat{a}$ and $\hat{b}$ to minimize the sum of the squares of the n differences between $\hat{x}_t$ and x_t. That is (Silver, Pike, & Peterson, 1998),

$$S = \sum_{t=1}^{n} (x_t - \hat{a} - \hat{b}t)^2$$

Using calculus we can show that

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[8] Multivariate: analysis of more than one statistical variable

[9] The term high, medium, and low refers to the relative accuracy of methods. No percentage errors are given because percentage accuracy is dependent on the level and variance of the demand pattern (DeLurgio, 1998).

$$\hat{b} = \frac{\sum_{t=1}^{n} t x_t - (\frac{n+1}{2}) \sum_{t=1}^{n} x_t}{n(n^2-1)/12}$$

and

$$\hat{a} = \sum_{t=1}^{n} x_t/n - \hat{b}(n+1)/2$$

Once the parameters a and b are estimated, the following model can be used to forecast demand in a future period:

$$\hat{x}_{t,t+\tau} = \hat{a} + \hat{b}t \qquad [4.8]$$

4.3.2 Croston's method

The exponential smoothing forecast methods described earlier have been found to be ineffective where transactions occur on an infrequent basis. Croston's method could be appropriate when dealing with intermittent demand. Croston's method makes separate exponential smoothing estimates of the average size of a demand and the average interval between demands. The method updates the estimates after demand occurs; if a review period t has no demand, the method just increments the number of time periods since the last demand. The method uses the following formulas (Willemain et al., 1994):

$$if \qquad x_t = 0$$
$$z"_t = z"_{t-1}$$
$$p"_t = p"_{t-1}$$
$$q = q + 1$$
$$Else$$
$$z"_t = z"_{t-1} + a(x_t - z"_{t-1})$$
$$p"_t = p"_{t-1} + a(q - p"_{t-1})$$
$$q = 1$$
$$x_t = demand\ for\ an\ item\ at\ time\ t$$
$$z"_t = Croston's\ estimate\ of\ mean\ demand\ size$$
$$p"_t = Croston's\ estimate\ of\ mean\ interval\ between\ demands$$
$$q = time\ interval\ since\ last\ demand$$
$$y"_t = Croston's\ estimate\ of\ mean\ demand\ per\ period$$
$$a = smoothing\ constant$$

Combining the estimates for demand and interval provides the estimate for the mean demand per period:

$$y"_t = \frac{z"_t}{p"_t} \qquad [4.9]$$

These estimates are only updated when demand occurs. When demand occurs in every review interval, Croston's method is identical to simple exponential smoothing.

4.3.3 Box- Jenkins method

The stochastic variations in the demand models that we have considered in the aforementioned models are assumed to be independent. This is a major simplification. It is easy to imagine situations where this is not the case. When dealing with only a small number of large customers, it is to be expected that demands in consecutive periods will sometimes be negatively correlated. A high demand in one period can indicate that several of the customers have replenished their supplies, and that it is reasonable to expect demand in the next period to be somewhat lower. However, situations also exist where demand is correlated positively. A high demand in one period may mean that the product has been exposed to more potential customers, and that demand can be expected to be high again in the next period. Forecasting techniques that can handle correlated stochastic demand variations and other more general demand processes have been developed by Box and Jenkins (1970). The models proposed by Box and Jenkins are more complex than either simple regression models or exponential smoothing procedures.

4.4 Forecast models used in other food organizations

Some industries and companies are affected by cyclical fluctuations in the economy (or other environmental factors). Forecasting cyclical changes is difficult, as the length and depth of cycles vary - sometimes considerably. Makridakis (1986) claims that companies in anti-cyclical industries, such as the food and medical industry, can rely on quantitative forecast methods. FrieslandCampina focuses on the food industry, so quantitative models could be appropriate for the company.

Miller et al. (1991) researched food production forecasting through simple time series models. In their study, they explored simple models with minimal data storage. They found that simple models perform better than the naive model, which is used at FrieslandCampina right now.

Koehler (1985) analyzed forecast methods for consumer food products. The paper describes an empirical study of time series data for consumer products in the food processing industry at the stock keeping unit level. The results show that two types of simple models prevail: models that require information from only the previous time period and simple seasonal models. The simple exponential smoothing model, without trend and seasonality, was shown to be a robust forecasting model for the given data.

Arinze (1994) performed research on selecting appropriate forecast models using rule induction. The study was carried out on different food items in the US economy. Holt's exponential forecast method was selected as the best forecast method.

After exploring literature for appropriate forecast models used in other food organizations, we concluded that quantitative forecast methods will probably improve forecast accuracy for FrieslandCampina because it operates in an anti-cycling industry, namely, the food industry. However, since demands vary between food organizations, the most accurate forecast model must also vary between each type of food organization.

In the early literature of forecasting, considerable time and effort were spent trying to find the best all-purpose statistical forecast method, one that would forecast all situations accurately. Eventually, researchers realized that no such method existed. To find the best forecast method, DeLurgio (1998) advises selecting several models, measuring and fitting them, and then selecting the best method. That is why we first propose several forecast measures.

4.5 Forecast measures

The search for the most accurate forecast model is based on minimizing the forecast error. Decisions concerning the adequacy of a particular forecast model depend on a measure of the model's variability in recent forecasts.

4.5.1 Measures of accuracy

One measure of variability is the mean absolute deviation (MAD). For n periods of data, the estimate of the MAD would be:

$$MAD = \sum_{t=1}^{n} \left| x_t - \hat{x}_{t-1,t} \right| / n \qquad [4.10]$$

The term $x_t - \hat{x}_{t-1,t}$ is the error or the deviation in the forecast for period t.
Another measure of accuracy is the mean square error, MSE. The MSE can easily be computed and is given by (Chatfield, 2000):

$$MSE = \frac{1}{n} \sum_{t=1}^{n} (x_t - \hat{x}_{t-1,t})^2 \qquad [4.11]$$

This measure is more susceptible to the occasional large error than other measures; the squaring process gives disproportionate weight to very large errors. The problem with the MSE is that it is not easily interpreted by itself.
The mean absolute percentage error, MAPE, is another intuitive measure of variability. Generally, it is not affected by the magnitude of demand values because it is expressed as a percentage. It is, however, not appropriate if demand values are very low. For example, a forecast of two units of demand matched with the actual value of one unit shows an error of 100 percent. The MAPE is given by (Armstrong & Collopy, 1992):

$$MAPE = \left[\frac{1}{n} \sum_{t=1}^{n} \left| \frac{x_t - \hat{x}_{t-1,t}}{x_t} \right| \right] * 100 \qquad [4.12]$$

Armstrong & Collopy (1992) compared different forecast error measures. They found that the MAPE provides good sensitivity and construct validity.

4.5.2 Measures of Bias

The question frequently arises whether or not a forecast is biased. The word bias is used to indicate that, on average, forecasts are substantially above or below actual demands. Because of the random components in a demand pattern, it is difficult to detect an underlying bias; the noise tends to camouflage it. In general, the forecast error should fluctuate around zero.
It is convenient to have a relative measure of forecast bias that facilitates forecast model comparison. The MPE is such a measure (DeLurgio, 1998):

$$MPE = \left[\frac{1}{n} \sum_{t=1}^{n} \frac{x_t - \hat{x}_{t-1,t}}{x_t} \right] * 100 \qquad [4.13]$$

4.5.3 Coefficient of determination

Herrin (2007) advises incorporating the coefficient of determination to determine the forecastability[10]. The coefficient of determination gives an indication of how closely the forecasts are related to the actual sales. This coefficient varies between 0 and 1. The closer this value approach 1, the easier forecasting becomes. In statistics, the coefficient of determination (R^2) is used for statistical models whose main purpose is the prediction of future outcomes. It estimates the likelihood of the model's accurate prediction of future outcomes. R^2 is given by (Nagelkerke, 1991)**:**

$$Coefficient\ of\ determination = R^2 = 1 - \frac{SSE}{SS_{yy}} \quad [4.14]$$

$$SSE = \sum_t (x_t - \hat{x}_{t,t+\tau})^2$$

$$SS_{yy} = \sum_t (x_t - \bar{x})^2$$

$x_t = demand\ for\ an\ item\ at\ time\ t$

$\hat{x}_{t,t+\tau} = the\ forecast, made\ at\ the\ end\ of\ period\ t, of\ the\ demand\ in\ period\ t + \tau$

$\bar{x} = average\ x$

We have explored several statistical forecast models that are useful to FrieslandCampina (research question 4). We want to use all the statistical forecast models described in Section 4.2 and 4.3., except the Box-Jenkins method. The Box-Jenkins method is more complex than the other methods and does not provide better forecast results when compared to the smoothing methods (Gardner, 2006). Therefore, we have decided not to incorporate the Box-Jenkins method in our research.
In this chapter we also answered research question 5; how can the forecast performance be measured? We will use the MAPE to calculate forecast accuracy because this measure is easily calculated and can be used for performance evaluation. The MAPE also provides good sensitivity and construct validity. This is an appropriate method for FrieslandCampina because demand values are never very low (smaller than 50).
We want to use the MPE to calculate forecast bias because this measure is easily calculated and facilitates forecast model comparison.
In Chapter 5 we will apply these statistical forecast models and measures.

[10] Forecastability: the ability to statistically forecast the product

5. MODEL SELECTION METHOD

Having explored the different types of markets defined by FrieslandCampina and having searched literature for different statistical forecast methods and forecast measures, we can begin selecting the statistical forecast model. This chapter focuses on research question five. In this research question we explore cleaning methods to obtain the baseline demand (Section 5.1) and design the model selection method (Section 5.2) to obtain the best forecast models for FrieslandCampina. We start by cleaning historic data to obtain an accurate baseline demand.

5.1 Cleaning historic data

Figure 5.5 in Section 5.2 shows the model selection method. The method starts by downloading historic data. Sales patterns saved by FrieslandCampina are stored as total demand, without separating push and promotion demand. We want to create the baseline demand, in other words, demand without promotions. To obtain the baseline demand, we need to remove the promotions from the total demand.

5.1.1 Remove promotions

The demand created by promotions is registered, but the registered amounts are not reliable. To improve the accuracy of historic demand, we will replace the demand in the promotion weeks.

DeLurgio (1998) proposes replacing the demand in the promotion weeks by the mean of the series when series are random. If the series contain a trend, it can be replaced by the mean of the two adjacent values. We cannot use the mean of the total series because FrieslandCampina has peaks in its demand patterns due to promotions. We cannot use the mean of the two adjacent values because of the decrease in demand that is caused by the forward buying effect after promotions. The forward buying effect takes place in the weeks after the promotion. Forward buying refers to the tendency of customers and consumers to buy more than they would normally do, so that demand becomes low after a promotion. When we use the mean of the two adjacent values, the forward buying effect increases. The implementation section of this project explains how we handle the forward buying effect.

Demand patterns saved by FrieslandCampina are subject to fluctuation, periodic increase and decrease and the forward buying effect of promotions. Therefore, we replace the demand in promotion weeks with the four period moving average over the last four weeks (cleaned data) before a promotion. Because of this, recent data is weighted heavily and, thus, changes are picked up quickly. Aside from this, the fluctuations are smoothed into adjusted values (Silver et al., 1997).

After removing promotions from the total demand (see Figure 5.1), we obtain the baseline demand (see Figure 5.2).

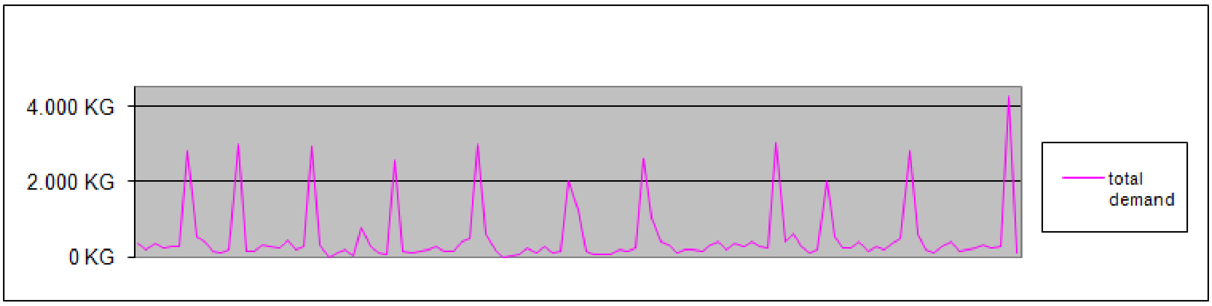

Figure 5.1: Total demand

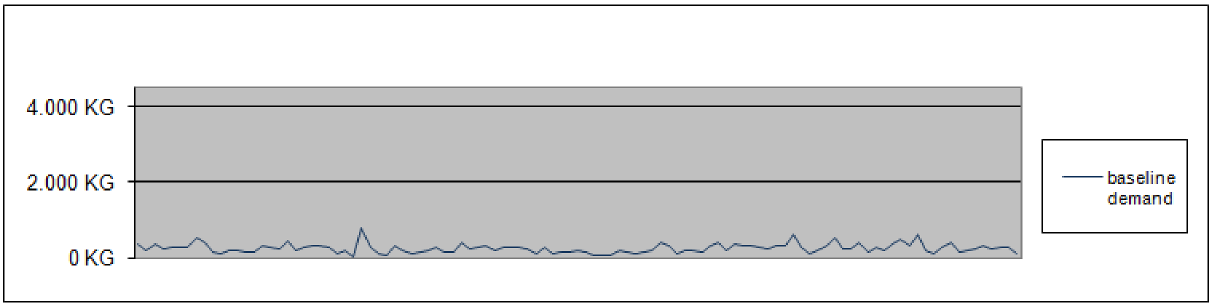

Figure 5.2: Baseline demand

Promotions are planned per customer on the commercial article level, the lowest aggregation level. Therefore, we must remove promotions at the lowest aggregation level.

5.1.2 Outlier detection

Aside from promotions, the outliers of the baseline demand should also be removed. When outliers adversely affect the patterns in the time series, they should be adjusted (DeLurgio, 1998). To detect outliers, we use the modified z-score method. We choose the modified z-score method because the parameters used to calculate the modified z-score are minimally affected by outliers (Moore & McCabe, 2002). The modified z-score method creates a predetermined bound (z-score). All the data points that are located outside the bound are labeled outliers and are replaced by the four period moving average. It is possible that a promotion is not registered. Promotions cause a peak in demand and can therefore be seen as outliers. When a promotion is not registered, it is identified as an outlier. We use the four period moving average in promotion weeks. Therefore, we use the four period moving average as a replacement for the outlier.
See Figure 5.3 and Figure 5.4 for examples of outlier correction.

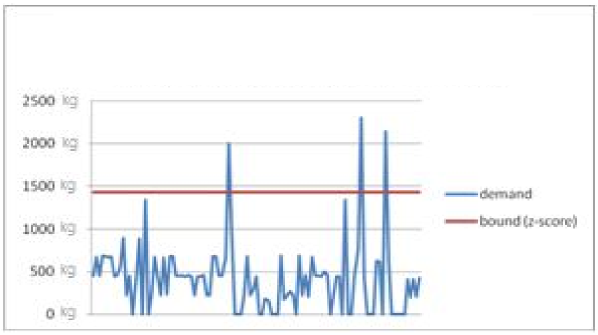

Figure 5.3: Removing outliers (incl. outliers)

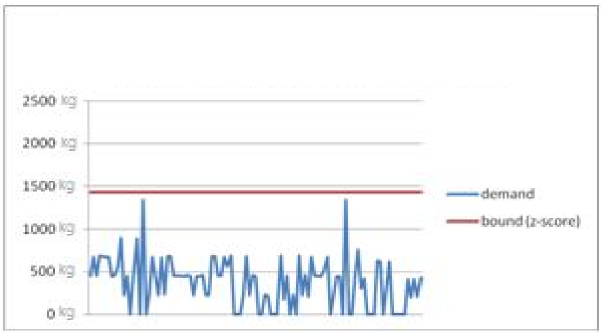

Figure 5.4: Removing outliers (excl. outliers)

When a standard z-score test is used, the mean and standard deviations of the entire data set are used to obtain a z-score for each data point. The standard z-score test is not a reliable way of labeling outliers, since both the mean and standard deviation are affected by outliers. In a modified z-score test, the z-score is determined on the basis of outlier resistant estimators. Such an estimator is the median of absolute deviations:

$$Median\ of\ absolute\ deviation = median\{|x_i - x_m|\} \qquad [5.1]$$

x_m = $median\ over\ all\ data$

The median of absolute deviation is used instead of the standard deviation in the normal z-score method. This is a reliable test, since the parameters used to calculate the modified z-score are minimally affected by outliers.
The following formula is used:

$$z_i = \frac{(x_i - x_m)}{Median\ of\ absolute\ deviation} \qquad [5.2]$$

Outliers are minimally affected because the median is used (Moore & McCabe, 2002).
Iglewicz (1993) created a test to obtain a reliable bound (z-score). The test heuristic states that an observation with a modified z-score greater than three and a half should be labeled an outlier. Hence, each data point greater than the bound should be labeled an outlier and replaced by the four period moving average.

5.2 Model selection method

After creating the baseline demand, we start testing different statistical forecast models.
We test the following models:

- Simple moving average (period 3 to 12)
- Weighted moving average (period 4, 8 and 12)
- Simple exponential smoothing
- Double exponential smoothing
- Exponential smoothing with trend
- Exponential smoothing with damped trend
- Simple linear regression
- Croston's method

These models are explained in Sections 4.2 and 4.3. If a time series includes seasonality, its data requirements are greater than those of other methods. To adequately measure seasonality, the use of at least three seasons of weekly data (156 weeks) is suggested. Data from before January 2010 is unusable because of incorrect registration and therefore, we do not have the minimum of three seasons of data. Hence, we cannot analyze the parameters for the seasonal model. Therefore, we have decided not to incorporate the seasonal smoothing models in our research.

We have created a model selection method that we will follow during our research. Figure 5.5 shows which steps to take to select a forecasting model and its corresponding parameters per demand pattern. The different forecast models are tested on forecast accuracy and bias.

We have also built an advanced forecast tool in Microsoft Excel[11]. This forecast tool contains the steps defined in the model selection method. After cleaning the data, we start by choosing the forecast horizon.

5.2.1 Forecast horizon

The forecast horizon is divided into two terms; forecast horizon for packaging forecast and forecast horizon for production forecast. The forecast horizon for packaging is a fixed horizon of two weeks. The forecast horizon for production is more complicated because it depends on the age of the article. The forecast horizon for production is the age of the article plus two weeks. If a cheese needs to ripen for nine weeks, the forecast horizon for production, then, needs to be eleven weeks (see figure 3.7). Hence, the forecast horizon for production varies per article. The forecast buckets for both packaging and production are determined in weeks.

5.2.2 In-sample data and out-of-sample data

When there are sufficient observations within a demand pattern, dividing the data into two groups can provide some insight. When a data set is divided this way, models are built using the first data set by estimating model parameters. After fitting the model to the first set of data, the model is used to forecast the second set of data (DeLurgio, 1998). The first group, which is called in-sample data, is used to construct the model. The second group, which is called out-of-sample data, is used to validate the model. Using out-of-sample data is an effective way of judging the effectiveness of a model. In our research we use in-sample data from the time period from January 2010 to December 2010. Data which was registered within the time period January 2011 (week 1) until July 2011 (week 30) is used for out-of-sample data.

In-sample data: 2010 week 1 – 2010 week 52
Out-of-sample data: 2011 week 1 – 2011 week 30

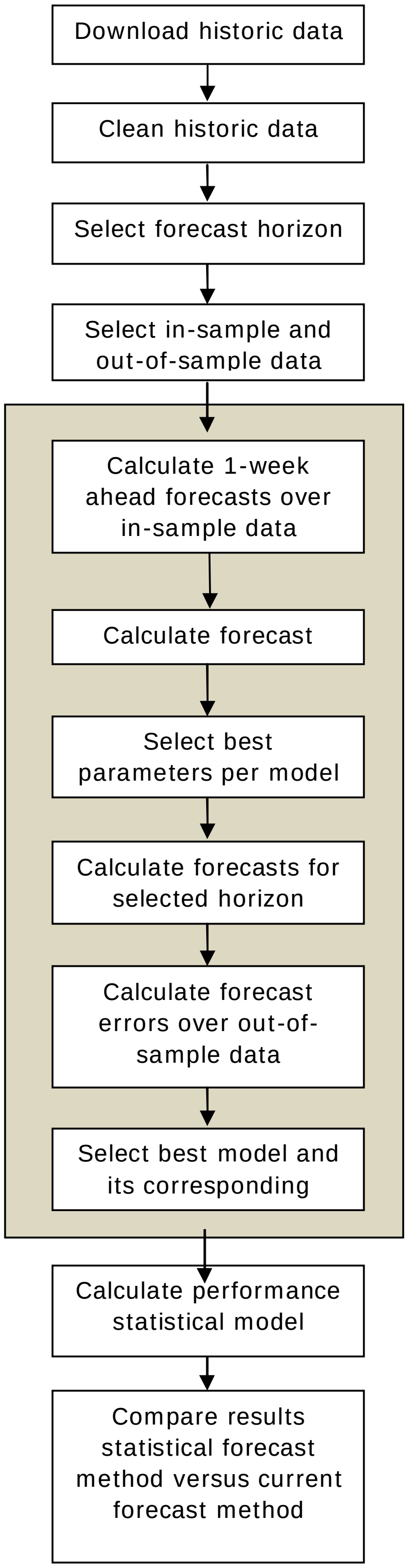

Figure 5.5: Model selection method

[11] Forecast tool is tested and compared to APO and gives same forecast values

5.2.3 Select parameters

We calculate the 1-week ahead forecast over 2010 (in-sample data) for all described models and their parameters. Appendix D describes the parameter range per model. For each week, we calculate the deviation of the forecast compared to the baseline demand. The parameters are selected by use of a grid search. We use the parameters for each model, which minimizes the mean absolute percentage error (MAPE, see Section 4.5) over the in-sample data. Hence, we select the parameters with the lowest MAPE from the data from 2010. We choose to optimize the MAPE because this measure is easily calculated and is used for performance evaluation. Makridakis, Wheelwright, and McGee (1983) suggest that a relative error criterion, such as the MAPE, is an appropriate method to evaluate the different models.

5.2.4 Select model

After selecting the best parameters for each model, we will select the best model. The best model is selected by using out-of-sample data. We calculate the forecast over the selected forecast horizon. We select the best model and its best corresponding parameters, which minimizes the MAPE over the out-of-sample data.
Hence, we forecast thirty times over the out-of-sample data (see Figure 5.6) e.g. in case we forecast packaging (forecast horizon: 2 weeks) in week 1, we forecast for week 3. In week 2, we forecast for week 4 (using the data available in week 2). We apply this method until week 30. Now, we have thirty forecasts. We select the model with the lowest MAPE from these thirty forecasts.

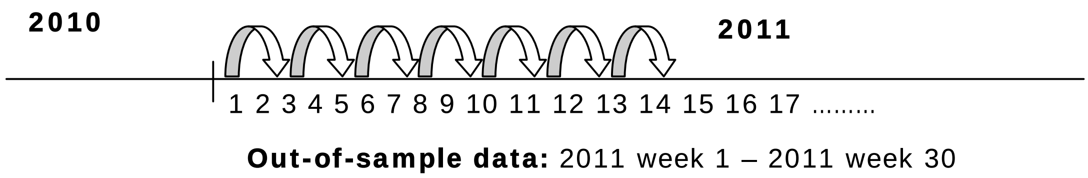

Figure 5.6: Forecast packaging over out-of-sample data

5.2.5 Performance statistical forecasting

After selecting the best model and its corresponding parameters, the statistical model is tested for bias and forecast accuracy. As described in Chapter 4, bias indicates whether, on average, the forecast is higher or lower than the demand. By using the mean percentage error (MPE, see Section 4.5), we can evaluate whether or not the statistical model contains bias. We use the MAPE to calculate the forecast accuracy. We use the MPE and the MAPE because these measures are easily calculated and because FrieslandCampina is already familiar with them. Aside from that, these measures provide a degree of relativity regarding the forecast performance because they are relative measures (DeLurgio, 1998). The MPE and the MAPE are both calculated over out-of-sample (30 weeks) data. The 30 weeks provide sufficient data to reliably measure the forecast performance.

5.2.6 Comparison

At this point, the statistical forecast is compared to the forecast created in the current situation. The comparison is made over the out-of-sample data. The problem at FrieslandCampina is that data is stored for complete sales. Therefore, we need to clean the historic sales to obtain the baseline sales. FrieslandCampina also stores the forecast for the total sales. Therefore, we also need to clean the total forecast to obtain the baseline forecast.

See Figure 5.7 for an example of cleaning the historic data to obtain the baseline sales and baseline forecast packaging. First, we start cleaning the total forecast packaging (within the current situation), in order to obtain the baseline forecast packaging (within the current situation). Second, we create the baseline sales by cleaning the total sales from the same time period. Third, we create the statistical forecast based on the baseline sales. The statistical forecast needs to be made two weeks in advance. This is because the current packaging forecast is registered on the packaging date and the statistical forecast is created two weeks before the packaging date. Last, we compare the baseline forecast packaging (within the current situation) to the statistical forecast. This method is also used for the production forecast.

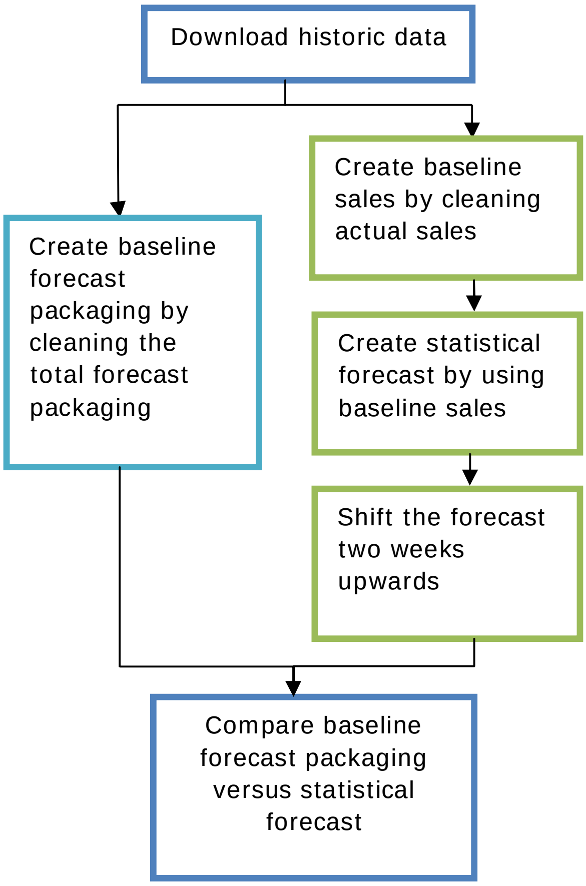

Figure 5.7: Cleaning historic data

We create the current baseline forecast by cleaning the fixed forecast packaging[12] and the fixed forecast production[13].

See Figure 5.8 for an example of the fixed forecast packaging. The red line shows the z-score bound.

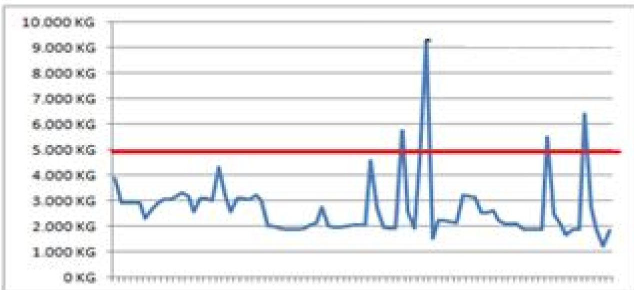

Figure 5.8: Registered forecast packaging

The fixed forecast packaging and fixed forecast production are cleaned. Cleaning is done by using the modified z-score method described in Section 5.1.2. Using this method, the baseline forecast packaging, baseline forecast production and baseline sales are created. See Figure 5.9 for an example of baseline forecast packaging.

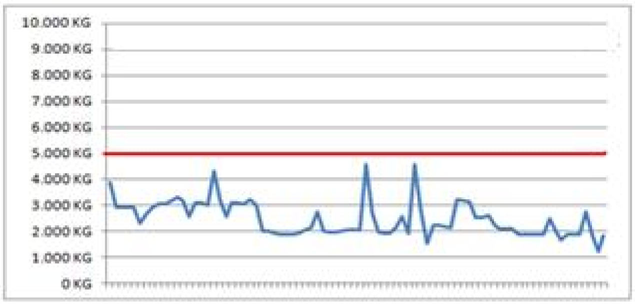

Figure 5.9: Baseline forecast packaging

The MAPE and MPE in the current situation are calculated using the baseline forecast and baseline sales. The MAPE and the MPE for statistical forecasting are calculated using the statistical forecast and baseline sales. Based on the MAPE

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[12] Fixed forecast packaging: Registered forecast for packaging used in current situation
[13] Fixed forecast production: Registered forecast for production used in current situation

and the MPE differences from statistical forecasting compared to the current forecast method, the appropriateness of statistical forecasting to each case can be determined. Figure 5.10 shows a close-up of the sales pattern for the baseline sales, baseline forecast packaging and statistical forecast over 30 weeks of data from 2011 for one article. The graph shows a strongly fluctuating baseline sales pattern. The baseline sales pattern in Figure 5.10 suggests that the promotions are still present, because the pattern contains several peaks. That is, not the case, since a baseline sales pattern can contain several peaks.

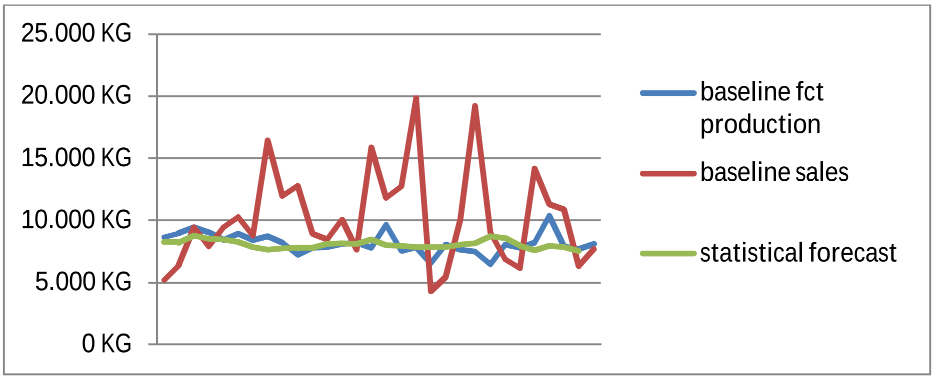

Figure 5.10: Cleaned data

Figure 5.11 shows the normal sales and promotion sales for the same article over the complete course of the available time period (2010 and 2011). Although, in some weeks, there are no promotions, the sales pattern still fluctuates. The striped box in Figure 5.11 contains the same article and time period that are displayed in Figure 5.10. This time period contains two promotion weeks (see promotions in Figure 5.11). In weeks without promotions the sales pattern still fluctuates greatly. After removing promotions, the baseline sales data is obtained (see Figure 5.10). However, the baseline sales pattern in Figure 5.10 still has some peaks after promotions have been removed. It can therefore be concluded that a baseline sales pattern can contain several peaks.

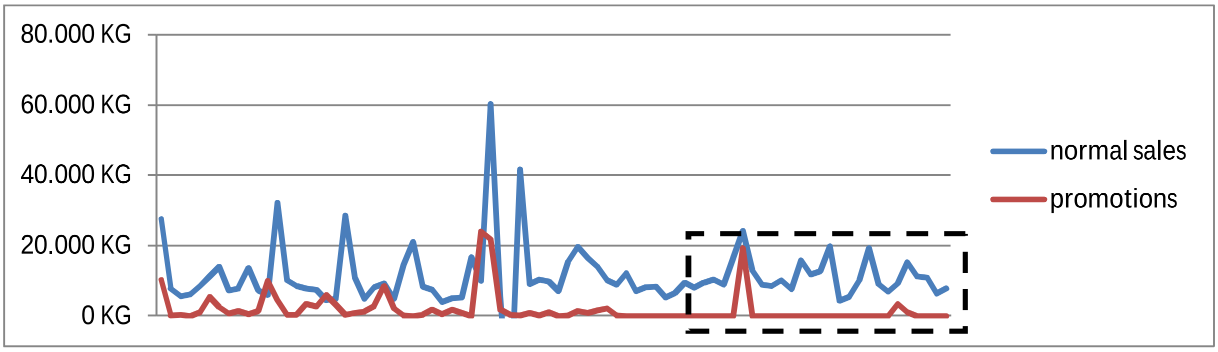

Figure 5.11: Normal sales and promotions

In this chapter we described how to clean historic data in order to obtain the baseline sales (research question 6) and baseline forecast (within the current situation). We also proposed a statistical forecast model selection method (research question 7) to select the best appropriate model for each product. By using the cleaning method and model selection method, we created statistical forecasts for the baseline sales. In Chapter 6, we will analyze the statistical forecast performance.

6. STATISTICAL FORECAST PERFORMANCE

In this chapter we focus on the statistical forecast results. We compare the forecast performance in the current situation to the statistical forecast performance (Section 6.2). We describe the best statistical forecast model and parameters for each article (Section 6.3). We cannot analyze the forecast results for all articles sold by FrieslandCampina, and therefore, use a selection of articles (Section 6.1).

6.1 Article selection

FrieslandCampina differentiates five kinds of markets, namely, the cheese specialties market, cheese (non-branded) market, indirect market, business-to-business market, and international markets (see Section 3.2). FrieslandCampina wants to see the added value of statistical forecasting for each of these markets. Each market, contains important characteristics, namely, demand volume, importance of customers, and variance in demand. Therefore, we have created eight groups of articles that cover all markets and characteristics. We have decided to choose five articles from each group, with the objective of making more extensive analyses of forecast results for each article. Hence, all the markets will be covered, while the limitation on the number of articles (forty articles) will make analysis feasible. The articles for each group are selected in deliberation with FrieslandCampina. The articles for each group are selected on the basis of brand, age of article and variance in demand.

6.1.1 Group division

The group division is based on market type, volume, and importance of customer.
The importance of a customer is based on the quantity of orders, the amount of orders, and the time FrieslandCampina has been doing business with the customer. Volume division is based on a Pareto analysis.
Figure 6.1 shows the first three groups. The figure contains a horizontal axis, which classifies customers according to their importance (A, B or C), and a vertical axis, which classifies products according to their volume (A, B or C). If an article is sold to, e.g., both customers A and C, the article is assigned to customer A. Therefore, an article can only appear in one classification. The figure shows which classifications belong to each group. All the groups in Figure 6.1 belong to the cheese specialties market. Group 1 contains products that are sold in great volumes to the most important customers. Group 2 contains products that are sold in smaller volumes to the most important customers. Group 3 contains products that are sold in small volumes and are sold to less important customers in the cheese specialties market.

		CUSTOMER IMPORTANCE		
	Pareto (vol.)	A	B	C
PRODUCT VOLUME	A	1	1	
	B	1	1	3
	C	2	2	3

Figure 6.1: Group division cheese specialties market

		Customers
	Pareto (vol.)	All customer specific items
PRODUCT VOLUME	A	4
	B	4
	C	5

Figure 6.2: Group division cheese market

Figure 6.2 shows groups 4 and 5, which belong to the cheese (non-branded) market. Group 4 contains products that are sold in great volumes, and group 5 contains products that are sold in smaller volumes on the cheese market.

<table>
<tr><th></th><th></th><th colspan="2">Demand variability</th></tr>
<tr><th rowspan="4">Market</th><th></th><th>Low variability</th><th>High variability</th></tr>
<tr><td>B2B</td><td rowspan="3">6</td><td rowspan="2">7</td></tr>
<tr><td>Indirect</td></tr>
<tr><td>IM</td><td>8</td></tr>
</table>

Figure 6.3: Group division indirect, B2B and international markets

Groups 6 to 8 belong to the indirect, B2B and international markets (see Figure 6.3). We combine these three markets because the demand characteristics of these markets are comparable. In addition, most of the products in these markets have a Pack to Order (PTO) strategy. PTO strategy means that products are packaged based on orders, and are produced based on forecast.

We divide groups 6 to 8 by the demand variability in their demand pattern. The qualification for low variability or high variability is made by the coefficient of variation (CV). The CV is calculated by dividing the standard deviation of demand by the average demand. According to Hendricks & Robey (1936), a CV lower than one is considered low-variance, and a CV higher than one is considered high-variance. For each product we calculate the CV in the time period from January 2010 until July 2011. Products with a CV lower than one belong to group 6. Products with a CV higher than one belong to group 7 or 8. High-variance products are divided into group 7 (B2B and indirect) and group 8 (IM). Several products in the groups 6 to 8 have a Make to Order (MTO) strategy. MTO-products are included in our research because FrieslandCampina is also interested in the statistical forecast performance for these products.

Products within the groups 1 to 5 need to be forecasted on commercial article level because each different commercial article requires a forecast.

Products in groups 1 to 5 need to be forecasted on the commercial article level because each different commercial article requires an individual forecast.

Products in groups 6 to 8 need to be forecasted on the basic material/age combination level because most of these products have a Pack to Order strategy. In addition, the demand patterns for these products fluctuate heavily on the commercial article level.

6.2 Statistical forecasting vs. current forecast method

The most important analysis is the comparison of the statistical forecast results with the forecast results of the current situation. As described in Section 6.1, we have set up eight groups that need to be evaluated. For each group we evaluate whether or not the statistical forecast seems appropriate and compare the statistical forecasting performance to the current forecast performance.

6.2.1 Group 1

As described in Section 6.1, group 1 contains products that are sold in great volumes to the most important customers in the cheese specialties market. We start by analyzing the results of the comparison of statistical forecasting with the current forecast method.

The MAPE comparison for each article for both the statistical forecast and the current forecast method are presented in Table 6.1. The table shows the commercial article and forecast horizon for each product. The packaging forecast is required two weeks before packaging. Therefore, the forecast horizon for statistical forecasting for the packaging forecast is two weeks. The production forecast is needed two weeks before production. Therefore, the forecast horizon for statistical forecasting for the production forecast is the commercial age of the article plus two weeks. If Table 6.1 shows a forecast horizon of two weeks, we forecast packaging. If the forecast horizon is longer than two weeks, we forecast production. For each article, we forecast packaging and production. Furthermore, we show the CV and average sales in kilograms per product. The CV is shown to give an impression of the forecast performance per CV value. The average sales are provided in order to give an impression of the sales quantity. The last column in Table 6.1 shows the difference between the current forecast method and statistical forecasting.

group	Commercial article	forecast horizon	coefficient of variance	average sales	current MAPE	statistical MAPE	difference MAPE
1	1	2	0,26	1651	15,1%	12,8%	2,3%
1	2	11	0,26	1651	13,1%	12,6%	0,5%
1	3	2	0,43	3512	13,1%	10,1%	3,0%
1	4	20	0,43	3512	17,3%	15,3%	2,0%
1	5	2	0,75	1999	25,6%	14,7%	10,9%
1	6	20	0,75	1999	48,5%	16,0%	32,5%
1	7	2	0,51	6647	34,4%	12,9%	21,5%
1	8	20	0,51	6647	36,4%	21,6%	14,8%
1	9	2	0,78	9316	22,4%	18,7%	3,7%
1	10	6	0,78	9316	23,1%	19,9%	3,2%

Table 6.1: Forecast accuracy group 1

group	Commercial article	forecast horizon	coefficient of variance	average sales	current MPE	statistical MPE	difference MPE
1	1	2	0,26	1651	-13,5%	-1,4%	12,1%
1	2	11	0,26	1651	-10,9%	-5,9%	5,1%
1	3	2	0,43	3512	-2,2%	0,6%	1,6%
1	4	20	0,43	3512	16,5%	15,1%	1,4%
1	5	2	0,75	1999	-18,6%	-0,7%	17,9%
1	6	20	0,75	1999	-44,2%	5,1%	39,1%
1	7	2	0,51	6647	-30,0%	-6,6%	23,4%
1	8	20	0,51	6647	-31,6%	-5,0%	26,6%
1	9	2	0,78	9316	-5,0%	-1,7%	3,2%
1	10	6	0,78	9316	-5,3%	-1,8%	3,5%

Table 6.2: Forecast bias group 1

The MPE comparison for each article for both the statistical forecast and the current forecast method are presented in Table 6.2. The last column in this table shows the difference between the current forecast method and statistical forecasting.
The results presented in Tables 6.1 and 6.2 show that the forecast performance increases significantly for all articles in group 1. Therefore, we can conclude that statistical forecasting is appropriate for the articles in group 1.
One article shows a huge increase in forecast performance when statistical forecasting is used. We analyze this extreme increase (compared to other articles within this group) in performance. The forecast for article 1 is more accurate for the production forecast performance than for the packaging forecast performance within the current situation. We also analyze this anomalous result.

Forecast accuracy for the production forecast of article 5 is very low (MAPE: 48,5%) in the current situation. This extreme value in forecast accuracy needs to be analyzed. The following graph shows the statistical forecast, the baseline forecast[14] packaging and the baseline sales over the out-of-sample data[15] (see Figure 6.4).

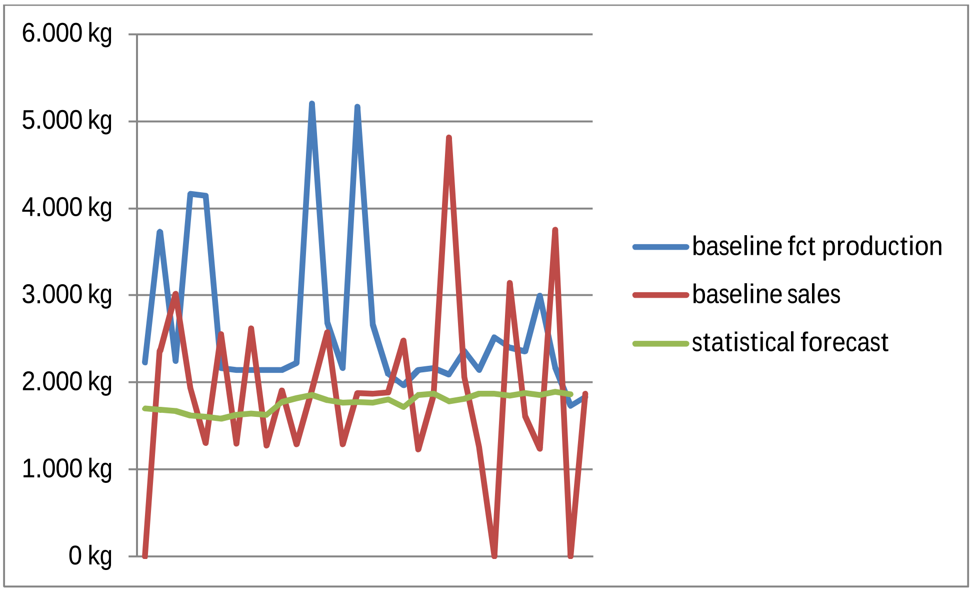

Figure 6.4: Production forecast comparison

The damped trend model is the best statistical model for this article and shows good results. The current forecast (baseline fct production) shows bad results. Between week eleven and week seventeen the baseline fct production shows two peaks. The low forecast performance is caused by these peaks. The two peaks appear within the z-score bound described in Section 5.2 and are therefore not labeled outliers.
Looking at the normal demand (including promotions), there were no promotions registered between week eleven and week seventeen. However, according to the graph (Figure 6.4), the sales planner expected two promotions at the time of the forecast. Since these two promotions never took place, the production forecast in the current situation shows very bad results.

Article 1 shows strange forecast accuracy performance in the current situation. The production forecast shows better results than the packaging forecast while the production forecast has a longer forecast horizon. We compare the baseline sales pattern, packaging forecast pattern and production forecast pattern.

[14] Baseline forecast in the current situation
[15] Data over 2011 (week 1 until week 30)

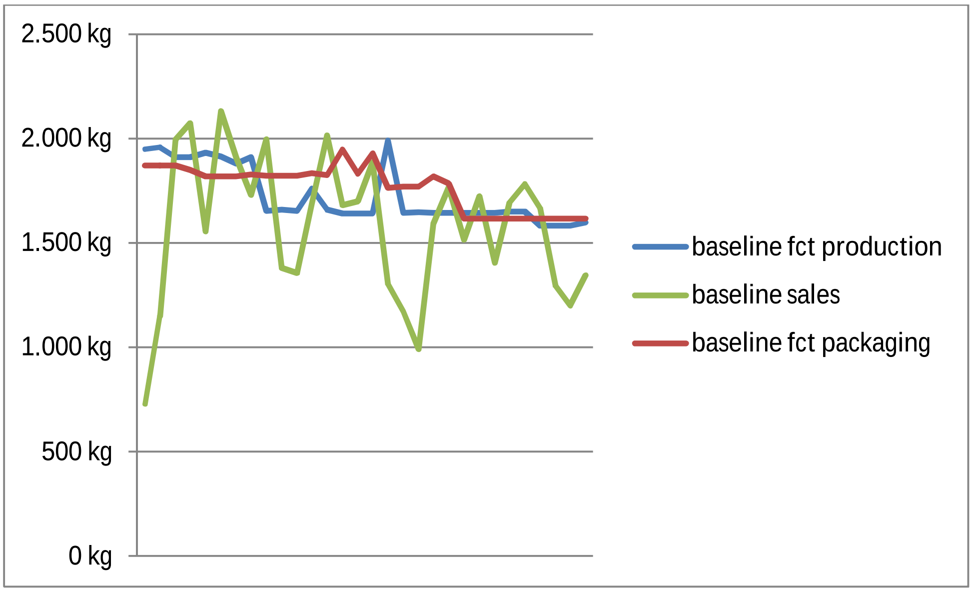

Figure 6.5: Packaging- and production forecast comparison

Figure 6.5 shows the packaging and production forecast in the current situation. At two time periods (week 9 to 15 and week 17 to 20), the packaging forecast is higher than the production forecast. The sales planner has made the packaging forecast slightly higher than the production forecast in these time periods to ensure that there is no shortage for this product. Meanwhile, the baseline sales remain lower than expected in these time periods. Therefore, the production forecast performs better than the packaging forecast in these time periods.

There is one last remark we want to include about the current forecast in group 1. For most products in this group, the MPE (see Table 6.2) is negative and has a high value. A negative MPE indicates that, on average, the forecast is too high (see formula 4.13), which is called over-forecasting. Table 6.2 shows that, in the current situation, most articles are being over-forecast. By using statistical forecasting, we can remove a large part of this bias. Table 6.2 shows better forecast bias results when statistical forecasting is used.

6.2.2 Group 2

Group 2 also belongs to the cheese specialties market. This group contains products that are sold in smaller volumes to the most important customers. The results in forecast accuracy for the articles in group 2 are presented in Table 6.3. A red cell in the last column indicates that using statistical forecasting decreases forecast accuracy.

group	Commercial article	forecast horizon	coefficient of variance	average sales	current MAPE	statistical MAPE	difference MAPE
2	1	2	0,81	960	70,5%	39,2%	31,2%
2	2	7	0,81	960	72,7%	39,0%	33,6%
2	3	2	1,44	82	51,9%	47,3%	4,6%
2	4	20	1,44	82	59,1%	48,5%	10,6%
2	5	2	0,41	1301	23,0%	25,0%	-2,0%
2	6	7	0,41	1301	20,3%	27,4%	-7,1%
2	7	2	0,50	329	35,9%	14,6%	21,3%
2	8	20	0,50	329	35,5%	17,2%	18,3%
2	9	2	0,49	297	45,2%	18,4%	26,8%
2	10	7	0,49	297	63,3%	18,0%	45,3%

Table 6.3: Forecast accuracy group 2

The MPE comparison for each article from both the statistical forecast and the current forecast method are presented in Table 6.4. A red cell in the last column indicates that the forecast bias for this article increases when statistical forecasting is used.

group	Commercial article	forecast horizon	coefficient of variance	average sales	current MPE	statistical MPE	difference MPE
2	1	2	0,81	960	-68,7%	-7,5%	61,2%
2	2	7	0,81	960	-72,3%	-6,0%	66,3%
2	3	2	1,44	82	-32,3%	11,6%	20,7%
2	4	20	1,44	82	-33,3%	26,7%	6,5%
2	5	2	0,41	1301	-18,1%	-18,2%	-0,1%
2	6	7	0,41	1301	-16,2%	-22,8%	-6,6%
2	7	2	0,50	329	-35,9%	-7,3%	28,7%
2	8	20	0,50	329	-35,5%	-14,4%	21,0%
2	9	2	0,49	297	-43,6%	4,7%	38,9%
2	10	7	0,49	297	-63,3%	-8,4%	54,9%

Table 6.4: Forecast bias group 2

Most articles in group 2 show huge improvements in forecast performances when statistical forecasting is used. One article does not show an increase in performance. Starting in week 13 of 2011, the sales pattern for this product fluctuates greatly, resulting in a bad statistical forecast performance. However, the forecast performance for this article decreases only slightly and the statistical forecast performance remains acceptable. Therefore, we conclude that it is appropriate to use statistical forecasting for the articles in group 2. See Appendix F for figures about demand and forecast patterns for each article in group 2.

6.2.3 Group 3

Group 3 contains products that are sold in smaller volumes to less important customers in the cheese specialties market. Table 6.5 and Table 6.6 show the forecast accuracy and forecast bias for group 3.

group	Commercial article	forecast horizon	coefficient of variance	average sales	current MAPE	statistical MAPE	difference MAPE
3	1	2	0,75	998	71,9%	34,3%	37,6%
3	2	11	0,75	998	66,5%	42,9%	23,6%
3	3	2	0,64	625	70,9%	20,7%	50,2%
3	4	11	0,64	625	43,6%	22,1%	21,5%
3	5	2	0,72	934	52,4%	17,6%	34,8%
3	6	7	0,72	934	51,0%	31,4%	19,6%
3	7	2	0,77	252	1,1%	1,0%	0,1%
3	8	6	0,77	252	1,1%	1,6%	-0,5%
3	9	2	1,15	126	40,6%	38,4%	2,2%
3	10	7	1,15	126	37,6%	35,0%	2,6%

Table 6.5: Forecast accuracy group 3

group	Commercial article	forecast horizon	coefficient of variance	average sales	current MPE	statistical MPE	difference MPE
3	1	2	0,75	998	42,4%	-12,5%	29,9%
3	2	11	0,75	998	65,0%	-21,6%	43,4%
3	3	2	0,64	625	-70,9%	-6,1%	64,8%
3	4	11	0,64	625	-37,0%	-13,1%	23,9%
3	5	2	0,72	934	-49,5%	-6,1%	43,4%
3	6	7	0,72	934	-47,3%	-10,2%	37,1%
3	7	2	0,77	252	-0,7%	0,3%	0,4%
3	8	6	0,77	252	-0,7%	1,1%	-0,4%
3	9	2	1,15	126	-14,0%	-9,6%	4,4%
3	10	7	1,15	126	-9,5%	-14,9%	-5,3%

Table 6.6: Forecast bias group 3

Overall, the forecast performances for the articles in group 3 improve when statistical forecasting is used. Two articles show some decline in forecast performance. However, the statistical forecast performance for both these articles remains acceptable. Therefore, we conclude that statistical forecasting is appropriate for the articles in group 3. See Appendix G for figures about demand and forecast patterns for each article in group 3.

6.2.4 Group 4

Group 4 contains products that are sold in great volumes on the cheese (non-branded) market. Table 6.7 and Table 6.8 show the forecast accuracy and forecast bias for group 4.

group	Commercial article	forecast horizon	coefficient of variance	average sales	current MAPE	statistical MAPE	difference MAPE
4	1	2	0,31	3482	13,6%	8,9%	4,8%
4	2	9	0,31	3482	11,6%	7,3%	4,3%
4	3	2	0,23	33867	13,2%	9,0%	4,2%
4	4	15	0,23	33867	10,1%	8,6%	1,6%
4	5	2	0,35	2815	20,3%	18,6%	1,8%
4	6	25	0,35	2815	21,3%	16,3%	4,9%
4	7	2	0,40	7286	26,2%	19,3%	6,9%
4	8	6	0,40	7286	22,5%	25,8%	-3,4%
4	9	2	0,77	32024	32,0%	24,8%	7,2%
4	10	6	0,77	32024	35,4%	32,8%	2,6%

Table 6.7: Forecast accuracy group 4

group	Commercial article	forecast horizon	coefficient of variance	average sales	current MPE	statistical MPE	difference MPE
4	1	2	0,31	3482	-12,5%	-2,9%	9,6%
4	2	9	0,31	3482	-7,6%	-1,5%	6,1%
4	3	2	0,23	33867	-0,8%	0,2%	0,6%
4	4	15	0,23	33867	-5,1%	-2,5%	2,5%
4	5	2	0,35	2815	-13,8%	-7,5%	6,3%
4	6	25	0,35	2815	-15,6%	-8,1%	7,4%
4	7	2	0,40	7286	-21,4%	-6,4%	15,0%
4	8	6	0,40	7286	-14,7%	-8,9%	5,8%
4	9	2	0,77	32024	13,2%	-1,3%	11,9%
4	10	6	0,77	32024	10,7%	-9,5%	1,2%

Table 6.8: Forecast bias group 4

Using statistical forecasting improves the forecast performances for most articles in group 4. However, the forecast accuracy of the production forecast for one article does not increase. Still, the decrease in accuracy is minimal for this article. Therefore, we conclude that statistical forecasting is appropriate for the articles in group 4. See Appendix H for figures about demand and forecast patterns for each article in group 4.

6.2.5 Group 5

Group 5 contains products that are sold in smaller volumes on the cheese (non-branded) market. Table 6.9 and Table 6.10 show the forecast accuracy and forecast bias for group 5.

group	Commercial article	forecast horizon	coefficient of variance	average sales	current MAPE	statistical MAPE	difference MAPE
5	1	2	0,61	1286	15,2%	17,8%	-2,6%
5	2	6	0,61	1286	15,2%	16,9%	-1,7%
5	3	2	0,19	1089	10,4%	8,8%	1,6%
5	4	6	0,19	1089	10,9%	8,4%	2,6%
5	5	2	0,48	1104	27,3%	19,2%	8,1%
5	6	6	0,48	1104	24,5%	18,6%	5,9%
5	7	2	0,55	683	34,0%	26,3%	7,7%
5	8	7	0,55	683	36,1%	25,8%	10,2%
5	9	2	0,96	221	31,2%	22,9%	8,3%
5	10	6	0,96	221	32,3%	23,1%	9,2%

Table 6.9: Forecast accuracy group 5

group	Commercial article	forecast horizon	coefficient of variance	average sales	current MPE	statistical MPE	difference MPE
5	1	2	0,61	1286	-3,4%	4,9%	-1,5%
5	2	6	0,61	1286	-3,4%	-0,9%	2,5%
5	3	2	0,19	1089	-2,8%	0,8%	2,1%
5	4	6	0,19	1089	-0,4%	1,1%	-0,7%
5	5	2	0,48	1104	-17,4%	-5,2%	12,2%
5	6	6	0,48	1104	-14,6%	-5,1%	9,5%
5	7	2	0,55	683	-23,3%	-6,0%	17,4%
5	8	7	0,55	683	-26,7%	-5,3%	21,4%
5	9	2	0,96	221	-9,6%	-4,4%	5,2%
5	10	6	0,96	221	-14,3%	-9,6%	4,7%

Table 6.10: Forecast bias group 5

The tables show that, for most articles, forecast performance improves when statistical forecasting is used. A small number of articles show an acceptable decline in forecast performance. Therefore, we conclude that statistical forecasting is appropriate for the articles in group 5. See Appendix I for figures about demand and forecast patterns for each article in group 2.

6.2.6 Group 6

Group 6 contains the basic materials/age combinations located in the business-to-business, indirect or international markets, which have a low coefficient of variance in their demand pattern. Table 6.11 shows the forecast accuracy for group 6. The table shows the basic material, age and forecast horizon for each product. Table 6.11 and Table 6.12 show the forecast accuracy and forecast bias for group 6.

				packaging/	coefficient	average	current	statistical	difference
group	market	basic material	age	production	of variance	sales	MAPE	MAPE	MAPE
6	BtoB	1	4	packaging	0,22	214932	15,8%	14,7%	1,0%
6	BtoB	2	4	production	0,22	214932	26,7%	14,6%	12,1%
6	BtoB	3	6	packaging	0,29	136371	27,5%	14,5%	13,0%
6	BtoB	4	6	production	0,29	136371	39,8%	16,9%	22,9%
6	Indirect	5	13	packaging	0,52	21807	15,0%	15,4%	-0,4%
6	Indirect	6	13	production	0,52	21807	15,1%	14,7%	0,3%
6	IM	7	4	packaging	0,55	11460	32,35%	18,3%	14,1%
6	IM	8	4	production	0,55	11460	54,30%	17,8%	36,5%
6	Indirect	9	5	packaging	0,80	33243	12,3%	36,3%	-24,0%
6	Indirect	10	5	production	0,80	33243	20,7%	63,3%	-42,6%

Table 6.11: Forecast accuracy group 6

				packaging/	coefficient	average	current	statistical	difference
group	market	basic material	age	production	of variance	sales	MPE	MPE	MPE
6	BtoB	1	4	packaging	0,22	214932	-14,0%	-1,0%	13,0%
6	BtoB	2	4	production	0,22	214932	-24,5%	-0,4%	24,1%
6	BtoB	3	6	packaging	0,29	136371	-24,0%	-3,3%	20,6%
6	BtoB	4	6	production	0,29	136371	-39,6%	-3,2%	36,5%
6	Indirect	5	13	packaging	0,52	21807	-2,4%	-7,9%	-5,5%
6	Indirect	6	13	production	0,52	21807	-2,6%	-9,3%	-6,7%
6	IM	7	4	packaging	0,55	11460	-21,4%	-7,1%	14,3%
6	IM	8	4	production	0,55	11460	-51,3%	-9,3%	42,0%
6	Indirect	9	5	packaging	0,80	33243	-4,9%	-9,6%	-4,6%
6	Indirect	10	5	production	0,80	33243	-7,2%	-27,7%	-20,5%

Table 6.12: Forecast bias group 6

The table shows that, for most articles in group 6, forecast performance improves when statistical forecasting is used. Basic material 9 shows a huge decline in performance. This article is a Made-to-Order (MTO) product, which means that it is produced only when an order is received. FrieslandCampina registers' the order volumes for these MTO products as forecasts. See Appendix J for figures about demand and forecast patterns for each basic material in group 6. The current forecast pattern is very close to the sales pattern. The forecast in the current situation is not 100% accurate because of the effect of canceled orders and new orders that are received when production has already begun. It is illogical to apply statistical forecasting to MTO products. We conclude that statistical forecasting is appropriate for the articles in group 6.

6.2.7 Group 7

Group 7 contains the basic materials/age combinations located in the business-to-business and indirect markets, which have a high coefficient of variance in their demand pattern. Table 6.13 and Table 6.14 show the forecast accuracy and forecast bias for group 7.

group	market	basic material	age	packaging/ production	coefficient of variance	average sales	current MAPE	statistical MAPE	difference MAPE
7	Indirect	1	4	packaging	1,96	2266	13,6%	13,4%	0,3%
7	Indirect	2	4	production	1,96	2266	13,6%	13,6%	0,0%
7	Indirect	3	5	packaging	1,08	15461	35,7%	79,3%	-43,6%
7	Indirect	4	5	production	1,08	15461	35,8%	81,2%	-45,4%
7	Indirect	5	4	packaging	1,05	9566	63,9%	49,3%	14,6%
7	Indirect	6	4	production	1,05	9566	71,9%	49,6%	22,3%
7	Indirect	7	2	packaging	1,31	1925	21,8%	47,3%	-25,5%
7	Indirect	8	2	production	1,31	1925	22,6%	47,0%	-24,4%
7	Indirect	9	16	packaging	1,54	1349	75,6%	48,5%	27,1%
7	Indirect	10	16	production	1,54	1349	71,5%	65,6%	6,0%

Table 6.13: Forecast accuracy group 7

group	market	basic material	age	packaging/ production	coefficient of variance	average sales	current MPE	statistical MPE	difference MPE
7	Indirect	1	4	packaging	1,96	2266	8,8%	-1,2%	7,6%
7	Indirect	2	4	production	1,96	2266	8,8%	-1,2%	7,6%
7	Indirect	3	5	packaging	1,08	15461	33,0%	-75,3%	-42,3%
7	Indirect	4	5	production	1,08	15461	33,0%	-75,3%	-42,3%
7	Indirect	5	4	packaging	1,05	9566	-30,7%	-8,1%	22,6%
7	Indirect	6	4	production	1,05	9566	-42,4%	-6,8%	35,7%
7	Indirect	7	2	packaging	1,31	1925	-11,8%	26,3%	-14,5%
7	Indirect	8	2	production	1,31	1925	-9,4%	27,9%	-18,5%
7	Indirect	9	16	packaging	1,54	1349	-43,5%	4,0%	39,5%
7	Indirect	10	16	production	1,54	1349	-63,9%	-43,7%	20,3%

Table 6.14: Forecast bias group 7

The table shows that, for more than half of the products in group 7, forecast performance improves when statistical forecasting is used. The forecast performance for the other products declines hugely. These are MTO products, to which statistical forecast does not need to be applied. We conclude, therefore, that statistical forecasting is appropriate for the products in group 7. See Appendix K for figures about demand and forecast patterns for each basic material in group 7.

6.2.8 Group 8

Group 8 contains the basic materials/age combinations located in the international markets, which have a high coefficient of variance in their demand pattern. Table 6.15 and Table 6.16 show the forecast accuracy and forecast bias for group 8.

group	market	basic material	age	packaging/ production	coefficient of variance	average sales	current MAPE	statistical MAPE	difference MAPE
8	IM	1	22	packaging	1,01	3442	50,4%	19,8%	30,6%
8	IM	2	22	production	1,01	3442	44,2%	22,9%	21,3%
8	IM	3	3	packaging	2,85	11357	45,3%	49,5%	-4,2%
8	IM	4	3	production	2,85	11357	50,5%	53,2%	-2,7%
8	IM	5	3	packaging	1,38	1808	55,5%	40,3%	15,2%
8	IM	6	3	production	1,38	1808	51,0%	37,7%	13,3%
8	IM	7	8	packaging	1,67	1389	36,1%	43,0%	-6,9%
8	IM	8	8	production	1,67	1389	37,4%	43,3%	-6,0%
8	IM	9	7	packaging	1,36	4251	36,7%	30,6%	6,1%
8	IM	10	7	production	1,36	4251	35,1%	31,9%	3,2%

Table 6.15: Forecast accuracy group 8

group	market	basic material	age	packaging/ production	coefficient of variance	average sales	current MPE	statistical MPE	difference MPE
8	IM	1	22	packaging	1,01	3442	12,2%	-4,1%	8,1%
8	IM	2	22	production	1,01	3442	-24,7%	-3,1%	21,7%
8	IM	3	3	packaging	2,85	11357	43,6%	48,9%	-5,3%
8	IM	4	3	production	2,85	11357	49,2%	44,5%	4,7%
8	IM	5	3	packaging	1,38	1808	14,7%	20,1%	-5,5%
8	IM	6	3	production	1,38	1808	2,0%	-5,9%	-3,9%
8	IM	7	8	packaging	1,67	1389	8,8%	-31,1%	-22,3%
8	IM	8	8	production	1,67	1389	7,2%	5,8%	1,4%
8	IM	9	7	packaging	1,36	4251	-21,5%	-9,2%	12,3%
8	IM	10	7	production	1,36	4251	-12,5%	2,8%	9,8%

Table 6.16: Forecast bias group 8

The table shows that, for half of the articles, the forecast performance improves when statistical forecasting is used. The articles with a bad forecast performance when statistical forecasting is used, have strongly intermittent and fluctuating demand patterns (see Appendix L) and are therefore difficult to forecast.

We conclude that statistical forecasting is appropriate for the articles in group 8. All the articles show an acceptable performance when statistical forecasting is used. There are some problems with forecasting for articles with strongly intermittent and fluctuating demand patterns. Still, it is common for these articles to cause some decline in forecast performance.

6.3 Conclusion forecast performance

The use of statistical forecasting improves forecast performance when compared to the current situation. We conclude that statistical forecasting is appropriate for all groups. Overall, the forecast accuracy increases by 11,4%[16] when statistical forecasting is used. The forecast bias performance improves by 14,4%[16].

When we analyze the results per group, we obtain the following results (see Table 6.17).

[16] Average improvement in case the performances for MTO and PTO products are removed

	average forecast packaging improvement accuracy performance	average forecast production improvement accuracy performance	average forecast packaging improvement bias performance	average forecast production improvement bias performance	percentage of products that show an improvement
group 1	8,3%	10,6%	11,6%	15,1%	100%
group 2	16,4%	20,1%	29,9%	28,4%	80%
group 3	25,0%	13,4%	28,6%	19,7%	80%
group 4	5,0%	2,0%	8,7%	4,6%	90%
group 5	4,6%	5,3%	7,1%	7,5%	70%
group 6	6,9% [17]	18,0% [17]	10,6% [17]	24,0% [17]	60%
group 7	14,0% [17]	9,4% [17]	23,2% [17]	21,2% [17]	60%
group 8	8,2% [17]	5,8% [17]	-2,5% [17]	6,7% [17]	40%

Table 6.17: Forecast improvement

Groups 1 to 5 are part of the cheese retail sector. Results show that forecasting for articles in groups 4 and 5 improves less than for those in groups 1 to 3. This is due the following reason; groups 1 to 3 are part of the cheese specialties market. These groups all show similar results. In this market, the expected sales are completely uncertain. Group 4 and 5 belong to the cheese (non-branded) market. In this market, global sales volumes are agreed to in contracts. Therefore, weekly sales volumes are indicated and there is less improvement through statistical forecasting in the cheese (non-branded) market.
Groups 6 to 8 show a lower percentage of products in which the forecast performance improves through statistical forecasting. This is because these groups contain MTO products. MTO products are produced on order. Group 8 contains products which have a high CV (>1) and have a lower increase in forecast performance[17] then the groups 6 and 7. This is because sales patterns in group 8 fluctuate more strongly.

27,5% of all products[18] do not show an increase in forecast performance due to the following reasons:

- Products are MTO products
- Products have a very fluctuating sales pattern
- Products have an unpredictable intermittent sales pattern

A fluctuating or unpredictable intermittent sales pattern results in a high CV. Therefore, we can conclude that statistical forecasting is inappropriate for products with a high CV in their demand pattern.

In conclusion, we advise using statistical forecasting for the products in **all eight groups** because each group shows an improved performance. As expected, statistical forecasting is not appropriate for MTO products or products with a high coefficient of variation in their demand pattern.

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[17] MTO products are excluded
[18] Analyzed in our research

6.4 Coefficient of variation boundary

The above results show good forecast results for products with a low coefficient of variation (CV). Products with a high CV show bad forecast results. Therefore, we must analyze the maximum CV for which statistical forecasting is still appropriate in order to create a boundary for the CV.
We analyze several basic materials with a high CV in demand. We compare the forecast accuracy and forecast bias for the statistical forecast to a forecast based on a 1-year simple moving average. We want to use the 1-year simple moving average for products with a high CV in demand (see Section 7.5). Appendix N shows the results of the MAPE and the MPE performance for statistical forecasting compared with 1-year simple moving average. The appendix shows it is difficult to create a clear bound for the CV. The results in the appendix show that statistical forecasting is certainly appropriate up to a CV of 1,3. The precise bound of the CV is difficult to determine, because the results are precarious (if the CV is higher than 1,3).
Herrin (2007) advises incorporating the coefficient of determination (see Section 4.5) and the MAPE, in addition to the CV, to determine forecastability. The coefficient of determination gives an indication of how closely forecasts are related to actual sales. This coefficient varies between 0 and 1. The closer this value approach 1, the easier forecasting becomes. Herrin advises setting targets for the coefficient of determination and the MAPE in order to determine forecastability per product. These two measures can only be determined if the forecast has already been created.
Therefore, we advise using the CV to determine forecastability for each product before using statistical forecasting. After statistical forecasting has been used for a period of time, we advise reviewing forecastability per product, based on the MAPE and the coefficient of determination.

6.5 Best model and parameters

After following the steps described in the model selection method (see Section 5.2), we select the best model and its parameters for each article. The best model is selected by optimizing the MAPE. Appendix E shows the best model and its optimal parameters per selected article. We analyze which model and parameters are best for each article and analyze whether or not there is a single model that can be used for all articles in a group.

Group 1

The table in the appendix shows a diversity of best models for the articles in group 1. The most often selected models are the damped trend model (50%) and the twelve-period weighted moving average (20%). The parameters of the articles that were used to select the damped trend model differ. Implementing these models in APO is difficult because APO does not have the functionality to optimize the parameters for all the models. APO can optimize the parameters for the simple exponential smoothing model and the double exponential smoothing model. Therefore, we compare the MAPE of the best model to versus the best of the simple exponential smoothing model and the double exponential smoothing model (see Appendix E). On average, there is a 1,71% decrease in forecast accuracy for group 1 when we use the best of the two models. 10% of all products in group 1 show a decrease in forecast accuracy larger than 5% when the best of the simple or double exponential smoothing model is used.

Group 2

The most often selected models in group 2 are simple exponential smoothing (30%) and double exponential smoothing (20%). We compare the best model with the best of the simple exponential smoothing model and the double exponential smoothing model for all the articles in group 2. On average, there is a 0,74% decrease in forecast accuracy for group 2 when the two models are used. 10% of all products in group 2 show a decrease in forecast accuracy larger than 2%.

Group 3

There is a lot of diversity in the best models selected for group 3. The most often selected models are simple exponential smoothing (20%), double exponential smoothing (20%), four-period weighted moving average (20%), and eight-period weighted moving average (20%). We compare the best model with the best of the simple exponential smoothing model and the double exponential smoothing model for all the articles in group 3. On average, there is a 3,09% decrease in forecast accuracy. 30% of all products in group 3 show a decrease in forecast accuracy larger than 5%. However, products in group 3 have low average sales values. Therefore, the importance of this decrease in accuracy is of minor importance to the company.

Group 4

Exponential smoothing with damped trend (40%) and twelve-period weighted moving average (20%) are the most often selected models in group 4. On average, there is a 0,63% decrease in forecast accuracy when the best model is compared with the best of the simple exponential smoothing model and the double exponential smoothing model. 10% of all products in group 4 show a decrease in forecast accuracy larger than 2%.

Group 5

Simple exponential smoothing (40%) and exponential smoothing with damped trend (20%) are the most often selected models in group 5. On average, there is a 0.61% decrease in forecast accuracy when the best model is compared with the best of the simple exponential smoothing model and the double exponential smoothing model. None of the products in group 5 shows a decrease in forecast performance larger than 2%.

Group 6

The most often selected models in group 6 are exponential smoothing with damped trend (50%) and four-period weighted moving average (20%). We compare the best model to the best of the simple exponential smoothing model and the double exponential smoothing model for all the articles in group 6. On average, there is a 4,28% decrease in forecast accuracy. 30% of all products in group 6 show a decrease in forecast accuracy larger than 5%.

Group 7

The most often selected model in group 7 is simple exponential smoothing (50%). Comparing the best model with the best of the simple exponential smoothing model and the double exponential smoothing model shows a 1,48% decrease in forecast accuracy. 20% of all products show a decrease in forecast accuracy larger than 5%.

Group 8

The most often selected models in group 8 are exponential smoothing models with damped trend (30%) and moving average (30%). We compare the best model with the best of the simple exponential smoothing model and the double exponential smoothing model. On average, there is a 2,53% decrease in forecast accuracy for the articles in group 8. 40% of all products in group 8 show a decrease in forecast accuracy larger than 2%.

This chapter demonstrates that FrieslandCampina would benefit from the implementation of statistical forecasting. Overall, the forecast accuracy of baseline sales improves by 11,4%[19] when statistical forecasting is used, and the forecast bias performance of baseline sales improves by 14,4%[19].
72,5% of the products we analyzed shows an improvement in forecast performance when statistical forecasting is used.
Appendix E shows that it is not possible to select one model with fixed parameters for each group, because there are huge differences in model and parameters between the articles within each group. Implementing the models in APO is difficult because APO does not have the functionality to optimize the parameters for all models. In the implementation phase of this project, we explain how to handle these difficulties in more detail.

[19] Average improvement over the products analyzed in this project in case the performances for MTO and PTO products are removed

7. IMPLEMENTATION

In Chapter 6, we analyzed whether or not statistical forecasting is appropriate for the products sold by FrieslandCampina. This chapter focuses on the implementation of statistical forecasting (Section 7.1, 7.2, 7.3, and 7.4). In Section 7.5 we explain how to manage the forecast per product category. In Section 7.6 we describe our improved forecast process and the steps that need to be taken.
Figure 7.9 shows the steps to take in our improved forecast process. One step in the process is to select the statistical forecast model and its parameters. This selection can be done by APO (forecast module in SAP). We start by describing the implementation of APO into the new forecast process.

7.1 APO implementation

In Section 3.4 we described the insufficient use of system functionalities in the current forecast procedure. In our proposed forecast process (see Figure 7.9), we advise using APO as a tool for statistical forecasting. APO has the functionality to automatically select the optimal model and its parameters. Automatic model selection is problematic, since three years of data are required. As described before, we only have a year one and a half years of data. Therefore, we must select the best model manually.
All the models we explored in our research are available in APO. However, the parameters for most models must be filled in and cannot be optimized by the system. If we want to use all the models, we must optimize the parameters in the advanced forecast tool in Microsoft Excel, which was built for this research project. This will take a lot of effort on the part of FrieslandCampina. Therefore, we propose the following; APO has the functionality to optimize the parameters for the simple exponential smoothing model and the double exponential smoothing model. We advise using one of these models for every article. This will, however, cause a decrease in forecast accuracy. When we compare, per article, the accuracy of the optimum model, with the accuracy of the best of the simple or double exponential smoothing model, (Results in Appendix N) we see that, on average, forecast accuracy decreases by 1,4% when the best of simple or double exponential smoothing is used. 77% of all products shows a decrease of less than 2% in accuracy performance when we use the best of the simple or double exponential smoothing model. Analyzing the difference in bias between the models, Appendix O shows that, when the same simple or double exponential smoothing model from Appendix N is used, there is a 3,27% decline in bias performance. 73% of all products show a decline of less than 2% in bias performance when the best of the simple or double exponential smoothing model is used.
Table 7.1, shows the average decrease in forecast accuracy for each group when the simple or double exponential smoothing model is used. The table shows that if we use only the simple exponential smoothing model, performance decreases less than when we use only the double exponential smoothing model.

group	average MAPE decrease by using the simple exponential smoothing model	average MAPE decrease by using the double exponential smoothing model
1	-2,5%	-8,8%
2	-1,2%	-2,2%
3	-3,7%	-4,8%
4	-0,8%	-2,2%
5	-0,9%	-1,2%
6	-3,3%	-6,2%
7	-1,2%	-7,1%
8	-4,5%	-5,7%

Table 7.1: Performance comparison simple/double exponential smoothing

In our opinion, this small decline in performance is preferable over the extra work it takes to optimize the parameters for all the models in the Excel forecast tool. Therefore, we advise FrieslandCampina to use the simple exponential smoothing and double exponential smoothing models.

7.2 Aggregation levels

Another step in our improved forecast process (Figure 7.9) is selecting the proper aggregation level for each product. In this section we describe when to use which aggregation level.
In general, forecasts of groups of items are more accurate than forecasts of individual items (DeLurgio, 1998). This means that forecasting results on higher aggregation levels will be more accurate. The planning department at FrieslandCampina requires a production forecast (on the basic material/age level) and a packaging forecast (on the commercial article level). In addition, forecasts on the commercial article level are required ten weeks before packaging i.e. if the age of an article is four weeks (less than ten weeks), the production forecast is also required on the commercial article level.
Dangerfield and Morris (1992) suggested two approaches for forecasting items. One is the top-down approach, which uses an aggregate forecast model to develop a summary forecast. This approach disaggregates individual items on the basis of their relative frequency in historic demand. The other approach, the bottom-up approach, makes an individual forecast model for each item and adds up the individual forecasts. Therefore, we explore two forecast approaches. First, we compare an aggregate forecast (on the basic material/age level) for the production forecast with the bottom-up approach (on the commercial article level) for the production forecast. Second, we compare an aggregate forecast (on the basic material/age level) and a disaggregate forecast (on the commercial article level) for the packaging forecast with a forecast (on the commercial article level) for the packaging forecast.
Using the first approach, Appendix P shows that for 91%, the forecast performance shows better results when we forecast on the basic material/age level for the production forecast.
Using the second approach, Appendix Q shows that for 89%, the forecast performance shows better results when we forecast on the commercial article level for the packaging forecast.

Therefore, we advise forecasting production on the basic material/ age level (in case the age is older than 10 weeks) and forecasting packaging on the commercial article level.

7.3 Forward buying effect

The improved forecast process (Figure 7.9) describes the incorporation of the forward buying effect. This section describes how the forward buying effect should be incorporated.

Products in the cheese specialties market have promotional actions in their sales pattern. In Section 5.1, we described how to remove these promotions to obtain the baseline demand. Due to these promotions, a fraction of the ordinary sales after a promotion is lost (see the striped boxes in Figure 7.1).

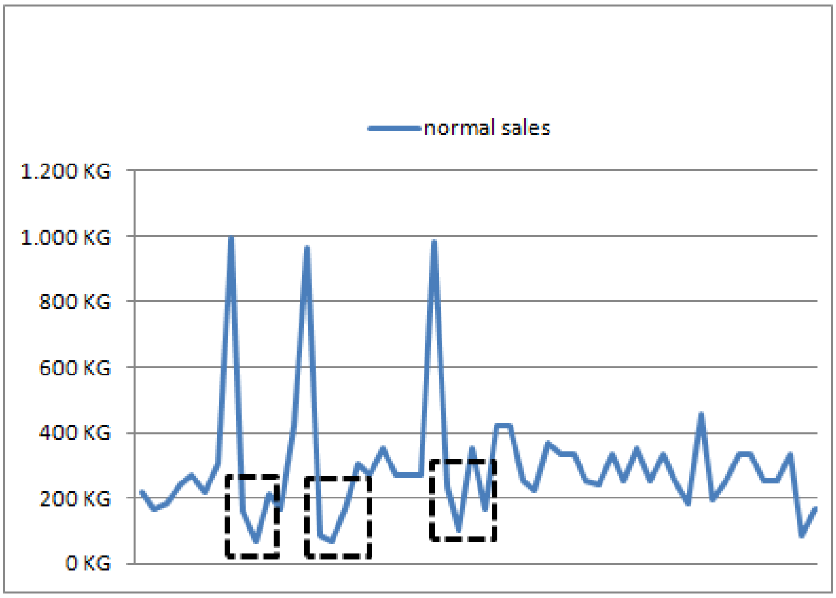

Figure 7.1: Forward buying effect

This loss of sales is called the forward buying effect (Abraham & Lodish, 1987). The forward buying effect takes place in the weeks after a promotion. During a promotion customers buy more than they would normally do, causing demand after a promotion to become low, since customers still have some inventory left. In these situations, the customers and consumers make a choice between having a higher inventory and the benefit of buying during a promotion.

If we analyze the forward buying effect of the promotions of the articles in group 1, our analyses indicate that the forward buying effect takes place in the first two weeks after a promotion. Therefore, we should analyze the forward buying effect in the first two weeks after a promotion.

We analyze the forward buying effect for the articles in group 1. We choose articles from group 1 because they are the subject of many promotions. Promotions take place at the commercial article aggregation level for each planning customer. Therefore, we must calculate the forward buying effect over this aggregation level. To perform our analysis, we take the median of the sales data. After every promotion, we calculate the deviation from the sales of the first two weeks after a promotion and compare it to the median sales. These deviations are calculated per customer for all the articles in group 1. Appendix R shows the average deviation for the first two weeks after a promotion for each article. On average, the forward buying effect is 30,5%. Hence, on average, sales drop by 30,5% in the first two weeks after a promotion.

7.3.1 Remove forward buying effect

In Section 5.1 we described how to create the baseline demand by removing promotions from the normal demand. Figure 7.2 shows the baseline sales when promotions have been removed. The figure shows that the forward buying effect (striped boxes) is still present.

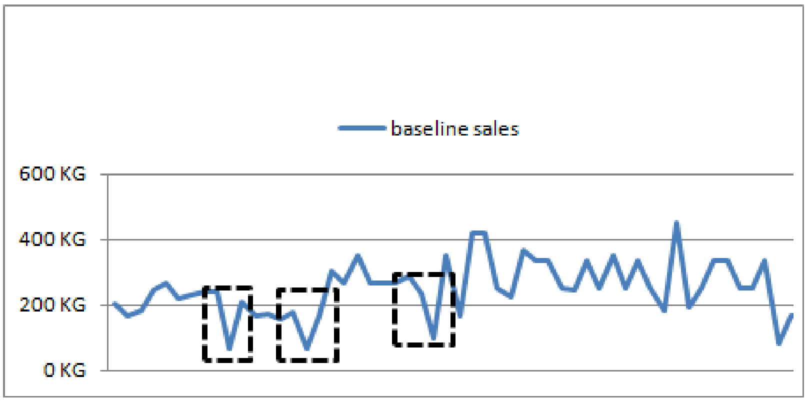

Figure 7.2: baseline sales by removing promotions

Analysis shows that promotions cause a noticeable forward buying effect. The forward buying effect should be removed in order to create a more accurate baseline demand pattern. Abraham & Lodish (1987) suggest that the forward buying effect should be removed when the sales after a promotion fall below a predetermined treshold. The treshold is calculated by taking the following steps:
Firstly, we calculate the median of the data for one article over the complete available data period. Secondly, we calculate the deviations from the baseline sales data compared to the median sales. Abraham & Lodish (1987) suggest calculating the standard deviation of all negative deviations, excluding the promotion weeks and the two weeks after a promotion, to obtain a treshold. The treshold is one standard deviation below the median sales. Hence, if , in the two weeks after a promotion, a sales value drops to one standard deviation (calculated over all the negative deviations) below the median sales, the sales value should be replaced. We advise replacing the value with the four-period moving average of the corrected sales data. Figure 7.3 shows the baseline sales, including the removal of the forward buying effect.

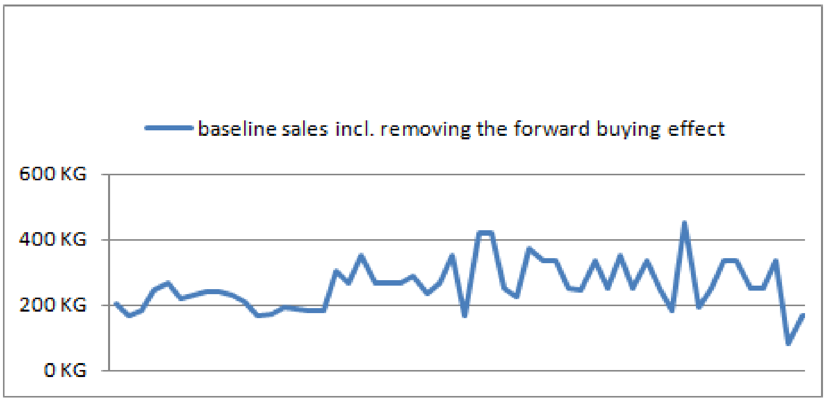

Figure 7.3: Baseline sales incl. removing the forward buying effect

7.3.2 Add forward buying effect

Statistical forecasting is based on the baseline sales, which means that promotions and the forward buying effect are not included in the sales pattern. After creating a statistical forecast, we can now create the forecast for the complete sales. To obtain the complete sales, we add promotions to the statistical forecast. When promotions are added, we should also incorporate the forward buying effect.

Statistical forecasting is performed on the commercial article level and promotions are planned on the commercial article level for each customer. Therefore, we cannot simply subtract a certain percentage from the baseline sales to incorporate the forward buying effect. When a promotion is planned for a commercial article and customer combination, we advise subtracting 30% from the median sales of that customer for the first two weeks after a promotion. For example, if we use statistical forecasting to forecast 3000 kg of a Milner article in week 2,3 and 4., and Albert Hein has a median sale of 1000 kg per week and plans a promotion in week 2, then we subtract 300 kg (30% *1000kg) from the total 3000 kg forecast in weeks 3 and 4.

7.4 Control mechanism

After selecting the appropriate forecast method and parameters for each article and forecast horizon, the sales planners start using statistical forecasting. To ensure that the forecasts stay accurate and unbiased, the model and parameters need to be updated. The main risk of not updating the forecast is that a sudden change in the delivery time series could be left unnoticed in the forecast. Updating the forecast method and parameters every month involves a lot of work and will not always enhance the forecast performance (Loonen, 2010). To overcome these problems, a forecast control mechanism would be very helpful. Such a mechanism indicates when a forecast model or parameters require a change. Our improved forecast process (Figure 7.9) contains such a control mechanism. The forecast control mechanism we want to use is called a tracking signal.

7.4.1 Tracking signal

A tracking signal indicates when a forecast is out of control and needs to be updated. It indicates if the forecast is consistently biased high or low. Tracking is recomputed each period. The movement of the tracking signal is compared to the control limits; as long as the tracking signal is within these limits, the forecast is under control.

Trigg (1964) provides a tracking signal (TST_t) based on the smoothed average of forecast errors. Gardner (1983) provides an excellent review of tracking signals. An advantage of TST_t is that it is less sensitive to certain types of false trips[20]. The following formulas should be used:

$$TST_t = Trigg\ Tracking\ Signal = SAD_t / MAD_t$$
$$SAD_t = Smoothed\ Average\ Deviation = \alpha e_t + (1-\alpha)SAD_{t-1}$$
$$MAD_t = Mean\ Absolute\ Deviation = \alpha|e_t| + (1-\alpha)MAD_{t-1}$$
$$with\ \alpha = 0.10$$

where

$$e_t = error\ at\ time\ t$$

[20] Trips: tracking signal exceeds control limits

Trigg tracking signal (TST_t) varies between -1 and +1. For unbiased errors, TST_t should fluctuate around zero. Nevertheless, when bias occurs, the TST_t will approach either +1 or -1, depending on the direction of the bias.

The tracking signal needs to be compared to its control limits; as long as the tracking signal is within these limits, the forecast model is appropriate. Brown (1963) suggests control limits for Trigg's tracking signal, $STST_t$:

$STST_t = 0.55\sqrt{a}$

Brown advises using the usual two standard errors and $\alpha = 0.1$. Hence, when TST_t exceeds 0.35 ($=2 * 0.55\sqrt{0.1}$) the model is out-of-control and should not be accepted. See Figures 7.4 and 7.5 for an example. In week 7 and week 18, the forecast is out of control.

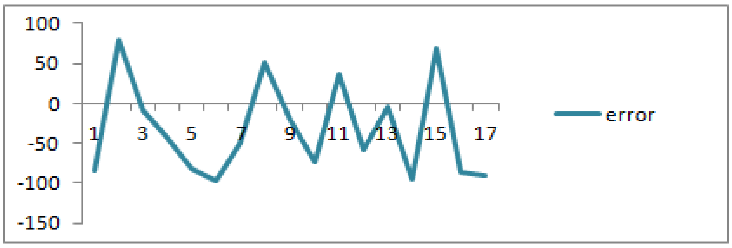

Figure 7.4: Forecast error

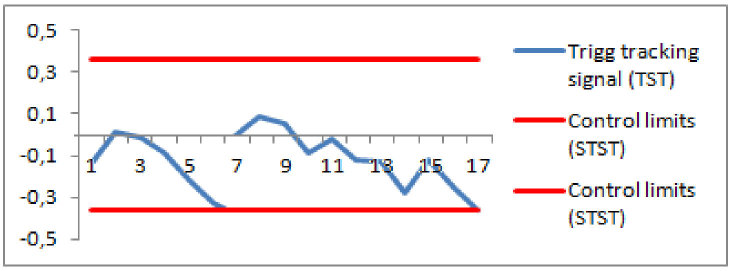

Figure 7.5: Trigg tracking signal compared to control limits

We advise continuously updating this tracking signal when a forecast is created. When the tracking signal exceeds 0.35, the model and its parameters need to be updated. After updating the model and its parameters, the tracking signal should be reset to zero (DeLurgio, 1998).

7.5 Managing products

The main objective of the sales and operations planning (S&OP) is to deliver operations plans that balance supply and demand in such a way that production assets and raw materials are efficiently utilized, service level agreements are met or exceeded, and working capital requirements are minimized. The S&OP process accounts for demand uncertainty by managing a balance among supply flexibility, customer service levels, and inventory. Since not each article and market combination has the same characteristics and importance to FrieslandCampina, we do not recommend using the same strategy for each article. Therefore, the S&OP must use segmentation strategies. Segmentation strategies involve dividing the articles into groups with similar characteristics and degrees of importance to FrieslandCampina. The segmentation strategy is best implemented by categorizing products into quadrants (Herrin, 2007). We create the quadrants based on demand variability (forecastability) and sales volume. Herrin (2007) advises measuring the forecastability by using the coefficient of variance (CV). The CV shows the percentage of variation in the data around the mean. The higher the degree of variation in the data, the more difficult it is to forecast. In Section 6.1, we explained that a CV lower than one is considered low-variance, and a CV higher than one is considered high-variance. 80% of the volume of the products, which amounts to 10% of the products, are considered high sales volume products. 20% of the volume of the products, which amounts to 90% of the products, are considered low sales volume products. Both characteristics are calculated on the basic material/age level.

Coefficient of variance	<1	**Q2:** Stable demand and low sales volume	**Q1:** Stable demand and high sales volume
	>1	**Q3:** Variable demand and low sales volume	**Q4:** Variable demand and high sales volume
		low	high
		Sales volume	

Figure 7.6: Products by sales volume and coefficient of variance

We create four quadrants to segment the products sold by FrieslandCampina (see Figure 7.6). Quadrant 1 contains products with a stable sales pattern and a high sales volume. Quadrant 2 contains products with a stable sales pattern and a low volume. Quadrant 3 contains products with a variable sales pattern and a low volume and Quadrant 4 contains products with a variable sales pattern and a high sales volume.

7.5.1 Planning strategy

Having subdivided the products in quadrants, we can now develop the best strategy for managing the items in each quadrant (see Figure 7.8).

Quadrant 1

Since the demand for the products in this quadrant is stable, it is easy to forecast when statistical forecasting is used. Therefore, we advise generating a statistical forecast for all products in Quadrant 1. These forecasts are made at a 90% confidence interval (Herrin, 2007). Because the products in this quadrant are important to FrieslandCampina, we advise including market knowledge of sales planners after executing statistical forecasting to improve forecast performance. If sales planners feel that the demand pattern of a given item will be significantly different from the statistical forecast pattern, they can overwrite the forecast. If the override is outside the bounds of the confidence interval, they are required to explain their choice; i.e. the forecast should be right ninety times

Coefficient of variance	<1	statistical forecasting	statistical forecasting + market knowledge
	>1	simple moving average	Intensify customer collaboration
		low	high
		Sales volume	

Figure 7.8: Strategy per quadrant

out of a hundred (90% confidence interval). If the forecast is correct only eighty times out of a hundred, the sales planner should document the reason for corrections. It is possible that the assumptions in preparing a statistical forecast are not valid. Hence, if the forecast is corrected too many times, it could be that the forecast model, its parameters or coefficient of variation are incorrect and should be reassessed.

Quadrant 2

The products in Quadrant 2 are easy to forecast and are of low importance to FrieslandCampina. Therefore, statistical forecasting is appropriate for these products. Due to the low importance of these products to FrieslandCampina, we advise FrieslandCampina not to incorporate market knowledge from sales planners for these products. These products should be given minimal attention. If there are errors in the statistical forecast when compared with actual sales, the consequences are minimal. Therefore, we advise using only statistical forecasting for these products.

Quadrant 3

Products in Quadrant 3 are difficult to forecast and are of low importance to FrieslandCampina. Since these items are difficult to forecast, we cannot use statistical forecasting for these product on the commercial article level. We can try to improve their forecast performance through aggregation. Groups 6,7 and 8 in Section 6.3 show that the statistical forecast accuracy is reasonable when we forecast on the basic material/age aggregation level. In this case we aggregate the forecast to a higher level (e.g. at the basic material/age level instead of the commercial article level). We can use the forecast on the higher level for the production forecast. Packaging is done when an order is received (PTO-products). We also advise supplying products in Quadrant 3 on a made-to-order basis or via Vendor Managed Inventory (VMI) processes. In the VMI process, the vendor assumes the task of generating purchase orders to replenish a customer's inventory. In this case, no forecast is required.
If both options do not work, we advise creating a forecast based on the simple moving average over the last year for these products. Because not all options will be highly accurate, we advise giving no guarantees on the service level for products in this quadrant.

Quadrant 4

Products in this quadrant are difficult to forecast, but are important to FrieslandCampina. We advise improving forecasting for these products through intensive collaboration with customers and/or through aggregation. Forecast performance improves when we forecast on a higher aggregation level (see Section 7.2). Therefore, we advise improving delivery performance by obtaining forecasts created by customers, or by making forecasts on higher aggregation levels. Another option for Quadrant 4 is to supply products on a made-to-order basis.

7.6 Improved forecast process

At the start of this master project, FrieslandCampina was dissatisfied with their forecast accuracy. The forecast inaccuracy in the current situation was caused by an inaccurate forecast procedure, insufficient use of system functionalities, and inaccurate use of performance evaluation.
Therefore, we advise a new planning strategy for each product (Section 7.5), a forecast control mechanism (Section 7.4), the best aggregation level per forecast (Section 7.3), a

cleaning method to remove promotions (Section 5.1), a cleaning method to exclude the forward buying effect (Section 7.2) and we advise FrieslandCampina to implement statistical forecasting (Section 7.1). On the basis of this advice, we created a new forecast process, which is displayed in Figure 7.9.

The forecast process starts by determining the article type. In case the article is an MTO product, it does not require a forecast, because it is produced on order. PTO products require forecasts for production, but not for packaging. Therefore, the forecast process is only appropriate for production forecasts. Packaging is done on order. MTS products require forecasts for production and packaging. In Section 7.2 we described that the production forecast is made on the basic material/age level and the packaging forecast is made on the commercial age level. After determining the article type, we explore the planning strategy. For products located in Quadrants 1 and 2, we use statistical forecasting. For products in Quadrant 3, we use a forecast based on the 1-year simple moving average, and for products in Quadrant 4, we advise intensifying customer collaboration. As we described earlier, we will use statistical forecasting for the baseline sales. Therefore, we exclude the promotion sales from historic data to obtain the baseline sales (see Section 5.1). After removing the promotion sales, we exclude the forward buying effect. The next step is to remove outliers from the baseline sales. Once the baseline sales are obtained, we determine (using APO) the best forecast model and its parameters. The parameters are selected by optimizing the MAPE. In order to control the model and parameters, we advise using tracking signals. The next step is forecasting the baseline sales for the article. We add promotions and the forward buying effect to the baseline forecast. Thereby, we create the total forecast for products located in Quadrant 2. For products in Quadrant 1, we add market knowledge of the sales planners to create a more accurate forecast.

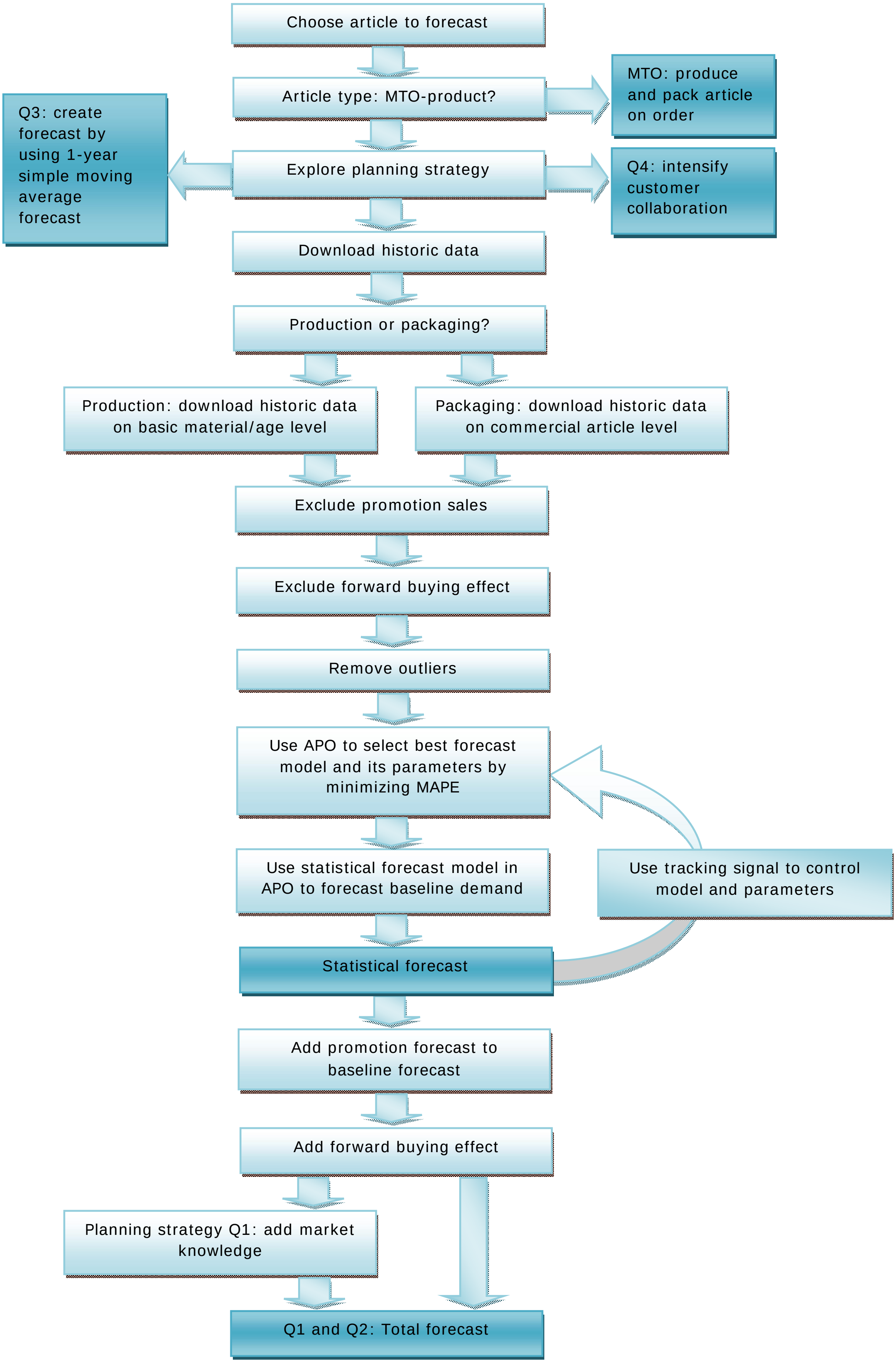

Figure 7.9: Improved forecast process

8. CONCLUSIONS AND RECOMMENDATIONS

This master thesis project focuses on the applicability of statistical forecasting to the portfolio of FrieslandCampina. In Chapter 2, we defined our project objective and problem statement. The management team of the supply chain department Cheese & Cheese Specialties wants to improve forecast accuracy. Our project objective was to analyze the usefulness of statistical forecasting for the baseline demand. By means of statistical forecasting, we want to increase the baseline forecast accuracy.
Based on our project objective, we created the following problem statement:

Is statistical forecasting an appropriate method to forecast the baseline demand for Cheese and Cheese Specialties products and, if so, which statistical forecast models does FrieslandCampina need to use for cheese products to improve their baseline forecast accuracy?

We managed to answer this problem statement. Statistical forecasting is an appropriate method to forecast the baseline demand for Cheese and Cheese Specialties products. In Section 6.1, we created eight groups that cover all markets in which FrieslandCampina is involved. The groups 1 to 3 belong to the cheese specialties (branded) market. Group 1 contains products that are sold in great volumes to the most important customers. Group 2 contains products that are sold in smaller volumes to the most important customers. Group 3 contains products that are sold in small volumes and are sold to less important customers in the cheese specialties market. The groups 4 and 5 belong to the cheese (non-branded) market. Group 4 contains products that are sold in great volumes and group 5 contains products that are sold in smaller volumes in the cheese market. Groups 6 to 8 belong to the indirect, B2B and international markets. For each group, we analyzed whether or not statistical forecasting would improve the forecast performance (see Figure 8.1).

	average forecast packaging improvement accuracy performance	average forecast production improvement accuracy performance	average forecast packaging improvement bias performance	average forecast production improvement bias performance	percentage of products that show an improvement
group 1	8,3%	10,6%	11,6%	15,1%	100%
group 2	16,4%	20,1%	29,9%	28,4%	80%
group 3	25,0%	13,4%	28,6%	19,7%	80%
group 4	5,0%	2,0%	8,7%	4,6%	90%
group 5	4,6%	5,3%	7,1%	7,5%	70%
group 6	6,9%[17]	18,0%[17]	10,6%[17]	24,0%[17]	60%
group 7	14,0%[17]	9,4%[17]	23,2%[17]	21,2%[17]	60%
group 8	8,2%[17]	5,8%[17]	-2,5%[17]	6,7%[17]	40%

Figure 8.1: Forecast improvement

Our results show that statistical forecasting is appropriate for all of FrieslandCampina's markets. Overall, statistical forecasting improves forecast accuracy by 11,4%[21] and the forecast bias performance improves baseline sales by 14,4%[21]. Statistical forecasting improves the forecast performance of 72,5% of the products we analyzed. When sales patterns fluctuate greatly or when products have an unpredictable intermittent sales pattern, statistical forecasting will not improve forecast performance.
This master thesis project explores several statistical forecast models. The best model and parameters differ greatly per product. The damped trend model is the best statistical model for 26,3% of the products and the simple exponential smoothing model is the best statistical model for 20% of the products.

8.1 Recommendations

The implementation of statistical forecasting results in an improvement of the forecast performance. To implement statistical forecasting, we provide FrieslandCampina with several recommendations.

Model and parameter selection

The forecast module APO can automatically select the appropriate statistical forecast model and optimize its parameters. This function requires three years of data. At this point, a year and half years of data are available. Therefore, we cannot automatically select the optimal model.
In this project, we created an advanced forecast tool in Microsoft Excel to select the best model and its optimal parameters. FrieslandCampina can use this forecast tool to select the best model and its parameters for the complete portfolio of FrieslandCampina. This requires a lot of work. Therefore, we advise FrieslandCampina to use the simple or double exponential smoothing model in APO. The parameters for these two models can be optimized by APO. We discovered that there is a 1,4% decrease in forecast accuracy and a 3,27% decrease in forecast bias performance when the best of the simple or double exponential smoothing model is used instead of the best model. We advise using the double exponential smoothing model when dealing with a (damped) trend in the sales pattern of the product, and using the simple exponential smoothing model when there is no trend.
When three years of data are available, we advise using the automatic model selection function in APO.

Aggregation levels

In Section 7.2, we analyzed which aggregation level should be used in each case. We advise forecasting production on the basic material/age level (in case the age is older than 10 weeks), and forecasting packaging on the commercial article level.

Outlier method

In Section 5.1, we described the modified z-score method, used to statistically remove outliers from the sales pattern. We use the modified z-score method because the parameters used to calculate the modified z-score are minimally affected by outliers. APO does not contain the modified z-score method but does contain the median method. The

[21] Average improvement over the products analyzed in this project in case the performances for MTO and PTO products are removed

median method calculates the median of the level-value and the median of the trend-value from past data. Based on these two median values, a tolerance lane is calculated. Values outside the tolerance lane are outliers. The median method does not use measures of error. This means that the tolerance lane values are absolute and do not depend on the scatter of the data.
We advise using the median method in APO to remove outliers. In case FrieslandCampina is dissatisfied with the results of this median method, we advise building a macro to create the modified z-score method that is used in this project.

Forward buying effect

In this master thesis project we analyzed the forward buying effect. The forward buying effect is the loss of sales after a promotion. Our analysis indicates that the forward buying effect takes place in the first two weeks after a promotion. We analyzed the quantity of the forward buying effect in the first two weeks. On average, there is a 30,5% decrease in sales in the first two weeks after a promotion.
The forward buying effect varies greatly between promotions. In some cases, the forward buying effect shows an 80% decrease in sales. In other cases there is an increase in sales after a promotion. Therefore, it is difficult for FrieslandCampina to incorporate the forward buying effect into its forecasts.
We advise FrieslandCampina to perform more research on the forward buying effect.

Tracking signal

The sales patterns of products can change over time. Therefore, it is possible for the statistical forecast model and parameters to become inappropriate. To control the model and parameters, we advise using Trigg's tracking signal. This tracking signal indicates when a forecast is out of control and the parameters need to be updated. A tracking signal indicates if the forecast is consistently biased high or low. The tracking signal should be recomputed each period. The movement of the tracking signal is compared to the control limits; as long as the tracking signal stays within these limits, the forecast is under control.

Improved forecast process

We created an improved forecast process (see Figure 7.9 in Section 7.6). The forecast process incorporates all the steps that are required to statistical forecast products including a new planning strategy per product and the forecast module APO to create statistical forecasts. We advise to use the improved forecast process.

Demand forecasting versus sales forecasting

The data we used in our research is based on actual sales. When sales are lost due to incorrect forecasting or capacity problems, sales orders from customers are not completely fulfilled . Therefore, the actual sales are not equal to the demand. When we make forecasts based on actual sales, we do not incorporate the complete demand and the forecasts will be incorrect.
Therefore, we advise basing forecasts on actual demand instead of actual sales.

8.2 Suggestions for future research

During this research project several ideas came up, which were not incorporated into this project. The following are suggestions for further research.

1. In Section 4.1, we described that we focused our research on univariate forecast methods. Univariate forecast methods are based on demand patterns from history. APO has the functionality to use multivariate forecasting methods. Multivariate forecasting methods incorporate more variables. For example, a forecast of cheese sales for a region may be based on last month's cheese sales, weather, and average income in that region. FrieslandCampina can perform further research on multivariate forecasting methods.
2. In Section 3.3 we described how the amount of cheese production per week depends on forecasting and milk supply. The factor milk supply has not been incorporated into our research. FrieslandCampina sees milk supply as an important constraint on cheese production. The milk quantity needed to produce cheese in a certain week has to be aligned with the milk supply for that specific week. The forecast in this research is based on historic sales. We suggest FrieslandCampina to perform research on incorporating milk supply into their forecast procedure.
3. This project focuses on forecasting existing products sold by FrieslandCampina. When new products are introduced, it is difficult to forecast future sales because of the absence of historic sales data. FrieslandCampina could perform research on forecasting sales for product introductions.
4. If we want to incorporate the forward buying effect, FrieslandCampina should perform more research on it. In our research, we identified a significant forward buying effect. Section 7.3 describes how to remove the forward buying effect to create the baseline sales. Based on the baseline sales, FrieslandCampina can statistically forecast the baseline forecast. If expected promotions are added to the baseline forecast, FrieslandCampina should also add the forward buying effect after promotions. Because the forward buying effect varies greatly between promotions, customers and products, we advise performing further research on the forward buying effect.
5. In this project, we performed research on the applicability of statistical forecasting to the baseline demand. Promotions are excluded from this research. Each promotion, each customer, and each product has different amounts and lengths of promotion sales. We suggest FrieslandCampina to perform research on promotion sales.
6. Section 7.3 describes the forward buying effect that is caused by a promotion. This indicates the occurrence of cannibalization in the weeks after a promotion. It is also possible that a cannibalization effect affects other products during a promotion, since a customer who buys more promotion products is likely to buy fewer other products. FrieslandCampina could perform research on the cannibalization effect on other products during a promotion.

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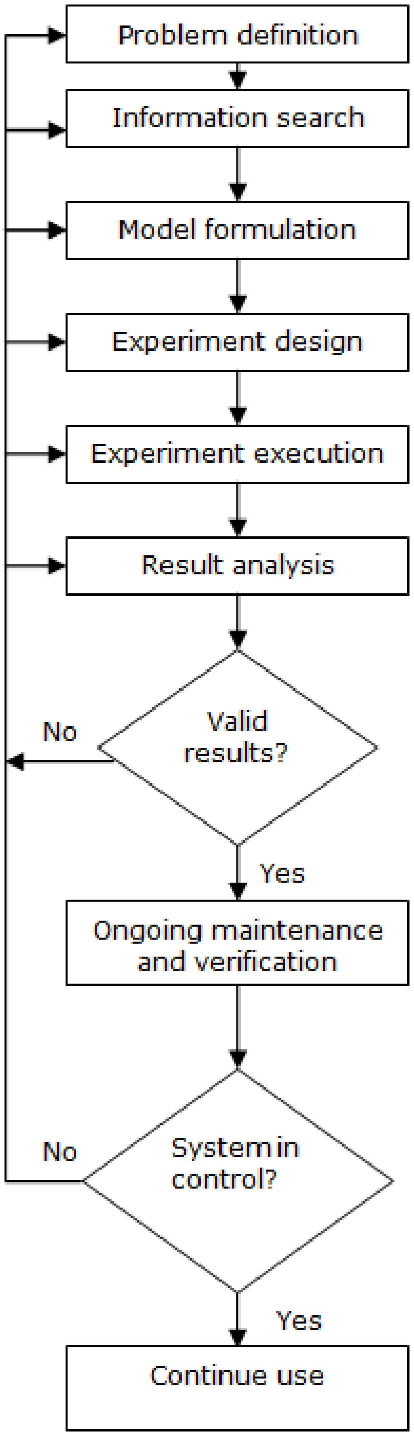
Appendix A

Confidential

Appendix B

Process of designing a forecast model (DeLurgio, 1998)



Appendix C

Available forecast models available in APO (Loonen, 2010)

Forecast models in APO:	Matching forecast method:
Constant models	Simple exponential smoothing, moving average or weighted moving average
Croston model	Croston's method
Trend models	Holt's linear method
Linear Regression model	linear regression method
Seasonal Trend model	Holt-Winters' method
Season + Linear Regr model	Seasonal linear regression method
Median model	Takes the median of the historical deliveries
Seasonal model	Seasonal exponential smoothing method
Manual Forecast method	Applies the seasonal trend model to the historical data. The planner can then experiment with the parameters of the model to see whether an improvement is possible
History	The planner can copy the historical values as a forecast
External Forecast	The planner can create its own forecast model
No Forecast	This can be chosen in case no forecast is required
Auto selection model 1	Tests on a trend and seasonal pattern and then selects an appropriate model
Auto selection model 2	Tests on a constant, trend and seasonal model

Appendix D

	alpha	*beta*	*dampening parameter*									
simple exp, Smoothing	0,01 - 1											
trend model	0,01 - 1	0,01 - 0,72										
damped trend model	0,01 - 0,6	0,01 - 1	0,1 - 1									
double exp smoothing	0,1 - 1											
Croston's method	0,1 - 1											
	periods											
moving average	3 - 12 periods											
	A(t-1)	*A(t-2)*	*A(t-3)*	*A(t-4)*								
Weighted moving avg(4)	0,1 - 0,7	0,1 - 0,4	0,1 - 0,3	0,1 to 0,2								
	A(t-1)	*A(t-2)*	*A(t-3)*	*A(t-4)*	*A(t-5)*	*A(t-6)*	*A(t-7)*	*A(t-8)*				
Weighted moving avg(8)	0,1 - 0,65	0,05 - 0,25	0,05 - 0,25	0,05 - 0,2	0,05 - 0,1	0,05 - 0,1	0,05 - 0,1	0,05 - 0,1				
	A(t-1)	*A(t-2)*	*A(t-3)*	*A(t-4)*	*A(t-5)*	*A(t-6)*	*A(t-7)*	*A(t-8)*	*A(t-9)*	*A(t-10)*	*A(t-11)*	*A(t-12)*
Weighted moving avg(12)	0,1 - 0,45	0,05 - 0,25	0,05 - 0,25	0,05 - 0,2	0,05 - 0,1	0,05 - 0,1	0,05 - 0,1	0,05 - 0,1	0,05 - 0,1	0,05	0,05	0,05
linear regression	all data											

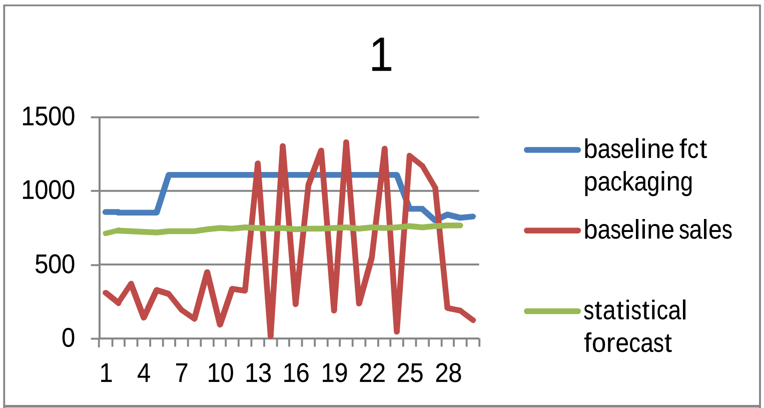
Appendix E

group	commercial article	horizon	packaging/ production	best model	parameters											
1	1	2	packaging	Weighted moving avg(12)	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,10	0,10	0,35
1	2	11	production	Weighted moving avg(12)	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,10	0,10	0,35
1	3	2	packaging	Weighted moving avg(4)	0,20	0,30	0,10	0,40								
1	4	20	production	damped trend model	0,50	0,95	0,80									
1	5	2	packaging	damped trend model	0,50	0,50	0,30									
1	6	20	production	damped trend model	0,50	0,50	0,30									
1	7	2	packaging	Weighted moving avg(8)	0,05	0,05	0,05	0,05	0,05	0,05	0,15	0,06				
1	8	20	production	moving average	1,00	periods										
1	9	2	packaging	damped trend model	0,10	0,53	0,70									
1	10	6	production	damped trend model	0,10	0,53	0,70									
2	11	2	packaging	simple exp. Smoothing	0,10											
2	12	7	production	simple exp. Smoothing	0,10											
2	13	2	packaging	double exp smoothing	0,10											
2	14	20	production	Croston's method	0,10											
2	15	2	packaging	Weighted moving avg(8)	0,05	0,05	0,05	0,05	0,05	0,05	0,25	0,45				
2	16	7	production	simple exp. Smoothing	0,80											
2	17	2	packaging	Weighted moving avg(12)	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,15	0,15	0,15	0,15
2	18	20	production	damped trend model	0,50	0,50	0,10									
2	19	2	packaging	double exp smoothing	0,70											
2	20	7	production	moving average	5,00	periods										
3	21	2	packaging	Weighted moving avg(8)	0,05	0,05	0,05	0,05	0,10	0,20	0,20	0,30				
3	22	11	production	double exp smoothing	0,20											
3	23	2	packaging	Weighted moving avg(12)	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,15	0,15	0,15	0,15
3	24	11	production	moving average	4,00	periods										
3	25	2	packaging	Weighted moving avg(4)	0,20	0,10	0,10	0,60								
3	26	7	production	Weighted moving avg(4)	0,20	0,10	0,10	0,60								
3	27	2	packaging	simple exp. Smoothing	0,86											
3	28	6	production	Weighted moving avg(8)	0,05	0,05	0,05	0,05	0,05	0,25	0,25	0,25				
3	29	2	packaging	simple exp. Smoothing	0,13											
3	30	7	production	Croston's method	0,90											
4	31	2	packaging	double exp smoothing	0,10											
4	32	9	production	Weighted moving avg(12)	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,10	0,10	0,10	0,30
4	33	2	packaging	damped trend model	0,50	0,50	0,60									
4	34	15	production	Weighted moving avg(4)	0,20	0,30	0,10	0,40								
4	35	2	packaging	damped trend model	0,15	0,45	0,20									
4	36	25	production	damped trend model	0,15	0,45	0,20									
4	37	2	packaging	Weighted moving avg(12)	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,10	0,10	0,35
4	38	6	production	damped trend model	0,15	0,57	0,60									
4	39	2	packaging	double exp smoothing	0,14											
4	40	6	production	simple exp. Smoothing	0,34											
5	41	2	packaging	damped trend model	0,50	0,50	0,30									
5	42	6	production	Weighted moving avg(12)	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,10	0,10	0,15	0,15	0,15
5	43	2	packaging	damped trend model	0,50	0,50	0,90									
5	44	6	production	damped trend model	0,50	0,50	0,90									
5	45	2	packaging	simple exp. Smoothing	0,40											
5	46	6	production	simple exp. Smoothing	0,40											
5	47	2	packaging	simple exp. Smoothing	0,20											
5	48	7	production	simple exp. Smoothing	0,20											
5	49	2	packaging	double exp smoothing	0,50											
5	50	6	production	Weighted moving avg(4)	0,10	0,30	0,30	0,30								

				packaging/ production													
group	market	basic material	age	packaging	best model	parameters											
6	BtoB	51	4	production	damped trend model	0,50	0,50	0,60									
6	BtoB	52	4	packaging	damped trend model	0,50	0,50	0,60									
6	BtoB	53	6	production	Weighted moving avg(8)	0,50	0,10	0,10	0,10	0,15	0,15	0,15	0,20				
6	BtoB	54	6	packaging	damped trend model	0,10	1,00	1,00									
6	Indirect	55	13	production	damped trend model	0,15	0,85	1,00									
6	Indirect	56	13	packaging	Weighted moving avg(4)	0,20	0,20	0,30	0,30								
6	IM	57	4	production	Weighted moving avg(12)	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,45
6	IM	58	4	packaging	Weighted moving avg(4)	0,10	0,30	0,20	0,40								
6	Indirect	59	5	production	damped trend model	0,60	0,75	0,20									
6	Indirect	60	5	packaging	linear regression	all	periods										
7	Indirect	61	4	production	Weighted moving avg(8)	0,05	0,10	0,10	0,10	0,15	0,15	0,15	0,20				
7	Indirect	62	4	packaging	moving average	11	periods										
7	Indirect	63	5	production	Weighted moving avg(4)	0,10	0,30	0,30	0,30								
7	Indirect	64	5	packaging	Weighted moving avg(12)	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,15	0,15	0,15	0,15
7	Indirect	65	4	production	simple exp. Smoothing	0,10											
7	Indirect	66	4	packaging	simple exp. Smoothing	0,10											
7	Indirect	67	2	production	simple exp. Smoothing	0,10											
7	Indirect	68	2	packaging	simple exp. Smoothing	0,10											
7	Indirect	69	16	production	simple exp. Smoothing	0,25											
7	Indirect	70	16	packaging	moving average	12	periods										
8	IM	71	22	production	Weighted moving avg(12)	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,10	0,10	0,10	0,30
8	IM	72	22	packaging	moving average	12	periods										
8	IM	73	3	production	damped trend model	0,50	0,50	0,10									
8	IM	74	3	packaging	damped trend model	0,50	0,50	0,10									
8	IM	75	3	production	Croston's method	0,20											
8	IM	76	3	packaging	damped trend model	0,50	0,50	0,10									
8	IM	77	8	production	simple exp. Smoothing	0,1											
8	IM	78	8	packaging	Weighted moving avg(12)	0,05	0,05	0,05	0,05	0,05	0,05	0,10	0,10	0,10	0,10	0,15	0,15
8	IM	79	7	production	moving average	11	periods										
8	IM	80	7	packaging	Weighted moving avg(12)	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,10	0,10	0,10	0,15	0,20

Explanation of parameters per row												
model	1e row	2e row	3e row	4e row	5e row	6e row	7e row	8e row	9e row	10e row	11e row	12e row
simple exp, Smoothing	alpha											
trend model	alpha	beta										
damped trend model	alpha	beta	dampening parameter									
double exp smoothing	alpha											
Croston's method	alpha											
moving average	number of periods											
Weighted moving avg(4)	weight(x-4)	weight(x-3)	weight(x-2)	weight(x-1)								
Weighted moving avg(8)	weight(x-8)	weight(x-7)	weight(x-6)	weight(x-5)	weight(x-4)	weight(x-3)	weight(x-2)	weight(x-1)				
Weighted moving avg(12)	weight(x-12)	weight(x-11)	weight(x-10)	weight(x-9)	weight(x-8)	weight(x-7)	weight(x-6)	weight(x-5)	weight(x-4)	weight(x-3)	weight(x-2)	weight(x-1)
linear regression	all data											

Appendix F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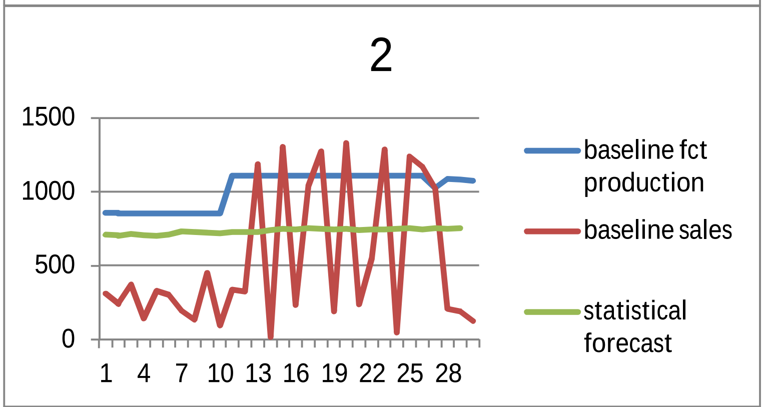
baseline fct packaging
baseline sales
statistical forecast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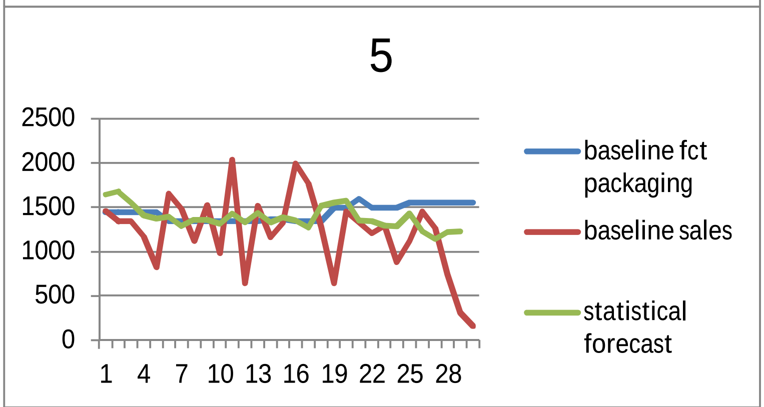
baseline fct production
baseline sales
statistical forecast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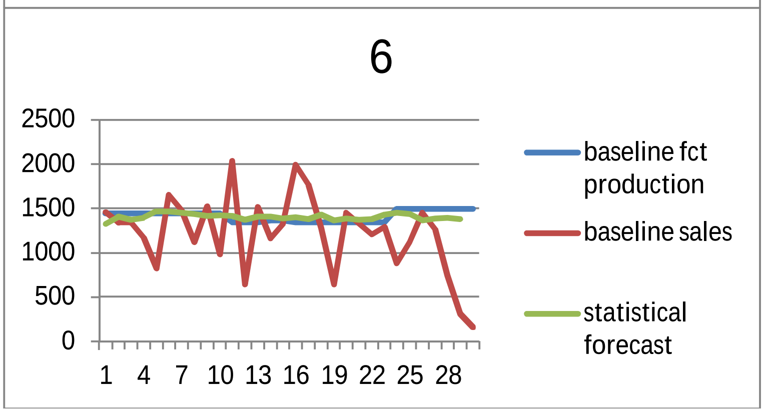
baseline sales
statistical forecast


6
2500
2000
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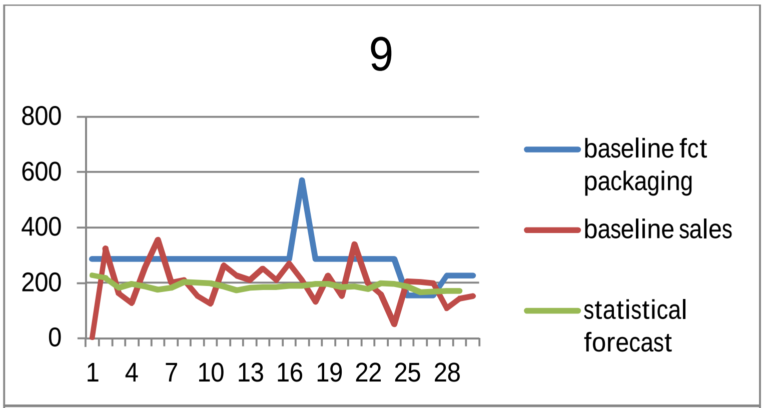
baseline fct production
baseline sales
statistical forecast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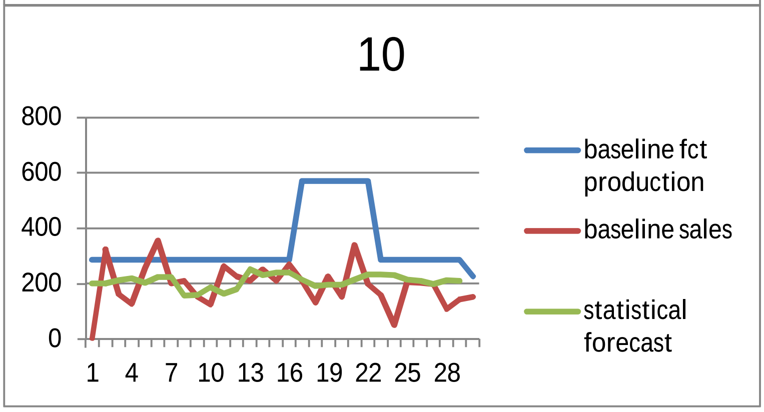
baseline fct packaging
baseline sales
statistical forecast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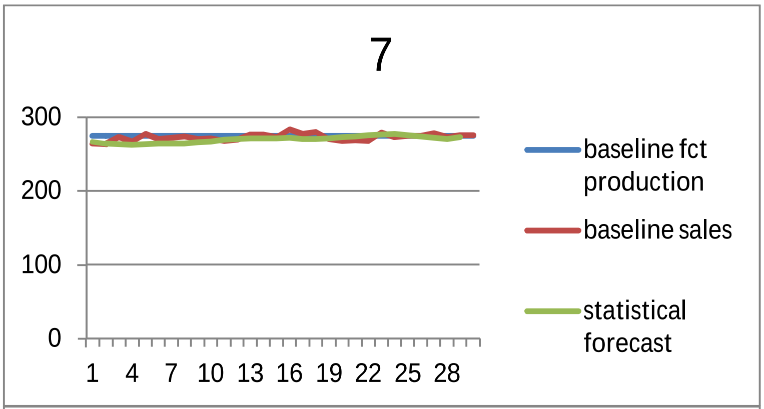
baseline fct production
baseline sales
statistical forecast

Appendix G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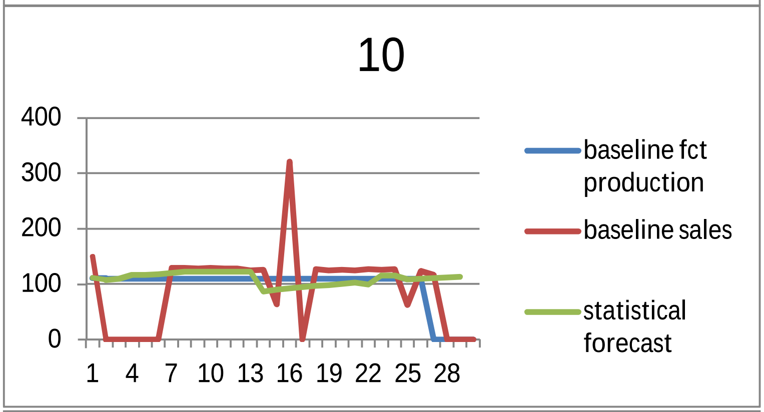
statistical forecast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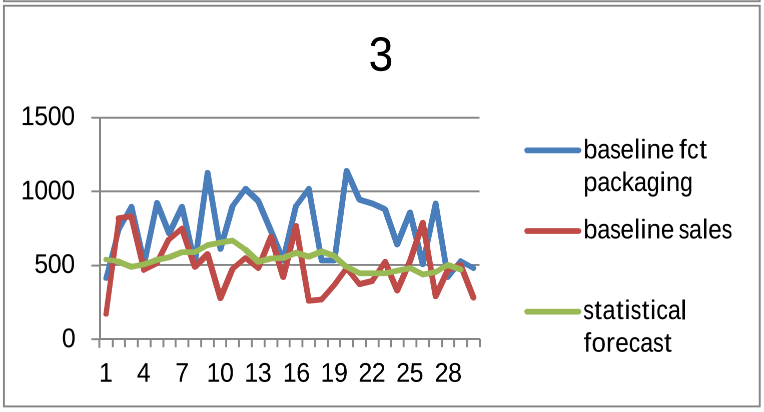
statistical forecast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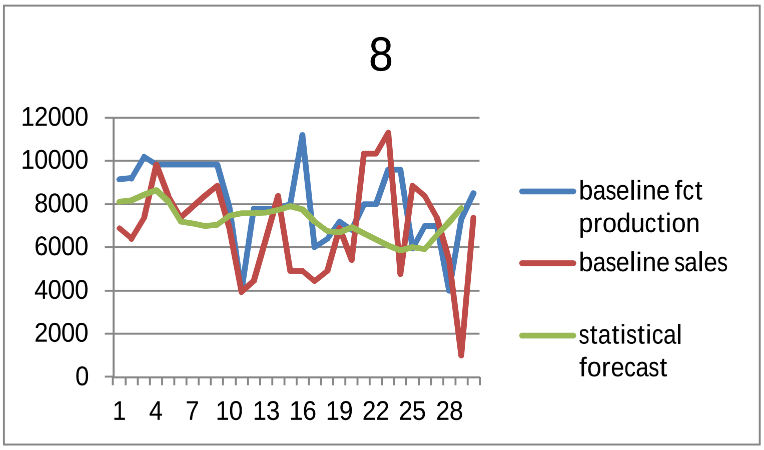
baseline fct packaging
baseline sales
statistical forecast

Appendix H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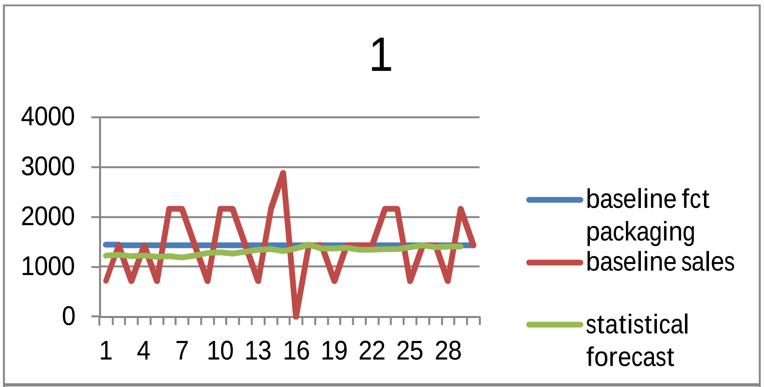
baseline fct production
baseline sales
statistical forecast

Appendix I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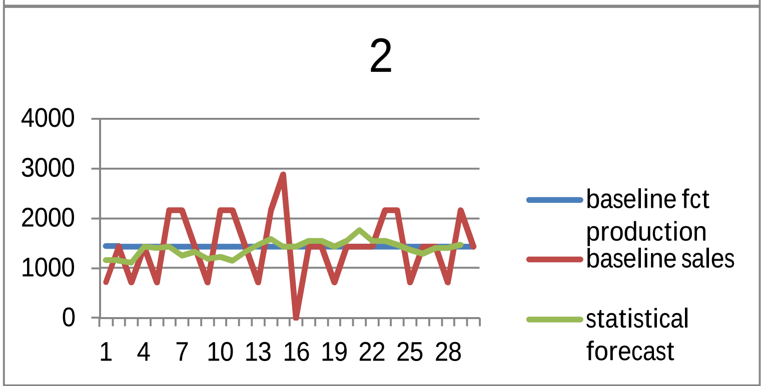
statistical forecast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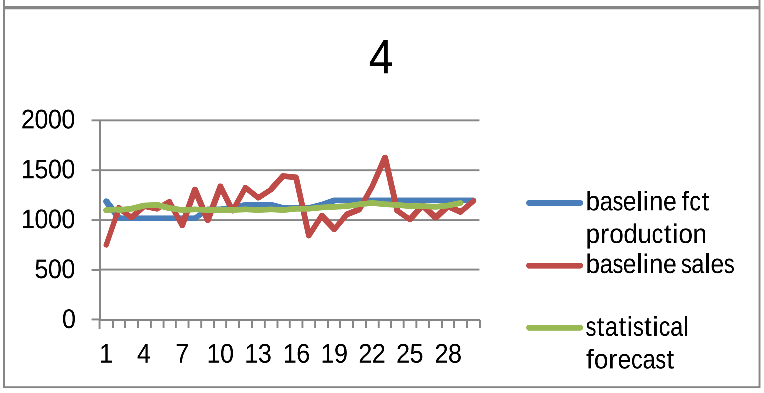
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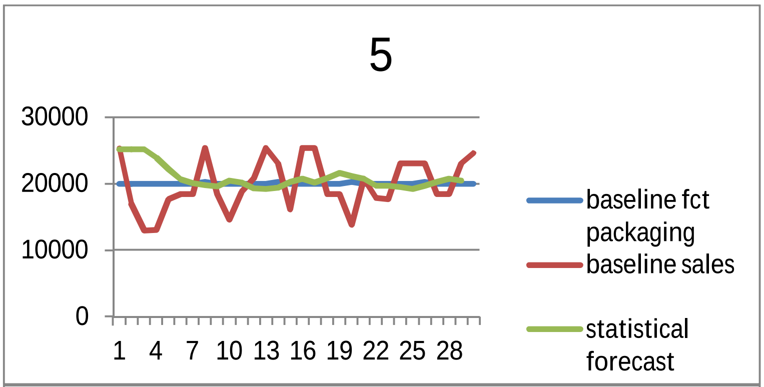
baseline sales
statistical forecast

Appendix J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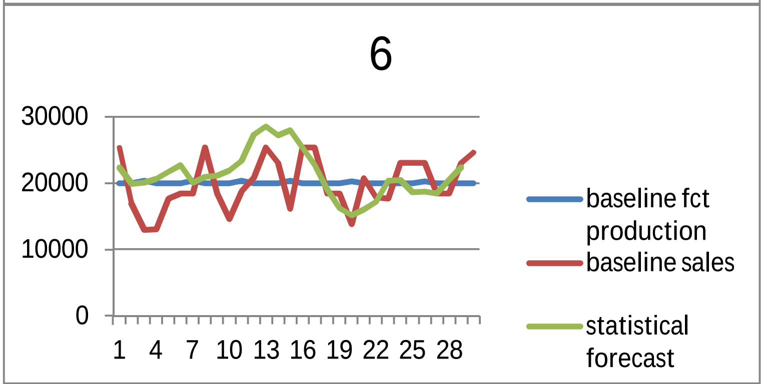
statistical forecast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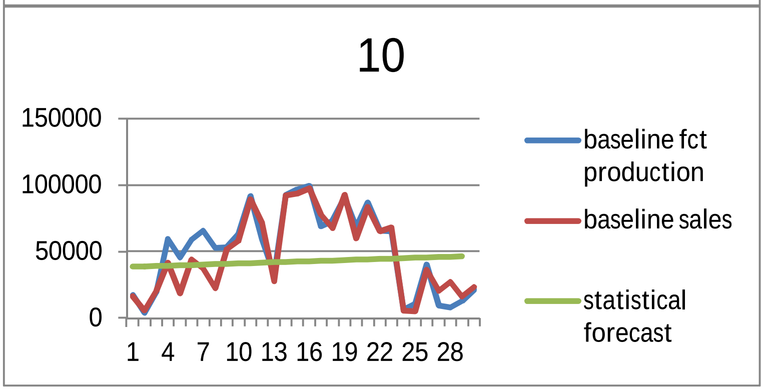
statistical forecast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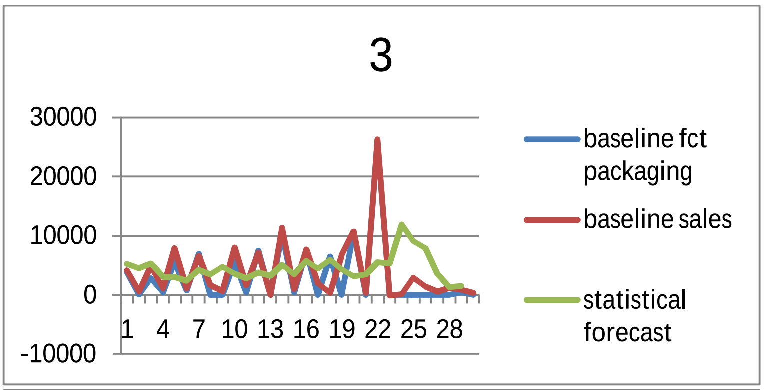
baseline sales
statistical forecast

Appendix K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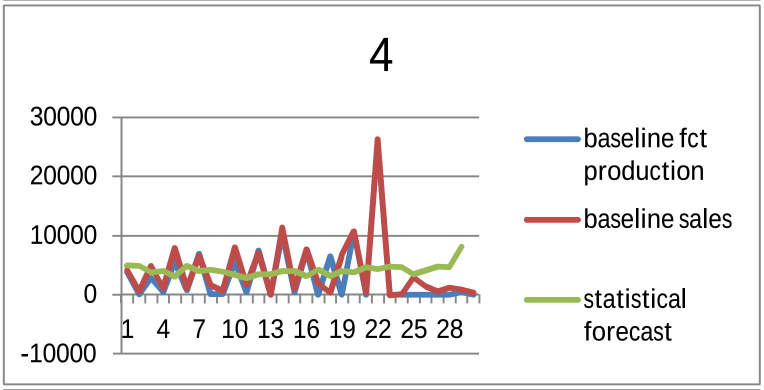
statistical forecast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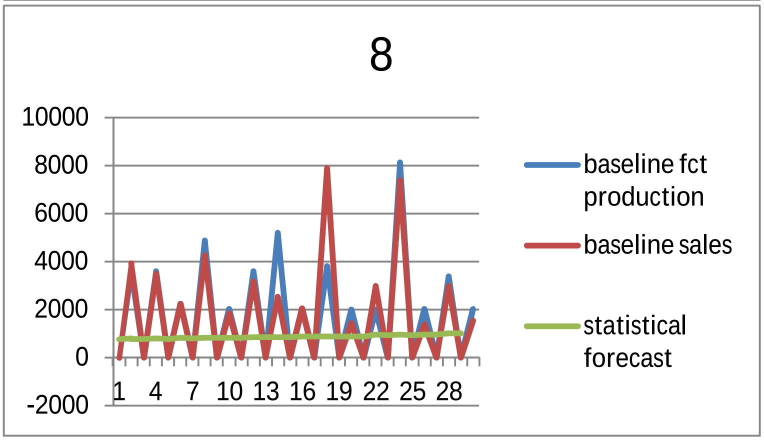
baseline sales
statistical forecast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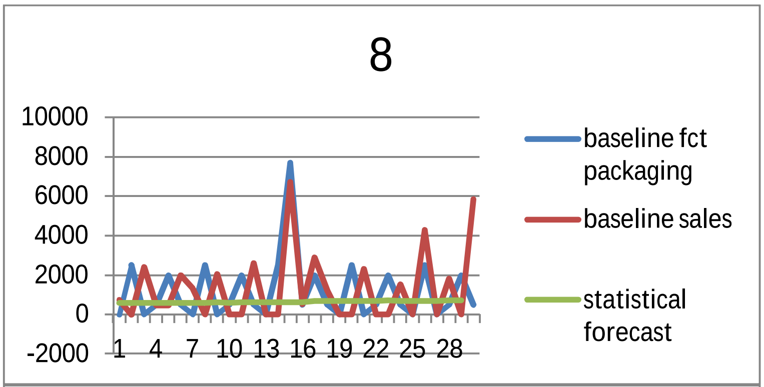
baseline fct production
baseline sales
statistical forecast

Appendix L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4000
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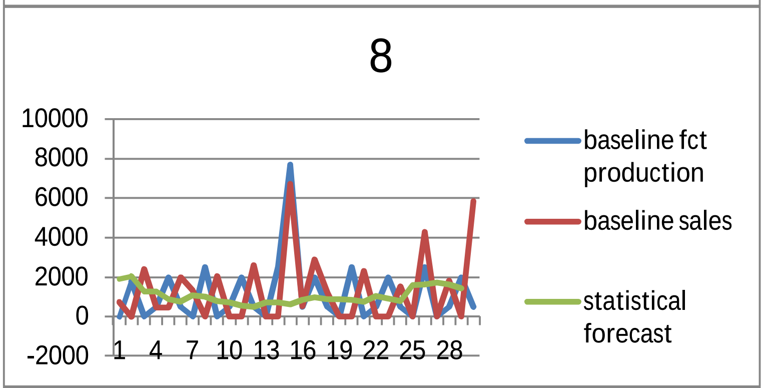
baseline fct packaging
baseline sales
statistical forecast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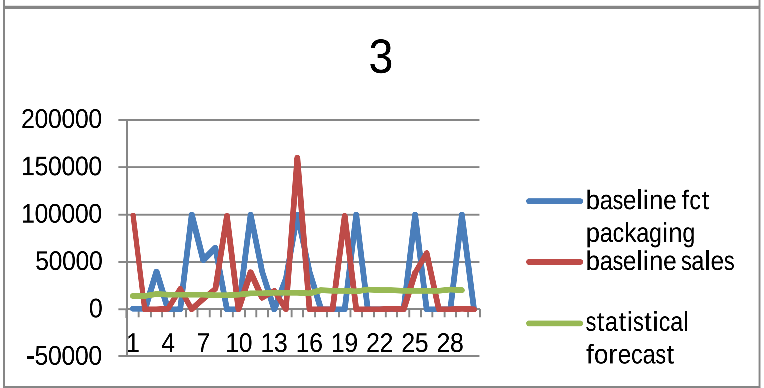
baseline fct production
baseline sales
statistical forecast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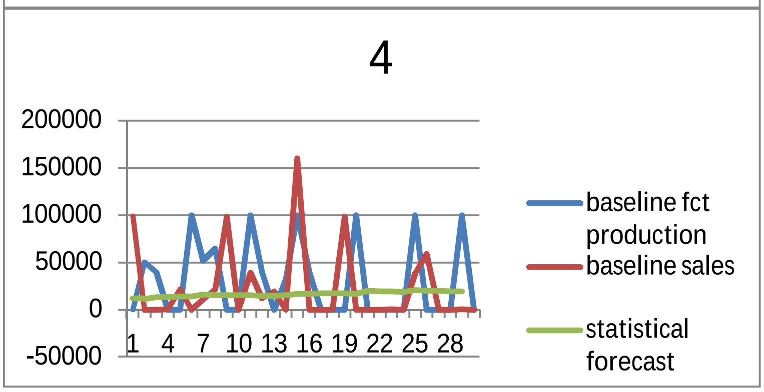
baseline fct packaging
baseline sales
statistical forecast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1 4 7 10 13 16 19 22 25 28
baseline fct production
baseline sales
statistical forecast

Appendix M

coefficient of variation	market	basic material	age	1-year simple moving average MAPE	statistical forecast MAPE	difference MAPE
0,714	BtoB	1	4	73,4%	41,7%	31,7%
0,909	Indirect	2	4	75,3%	52,4%	22,9%
0,913	Indirect	3	4	66,3%	32,3%	34,0%
0,950	BtoB	4	7	57,9%	47,6%	10,2%
1,045	BtoB	5	6	67,5%	32,5%	35,1%
1,096	Indirect	6	24	58,4%	31,3%	27,1%
1,115	Indirect	7	4	78,2%	46,9%	31,3%
1,265	Indirect	8	6	45,6%	11,5%	34,1%
1,317	Indirect	9	11	56,3%	73,3%	-17,0%
1,526	Indirect	10	8	63,1%	34,0%	29,1%
1,539	Indirect	11	6	87,1%	72,1%	15,0%
1,544	Indirect	12	13	88,9%	72,0%	16,9%
1,655	BtoB	13	4	32,1%	55,3%	-23,3%
1,810	BtoB	14	5	70,8%	83,6%	-12,8%

coefficient of variation	market	basic material	age	1-year simple moving average MPE	statistical forecast MPE	difference MPE
0,714	BtoB	1	4	73,4%	-23,6%	49,8%
0,909	Indirect	2	4	57,9%	18,3%	39,6%
0,913	Indirect	3	4	60,1%	12,3%	47,8%
0,950	BtoB	4	7	78,2%	-12,1%	66,1%
1,045	BtoB	5	6	36,3%	39,3%	-3,0%
1,096	Indirect	6	24	47,2%	2,8%	44,4%
1,115	Indirect	7	4	63,1%	0,6%	62,4%
1,265	Indirect	8	6	-94,9%	9,6%	85,4%
1,317	Indirect	9	11	1,7%	14,4%	-12,7%
1,526	Indirect	10	8	64,4%	-32,1%	32,3%
1,539	Indirect	11	6	-15,0%	39,1%	-24,2%
1,544	Indirect	12	13	56,0%	9,8%	46,1%
1,655	BtoB	13	4	62,8%	83,2%	-20,4%
1,810	BtoB	14	5	8,0%	-12,4%	-4,4%

Appendix N

group	commercial article	production/ packaging	best model	best model MAPE	simple exp. smoothing MAPE	double exp. smoothing MAPE	difference best model vs best(simple or double) MAPE
1	1	packaging	Weighted moving avg(12)	12,8%	14,2%	16,7%	-1,4%
1	2	production	Weighted moving avg(12)	12,6%	15,2%	36,6%	-2,6%
1	3	packaging	Weighted moving avg(4)	10,1%	8,3%	9,1%	1,7%
1	4	production	damped trend model	15,3%	20,5%	28,0%	-5,1%
1	5	packaging	damped trend model	14,7%	17,6%	15,1%	-0,4%
1	6	production	damped trend model	16,0%	19,4%	16,8%	-0,8%
1	7	packaging	Weighted moving avg(8)	12,9%	13,8%	17,2%	-0,9%
1	8	production	moving average	21,6%	24,2%	58,4%	-2,6%
1	9	packaging	damped trend model	18,7%	23,1%	20,6%	-1,9%
1	10	production	damped trend model	19,9%	23,0%	24,3%	-3,1%
2	11	packaging	simple exp. Smoothing	39,2%	39,2%	43,1%	0,0%
2	12	production	simple exp. Smoothing	39,0%	39,0%	41,8%	0,0%
2	13	packaging	double exp smoothing	47,3%	48,1%	47,3%	0,0%
2	14	production	Croston's method	48,5%	48,7%	48,6%	-0,1%
2	15	packaging	Weighted moving avg(8)	25,0%	26,1%	29,3%	-1,1%
2	16	production	simple exp. Smoothing	27,4%	27,4%	31,3%	0,0%
2	17	packaging	Weighted moving avg(12)	14,6%	17,6%	16,2%	-1,6%
2	18	production	damped trend model	17,2%	18,6%	18,0%	-0,8%
2	19	packaging	double exp smoothing	18,4%	20,1%	18,4%	0,0%
2	20	production	moving average	18,0%	21,9%	22,3%	-3,9%
3	21	packaging	Weighted moving avg(8)	34,3%	41,7%	39,7%	-5,4%
3	22	production	double exp smoothing	42,9%	45,0%	42,9%	0,0%
3	23	packaging	Weighted moving avg(12)	20,7%	21,5%	21,5%	-0,9%
3	24	production	moving average	22,1%	22,3%	23,6%	-0,2%
3	25	packaging	Weighted moving avg(4)	17,6%	25,5%	36,5%	-7,9%
3	26	production	Weighted moving avg(4)	31,4%	40,8%	38,8%	-7,4%
3	27	packaging	Croston's method	1,0%	1,0%	1,3%	0,0%
3	28	production	Weighted moving avg(8)	1,6%	1,8%	2,8%	-0,2%
3	29	packaging	simple exp. Smoothing	38,4%	38,4%	39,6%	0,0%
3	30	production	Croston's method	35,0%	43,9%	45,8%	-8,9%
4	31	packaging	double exp smoothing	8,9%	9,2%	8,9%	0,0%
4	32	production	Weighted moving avg(12)	7,3%	9,1%	8,6%	-1,3%
4	33	packaging	damped trend model	9,0%	9,4%	10,2%	-0,4%
4	34	production	Weighted moving avg(4)	8,6%	9,3%	11,5%	-0,7%
4	35	packaging	damped trend model	18,6%	18,6%	18,9%	0,0%
4	36	production	damped trend model	16,3%	16,4%	21,6%	0,0%
4	37	packaging	Weighted moving avg(12)	19,3%	21,8%	22,3%	-2,5%
4	38	production	damped trend model	25,8%	27,1%	29,5%	-1,3%
4	39	packaging	double exp smoothing	24,8%	26,0%	24,8%	0,0%
4	40	production	simple exp. Smoothing	32,8%	32,8%	36,9%	0,0%
5	41	packaging	damped trend model	17,8%	20,3%	18,8%	-1,0%
5	42	production	Weighted moving avg(12)	16,9%	20,8%	18,9%	-2,0%
5	43	packaging	damped trend model	8,8%	9,3%	9,4%	-0,4%
5	44	production	damped trend model	8,4%	9,0%	9,6%	-0,6%
5	45	packaging	simple exp. Smoothing	19,2%	19,2%	19,8%	0,0%
5	46	production	simple exp. Smoothing	18,6%	18,6%	19,2%	0,0%
5	47	packaging	simple exp. Smoothing	26,3%	26,3%	26,4%	0,0%
5	48	production	simple exp. Smoothing	25,8%	25,8%	25,9%	0,0%
5	49	packaging	double exp smoothing	22,9%	23,8%	24,9%	-0,9%
5	50	production	Weighted moving avg(4)	23,1%	24,2%	26,3%	-1,1%

group	basic material	age	production/ packaging	best model	best model MAPE	simple exp. smoothing MAPE	double exp. smoothing MAPE	difference best model vs best(simple or double) MAPE
6	51	4	packaging	damped trend model	14,60%	16,20%	17,20%	-1,60%
6	52	4	production	damped trend model	15,30%	16,30%	18,30%	-1,00%
6	53	6	packaging	Weighted moving avg(8)	14,5%	14,7%	16,5%	-0,3%
6	54	6	production	damped trend model	16,9%	16,9%	19,7%	0,0%
6	55	13	packaging	damped trend model	15,4%	24,5%	21,8%	-6,3%
6	56	13	production	Weighted moving avg(4)	14,7%	26,6%	25,7%	-10,9%
6	57	4	packaging	Croston's method	18,3%	21,4%	25,1%	-3,1%
6	58	4	production	Croston's method	17,8%	17,9%	28,9%	-0,1%
6	59	5	packaging	damped trend model	36,3%	36,4%	43,7%	-0,1%
6	60	5	production	linear regression	63,3%	87,3%	83,2%	-19,9%
7	61	4	packaging	Weighted moving avg(8)	13,4%	13,9%	13,8%	-0,4%
7	62	4	production	moving average	13,6%	14,0%	14,0%	-0,3%
7	63	5	packaging	Weighted moving avg(4)	79,3%	89,3%	81,3%	-2,0%
7	64	5	production	Weighted moving avg(12)	81,2%	92,2%	87,3%	-6,1%
7	65	4	packaging	simple exp. Smoothing	49,3%	49,3%	63,1%	0,0%
7	66	4	production	simple exp. Smoothing	49,6%	49,6%	64,2%	0,0%
7	67	2	packaging	simple exp. Smoothing	47,3%	47,3%	57,4%	0,0%
7	68	2	production	simple exp. Smoothing	47,0%	47,0%	56,3%	0,0%
7	69	16	packaging	simple exp. Smoothing	48,5%	48,5%	50,4%	0,0%
7	70	16	production	moving average	65,6%	71,5%	77,3%	-5,9%
8	71	22	packaging	Weighted moving avg(12)	19,8%	21,0%	29,8%	-1,2%
8	72	22	production	moving average	22,9%	28,1%	43,7%	-5,2%
8	73	3	packaging	damped trend model	49,5%	59,4%	57,4%	-7,9%
8	74	3	production	damped trend model	53,2%	58,9%	59,6%	-5,7%
8	75	3	packaging	Croston's method	40,3%	48,4%	42,2%	-1,9%
8	76	3	production	damped trend model	37,7%	49,6%	38,2%	-0,5%
8	77	8	packaging	moving average	43,0%	43,0%	46,5%	0,0%
8	78	8	production	double exp smoothing	43,3%	43,6%	43,3%	0,0%
8	79	7	packaging	moving average	30,6%	31,3%	32,4%	-0,7%
8	80	7	production	Weighted moving avg(12)	31,9%	34,3%	36,2%	-2,4%

Appendix O

group	commercial article	production/ packaging	best model	best model MPE	simple exp. smoothing MPE	double exp. smoothing MPE	difference best model vs best(simple or double) MPE
1	1	packaging	Weighted moving avg(12)	-1,4%	0,0%		1,4%
1	2	production	Weighted moving avg(12)	-5,9%	-5,3%		0,5%
1	3	packaging	Weighted moving avg(4)	0,6%	0,7%		0,0%
1	4	production	damped trend model	15,1%	16,5%		-1,4%
1	5	packaging	damped trend model	-0,7%		4,6%	-4,0%
1	6	production	damped trend model	5,1%		9,0%	-3,9%
1	7	packaging	Weighted moving avg(8)	-6,6%	-4,8%		1,8%
1	8	production	moving average	-5,0%	-8,3%		-3,3%
1	9	packaging	damped trend model	-1,7%	-2,2%		-0,4%
1	10	production	damped trend model	-1,8%	-2,5%		-0,6%
2	11	packaging	simple exp. Smoothing	-7,5%	-7,5%		0,0%
2	12	production	simple exp. Smoothing	-6,0%	-6,0%		0,0%
2	13	packaging	double exp smoothing	11,6%		11,6%	0,0%
2	14	production	Croston's method	26,7%	26,5%		0,3%
2	15	packaging	Weighted moving avg(8)	-18,2%	-21,0%		-2,8%
2	16	production	simple exp. Smoothing	-22,8%	-22,8%		0,0%
2	17	packaging	Weighted moving avg(12)	-7,3%		-13,6%	-6,4%
2	18	production	damped trend model	-14,4%		-16,1%	-1,7%
2	19	packaging	double exp smoothing	4,7%	-10,9%		-6,2%
2	20	production	moving average	-8,4%	-17,0%		-8,6%
3	21	packaging	Weighted moving avg(8)	-12,5%		-18,7%	-6,2%
3	22	production	double exp smoothing	-21,6%		-21,6%	0,0%
3	23	packaging	Weighted moving avg(12)	-6,1%	-4,9%		1,2%
3	24	production	moving average	-13,1%	-12,7%		0,4%
3	25	packaging	Weighted moving avg(4)	-6,1%	-35,9%		-29,9%
3	26	production	Weighted moving avg(4)	-10,2%	-37,6%		-27,4%
3	27	packaging	Croston's method	0,3%	0,3%		0,0%
3	28	production	Weighted moving avg(8)	1,1%	0,9%		0,2%
3	29	packaging	simple exp. Smoothing	-9,6%	-9,6%		0,0%
3	30	production	Croston's method	-14,9%	-11,7%		3,2%
4	31	packaging	double exp smoothing	-2,9%		-2,9%	0,0%
4	32	production	Weighted moving avg(12)	-1,5%		-3,2%	-1,6%
4	33	packaging	damped trend model	0,2%	-1,7%		-1,5%
4	34	production	Weighted moving avg(4)	-2,5%	0,6%		1,9%
4	35	packaging	damped trend model	-7,5%	-7,4%		0,0%
4	36	production	damped trend model	-8,1%	-8,1%		0,0%
4	37	packaging	Weighted moving avg(12)	-6,4%	-6,7%		-0,3%
4	38	production	damped trend model	-8,9%	-8,9%		0,0%
4	39	packaging	double exp smoothing	-1,3%	-6,0%		-4,6%
4	40	production	simple exp. Smoothing	-9,5%	-9,5%		0,0%
5	41	packaging	damped trend model	4,9%		10,7%	-5,8%
5	42	production	Weighted moving avg(12)	-0,9%		12,1%	-11,2%
5	43	packaging	damped trend model	0,8%	0,3%		0,5%
5	44	production	damped trend model	1,1%	0,6%		0,5%
5	45	packaging	simple exp. Smoothing	-5,2%	-5,2%		0,0%
5	46	production	simple exp. Smoothing	-5,1%	-5,1%		0,0%
5	47	packaging	simple exp. Smoothing	-6,0%	-6,0%		0,0%
5	48	production	simple exp. Smoothing	-5,3%	-5,3%		0,0%
5	49	packaging	double exp smoothing	4,4%		4,4%	0,0%
5	50	production	Weighted moving avg(4)	9,6%	8,0%		1,6%

group	basic material	age	production/ packaging	best model	best model MPE	simple exp. smoothing MPE	double exp. smoothing MPE	difference best model vs best(simple or double) MPE
6	51	4	packaging	damped trend model	14,60%	16,20%	17,20%	-1,60%
6	52	4	production	damped trend model	15,30%	16,30%	18,30%	-1,00%
6	53	6	packaging	Weighted moving avg(8)	-3,31%	-3,32%		0,00%
6	54	6	production	damped trend model	-3,18%	-3,61%		-0,42%
6	55	13	packaging	damped trend model	-7,88%		-21,64%	-13,76%
6	56	13	production	Weighted moving avg(4)	-9,27%		-25,69%	-16,42%
6	57	4	packaging	Croston's method	-14,39%	-14,40%		-0,01%
6	58	4	production	Croston's method	-14,30%	-14,22%		0,07%
6	59	5	packaging	damped trend model		MTO-product		
6	60	5	production	linear regression				
7	61	4	packaging	Weighted moving avg(8)	-1,25%		3,48%	-2,23%
7	62	4	production	moving average	-1,22%		3,90%	-2,69%
7	63	5	packaging	Weighted moving avg(4)		MTO-product		
7	64	5	production	Weighted moving avg(12)				
7	65	4	packaging	simple exp. Smoothing	-8,08%	-8,08%		0,00%
7	66	4	production	simple exp. Smoothing	-6,75%	-6,75%		0,00%
7	67	2	packaging	simple exp. Smoothing		MTO-product		
7	68	2	production	simple exp. Smoothing				
7	69	16	packaging	simple exp. Smoothing	4,03%	4,03%		0,00%
7	70	16	production	moving average	-43,69%	-51,08%		-7,39%
8	71	22	packaging	Weighted moving avg(12)	-4,13%	-5,70%		-1,57%
8	72	22	production	moving average	-3,05%	4,85%		-1,80%
8	73	3	packaging	damped trend model	48,88%		36,61%	12,27%
8	74	3	production	damped trend model	44,49%		34,19%	10,30%
8	75	3	packaging	Croston's method	20,15%		-42,22%	-22,08%
8	76	3	production	damped trend model	-5,85%		-38,15%	-32,30%
8	77	8	packaging	moving average		MTO-product		
8	78	8	production	double exp smoothing				
8	79	7	packaging	moving average	-9,24%	31,50%		-22,26%
8	80	7	production	Weighted moving avg(12)	2,76%	32,10%		-29,34%

Appendix P

				aggreagate forecast	sum up direct forecast	difference
market	packaging/ production	basic material	age	MAD	MAD	MAD
Retail	packaging	1	4	3111	3768	-658
Retail	production	1	4	3300	4323	-1023
Retail	packaging	1	10	3213	4841	-1629
Retail	production	1	10	3221	5326	-2105
Retail	packaging	1	18	5426	6966	-1540
Retail	production	1	18	5330	7583	-2253
Retail	packaging	1	24	3640	3411	228
Retail	production	1	24	3345	3168	176
Indirect	packaging	2	4	291	410	-119
Indirect	production	2	4	268	404	-136
Indirect	packaging	2	10	536	662	-126
Indirect	production	2	10	569	664	-95
Indirect	packaging	2	18	295	438	-143
Indirect	production	2	18	520	565	-45
Indirect	packaging	2	24	164	185	-22
Indirect	production	2	24	267	288	-21
IM	packaging	3	10	1247	1782	-535
IM	production	3	10	1296	1831	-535
Retail	packaging	3	10	879	1220	-340
Retail	production	3	10	899	1281	-381
Indirect	packaging	3	10	2966	4950	-1984
Indirect	production	3	10	2470	4771	-2301

Appendix Q

market	basic material	age	commercial article	disaggregate forecast MAD	direct forecast MAD	difference MAD
Indirect	1	10	1	91	29	62
Indirect	1	10	2	24	15	8
Indirect	1	10	3	53	48	5
Indirect	1	10	4	382	385	-4
Indirect	1	10	5	206	183	23
retail	1	4	6	402	367	35
retail	1	4	7	2765	2696	70
retail	1	4	8	186	166	20
retail	1	4	9	339	300	39
retail	1	4	10	191	120	71
retail	1	4	11	177	120	57
retail	1	18	12	356	291	65
retail	1	18	13	3874	3880	-6
retail	1	18	14	173	137	36
retail	1	18	15	1664	1296	368
retail	1	18	16	1479	1361	118
Indirect	2	10	17	56	46	9
Indirect	2	10	18	1402	1118	284
Indirect	2	10	19	1887	1616	271
Indirect	2	10	20	23	21	2
Indirect	2	10	21	20	13	7
Indirect	2	10	22	165	151	14
Indirect	2	10	23	2058	1981	77
Retail	2	10	24	300	295	5
Retail	2	10	25	192	174	18
Retail	2	10	26	743	749	-6

Appendix R

article	average deviation from the median for the first two weeks after a promotion	average sales
1	-29,1%	6674
2	-30,2%	9318
3	-43,1%	1999
4	-27,3%	3512
	weighted average deviation:	-30,5%

commercial article	customer	average deviation from the median for the first two weeks after a promotion
1	1	-30,0%
1	2	-27,3%
1	3	-28,3%
1	4	-34,0%
2	5	-64,3%
2	6	-37,3%
2	7	-34,7%
2	8	-31,1%
2	9	-23,1%
2	10	-39,3%
2	11	-27,5%
3	12	-43,1%
4	13	-22,2%
4	14	-33,3%
4	15	-33,4%
4	16	-29,0%
4	17	-18,8%