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Improving forecasting accuracy through model implementation and process improvement. A case study of Continental Tires Norway.

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Preface

This thesis is submitted as partial fulfillment of the requirements for the Master's degree in Logistics at Molde University College, Norway.

The research topic has been executed under the guidance of supervisor Asmund Olstad. The primary focus of the research was to identify a potential for improving the forecast accuracy at Continental Tires Norway where I work full-time as a supply chain coordinator. Most of the research is focused around creating a forecast model which can be used in the forecasting process at Continental. I have no previous training is using forecast models from my earlier studies, so this has been a unique learning experience.

I would like to thank Asmund Olstad for his guidance in this process, and I also wish to thank Continental Tires Norway for allowing me to use their company as a basis for this thesis.

Preben Hagevik
Oslo, Norway
May 2011

Summary

The purpose of this thesis is to identify ways of improving the forecasting accuracy at Continental Tires Norway through model implementation and process improvement. The potential for improvement will be determined by analyzing the forecasting processes and the model performance.

The Continental Corporation is a German automotive supplier which is represented in 46 countries, with Continental Tires Norway as the company's sales channel for passenger and truck tires in Norway. Production plans and replenishments to markets, along with several other supply chain processes, are to a large extent steered by the forecasts. However, most markets also have a high forecast error. In Norway, the forecast error varied between 50% and 80% on article level in 2010, and it is therefore likely that there is a potential for improvement here.

Previous research on forecasting management suggests that the forecasting process can be analyzed by focusing on three main parameters – forecasting techniques, the use of information in forecasting, and the role of forecasting in decision making processes. Forecasting techniques are divided into subjective and objective methods. While the subjective methods are based on human factors, the objective methods are based on models which calculate a forecast based on data provided to the model. Such models can take into account variations, seasonal curves and trend developments.

This thesis is a single-case study which follows a descriptive design, and it is also deductive since it seeks to support the theory with empirical work. Both quantitative and qualitative data sources will be used for this thesis, and all data sources are primary.

The analysis of the forecasting process showed that there is a potential room for improvement if forecasting models were used at Continental. By using such models as a basis in the forecasting process, it should be possible to improve the forecast accuracy. In addition, the process could be improved further by increasing the amount of external information used in the process. The analysis also points out that the weight given to the forecast in the decision making process should be mirrored by the actual accuracy of the forecast.

Through model testing, it was evident that a forecasting model could improve the forecast accuracy significantly. A test on aggregated level of Continental brand summer tires showed a yearly forecast error of 16.59% in 2010 by using Winters' trend-seasonal model, compared to the actual forecast error which was 29.71%. However, the model could benefit from adjustments to fit the ever changing availability situation at Continental.

Through analysis of the forecasting process and model tests, this thesis has uncovered a potential for improving the forecasting accuracy at Continental Tires Norway. Even though further research should be conducted, it is obvious that Continental Tires Norway could benefit from using a model in the forecasting process, and the company should therefore consider implementing such a model in the future.

Contents

1. Introduction

The purpose of this thesis is to find ways of improving the forecast accuracy and the forecasting process at Continental Tires Norway. Many of the supply chain processes at Continental are based on the forecast, including crucial processes like production planning and replenishments to markets, thus making forecast accuracy very important. However, there is currently no common forecasting model in use neither at Continental Tires Norway, or in the other countries in Business Unit EMEA (Europe, Middle East, Africa). Further, the forecast error on article level in 2010 for Norway was in the interval 50-80% all through the year, a number which is representative for the other countries in the Business Unit as well. It therefore seems apparent that there is a potential for improving the forecast accuracy at Continental, thus also allowing the supply chain process to function with more correct input.

In this thesis, the task of improving the forecast accuracy will be approached from two ends. The main part of the thesis will focus on creating a forecast model which can yield better results than the actual forecast from Continental. After explaining basic forecasting theory, two models which should be suited for the task at hand will be presented. These models will then be tested against the actual forecast from 2010, and the results will be analyzed. The intention is that one model will serve as a benchmark for the other, thus demonstrating which model is best for this case.

One important issue to keep in mind is that Continental tends to operate with a lower production capacity than necessary to cover the customer demand. This capacity constraint sometimes leads to shortage situations on several articles. Since there does not seem to be any studies done on forecasting models in shortage situations, the thesis will stick to the standard models and try to identify areas where adaptations should be made.

The second part of this thesis will focus on the actual forecasting process. Even a well-functioning model cannot be expected to create the best possible forecast alone, and it is therefore necessary to analyze the current forecasting process at Continental and identify potential areas of improvement.

Upon completing these two tasks, the aim is to give concrete recommendations as to what Continental Tires Norway should do in order to significantly improve the forecasting process. If these recommendations are followed and result in a significant improvement, this process can potentially serve as a best practice for the rest of Business Unit EMEA, and hopefully contribute to an improvement in the entire supply chain process.

Since creating the best possible forecasting model for Continental is expected to be a vast task, this thesis will be limited to demonstrating the potential improvements of using such a model. If possible, recommendations regarding ways to adapt the model to Continental's needs will be identified and suggested as further research.

"It is often said there are two types of forecasts ... lucky or wrong!!!!"

(In "Control" magazine, published by Institute of Operations Management)

2. Company Background

This section will provide a description of Continental. First, there will be a brief presentation about the mother company in Germany, and then a more detailed description about the company's operation in Norway will be described. Special attention will be given to the supply chain and forecasting processes.

2.1 The Continental Corporation

The Continental Corporation is a German automotive supplier with a main seat in Hanover, Germany. The company is among the top 5 automotive suppliers worldwide, and holds the number two spot in Europe. The Continental Corporation is a supplier of brake systems, systems and components for powertrains and chassis, instrumentation, infotainment solutions, vehicle electronics, tires and technical elastomers.

With 148,228 employees (per December 31, 2010) in 46 countries, the Continental Corporation is divided into the Automotive Group and the Rubber Group, and consists of six divisions:

- *Chassis & Safety* embraces the company's core competence in networked driving safety, brakes, driver assistance, passive safety and chassis components.
- *Powertrain* represents innovative and efficient system solutions for vehicle powertrains.
- *Interior* combines all activities relating to the presentation and management of information in the vehicle.
- *Passenger and Light Truck Tires (PLT)* develops and manufactures tires for compact, medium-size, and full-size passenger cars, as well as for SUVs, vans, motorcycles, and bicycles.
- *Commercial Vehicle Tires (CVT)* offers a wide range of truck, bus, industrial, and off-road tires for the most diverse service areas and application requirements.
- *ContiTech* develops and produces functional parts, components, and systems for the automotive industry and for other key industries.

The company is divided into two groups with three subdivisions each. The *Automotive Group* comprises of *Chassis & Safety*, *Interior* and *Powertrain*, while the *Rubber Group* consists of *Passenger & Light Truck Tires*, *Commercial Vehicle Tires* and *ContiTech*.

2.1.1 Passenger & Light Truck Tires Division

The PLT division has production facilities at 27 locations in 16 countries and a workforce of 28,276. It generated sales of €5.8 billion in 2010. Passenger and Light Truck Tires comprises of five business units:

- Original Equipment
- Replacement Business, EMEA
- Replacement Business, The Americas
- Replacement Business, Asia Pacific
- Two-Wheel Tires

The two main distribution channels are Original Equipment (OE) and Replacement (RE). OE serves the car industry, and ensures that all new cars have a set of tires before they roll out of the production plant. RE serves the aftermarket, thus serving customers who wish to change their existing tires.

Since Continental has agreements with the auto makers to deliver tires in time, OE has the highest priority of the two distribution channels. This means that if production is only sufficient to cover the OE demand, no tires will be produced for RE.

2.1.2 Commercial Vehicle Tires Division

Commercial vehicle tires are manufactured at 15 locations in ten countries. In 2010, 7,156 employees generated sales totaling €1.4 billion. The division comprises of four business units:

- Truck Tires, EMEA
- Truck Tires, The Americas
- Truck Tires, Asia Pacific
- Industrial Tires

2.2 Continental Tires Norway

Continental Tires Norway is the sales channel in Norway for both the PLT division and the CVT division of the Continental Corporation. Since there are no noteworthy auto makers in Norway, all tires sold in Norway are sold through the RE distribution channel.

2.2.1 Sales split winter/summer

Even though most people would think that winter tires are mostly sold during the winter time, this is not the case in Norway. Since all new cars produced are delivered to the car dealers with summer tires, the Norwegian car dealers also need to supply their customers with winter tires for their new car. Even though the car customers only need winter tires if they get their car delivered during the winter season, most customers buy winter tires when they purchase a new car, regardless of the season. This leads to a huge demand for winter tires throughout the year, and even though winter tire sales peak in the autumn, the demand remains relatively high all year.

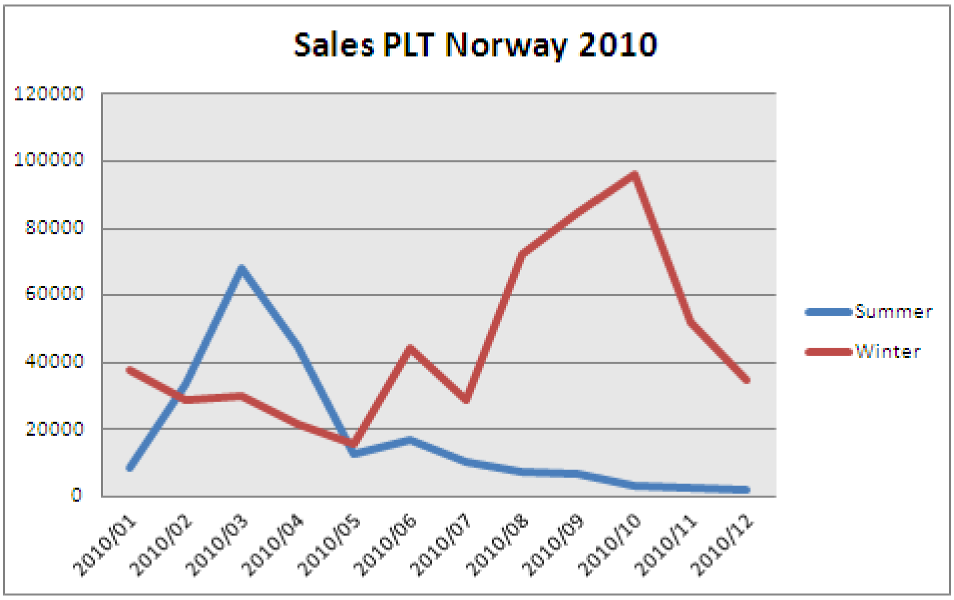


Figure 2.1 - Sales PLT Norway 2010

As seen from the table above, this also means that winter tires are by far the biggest segment for Continental. The winter tires sold in Norway are mainly tires especially made for Nordic conditions. This means that the fight for availability is mainly between Norway, Sweden, Finland, Russia and NAFTA. When it comes to summer tires, all markets share most of the same articles, so there is more internal competition for these tires.

2.2.2 Customer structure

Continental Tires Norway's biggest customers are the car dealers and Dekkmann. The car dealers are by far the largest customer segment for Continental, while Dekkmann is the second largest. Dekkmann is a tire chain with 42 stores across Norway, and it is fully owned by the Continental Corporation. So while car dealers and other customers can come and go, Dekkmann will always remain a customer.

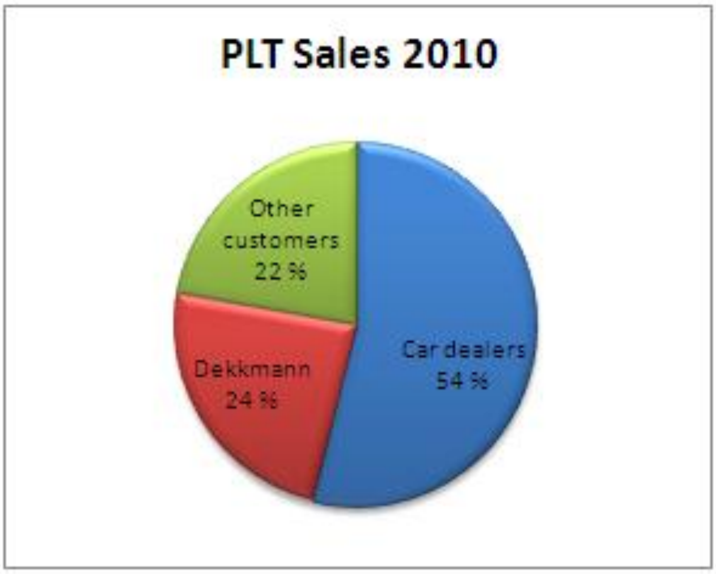


Figure 2.2 - Customer split

Dekkmann is required to take early deliveries of pre-season orders in order to reduce pressure during peak season. Other customers usually have a pre-season deadline, but can basically order when they want. This means that the demand from Dekkmann is known well before the season starts, while the demand from other customers is relatively uncertain until a few weeks before the season is expected to start.

2.2.3 Brand structure

Continental Norway operates with a multi-brand structure. Over the years, the Continental Corporation has bought several tire manufacturers, and they have kept the brands due to their market positions in the different markets. This allows markets to offer different brands to different prices, and to different customers. While most customers want to offer the premium brand to their customers, many of them also like to have cheaper brands available for customers that are more price sensitive. In addition, some customers like to have their own exclusive brand.

Brand	Type	Customer
Continental	Premium	All
Semperit	Quality	All
Uniroyal	Quality	All
Sportiva	Quality	All
Barum	Budget	All
General	Private	Dekkmann
Gislaved	Private	Wholesalers

Table 2.1 - Brand split 2010

While Continental and Barum are brands which are sold year round, the other brands are usually only sold on pre-season and refill orders to the customers, and thus not usually kept on stock in Norway.

2.2.4 Askim RDC

Continental Tires Norway has one large warehouse, or regional distribution center (RDC), in Norway. It is located in the quaint town of Askim, and has a floor space of 12.096m^2. It has a storage capacity of close to 200,000 tires, and it also houses production lines for complete wheels (KITs) and storage space for rims and other articles sold by Continental Tires Norway. Most of the sold volume is shipped to the customers from Askim RDC, but there is also a minor share of direct shipments from the plants. In addition, Continental has six business support points (BSP) in six major cities in Norway. These are mainly used for rush orders in cases where the customer can’t wait, and the volume distributed from these BSPs is also minor.

Askim RDC

2.3 Supply chain and forecasting process

Continental uses different ERP systems to manage the supply chain process. Even though the entire system landscape at Continental is quite complex, there are two major systems that are at the foundation of all important logistics processes.

2.3.1 FOS (I2)

The planning system used at Continental is FOS I-Grid. In this system, the forecaster can enter forecasts on both article and top level. Each market must always have a forecast for the next 18 months in the system. These figures are the basis for planning of future production demands, and are thus the main input from markets e.g. regarding needs for increased production capacity. The last 15 months of the forecast horizon are called budget figures, and they have no impact on actual replenishments to the markets. All replenishments are calculated based on the first 12 weeks in this 18 month period. This basically means that it's hard to say anything about availability beyond the coming 12 weeks as production plans have yet to be implemented for this period. In fact, production plans are usually just implemented for a 3-5 week horizon at a time to remain flexible.

Planning horizon	**Period**	**Major output**	**Frequency**
Replenishment Plan	Rolling 12 weeks	Shipment plan Replenishment plan	Twice per week
Master Plan	Rolling 18 months	Confirmed production demand Confirmed forecast	Once per week

Table 2.2 - Planning cycle

The actual calculations of replenishment plans and production demands are made by FOS I2. The replenishment runs are made every Sunday and Wednesday evening, with the results being available the next morning. So in case of changing demand, markets will have to wait a while before they see if they will get what they're asking for. As seen in the figure below, the forecast is measured against the stock level of the market, and the deviation between these figures is reported as a Supply Demand. The Supply Demands from all markets are then reported to the plants, and measured against the stock level of the plant to form a Production Demand. If no production restrictions or shortages are in place, the Production Demand will be confirmed, and the markets will get their Supply Demand confirmed, which in turn means that the markets forecasts are confirmed.

Figure 2.3 - Demand calculation process

In order to optimize earnings, Continental does not operate with over capacity. During the credit crunch in 2009, the company closed down two plants in Europe in order to cut costs and cope with the decreasing demand. In addition, several plants reduced their working hours. Since Continental never plans for over capacity, availability is always an issue. This means that even though a market forecasts a certain volume, it might not get the entire volume accepted in the production planning. The main reason for this is the fact that the forecast error worldwide is quite high, and in cases of unexpected demand, shortages will occur instantly. Also, in cases where the production demand towards the plant is higher than the actual capacity, plants are free to produce to cover the demands they choose, although within certain guidelines given by Central Management. Usually, this means that the plants produce the less resource intensive articles, which in turn leads to some articles being fully produced to demand, while others are hardly produced at all.

The deviation between the total demand and Continental's ability to fulfill orders in time is best seen in the Requested Delivery Date (RDD) Fill Rate. In 2010, this fill rate for RE markets was 51.7% for the company's premium brand, Continental. This is the brand with the highest priority in the production. The figure below shows the RDD fill rate for the top 10 markets with sales above 200,000 tires in this period, and underlines the challenges Continental are faced with when it comes to availability.

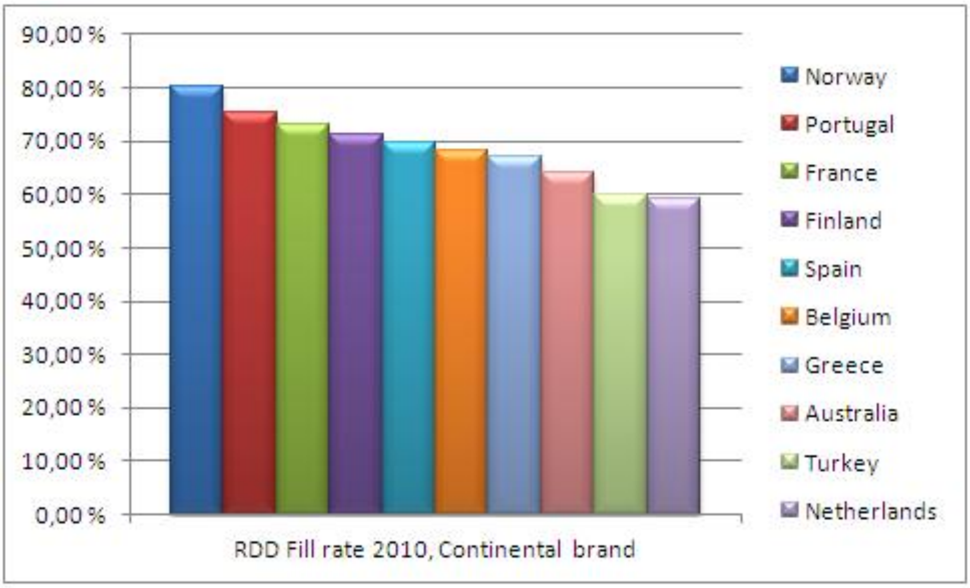


Figure 2.4 - RDD Fill Rate 2010

To catch this possible deviation of demand and availability, markets are issued a Released Forecast based on their Actual Forecast. In periods where the demand generally matches the possible production capacity, the Released Forecast will usually be the same as the Actual Forecast, but with expected shortages, markets are normally issued a lower forecast than they have asked for. This is an attempt to catch the deviations in the production process, thus avoiding plants being over booked. However, it is possible for a market to sell more than the Released Forecast, since this forecast merely controls the automatic replenishment process. Manual confirmation of orders is a daily occurrence at most plants, and Central Management may also make changes from time to time, e.g. allow a market to get more than its assigned share. This will in certain cases lead to some markets getting more than they have forecasted, while others get less.

2.3.2 SAP

SAP is used for pretty much everything except the planning activities performed in FOS I-Grid. For the logistics and sales department, this basically means order management. All orders are entered and maintained in SAP, and since SAP operates in real time, it is possible to access actual availability data in this system. Everything from the status of replenishments orders to incoming and outgoing shipments, and of course stock levels in all plants and markets.

2.3.3 Forecasting process

The forecasting process in Norway is basically the same as for any other market in Europe. One person sits with the forecasting responsibility, and this person uses historical sales data and any available market intelligence to create the forecast. Since the budget figures cover 18 months, the basic forecast will usually be a copy of last year's forecast. Before each season, the forecaster will do a rough adjustment of the forecast for the coming season based on some key factors.

The *expected seasonal peak* is perhaps the most important factor. For the summer season, the peak will usually build up towards the Easter weekend, but if there is a late Easter, the peak might come earlier. Since Dekkmann usually gets their orders earlier than the other customers, this peak will not be as steep in years with a late Easter as in other years. When it comes to the winter season, the peak is usually around October, but with orders for Dekkmann usually delivered in August or September.

In years with expected delivery problems worldwide, Central Management in Germany usually introduces *forecast limits*. This is an attempt to avoid markets planning higher sales than the production capacity in certain periods. These limits can affect the planned forecast, leading to tough choices. However, the forecast limits are only on top level on a monthly basis for each market. In practice, this means that usually only the other brands are reduced, while the forecast on Continental remains the same.

The *sizing trend* on new cars is also an important factor, but then mainly for the winter tires since almost all new cars in Norway are sold with winter tires. This means that a dimension which was big two years ago might not be big now. If the forecaster only bases the forecast on historical sales, one runs the risk of forecasting a dimension which is no longer sold with new cars.

When the rough forecast is ready for the coming season, the forecaster will focus mainly on the current and coming month. Each Friday, the forecast will be updated for the current month to reflect any unexpected changes in demand. If not, one runs the risk of ”selling out” the forecast, thus not reflecting the actual demand in the system. It is also important to tweak the forecast for the coming month since the lead time is two weeks in Norway. In the last week of the month, a forecast meeting is held, and the final forecast (Forecast One) is finalized for the coming month. This forecast reflects the open order situation and the expected sales, which is based on historical data and some guess work. After Forecast One is submitted to the system, each market will be issued a Released Forecast One which will be the actual forecast for that market. In most cases, though, this will be the same figure as Forecast One.

The figure below shows the forecast error for PLT RE in 2010. The forecast error is calculated as the absolute deviation of sales from Released Forecast One on article level.

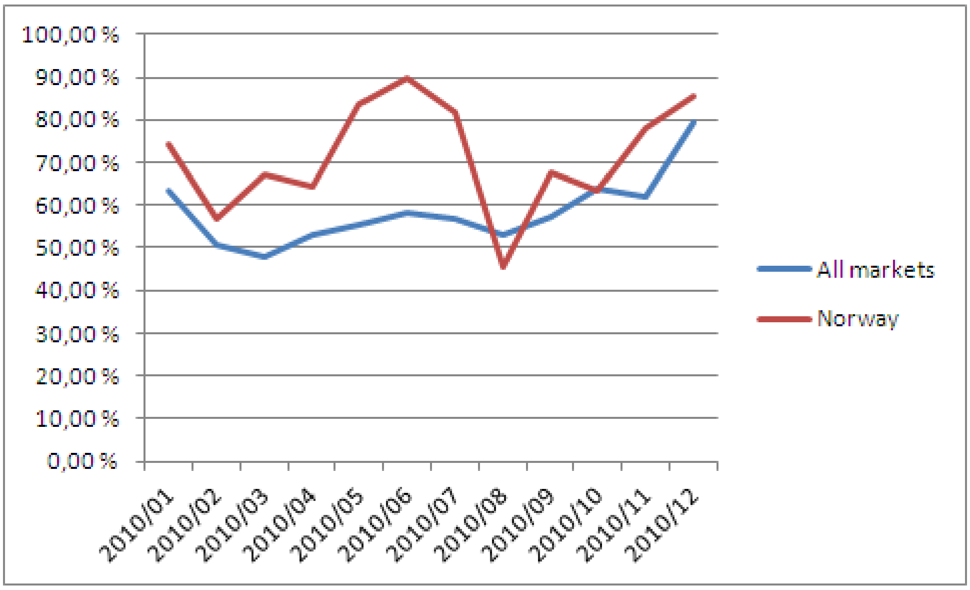


Figure 2.5 - Forecast error PLT RE 2010

From this figure, it is obvious that there is a potential for improvement. Since all production planning and all replenishments to markets are based on the forecast, there should be an opportunity to improve availability if the forecast is improved.

3. Literature Review

In this section, the thesis will review relevant forecasting techniques, and also take a closer look at forecasting process analysis. Forecasting techniques can either be objective or subjective. When using objective forecasting techniques, one uses past history to create a forecast, often with the help of a forecasting model. Subjective forecasting, on the other hand, is the result of either individual or group opinion (Nahmias, 2005).

Surveys on how forecasting is practiced have shown that subjective techniques are more widely used than objective. However, an extensive body of research supports the superiority of objective forecasting techniques (Davis & Mentzer, 2007).

3.1 Forecasting Management

Demand forecasting is an important issue for manufacturing companies. Everything from production planning and sales budgeting to new product launches and promotion planning are dependent on an accurate forecast. This has made the quest for techniques that will increase the forecasting accuracy a critical success factor for companies around the world (Danese and Kalchschmidt, 2011). However, while the hunt for the perfect forecasting system is ongoing, several researchers have suggested that forecasting technique adoption is not enough to guarantee good forecast accuracy, and that studies on forecasting should also consider other crucial topics linked to how the forecasting process is managed and organized (Mentzer and Bienstock, 1998; Moon et al., 2003).

There is more to forecasting management than just the relationship between forecasting techniques and forecast accuracy. Good forecasting management includes:

- **Decisions on information-gathering tools**
  What information should be collected, and how.

- **Organizational approaches to be adopted**
  Who should be in charge of forecasting, and what roles should be designed.

- **Interfunctional and intercompany collaboration for developing a shared forecast**

Using different sources of information within the company or supply network, joint elaboration of forecasts, etc.

- **Measurement of accuracy**
  Using the proper metric and defining proper incentive mechanisms

In literature, these are often mentioned as critical forecasting variables for significantly reducing forecast errors (Fildes and Hastings, 1994; Mentzer and Bienstock, 1998; Moon et al., 2003).

If a company has a proper forecasting process, it has the opportunity to better understand market dynamics and customers' behaviors. In addition, it can reduce uncertainty on future events, and provide the company's functions with useful analyses and information. In turn, this can influence cost and delivery performance. Even though a company might not consider the improvement of forecast accuracy as a priority, it could through better forecasting management achieve important improvements in cost and delivery performance by guiding the company's decisions on the basis of a better understanding of market dynamics and customer's behaviors (Moon et al., 2003).

In the following section, this thesis will look closer at ways to analyze the forecasting process in a company. The objective is to map out key variables to analyze when looking at the forecasting process.

3.1.1 Forecasting process analysis

In order to analyze the forecasting process at a firm, it is helpful to map out the different variables in order to get an overview of the actual situation. In order to organize these variables, it is helpful to have a solid framework. Different authors have proposed different frameworks for analyzing the forecasting process:

Fildes and Hastings' three variables (1994):

- Information flows (Using information on the environment)
- Technical characteristics of the forecast (Accuracy and bias)
- The forecaster and decision maker (Forecaster's training and use of forecasts for different decision making processes)

Mentzer and Bienstock's four areas of forecasting management (1998):

- Forecasting systems that allow the forecaster access to a common information base within the company and use of data from customers and suppliers
- Forecasting measurement concerning the type of metric used to measure forecast accuracy and operational performance related to the forecasting process
- Managerial forecasting approaches that differ not only with regard to the extent to which data and information from different sources are used, but also the extent to which decisions within the company are based on a single forecast
- The techniques that can be adopted to elaborate forecasts

Moon et al.'s forecasting model composed of four dimensions (2003):

- Approach (The kind of technique used)
- Functional integration (Degree of communication and coordination between functional areas)
- Systems (Electronic links, information availability)
- Performance measurement (Metric for accuracy)

Even though these frameworks are different in some aspects, there are three groups of variables that they all have in common. The *techniques* adopted, the *information* combined to elaborate forecasts and the *role* of forecasting in supporting decisions within the company. Thus, when attempting to analyze the forecasting process in a firm, these three variables may provide a solid framework for the analysis.

3.1.1.1 Forecasting techniques

Forecasting techniques are the actual technical methods a firm uses to create the expected sales figures. There are two general approaches to forecasting - an objective analysis or a subjective approach. The objective analyses can be divided into time-series models, which uses past data to make a forecast, and associative models where variables that might influence the quantity being forecasted are included. Subjective forecasts incorporate such factors as the decision maker's intuition, emotions, personal experiences and value system in reaching a forecast (Heizer & Render, 2006).

Examples of forecasting techniques can be:

- Objective time-series models (e.g., exponential smoothing)
- Objective associative models (e.g., regression of econometric analysis)
- Subjective models (e.g., market survey or sales quota)

In addition, a common approach to forecasting includes using a statistical model to create an initial forecast. This forecast is then reviewed by a jury of executive opinion and changes are made in order to reach a final forecast. This forecast is then a combination of a statistical forecast and managerial judgment (Fildes et al., 2009). According to Keen and Scott Morton (1978), a forecast support system, like such a model, is appropriate when managerial judgment and the model can provide a better solution than either alone.

3.1.1.2 Use of information in forecasting

Forecasting techniques might not always be sufficient to improve forecast accuracy (Moon et al., 2003). In order to create a correct forecast, it may prove useful to gather as much relevant information as possible. By combining information and data from different functions, suppliers and customers, one can obtain more knowledge about future trends, thus enabling the forecaster to more precisely predict future demand (Danese & Kalchschmidt, 2011).

Examples of information sources can be:

- Current economic conditions
- Customers' sales plans
- Supplier information
- Market research

3.1.1.3 The role of forecasting in decision making

Even though a company both has good forecasting techniques and takes an active approach to information gathering in this process, it will not do much good unless the forecast is included in the decision making process (Mentzer & Bienstock, 1998). Good forecasting requires that the forecast is shared within the organization (Danese & Kalchschmidt, 2011), and improved forecasting techniques are useful only "*if applied to an organization's decision making and planning processes*" (Winklhofer et al., 1996, p. 194).

Examples of such decisions and processes can be:

- Sales and budget preparation
- Production planning
- New product development
- Equipment planning

3.2 Objective Forecasting Techniques

The objective forecasting techniques which will be used to solve the research problem are quite advanced, and it is therefore necessary to through the basic techniques first. Upon doing this, the chapter will focus on the two models which shall be used in this thesis.

Forecasts that are connected to inventory and purchasing to cover future orders usually cover a relatively short time horizon (Axsäter, 2010). Such a time horizon will normally not cover more than one year ahead, and for such forecasts there are two types of approaches that may be of interest. The first, extrapolation of historical data, means that the forecast is based on previous demand data. The techniques involved in this process are grounded in statistical methods for analysis of time series, and this is the most common and important approach to obtain forecasts over a short time horizon. The second approach is forecasts based on other factors. In this case, the historical data is considered to be of little value, thus requiring a forecast based on other inputs. Examples of such scenarios are sales campaigns or spare parts for machinery with a changing demand curve. In these cases, a manual adjustment of the forecast will often prove to be the most practical method.

3.2.1 Demand models

In order to determine a suitable technique to extrapolate historical data, the stochastic demand must be modeled. There are three basic models which should first be considered when choosing a technique.

3.2.1.1 Constant model

In the constant model, the demands in different periods are represented by random deviations from an average that is assumed to relatively stable over time compared to the random deviations. We have to introduce some notations to explain the model:

x_t = demand in period t

a = average demand per period (assumed to vary slowly)

ε_t = independent random deviation with mean zero

A constant model means that we assume that the demand in period t can be represented as:

$$x_t = a + \varepsilon_t$$

Products which are at a mature stage in their life cycle and are used regularly can be represented by a constant model. In other words, the constant model will generally work well for all products where we don't expect a trend or a seasonal pattern.

3.2.1.2 Trend model

For products where the demand is expected to increase or decrease systematically, we can extend the model by also considering a linear trend.

a = average demand in period 0 (assumed to vary slowly)

b = trend (systematic increase or decrease per period)

In a trend model, the demand is modeled as:

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

A normal product life cycle includes an initial growth stage where it is natural to model with a positive trend and a phase-out stage where it is natural to model with a negative trend.

3.2.1.3 Trend-seasonal model

If we also want to add seasonal fluctuations to our model, we must add another factor.

F_t = seasonal index in period t (assumed to vary slowly)

The value of F_t indicates the seasonal deviation in period t. If $F_t = 1.1$, this means that we expect the demand to be 10% higher in period t. The demand in a trend-seasonal model can be expressed as:

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

We can also set $b = 0$ to get a constant-seasonal model. A seasonal model is only meaningful if the demand follows essentially the same pattern year after year.

3.2.1.4 Choosing a demand model

In general, one might assume that the model with the most input alternatives is the best choice for a forecaster. However, more alternatives offer more sources of error. Demands must always be expected to vary, and the more parameters which must be estimated, the greater the chance is for increasing the forecast error. It is therefore important to choose a more general model like the trend-seasonal model only if the extra input parameters are fairly certain. Also, historical sales data might not always be correct as these will not tell you the historical demand. It is therefore important to identify shortage periods in the historical sales data, and, if possible, estimate expected sales with full availability in order to get a more reliable historical data set.

3.2.2 Forecast error

Before continuing with the models, it is important to have an understanding for how forecast accuracy can be measured. In order to measure the accuracy of a forecasting model, the forecast can be compared to the actual sales. The forecast error can thus be expressed as:

$$\text{Forecast error} = \text{Actual demand} - \text{Forecast value}$$

There are several measures which can be used to calculate the overall forecast error. Two of the most commonly uses methods are mean absolute deviation and mean absolute percentage error (Heizer & Render, 2006).

It is important to note that the forecast error in itself will not say anything about whether it is good or bad. Forecasting methods might not always be chosen in order to optimize the forecasting accuracy, and some companies might value a least cost inventory policy over an accurate forecast method. Therefore, the evaluation of the forecast error depends on the purpose for which management requires the forecast (Wright, 1988).

3.2.2.1 Mean Absolute Deviation (MAD)

The mean absolute deviation is computed by taking the sum of the absolute values of the individual forecast errors and dividing by the number of periods of data (n):

$$\text{MAD} = \Sigma\ (\text{Actual - Forecast}) / n$$

The main problem with using MAD to calculate forecast accuracy is that its value depends on the magnitude of the item being forecasted. A MAD value of 100 doesn't tell us anything about the forecast performance unless we also know the forecast and actual demand.

3.2.2.2 Mean Absolute Percentage Error (MAPE)

In order to avoid potential problems with MAD, we can calculate the mean absolute percentage error, or MAPE. The MAPE is computed as the average of the absolute difference between the forecasted and absolute values, expressed as a percentage of the actual values.

$$\text{MAPE} = 100 * \Sigma\ ((\text{Actual - Forecast}) / \text{Actual}) / n$$

By using the MAPE, the reader will immediately get a clear picture of the forecast performance, thus making it a very useful measure.

3.2.3 Forecasting methods

With the three basic demand models as a basis, we can look at some methods for forecasting. There are several different techniques, each suited for different demand structures, and in this section we will go through four of the most common techniques.

3.2.3.1 Moving average

In cases where the demand a is not completely constant, but rather varying slowly, it can be prudent to give a higher weighting to the most recent values of the demand. By applying the moving average technique to the constant model, we take into account the average over the N most recent values.

$\hat{a}_t$ = estimate of a after observing the demand in period t

$\hat{x}_{t,\tau}$ = forecast for period $\tau > t$ after observing the demand in period t

The demand in the moving average model can be expressed as:

$$\hat{x}_{t,\tau} = \hat{a}_t = (x_t + x_{t-1} + x_{t-2} + \ldots + x_{t-N+1}) / N$$

The value of N should depend on how slowly we think that a is varying, and on the size of the stochastic deviations ε_t. We should use a high value of N if we have slow variations of a and large stochastic variations, and subsequently a low value of N if a varies rapidly and the stochastic variations are small. By having a period length of one month, N=12 will forecast the average over the preceding year. This is an advantage if one wishes to prevent seasonal variations from affecting the forecast.

In the example below, we use N=3. The forecast for Month 4 is therefore the average of the three previous months and so forth. As we can see, the forecast for this month is relatively high due to the high demand in Month 1.

Moving average - N=3

Month (t)	1	2	3	4	5	6	7	8	9	10	11	12
Demand	16	10	9	9	11	10	8	7	9	11	10	12
Forecast				12	9	10	10	10	8	8	9	10
Deviation				3	-2	0	2	3	-1	-3	-1	-2

Table 3.1 - Example of moving average

3.2.3.2 Exponential smoothing

In order to put more focus on recent demand development, we can use a technique called exponential smoothing. The model is similar to moving average, but while the N last period demands all have the weight 1/N in moving average, the weights in exponential smoothing decrease exponentially as we go backwards in time. We will then catch the minor deviations of a, and still have a constant model.

To update the forecast in period t, we use a linear combination of the previous forecast and the most recent demand x_t:

$$\hat{x}_{t,\tau} = \hat{a}_t = (1-\alpha)\,\hat{a}_{t-1} + \alpha x_t$$

where $\tau > t$ and

α = smoothing constant ($0 < \alpha < 1$)

In order to see how this works, we will look at a demand series over 12 periods. In the first table, a smoothing constant of 0.5 is applied. We assume a forecast of 1000 units in the first period.

Exponential smoothing α = 0,5

Month (t)	1	2	3	4	5	6	7	8	9	10	11	12
Demand	1030	1010	980	1050	1100	1150	1010	1100	1070	1010	1100	990
Forecast	1000	1015	1013	996	1023	1062	1106	1058	1079	1074	1042	1071
Deviation	30	5	33	54	77	88	96	42	9	64	58	81

Mean absolute deviation 637

Table 3.2 - Example of exponential smoothing

The absolute deviation for the period is 637 units. Even though the stochastic demand is varying, the underlying average is fairly stable. Due to this, we reduce the smoothing constant in order to see if this improves our forecast error.

Exponential smoothing α = 0,3

Month (t)	1	2	3	4	5	6	7	8	9	10	11	12
Demand	1030	1010	980	1050	1100	1150	1010	1100	1070	1010	1100	990
Forecast	1000	1009	1009	1001	1015	1041	1074	1054	1068	1069	1051	1066
Deviation	30	1	29	49	85	109	64	46	2	59	49	76

Mean absolute deviation 598

Table 3.3 - Example of exponential smoothing

We now see an improvement in the forecast error. It is therefore important to work with the smoothing constant in order to obtain the optimal value.

3.2.3.3 Exponential smoothing with trend

If the demand is not expected to be constant, but rather show a trend, we should use the trend model instead of the constant model as a basis. To forecast demand we need to estimate the two parameters *a* and *b*, compared to only *a* in case of a constant model. As before, we cannot predict the independent deviations εt. In order to estimate *a* and *b*, we can use Holt's method (1957). Estimates of *a* and *b* are successively updated according to the following models:

$$\hat{a}_t = (1-\alpha)(\hat{a}_{t-1} + \bar{b}_{t-1}) + \alpha x_t$$

$$\bar{b}_t = (1-\beta)\bar{b}_{t-1} + \beta(\hat{a}_t - \hat{a}_{t-1})$$

where α and β are smoothing constants between 0 and 1.

The "average" $\hat{a}_t$ corresponds to period t, i.e., the period for which we have just observed the demand, while $\bar{b}_t$ is the exponentially smoothed trend. The forecast for a future period $t+k$ is obtained as:

$$\hat{x}_{t,t+k} = \hat{a}_t + k * \bar{b}_t$$

To illustrate this in an example, we look at a demand series over 12 periods. There is an obvious trend, and the stochastic demand has some variations. While a high value of β gives more weight to recent trends, a lower value tends to smooth out the present trend. In our example, the trend is fairly constant, so we will apply a low value of β.

Exp. smoothing w/trend α = 0,5 β = 0,1

Month (t)	1	2	3	4	5	6	7	8	9	10	11	12
Demand	1000	1110	1200	1290	1410	1490	1580	1710	1800	1880	1970	2050
Forecast	1000	1050	1128	1210	1296	1399	1491	1582	1692	1793	1884	1974
Trend	100	95	93	92	92	93	93	92	94	95	95	94
T Forecast		1145	1221	1303	1388	1492	1583	1674	1786	1888	1979	2068
Deviation	0	35	21	13	22	2	3	36	14	8	9	18

Mean absolute deviation 180

Table 3.4 - Example of exponential smoothing with trend

The result of this model is that the forecasts for future periods are no longer the same, but rather adjusted for the expected development in the future. If the demand is a linear function without stochastic variations, the forecast will, in the long run independent of the initial values, estimate the future demand exactly. This is not the case when using simple exponential smoothing.

Exponential smoothing with trend allows us to follow systematic linear changes in demand better. As with exponential smoothing, larger values of the smoothing constants a and β will mean that the forecasting system reacts faster to changes, but will also make the forecasts more sensitive to stochastic deviations. If the initial values are very uncertain it can be reasonable, also for exponential smoothing with trend, to use extra large smoothing constants in an initial phase.

3.2.3.4 Multiplicative seasonal model

If the demand for a certain article fluctuate up and down in a time series that relate to recurring events like seasons of the year or holidays, it is necessary to develop these seasonal indices in the forecast model (Heizer & Render, 2006). By using a multiplicative seasonal model, seasonal factors are multiplied by an estimate of average demand to produce a seasonal forecast.

In order to do this, the average historical demand for each time period must first be determined. This can be done by summing the demand data for the previous months and dividing them by the number of years. This number is then divided by the average demand over all months to get the seasonal indices for each month.

	Demand			Average	Average	
				2008-2010	Monthly	Seasonal
Month	**2008**	**2009**	**2010**	**Demand**	**Demand**	**Index**
Jan	80	85	105	90	94	0,957
Feb	70	85	85	80	94	0,851
Mar	80	93	82	85	94	0,904
Apr	90	95	115	100	94	1,064
May	113	125	131	123	94	1,309
Jun	110	115	120	115	94	1,223
Jul	100	102	113	105	94	1,117
Aug	88	102	110	100	94	1,064
Sep	85	90	95	90	94	0,957
Oct	77	78	85	80	94	0,851
Nov	75	82	83	80	94	0,851
Dec	82	78	80	80	94	0,851
	Total average annual demand:			1128		
Average monthly demand:		1128/12 =		94		

Table 3.5 - Determining seasonal indices (adapted from Heizer & Render, 2006)

With the seasonal indices in place, it is possible to create a forecast for the coming year with seasonal curves included. If we assume that the forecast for 2011 is 1200 units, we divide the yearly forecast by the number of months and multiply each month with their seasonal indices.

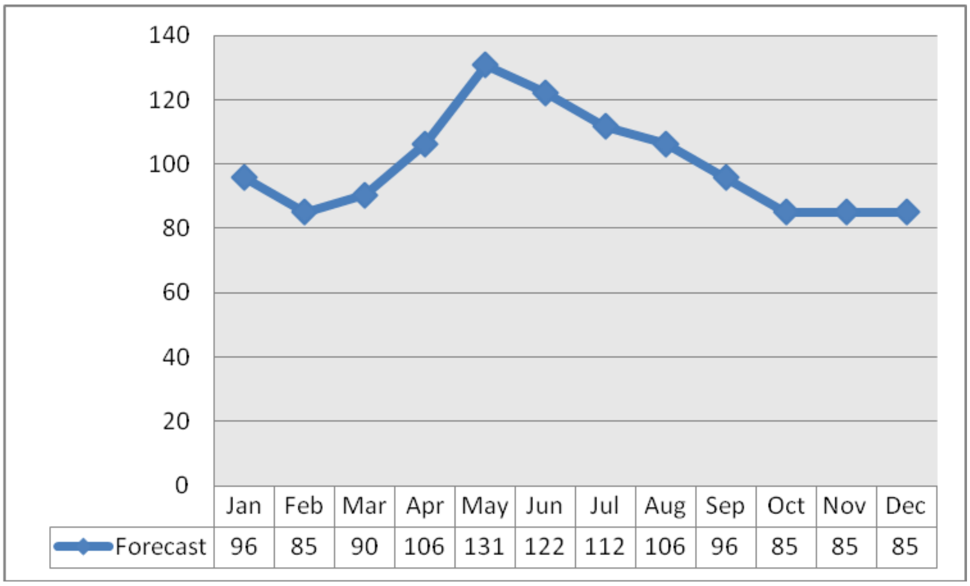


Figure 3.1 - Seasonal forecast example

3.2.3.4.1 Trend Projections

In cases where it is necessary to forecast the total volume for the coming period, it can prove helpful to calculate the trend projection for this period. If we decide to develop a linear trend line by a precise statistical method, we can apply the least squares method (Heizer & Render, 2006). By using this approach, we create a straight line that minimizes the deviations from the line to each of the actual observations. This line is expressed by the following equation:

$$\hat{y} = a + bx$$

Where the optimal values of A and B (which give the lowest quadratic error), are calculated based on the following formulas (Heizer & Render, 2006):

$$x_{avg} = \Sigma x / n$$

$$y_{avg} = \Sigma y / n$$

$$b = (\Sigma xy - n\, x_{avg} y_{avg}) / (\Sigma x^2 - n x_{avg}^2)$$

$$a = y_{avg} - b x_{avg}$$

We can use the following example to demonstrate this approach:

Year	Time Period (x)	Sales (y)	x^2	xy
2005	1	100	1	100
2006	2	118	4	236
2007	3	142	9	426
2008	4	159	16	636
2009	5	180	25	900
Sum	15	699	55	2298

Table 3.6 - Example of demand structure for least squares model

In order to calculate the forecast for 2010 (period 6), we use the equations in the model.

$$x_{avg} = 15 / 5 = 3$$

$$y_{avg} = 699 / 7 = 139{,}8$$

$$b = (2298 - 5 * 3 * 139{,}8) / (55 - 5 * 3^2) = 20{,}1$$

$$a = 139{,}8 - 20{,}1 * 3 = 79{,}5$$

$$\hat{y} = 79{,}5 + 20{,}1 * 6 = \underline{200{,}1}$$

Thus the forecast for 2010 should be 200 units assuming a linear trend.

3.2.3.5 Winters' trend-seasonal method

Another, and more advanced way, to include both trend and seasonality into the forecast model is Winters' trend-seasonal method (1960). Winters' method is a form of triple exponential smoothing, and this has the important advantage of being easy to update as new data becomes available.

From the trend-seasonal model, we know that $a + bt$ represents the development of demand if we disregard the seasonal variations. When we record the demand x_t in period t, we can similarly interpret $x_t / \bar{F}_t$ as the demand without seasonal variations. At this stage we have not updated $\bar{F}_t$ with respect to the new observation x_t. We can then expand our models from Holt's method to get:

$$\hat{a}_t = (1 - \alpha)(\hat{a}_{t-1} + \bar{b}_{t-1}) + \alpha(x_t / \bar{F}_t)$$

$$\bar{b}_t = (1 - \beta)\bar{b}_{t-1} + \beta(\hat{a}_t - \hat{a}_{t-1})$$

We have yet to update the seasonal indices. We first determine:

$$\bar{F}'_t = (1-\gamma)\,\bar{F}_t + \gamma(x_t / \hat{a}_t)$$

and:

$$\bar{F}'_{t-i} = \bar{F}_{t-i} \text{ for } i = 1, 2, \ldots, T\text{-}1,$$

where $0< \gamma <1$ is another smoothing constant and T is the number of periods per year. We must also require that the sum of T consecutive seasonal indices is equal to T. Therefore we need to normalize all indices:

$$\bar{F}_{t-i} = \bar{F}'_{t-i} \left(T / \sum_{k=0}^{T-1} \bar{F}'_{t-k}\right) \text{ for } i = 0, 1, \ldots , T\text{-}1$$

These indices are also applied to future periods until the indices are updated the next time. For example:

$$\bar{F}_{t-i+kT} = \bar{F}_{t-i} \text{ for } i = 0, 1, \ldots , T\text{-}1, \text{ and } k = 1, 2, \ldots$$

The forecast for period $t + k$ is obtained as:

$$\hat{x}_{t,t+k} = (\hat{a}_t + \text{k} * \bar{b}_t)\, \bar{F}_{t+k}$$

When using a trend-seasonal method, which also updates the seasonal indices, it is quite often difficult to distinguish systematic seasonal variations from independent stochastic variations. If a group of items can be expected to have very similar seasonal variations, it may be advantageous to estimate the indices from the total demand for the whole group of items. This can limit the influence of the purely stochastic variations.

In order to demonstrate this model, we will use a very simple demand structure.

		x	
t	2008	2009	2010
1	100	110	120
2	100	110	120
3	200	220	240
4	200	220	240
5	100	110	120
6	100	110	120
7	100	110	120
8	100	110	120
9	100	110	120
10	100	110	120
11	100	110	120
12	100	110	120

Table 3.7 - Demand structure 2008-2010, example

The model must first be initiated by computing the initial estimates of $\hat{a}_0$ and $\bar{b}_0$ using the data from 2008 and 2009. The estimate of the slope is found by taking the difference in the average demand for the two years and diving by the number of periods:

$$\bar{b}_0 = \hat{x}\, avg_{2009} - \hat{x}\, avg_{2008} / 12 = 128{,}33 - 116{,}67 / 12 = 0{,}97$$

In order to obtain $\hat{a}_0$, we first equate the trend value which is the average period number for the year.

$$2008 = (1+2+...+12) / 12 = 6{,}5$$

We then solve $\hat{a}_0$ using the following equation:

$$\hat{x}\, avg_{2008} = \hat{a}_0 + \bar{b}_0 * 6{,}5 \Rightarrow \hat{a}_0 = 110{,}35$$

With the initial factors in place, we must compute trend line estimates for the two years of data using the trend function.

$$\hat{x}_t = 110{,}35 + 0{,}97 * t,\ t = 1,\ldots,24$$

	Trend line estimates	
t	2008	2009
1	111,32	122,99
2	112,29	123,96
3	113,26	124,93
4	114,24	125,90
5	115,21	126,88
6	116,18	127,85
7	117,15	128,82
8	118,13	129,79
9	119,10	130,76
10	120,07	131,74
11	121,04	132,71
12	122,01	133,68

Table 3.8 - Trend line estimates 2008-2009, example

These trend line estimates can then be used to develop initial seasonal indices by taking the actual demand for each period and dividing by the trend line estimate for that period.

We must also normalize the average indices to ensure that they all add up to 12.

t	2008	2009	Avg index	Initial index
1	0,90	0,89	0,90	0,89
2	0,89	0,89	0,89	0,89
3	1,77	1,76	1,76	1,76
4	1,75	1,75	1,75	1,74
5	0,87	0,87	0,87	0,86
6	0,86	0,86	0,86	0,86
7	0,85	0,85	0,85	0,85
8	0,85	0,85	0,85	0,84
9	0,84	0,84	0,84	0,84
10	0,83	0,84	0,83	0,83
11	0,83	0,83	0,83	0,82
12	0,82	0,82	0,82	0,82
			12,05	12

Table 3.9 - Seasonal indices, example

The "Initial index" values are the initial estimates of the seasonal factors at time t = 1 (the first month of 2008). These values are denoted from $\bar{F}_{-11}$ for t = 1 to $\bar{F}_0$ for t = 12.

$$f_{1;0} = (\hat{a}_0 + \bar{b}_0)\, \bar{F}_{-11} = (110,35 + 0,97)\ 0,89 = 99,37$$

Since we have the actual demand for the first period (100), we can incorporate it into Winters' model updating equations to obtain new estimates for the parameters.

$$\hat{a}_1 = \alpha\, (x_1 / \bar{F}_{-11}) + (1-\alpha)\, (\hat{a}_0 + \bar{b}_0) = 0,2\ (100/0,89) + 0,8\ (110,35 + 0,97) = 111,46$$

$$\bar{b}_1 = \beta\, (\hat{a}_1 - \hat{a}_0) + (1-\beta)\, \bar{b}_0 = 0,1\ (111,46 - 110,35) + 0,9 * 0,97 = 0,99$$

$$\bar{F}_1 = \gamma\, (x_1 / \hat{a}_1) + (1-\gamma)\, \bar{F}_{-11} = 0,05\ (100 / 111,46) + 0,95 * 0,89 = 0,89$$

We can now compute the forecast for period 2 according to:

$$f_{2;1} = (\hat{a}_1 + \bar{b}_1)\, \bar{F}_{-10} = (111,46 + 0,97)\ 0,89 = 99,55$$

Continuing in this fashion, we get the following results for the three years of data using the smoothing parameters as shown.

α = 0,2
β = 0,1
γ = 0,05

Year	t	$\hat{a}$	$\hat{b}$	F	$\hat{x}$	x	MAD	MAPE	
2008	1	111,46	0,99	0,89	99,37	100	0,63	0,63 %	
	2	112,55	1,00	0,89	99,55	100	0,45	0,45 %	
	3	113,61	1,00	1,76	199,40	200	0,60	0,30 %	
	4	114,66	1,01	1,74	199,65	200	0,35	0,18 %	
	5	115,68	1,01	0,86	99,92	100	0,08	0,08 %	
	6	116,69	1,01	0,86	100,01	100	0,01	0,01 %	
	7	117,68	1,01	0,85	100,07	100	0,07	0,07 %	
	8	118,66	1,00	0,84	100,12	100	0,12	0,12 %	
	9	119,63	1,00	0,84	100,16	100	0,16	0,16 %	
	10	120,59	1,00	0,83	100,18	100	0,18	0,18 %	
	11	121,53	0,99	0,82	100,20	100	0,20	0,20 %	
	12	122,48	0,99	0,82	100,21	100	0,21	0,21 %	0,22 %
2009	1	123,41	0,98	0,89	110,24	110	0,24	0,22 %	
	2	124,36	0,98	0,89	110,14	110	0,14	0,13 %	
	3	125,32	0,98	1,76	220,13	220	0,13	0,06 %	
	4	126,30	0,98	1,74	220,01	220	0,01	0,00 %	
	5	127,28	0,98	0,86	109,96	110	0,04	0,04 %	
	6	128,28	0,98	0,86	109,92	110	0,08	0,07 %	
	7	129,28	0,98	0,85	109,90	110	0,10	0,09 %	
	8	130,29	0,98	0,84	109,88	110	0,12	0,11 %	
	9	131,31	0,99	0,84	109,87	110	0,13	0,12 %	
	10	132,33	0,99	0,83	109,86	110	0,14	0,12 %	
	11	133,35	0,99	0,82	109,86	110	0,14	0,12 %	
	12	134,38	1,00	0,82	109,87	110	0,13	0,12 %	0,09 %
2010	1	135,19	0,98	0,89	120,87	120	0,87	0,72 %	
	2	136,04	0,97	0,89	120,56	120	0,56	0,47 %	
	3	136,93	0,96	1,76	240,61	240	0,61	0,26 %	
	4	137,87	0,96	1,74	240,20	240	0,20	0,08 %	
	5	138,84	0,96	0,86	119,94	120	0,06	0,05 %	
	6	139,84	0,96	0,86	119,81	120	0,19	0,16 %	
	7	140,87	0,97	0,85	119,71	120	0,29	0,24 %	
	8	141,92	0,98	0,84	119,65	120	0,35	0,29 %	
	9	143,00	0,99	0,84	119,60	120	0,40	0,33 %	
	10	144,08	1,00	0,83	119,57	120	0,43	0,36 %	
	11	145,19	1,01	0,82	119,56	120	0,44	0,37 %	
	12	146,30	1,02	0,82	119,56	120	0,44	0,37 %	0,29 %

Table 3.10 - Forecast 2008-2010, example

As we can see, the Mean Absolute Deviation is very low in this example, something which also can be seen by calculating the Mean Absolute Percentage Error. Even though this is a very simple example, it shows how the model incorporates trend and seasonality in order to calculate the forecast.

3.3 Subjective Forecasting Techniques

Whereas objective forecasting methods use a variety of mathematical models to forecast demand, subjective forecasting methods incorporate the human factor. This can range from the forecaster's intuition and emotions to personal experiences and value system (ref?). In this section, four of the most common subjective forecasting techniques will be explored.

3.3.1 Jury of executive opinion

When launching new products, there may be no previous sales history available. In such cases, expert opinion might be the only source of information for preparing forecasts (Nahmias, 2005). But even if there is a sales history available, uncertainty about future trends can render the historical data almost useless since the past doesn't always tell us something about the future. In such cases, the opinions of a group of high-level experts or managers can be pooled to arrive at a group estimate of demand. This estimate may also be supported by statistical models if necessary (Heizer & Render, 2006).

3.3.2 Delphi method

The Delphi method is named for the Delphic oracle of ancient Greece, who purportedly had the power to predict the future. This method, like jury of executive opinion, uses expert opinions to reach a forecast. However, to avoid that the personalities of some group members overshadow the opinions of others, each expert express their opinions through an individual survey. These inputs are then collected, and a summary is returned to the experts, with special focus on those opinions that deviate from the group averages. The experts are then asked if the wish to change their opinion based on the group answers, and this process is repeated until a consensus is reached.

The strength of this method is that opinions can be expressed without any influence from people with other opinions. However, this method also requires that the question formulation in the survey is very clear and leave no room for doubt as to what is being asked about. Also, there is the risk that a group consensus might never be reached (Nahmias, 2005).

3.3.3 Sales force composite

A sales force composite is where each salesperson estimates the sales for his or her region. After checking these estimates, they are combined to make a total forecast for all regions (Heizer & Render, 2006). The estimates from the sales force can either be one number, or several numbers, such as pessimistic, expected and optimistic forecasts. With such a method, it is important to keep in mind that each salesperson might have a motivation to increase or decrease the estimates due to sales quotas or bonus schemes (Nahmias, 2005).

3.3.4 Consumer market surveys

With this method, a company gets input from customers or potential customers regarding future purchasing plans. This input can be valuable both in the forecasting process, and when it comes to improving product design and planning for new products (Heizer & Render, 2006). However, it is important to ensure that the data collection method is designed to guarantee that the results are statistically unbiased. In addition, it is important to keep in mind that customer expectations for the future might be overly optimistic (Nahmias, 2005).

4. Research Methodology

4.1 Research Design

A research design can be defined as the logic that links the collected data and the outlined conclusions to the initial research questions of the study (Yin, 1994). The purpose of this chapter is to focus on the theoretical aspects of research design, and look at the data collection methods which will be used to explore the research questions.

There are three different ways of doing research design (Bryman and Bell, 2003):

- An *explorative design* can be used when the researcher is not familiar with the area of study. Such studies can lead to theories or hypothesis, and they are commonly used to give the researcher a better understanding of the subject.
- The *descriptive design* can be used if the researcher is familiar with the area of study. Such research can lead to a deductive approach where already formulated theories are tested. It is therefore not uncommon for an exploratory study to be followed by a descriptive study.
- A *casual design* is used when the researcher seeks to find relationships between two or more variables.

This study can be described within the terms of a descriptive design as the research area is known. The study can also be characterized as deductive since we seek to support the theory with empirical work. Since Continental is the only case being researched, we can state that this is a single-case study.

4.2 Classification of Data

There are two types of data, primary and secondary. Primary data is data which is collected by the researcher for the specific study, while secondary data is originally collected for other purposes by other people. One of the main motivations for using secondary data is that this data has already been collected, categorized and evaluated, but there might also be validity problems attached to such data. Thus, primary data is the preferred source of data for any research (Bryman & Bell, 2003).

Data is also categorized into quantitative and qualitative data. Quantitative data is data that can be quantified, while qualitative data cannot. While quantitative data is most commonly used in descriptive designs, qualitative data is often used in an explorative design.

4.3 Data Collection

Good forecasting management encompasses more than just good forecasting techniques (Moon et al., 2003), and therefore this study will not only focus on the quantitative side of forecasting management. Even though the main focus will be on creating improved forecasting techniques, the qualitative aspect of the process will also be examined. This study will therefore use both quantitative and qualitative data.

The quantitative data will be collected from Continental's ERP system, FOS I-Grid. All forecast, demand and sales data is available here, thus making this a primary data source. The qualitative data sources will mainly be internal sources at Continental, mostly focusing on obtaining process descriptions through unstructured interviews with key personnel.

An important note is that there was a transport strike in Norway during the last half of May 2010. This significantly reduced the sales volume for this month, and though backorders were delivered in June, it is still reasonable to expect that there was a certain amount of lost sales due to the strike. However, since unexpected problems tend to occur on a regular basis at Continental, these figures will still be used for the calculations. Creating a model based on a problem-free year would be like modeling for the impossible, and it is therefore better to create models and methods of analysis which can cope with huge deviations and still produce an adequate result.

5. Forecasting Process Analysis

In order find potential areas of improvement for forecasting management at Continental, the current forecasting process must first be analyzed. The framework from Chapter 3.1.1 will be used as a basis for the analysis. Upon analyzing the different variables, potential areas of improvement will be identified and discussed, and recommendations will then be given.

5.1 Forecasting Techniques

As discussed in Chapter 2, there is no forecast modeling included in the forecasting process at Continental. Sales figures from previous years are used as a basis for future forecasts, and these are adjusted for expected seasonal peaks, sizing trends, central limitations and a management consensus regarding the total figure for the year. The day-to-day follow-up is mainly left up to the forecaster, while monthly forecast meetings are held were both Sales and Logistics meet to discuss the figures.

It is therefore possible to say that both subjective and objective forecasting techniques are being used at Continental. The basis for the forecast is historical sales figures, but the future forecast is reached both through a sales force composite and a jury of executive opinion.

5.1.1 Potential Areas of Improvement

With regards to forecasting techniques being applied at Continental, there are some potential weaknesses. By basing the forecast mainly on historical sales and general expectations for the future, certain trend developments can be overlooked since there is a vast amount of sales data to go over. By using the historical sales figures as a basis for a first opinion, there is also a risk that predictions about future sales will be weighted heavily on that first opinion. In addition, if the opinions of regional managers and executives are based mainly on a ”gut feeling”, there is a high risk of the forecast being adjusted to a desired state instead of a realistic state.

It could therefore prove helpful to use a forecasting model to create the primary forecast figures. Such a model could uncover undetected trend developments, thus making those involved in the forecasting process aware of these. By investigating the reasons for these developments, one could get more targeted market intelligence, thus getting a more complete picture of the overall market.

5.1.2 Recommendations

A forecasting model should be implemented at Continental. This model should be used as a basis for discussions of the forecast, thus ensuring that trends and developments doesn't go undetected, and that this basic forecast is not affected by any bias from forecasters or executives.

5.2 Use of Information in Forecasting

The main source of information gathering for Continental is the car dealers. Sales figures on new cars can give a good measurement as to which direction the demand for car tires is headed, thus giving Continental valuable intelligence. In addition, the car dealers also submit their expectations for the coming seasons. Dekkmann also gives their expected sales forecast for the coming seasons to Continental. These two elements alone are then proving Continental with expected sales and market development inputs from two thirds of the company's customer base.

Factors like current and expected economic conditions are not weighted to any extent in the process. There is also no extensive market research being conducted. However, tire tests from auto magazines can serve as a valuable information source as s test winner tends to lead to increased demand for this type of tire.

5.2.1 Potential Areas of Improvement

Continental could consider investigating the potential value of market research. Some potential questions could be:

- Are motorists tending towards more environmentally friendly tires, or is safety the number one issue? And what is the trend here?
- Is the customer in charge, or does the average customer follow the advice of the tire dealer?
- Are enough motorists aware of the importance of quality tires?
- How many potential premium brand customers are buying budget brands simply because they don't know what they need?

Answers to these questions could help to uncover areas where marketing and information campaigns could improve sales. In addition, it could help Continental to launch new products which are adapted to customer's demands to a higher extent than today.

Also, analyses of the economic development trends could be incorporated into the forecasting process. If economic growth leads to a higher demand for tires, it is useful to know how the economy is expected to develop. Also, if economic growth leads to a higher demand for luxury cars which require special tires, such an analysis could help Continental to be prepared for a higher demand within such segments.

5.2.2 Recommendations

Continental should consider doing a cost-benefit analysis of extensive market research to uncover any potential customer groups or customer needs which are not being served today. In addition, analyses of expected economic development trends should be incorporated into the forecasting process to ensure that the forecast is adjusted to real world expectations.

5.3 The Role of Forecasting in Decision Making

The sales forecast plays a crucial role in decision making at Continental. At local level in Norway, all budget plans are based on the forecast. This is not only reflected in expected earnings reported back to Central Management in Germany, but also when it comes to manning. If an increase in demand is expected, it might be necessary to hire more people, and vice versa.

On a Central level, the forecast is also crucial. Equipment planning, like purchasing new moulds for tires, is to a large extent planned based on the forecast. In addition, expansions of productions facilities, and even planning of new ones, are to a great extent based on the forecast.

5.3.1 Potential Areas of Improvement

The role of the forecast at Continental is very important, so there seem to be few areas of improvements in that regard. However, with the forecast errors being generally very high, it can be argued that the importance of the forecast in decision making should be downplayed. If you know that the forecast will be wrong, why make important decisions regarding equipment planning and new production facilities based on this forecast? The role of the forecast should mirror the accuracy of the forecast, so if the forecast is inaccurate, any important decision should be made with that in mind. If not, one may run the risk of acquiring new equipment which there is no need for, or simply plan for a lower demand for certain articles than there actually is. If it be equipment or facilities which are not needed, or lost sales and market shares, both are undesirable for any company.

5.3.2 Recommendations

Continental, both on local and Central level, should ensure that the degree of which decisions are based on the forecast, is mirrored in the certainty of the forecast. Currently, this means that the role of the forecast should either be downplayed on certain areas, or the forecast itself should be improved.

6. Forecasting Models - Tests and Analyses

In this section, the historical sales data from 2010 will be tested using a forecasting model. In order to initialize such a model, it must be provided with historical sales figures of the articles being tested. Since historical sales figures on article level can be very variable due to availability issues, the articles tested will be chosen on the basis of an actual stable sales history being available. However, this is also the only criterion. In order to get an honest test result, it is important that the articles have had an average availability in the past. Therefore, there has been no attempt to test only articles with perfect availability. Due to the constant availability issues, it has also not been possible to find such articles.

Since all articles are expected to display certain deviations due to availability issues, the model will also test the total sales figure of Continental brand summer tires. The test of these aggregated sales figures will to a large extent serve as a benchmark for the model's performance, but several single articles will also be tested in order to see if an improvement on aggregated level is also mirrored on the article level.

6.1 Testing the Forecasting Models

Looking at the sales development the last years, the seasonal curve seems to be the more dominant factor in monthly sales variations compared to level and trend. The main task of the model should therefore be to catch seasonal variations, though deviations and trends cannot be ignored. Winters' trend-seasonal model is therefore considered best suited for this task.

However, it is important to check that Winters' model performs well, and it will therefore be tested against the seasonal multiplicative model on aggregated article level. The test result from the seasonal multiplicative model will serve as a benchmark for Winters' model, together with the actual forecast. This should provide an adequate basis for evaluating the model's performance.

6.1.1 Seasonal Multiplicative Model

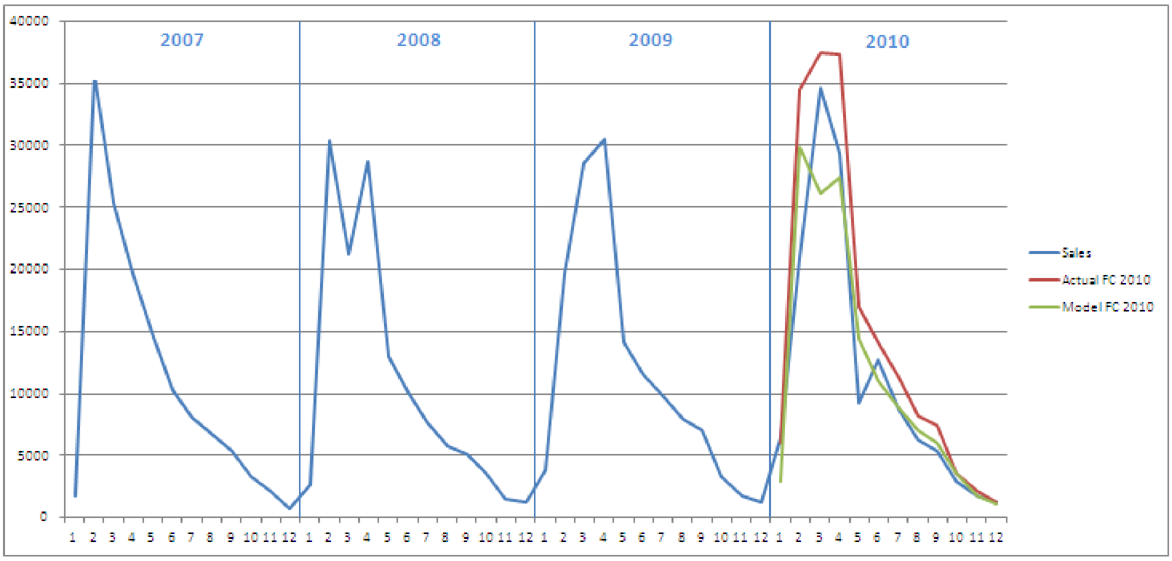
In order to initialize the model, the sales figures from 2007 to 2009 will be used to calculate seasonal indices. Since this model doesn't forecast an actual demand figure, but rather only seasonal indices, the least squares method will be used to create a forecast for 2010. Even though this might result in some unusual forecasts on article level due to availability issues, this should not be a problem on aggregated level which is also the only level being tested on this model.

First, the seasonal indices must be calculated:

	Demand			Average	Average	
				2007-2009	Monthly	Seasonal
Month	2007	2008	2009	Demand	Demand	Index
Jan	1760	2662	3870	2764	11218	0,246
Feb	35841	30331	19736	28636	11218	2,553
Mar	25348	21271	28577	25065	11218	2,234
Apr	19695	28760	30465	26307	11218	2,345
May	14492	12967	14149	13869	11218	1,236
Jun	10289	10076	11504	10623	11218	0,947
Jul	8069	7713	9875	8552	11218	0,762
Aug	6786	5762	7913	6820	11218	0,608
Sep	5337	5071	7000	5803	11218	0,517
Oct	3274	3583	3259	3372	11218	0,301
Nov	2085	1460	1692	1746	11218	0,156
Dec	692	1228	1245	1055	11218	0,094
	Total average annual demand:			134612		
Average monthly demand:		134612/12 =			11218	

Table 6.1 - Seasonal Multiplicative Model

In order to calculate the forecast for 2010, we assume a linear trend and use the least squares method. We then get a yearly forecast for 2010 of 140,229 units. The model is then ready to calculate the forecast for 2010 (see calculations in appendix 10.1).



2010												
Month	1	2	3	4	5	6	7	8	9	10	11	12
Model MAPE	55,06 %	42,13 %	24,61 %	6,45 %	56,33 %	13,31 %	2,50 %	12,28 %	11,51 %	22,56 %	3,32 %	9,10 %
Actual MAPE	6,31 %	64,38 %	8,27 %	27,35 %	83,94 %	10,35 %	29,33 %	29,20 %	37,67 %	22,64 %	25,17 %	5,87 %

Figure 6.1 – Test Results

As seen from the figure, the model outperforms the actual forecast in 8 of the months, with January and March as the only months with deviations larger than 5%. The yearly MAPE for the model is 23.01%, compared to the actual MAPE which was 29.71%.

6.1.2 Winters' Trend-Seasonal Model

Winters' model incorporates level, trend and seasonal deviations. It is therefore fair to expect that this model will yield a better accuracy than the seasonal multiplicative model. Since there are three smoothing parameters which can be adjusted in Winters' model, the optimal parameters must first be found. With no software for this task available, this process must be done manually.

In order to find the optimal smoothing parameters, all parameters will be tested on aggregated article level. By adjusting each parameter up and down compared to the other two, it is possible to see which direction the adjustments yield the best MAPE.

Test	1	2	3	4	5	6	7
α	0,5	0,4	0,5	0,5	0,4	0,5	0,4
β	0,5	0,5	0,4	0,5	0,4	0,4	0,5
γ	0,5	0,5	0,5	0,4	0,5	0,4	0,4
MAPE	34,05 %	30,97 %	33,13 %	34,98 %	30,01 %	34,03 %	31,98 %

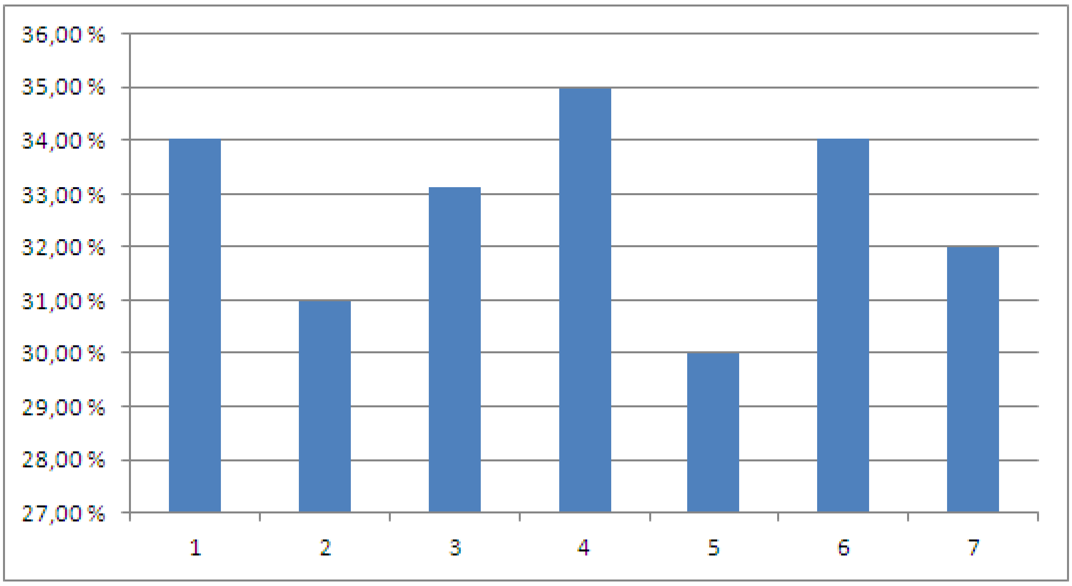
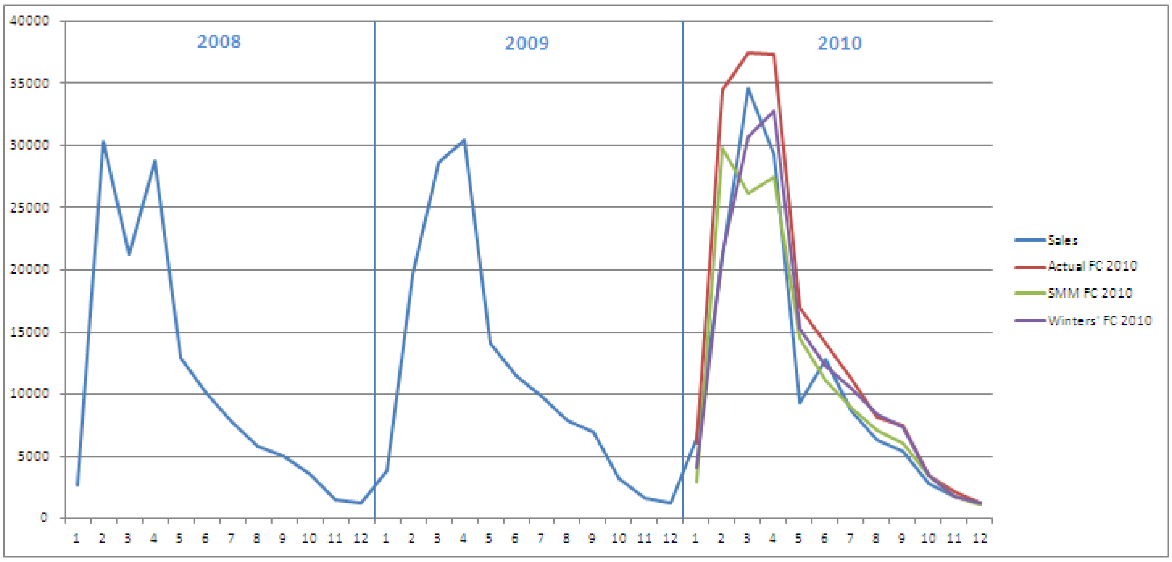


Figure 6.2 – Testing smoothing parameters

As seen from Figure 6.2, the MAPE is lowest when the seasonal smoothing parameter is higher than both other parameters. The parameters should therefore be adjusted further in this fashion in order to find the optimal settings. After several tests, the optimal smoothing parameters turns out to be $\alpha = 0.01$, $\beta = 0.01$ and $\gamma = 0.99$. These parameters will therefore be used in the following tests.

6.1.2.1 Test W1a – Aggregated Article Level

The first test is on the aggregated level. As mentioned, this level should not be as affected by deviations as single article level, and this test result should therefore be used to compare the model's performance to the seasonal multiplicative model and the actual forecast. As seen from the table below, the results show quite an improvement compared to the other two figures on a yearly MAPE level (see Appendix 10.2 for the calculations).



2010													
Month	∑	1	2	3	4	5	6	7	8	9	10	11	12
SMM MAPE	29,71 %	55,06 %	42,13 %	24,61 %	6,45 %	56,33 %	13,31 %	2,50 %	12,28 %	11,51 %	22,56 %	3,32 %	9,10 %
Actual MAPE	23,01 %	6,31 %	64,38 %	8,27 %	27,35 %	83,94 %	10,35 %	29,33 %	29,20 %	37,67 %	22,64 %	25,17 %	5,87 %
Winters' MAPE	16,59 %	35,62 %	2,05 %	11,47 %	11,96 %	64,50 %	3,68 %	21,08 %	32,56 %	36,12 %	20,17 %	1,06 %	8,41 %

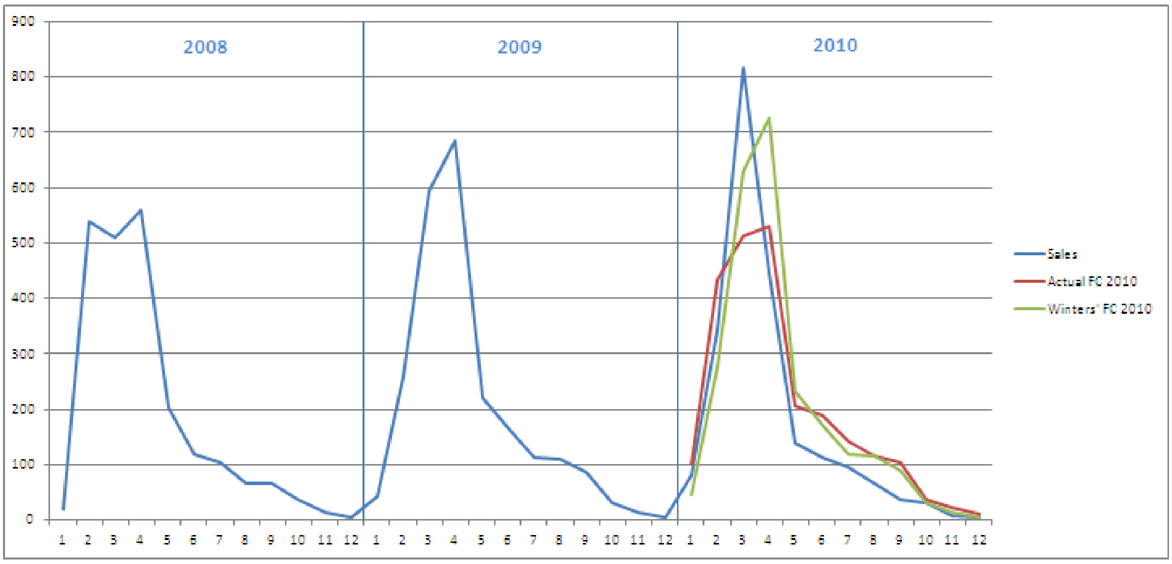
Figure 6.3 – Test W1a

The yearly MAPE was over 13% better than the actual forecast, and Winters' model had only one month with the highest MAPE throughout the year.

It is now time to see if this improvement will also be visible on article level. For presentational purposes, all forecast errors over 250% will be shown as 250%. The actual figures are available in the appendices.

6.1.2.2 Test W1b – Article 0352056

As seen from the results below, the first article test did not show any improvement at all (see Appendix 10.3 for the calculations). However, it the model did manage to outperform the actual forecast in several of the months.

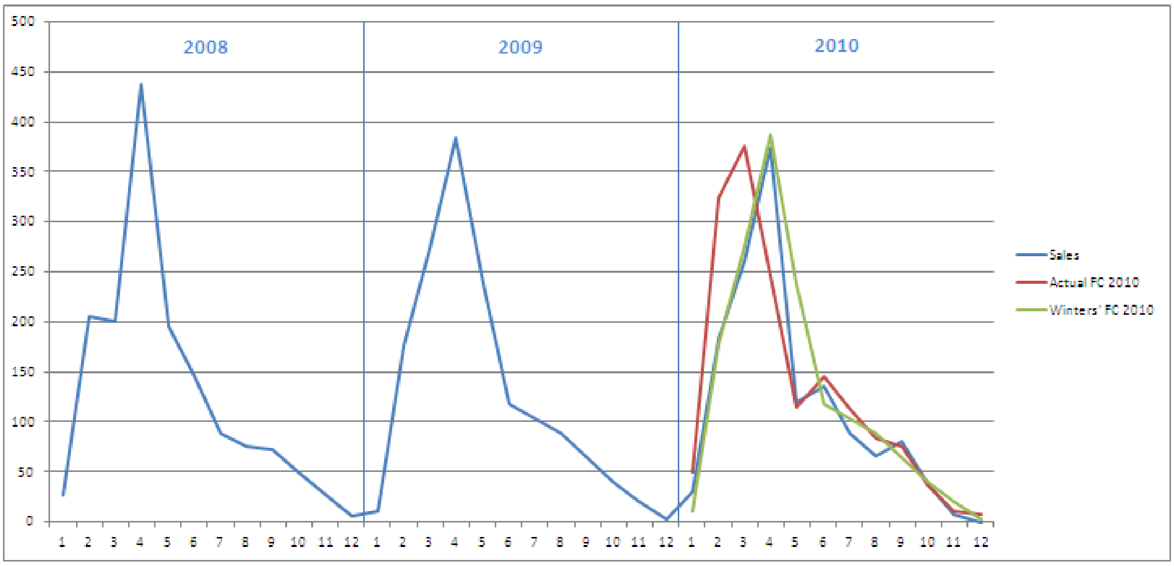


2010													
Month	∑	1	2	3	4	5	6	7	8	9	10	11	12
Actual MAPE	38,16 %	25,00 %	25,87 %	37,01 %	18,88 %	48,55 %	67,86 %	52,13 %	73,13 %	186,11 %	18,75 %	214,29 %	150,00 %
Winters' MAPE	39,49 %	42,81 %	19,36 %	22,91 %	63,39 %	69,19 %	53,25 %	25,61 %	71,18 %	145,56 %	0,42 %	105,31 %	53,24 %

Figure 6.4 – Test W1b

6.1.2.3 Test W1c – Article 0351890

The second article test shows a significant improvement of the yearly MAPE (see Appendix 10.4 for the calculations). It especially outperforms the actual forecast in February to April which are the months with the majority of the sales volume.

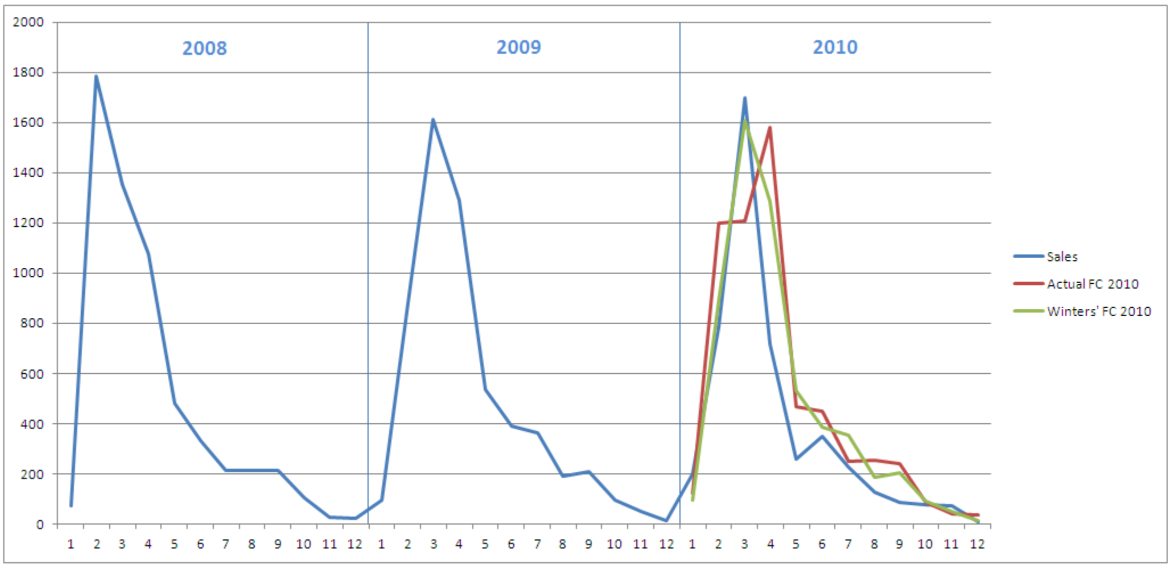


2010													
Month	∑	1	2	3	4	5	6	7	8	9	10	11	12
Actual MAPE	34,18 %	61,29 %	76,50 %	44,23 %	34,22 %	3,36 %	8,15 %	26,97 %	25,76 %	5,00 %	5,13 %	25,00 %	700,00 %
Winters' MAPE	18,52 %	67,67 %	2,90 %	5,59 %	3,37 %	100,25 %	12,41 %	15,51 %	34,19 %	19,05 %	2,72 %	151,25 %	200,00 %

Figure 6.5 – Test W1c

6.1.2.4 Test W1d – Article 0351882

The third article test also shows a significant improvement of the yearly MAPE (see Appendix 10.5 for the calculations). As with the previous article, the model outperforms the actual forecast in February to April.

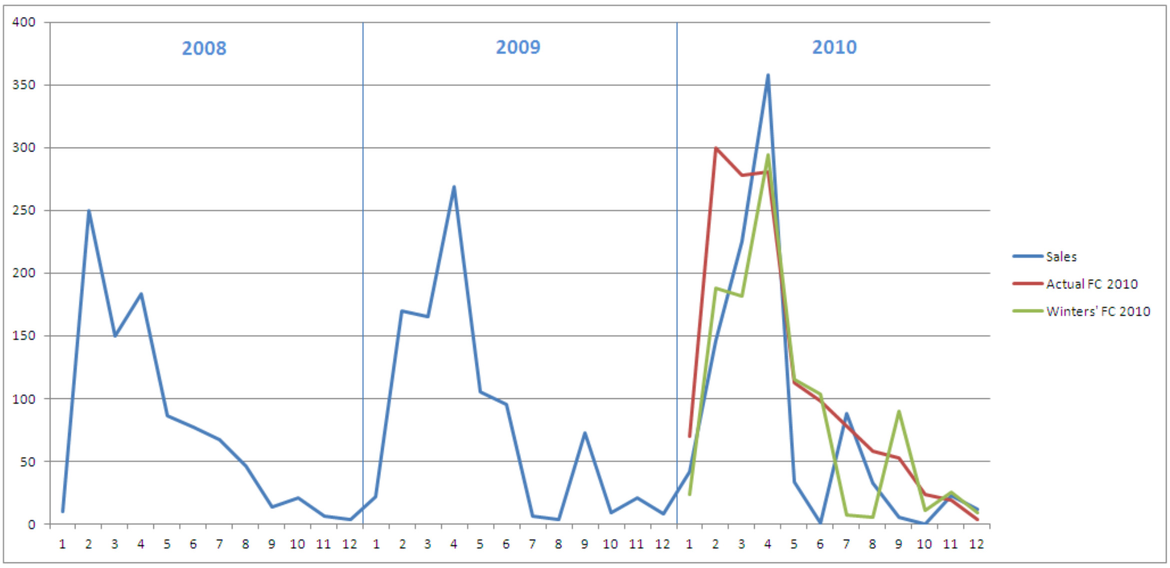


2010													
Month	∑	1	2	3	4	5	6	7	8	9	10	11	12
Actual MAPE	54,73 %	37,37 %	52,48 %	28,94 %	119,92 %	80,69 %	28,65 %	10,67 %	100,00 %	175,00 %	15,79 %	42,25 %	277,78 %
Winters' MAPE	32,86 %	52,32 %	13,10 %	5,41 %	78,70 %	104,58 %	10,12 %	56,92 %	46,22 %	129,45 %	19,62 %	33,05 %	50,82 %

Figure 6.6 – Test W1d

6.1.2.5 Test W1e – Article 0350093

In this test, the model performance was only slightly better than the actual forecast (see Appendix 10.6 for calculations). The MAPE is generally high for this article, indicating availability issues.

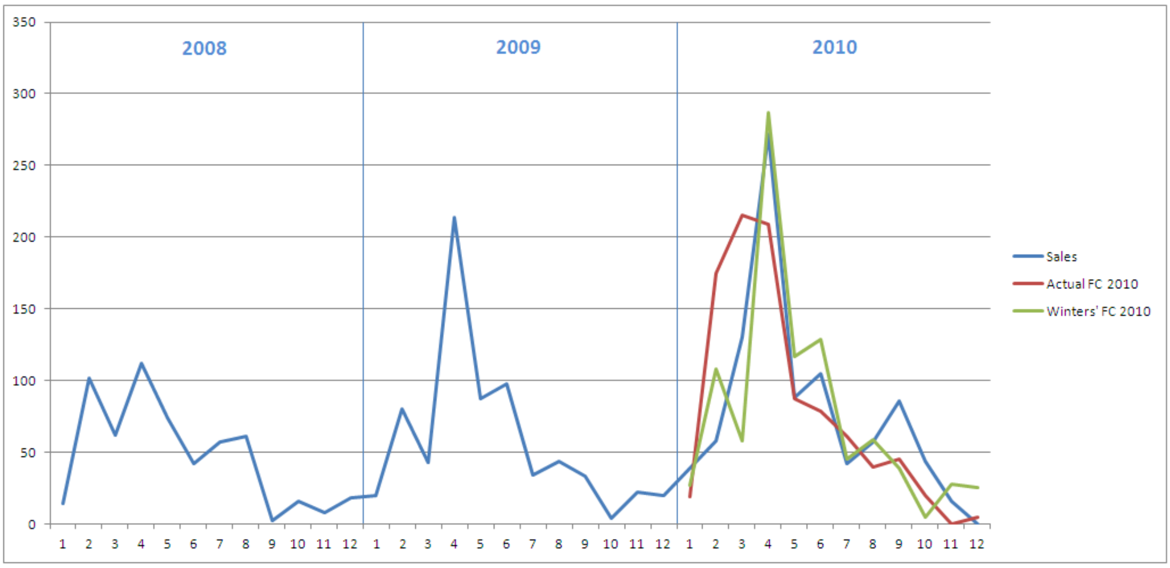


2010													
Month	∑	1	2	3	4	5	6	7	8	9	10	11	12
Actual MAPE	62,77 %	66,67 %	105,48 %	23,56 %	21,51 %	232,35 %	9700 %	11,36 %	75,76 %	960 %	100,00 %	17,39 %	66,67 %
Winters' MAPE	57,92 %	43,23 %	29,00 %	19,42 %	17,74 %	238,89 %	10236 %	91,79 %	83,59 %	1693 %	100,00 %	8,48 %	21,26 %

Figure 6.7 – Test W1e

6.1.2.6 Test W1f – Article 0350110

The final test also outperforms the actual forecast (see Appendix 10.7 for calculations), and the model scores better for most of the months, though there is a clear miss in both May and October.



2010													
Month	∑	1	2	3	4	5	6	7	8	9	10	11	12
Actual MAPE	46,32 %	51,28 %	201,72 %	65,38 %	23,16 %	1,14 %	24,76 %	45,24 %	29,82 %	47,67 %	54,55 %	100,00 %	100,00 %
Winters' MAPE	35,37 %	31,40 %	86,75 %	55,29 %	5,54 %	32,74 %	22,91 %	8,28 %	2,92 %	55,07 %	88,59 %	75,17 %	100,00 %

Figure 6.8 – Test W1f

6.2 Analysis of the Model Performance

In order to analyze the performance of Winters' model, it is helpful to create an overview of the results from each test. Forecasts which were higher than the actual sales are marked green, and lower forecasts are marked red.

Test/Month	1	2	3	4	5	6	7	8	9	10	11	12
W1a	35,62 %	2,05 %	11,47 %	11,96 %	64,50 %	3,68 %	21,08 %	32,56 %	36,12 %	20,17 %	1,06 %	8,41 %
W1b	42,81 %	19,36 %	22,91 %	63,39 %	69,19 %	53,25 %	25,61 %	71,18 %	145,56 %	0,42 %	105,31 %	53,24 %
W1c	67,67 %	2,90 %	5,59 %	3,37 %	100,25 %	12,41 %	15,51 %	34,19 %	19,05 %	2,72 %	151,25 %	200,00 %
W1d	52,32 %	13,10 %	5,41 %	78,70 %	104,58 %	10,12 %	56,92 %	46,22 %	129,45 %	19,62 %	33,05 %	50,82 %
W1e	43,23 %	29,00 %	19,42 %	17,74 %	238,89 %	10235,87 %	91,79 %	83,59 %	1692,68 %	100,00 %	8,48 %	21,26 %
W1f	31,40 %	86,75 %	55,29 %	5,54 %	32,74 %	22,91 %	8,28 %	2,92 %	55,07 %	88,59 %	75,17 %	100,00 %

Table 6.2 – Overview of Forecast Model Performance

As seen from the table above, the forecast was generally too low in January and March, and too high the rest of the year. Since the period January to April is the season for pre-season orders, it seems clear that many customers preferred a different delivery date in 2010 than previous years. This is especially true for January which shows a high forecast errors on all tests, and an especially high error on the aggregated level.

In May, the consequences of the transport strike are obvious. It is therefore not possible to make any evaluations for this month. Since a large number of the orders from May were sold in June, the forecast error was expected to be higher on the aggregated level for this month. This is supported by the actual orders entered for delivery in May and June. As seen in Figure 6.9 below, the forecast error measured against orders demand was higher than the forecast error against actual sales in May, while the opposite is the case for June.

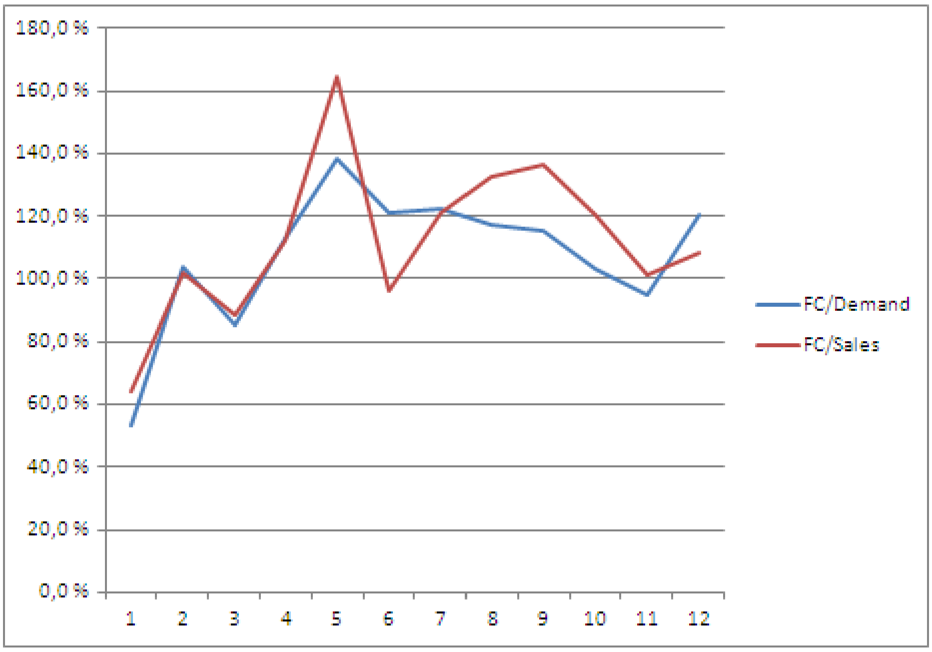


Figure 6.9 – Forecast vs. orders demand and sales

However, the low forecast error indicates that the forecast would have been too high if there had been no strike in May. This is supported by the fact that the months July to October are showing too high forecasts, indicating that this is a trend in the model. In order to find the explanation for this, the sales figures for previous years should be examined.

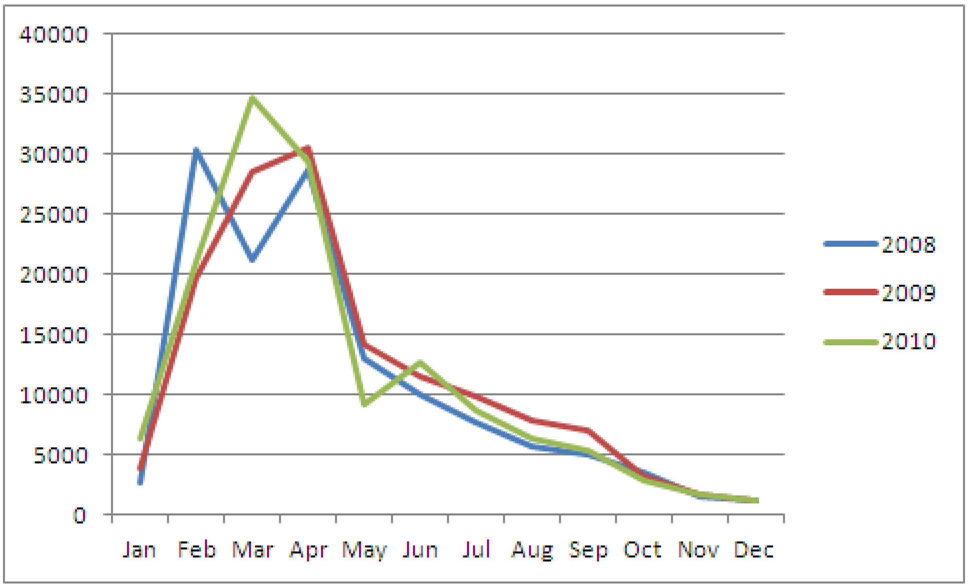


Figure 6.10 – Sales PLT Continental brand summer, 2008-2010

Looking at the actual sales figures from 2008 to 2009, it is possible to explain why the model is forecasting too high volumes. The aggregated sales in 2008 were 130,884, and in

2009 they were 139,285. Thus the sales volume is showing a growing trend, and the model therefore calculated a sales volume of 149,326 for 2010, while the actual sales were 139,608. Though the strike in May could be some of the reason for the decline in sales, sales are also lower in July to October compared with 2009, hence explaining why the model calculated too high forecasts for this period.

So, what does this mean for our model? It seems clear that if the pre-season orders could be manually incorporated into the model, the degree of error in the period January to April could be significantly reduced. Regarding the remaining months, the aggregated figures should be double checked for trends which are not expected to continue. Disregarding May and June, the trend curve for the rest of the year is very similar to the previous years, so it could be argued that it's just a matter of which level of demand one is expecting. For 2010, the model calculated a 7.2% increase in sales. If this is considered unrealistic, the level of demand on aggregated level should simply be adjusted down.

With regards to the major deviations on some of the single articles, it is obvious to see from the calculations that availability issues in the past are having dramatic effects on the forecast. This suggests that either historical sales figures or calculated forecast figures must be checked manually before the forecast is released.

In order to check if availability issues have in fact affected the sales of an article, one can look at forecast compared to both sales and actual orders in order to check for deviations. By also incorporating RDD Fillrate into this overview, it is possible to draw some fairly certain conclusions. It is important to stress that the RDD Fillrate does not tell us the general availability in a month, but merely how the availability was when the customers wanted their orders delivered. If there has been no availability the first 10 days of a 20 day month and full availability the last 10 days, the RDD Fillrate will be 50% assuming that the same volume was requested for delivery in each 10 day period. The RDD Fillrate can then mainly be used as an indication to explain deviations between orders demand and sales on article level. In order to demonstrate this, two of the tests will be examined.

Looking at Figure 6.11 below, the RDD Fillrate is close to 100% all through the year. This basically means that availability issues are not the reasons for the forecast errors. As seen from the first 8 months, there is also a correlation between orders entered and actual sales, supporting the assumption of full availability. This means that the forecast was too low for the first three months and too high for almost all the remaining months of the year, thus indicating that historical sales figures should be checked for deviations. With regards to the last four months, the volume is so low that high deviations occur with small changes in volume.

Month	Sales	Ordered	Forecast	FC/Demand	FC/Sales	RDD fillrate
1	80	96	46	47,7 %	57,2 %	100,00 %
2	344	336	277	82,6 %	80,6 %	100,00 %
3	816	827	629	76,1 %	77,1 %	99,00 %
4	445	439	727	165,6 %	163,4 %	100,00 %
5	138	152	233	153,6 %	169,2 %	100,00 %
6	112	111	172	154,6 %	153,2 %	100,00 %
7	94	90	118	131,2 %	125,6 %	100,00 %
8	67	72	115	159,3 %	171,2 %	98,60 %
9	36	53	88	166,8 %	245,6 %	100,00 %
10	32	40	32	79,7 %	99,6 %	100,00 %
11	7	14	14	102,7 %	205,3 %	100,00 %
12	4	4	6	153,2 %	153,2 %	100,00 %

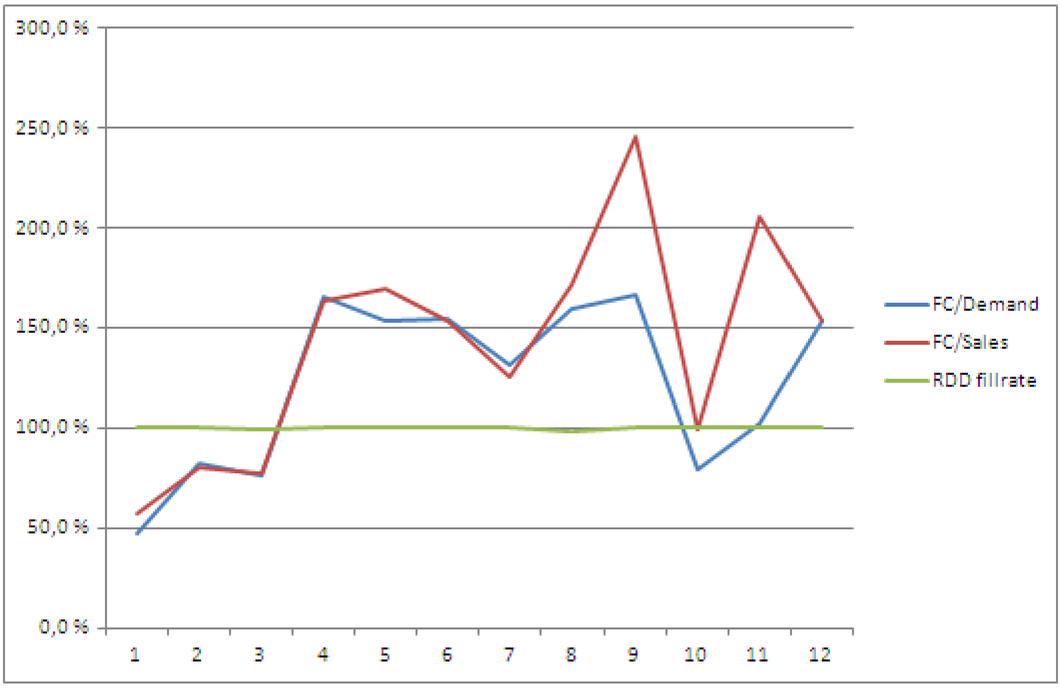


Figure 6.11 – Forecast vs. demand and sales, and RDD Fillrate – Test W1b

This figure will not provide the full picture, but it is possible to draw certain conclusions. In months were the RDD Fillrate has been 100%, we can conclude that any forecast deviation usually means that the forecast was wrong. A higher forecast than orders demand with full availability means that the forecast was too high, and a lower forecast than orders demand with full availability means that the forecast was too low. However, in months with a RDD Fillrate below 100%, there might be several explanations to the deviations. The main problem with this is that without any means of measuring lost sales, it is not possible to make any certain conclusions. We can assume that there is a certain amount of lost sales in months with low availability, but determining the relationship between lost sales and wrong forecast will be mere guesswork as both factors are unknown.

Continuing to test W1c, the RDD Fillrate indicates that the availability has not been equally stable as for the previous article. Looking at Figure 6.12 below, it is possible to see a clear correlation between RDD Fillrate, orders demand and sales in May. Though the strike in May renders the deviation between sales and orders demand rather irrelevant, it is still possible to say that the low order volume compared to the forecast is to an extent due to lost sales, and not only because of a too high forecast.

Month	Sales	Ordered	Forecast	FC/Demand	FC/Sales	RDD Fillrate
1	31	43	10	23,3 %	32,3 %	100,00 %
2	183	185	178	96,0 %	97,1 %	97,80 %
3	260	255	275	107,7 %	105,6 %	100,00 %
4	374	353	387	109,5 %	103,4 %	80,70 %
5	119	157	238	151,8 %	200,2 %	68,80 %
6	135	117	118	101,1 %	87,6 %	100,00 %
7	89	88	103	116,8 %	115,5 %	98,90 %
8	66	76	89	116,5 %	134,2 %	100,00 %
9	80	81	65	80,0 %	81,0 %	100,00 %
10	39	46	40	87,1 %	102,7 %	89,10 %
11	8	12	20	167,5 %	251,3 %	100,00 %
12	0	0	2	100,0 %	100,0 %	100,00 %

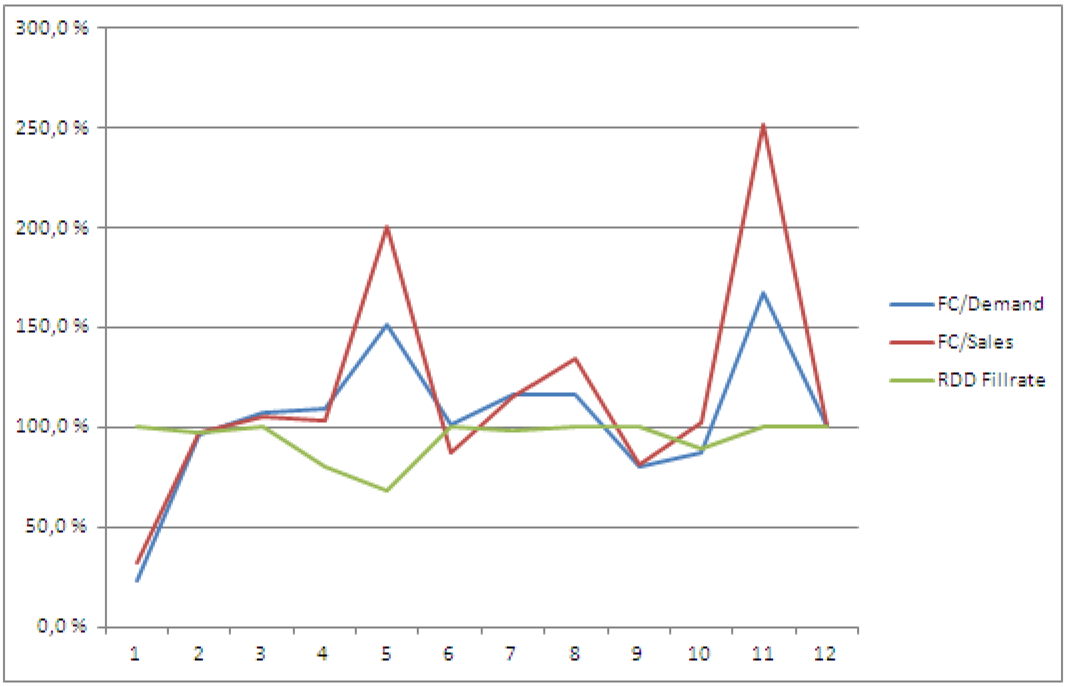


Figure 6.12 – Forecast vs. demand and sales, and RDD Fillrate – Test W1c

To summarize, it is difficult to make any absolute evaluations of the model's performance in cases where the availability is reduced. In cases with full availability on the other hand, it is relatively easy to evaluate the model's performance.

6.3 Discussion

As seen from the tests of Winters' model, it is obvious that this model can improve the forecasting accuracy at Continental. However, it is clear that the model in its current state can't be the only method for creating the forecast. As seen from the tests, variations in availability leads to deviations in the sales history which in turn leads to a forecast based on bad data. The fact that this forecast still shows a significant improvement on several of the articles tested only suggests that there is still room for improvements in the model.

As mentioned before, the main Achilles heel of the model is that it is based on historical sales, something which means that the data must be quality checked before letting the model create a forecast. Though this might be a small task on the aggregated level, it is a massive task on article level. It is also possible to let the model calculate a forecast based on the actual figures, and then do a quality check of the figures, but it's doubtful that this will reduce the work load. It is therefore possible that the model is only practical for use on aggregate level. However, if a method is found for reducing the effect of the availability issues, the model could also be used on article level without the need for massive manual adjustments. In the end, it all comes down to how work intensive the current forecasting process is compared to using the model. If the model can save the forecaster a great deal of time in the preparation process, this extra time could be used for a quality check on article level.

Even though the forecast model is having different effects on different articles, it is important to keep in mind that there are many different explanations for these deviations. Without any clear and repeating patterns in the different articles, it is difficult to model the expected demand for each article. A good model should therefore be focused on having a high accuracy on top level, while article forecasts should be manually checked for any clear deviations in either the historical or the forecasted data.

It is also important to keep in mind that the actual forecast figures are based on actual market intelligence and development trends. It is therefore possible that these figures will catch development trends that a basic Winters' model can't see. By using Winters' model as a basis for the forecast, it may be possible to achieve an even higher accuracy as obvious deviations from certain demands can be adjusted in the final forecast.

7. Conclusions

This thesis has focused on finding ways of improving the forecasting accuracy at Continental Tires Norway. The first part focused on improvements of the actual forecasting process. Through an analysis of these processes, it became clear that there were rooms for improvement. The forecasting techniques being used today do not include any use of models, despite the fact that there is a massive amount of data available. The recommendation was therefore that a model should be used as a basis for discussions of the forecast.

In addition, the process analysis showed that inputs from the biggest customer groups were more or less the only information being used to create the forecast. Even though this might be the most vital information for the forecast, there could also be a potential for improvement in conducting surveys to uncover areas where marketing and information campaigns can improve sales. The economic trends could also serve as valuable information in the forecasting process, ensuring that the forecast is adjusted to realistic demand expectations.

The role of the forecast in the decision making process was also analyzed. The findings showed that the forecast is a key figure in several important processes. However, with a very high forecast error, there is a risk that important decisions can be based on bad data. It is therefore important to ensure that the weight given to the forecast in the decision making process is mirrored by the forecast accuracy.

The second part of the thesis focused on testing a forecasting model to test if it was possible to increase the forecasting accuracy. By using Winters' trend-seasonal model, the forecast error was reduced from 29.71% to 16.59% on an aggregated level for Continental brand summer tires. Tests of single articles also showed some improvement, but a vulnerability to availability issues was also uncovered. Even though the model still might need some adjustments before it can yield optimal results, the improvements are too good to ignore.

Though this thesis has not given a detailed step-by-step method of improving the forecasting accuracy at Continental Tires Norway, it has demonstrated that there is room for improvement in several areas. This is especially true regarding the implementation of a forecasting model, and such a model should be included in the future forecasting process at Continental Tires Norway.

8. Further Research

Through tests and analyses of Winters' model, it is clear that further research should be conducted to specialize the model for the needs of Continental. One of the most important issues is to incorporate availability issues in the model. The main challenge here is that it's currently not possible to log all lost sales, thus making it impossible to register the true demand for any given period. In addition, it is difficult to calculate the availability throughout a month. The RDD Fillrate will only which dates any article was unavailable for delivery, thus not saying anything about how many customers that placed their order elsewhere at that time. It could therefore be helpful to create a model which uses several years of historical data to create an expected sales figure for each month, and cross-referencing this figure with the amount of days without availability, and also incorporating the amount of orders which are delivered in another month than the requested delivery month. Though such a figure might still not provide the actual demand, it should still serve as a reasonably good indication compared to merely checking the sales figures for the last years.

In addition, the model could benefit from adding pre-season order figures. Since the requested delivery dates of such orders change every year, it does not make sense to merely use Winters' model to calculate the forecast. If a way is found to extrapolate the pre-season orders from the historical data, it should be possible to create a forecast without these pre-season orders. The orders can then be added to the forecast afterwards, thus ensuring a higher accuracy.

It could also prove beneficial to include dynamic peaks into the model. Easter represents such a peak, and the date of the Easter is known. If the period right before and after Easter represents a boost in sales, it could be helpful to implement this in the model. Another dynamic peak is the first day of snow, which is also followed by a boost in sales. However, as most meteorologists also have problems forecasting long-term, it could prove difficult to add such a peak into the long-term forecast.

9. References

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10. Appendices

10.1 Seasonal Multiplicative Model

Test:	SMM	**Actual MAPE:**	29,71 %
Article:	All	**Model MAPE:**	23,01 %

	Demand			Average	Average	
				2007-2009	Monthly	Seasonal
Month	**2007**	**2008**	**2009**	**Demand**	**Demand**	**Index**
Jan	1760	2662	3870	2764	11218	0,246
Feb	35841	30331	19736	28636	11218	2,553
Mar	25348	21271	28577	25065	11218	2,234
Apr	19695	28760	30465	26307	11218	2,345
May	14492	12967	14149	13869	11218	1,236
Jun	10289	10076	11504	10623	11218	0,947
Jul	8069	7713	9875	8552	11218	0,762
Aug	6786	5762	7913	6820	11218	0,608
Sep	5337	5071	7000	5803	11218	0,517
Oct	3274	3583	3259	3372	11218	0,301
Nov	2085	1460	1692	1746	11218	0,156
Dec	692	1228	1245	1055	11218	0,094
	Total average annual demand:			134612		
	Average monthly demand:			11218		

Forecast 2010 - Least Sqares Method: 140229

2010 Average monthly demand	Month	Sales	Model Forecast	Model MAD	Model MAPE	Actual Forecast	Actual MAD	Actual MAPE
11686	Jan	6407	2879	3528	55,06 %	6003	404	6,31 %
11686	Feb	20989	29831	8842	42,13 %	34502	13513	64,38 %
11686	Mar	34636	26111	8525	24,61 %	37500	2864	8,27 %
11686	Apr	29293	27404	1889	6,45 %	37306	8013	27,35 %
11686	May	9242	14448	5206	56,33 %	17000	7758	83,94 %
11686	Jun	12765	11066	1699	13,31 %	14086	1321	10,35 %
11686	Jul	8692	8909	217	2,50 %	11241	2549	29,33 %
11686	Aug	6328	7105	777	12,28 %	8176	1848	29,20 %
11686	Sep	5421	6045	624	11,51 %	7463	2042	37,67 %
11686	Oct	2866	3513	647	22,56 %	3515	649	22,64 %
11686	Nov	1760	1819	59	3,32 %	2203	443	25,17 %
11686	Dec	1209	1099	110	9,10 %	1280	71	5,87 %
					23,01 %			29,71 %

10.2 Test W1a – All articles

α = **0,01**	**Test:** **W1a**	**Actual MAPE:**	**29,71 %**
β = **0,01**	**Article:** **All articles**	**Winters MAPE:**	**16,59 %**
γ = **0,99**			

Year	t	$\hat{a}$	$\hat{b}$	F	$\hat{x}$	x	Error	MAD	MAPE	
2008	1	10570,77	58,19	0,25	3114	2662	-452	452	16,97 %	
	2	10656,22	58,46	2,84	24139	30331	6192	6192	20,42 %	
	3	10703,19	58,34	1,99	23826	21271	-2555	2555	12,01 %	
	4	10762,94	58,36	2,67	28389	28760	371	371	1,29 %	
	5	10821,06	58,36	1,20	12996	12967	-29	29	0,22 %	
	6	10876,68	58,33	0,93	10337	10076	-261	261	2,59 %	
	7	10925,96	58,24	0,71	8409	7713	-696	696	9,02 %	
	8	10971,32	58,11	0,53	6527	5762	-765	765	13,27 %	
	9	11016,33	57,98	0,46	5755	5071	-684	684	13,49 %	
	10	11084,56	58,08	0,32	3279	3583	304	304	8,47 %	
	11	11139,18	58,05	0,13	1507	1460	-47	47	3,21 %	
	12	11201,34	58,09	0,11	1184	1228	44	44	3,55 %	9,47 %
2009	1	11300,26	58,50	0,34	2840	3870	1030	1030	26,61 %	
	2	11314,64	58,05	1,76	32265	19736	-12529	12529	63,48 %	
	3	11402,59	58,35	2,50	22628	28577	5949	5949	20,82 %	
	4	11460,36	58,35	2,66	30621	30465	-156	156	0,51 %	
	5	11521,60	58,38	1,23	13803	14149	346	346	2,44 %	
	6	11588,32	58,46	0,99	10730	11504	774	774	6,73 %	
	7	11670,08	58,69	0,84	8229	9875	1646	1646	16,67 %	
	8	11761,95	59,02	0,67	6168	7913	1745	1745	22,05 %	
	9	11854,64	59,36	0,59	5449	7000	1551	1551	22,16 %	
	10	11895,76	59,18	0,27	3848	3259	-589	589	18,07 %	
	11	11964,45	59,27	0,14	1567	1692	125	125	7,36 %	
	12	12017,09	59,21	0,10	1318	1245	-73	73	5,84 %	19,03 %
2010	1	12143,11	59,88	0,53	4125	6407	2282	2282	35,62 %	
	2	12200,53	59,85	1,72	21419	20989	-430	430	2,05 %	
	3	12276,27	60,01	2,82	30663	34636	3973	3973	11,47 %	
	4	12323,10	59,88	2,38	32795	29293	-3502	3502	11,96 %	
	5	12334,43	59,39	0,75	15203	9242	-5961	5961	64,50 %	
	6	12398,56	59,44	1,03	12295	12765	470	470	3,68 %	
	7	12436,31	59,22	0,70	10524	8692	-1832	1832	21,08 %	
	8	12464,84	58,92	0,51	8388	6328	-2060	2060	32,56 %	
	9	12490,53	58,58	0,44	7379	5421	-1958	1958	36,12 %	
	10	12528,05	58,37	0,23	3444	2866	-578	578	20,17 %	
	11	12585,10	58,36	0,14	1779	1760	-19	19	1,06 %	
	12	12633,65	58,26	0,10	1311	1209	-102	102	8,41 %	**16,59 %**

Actual FC one	Actual FC error	Actual MAD	Actual MAPE	
6003	404	404	6,31 %	
34502	-13513	13513	64,38 %	
37500	-2864	2864	8,27 %	
37306	-8013	8013	27,35 %	
17000	-7758	7758	83,94 %	
14086	-1321	1321	10,35 %	
11241	-2549	2549	29,33 %	
8176	-1848	1848	29,20 %	
7463	-2042	2042	37,67 %	
3515	-649	649	22,64 %	
2203	-443	443	25,17 %	
1280	-71	71	5,87 %	**29,71 %**

10.3 Test W1b – Article 0352056

α = 0,01	Test: V1b	Actual MAPE:	38,16 %
β = 0,01	Article: 0352056	Vinters MAPE:	39,49 %
γ = 0,99			

Year	t	$\hat{a}$	$\hat{b}$	$\hat{F}$	$\hat{x}$	x	Error	MAD	MAPE	
2008	1	182,98	0,59	0,11	31	20	-11	11	54,73 %	
	2	184,27	0,60	2,91	389	538	149	149	27,62 %	
	3	184,78	0,60	2,77	538	511	-27	27	5,21 %	
	4	185,24	0,60	3,03	606	560	-46	46	8,15 %	
	5	185,80	0,60	1,09	206	203	-3	3	1,57 %	
	6	186,14	0,59	0,63	137	118	-19	19	15,93 %	
	7	186,72	0,59	0,56	106	105	-1	1	0,83 %	
	8	186,90	0,59	0,36	86	67	-19	19	28,50 %	
	9	187,28	0,59	0,35	73	65	-8	8	12,35 %	
	10	188,07	0,59	0,19	32	36	4	4	9,73 %	
	11	188,71	0,59	0,07	14	14	0	0	3,02 %	
	12	189,36	0,59	0,03	6	6	0	0	2,99 %	12,75 %
2009	1	192,06	0,61	0,23	21	44	23	23	52,56 %	
	2	191,63	0,60	1,37	561	259	-302	302	116,59 %	
	3	192,45	0,60	3,08	532	594	62	62	10,46 %	
	4	193,39	0,61	3,54	584	686	102	102	14,85 %	
	5	194,08	0,61	1,14	212	221	9	9	4,08 %	
	6	195,32	0,61	0,84	124	164	40	40	24,63 %	
	7	195,99	0,61	0,58	110	113	3	3	2,49 %	
	8	197,72	0,62	0,56	71	111	40	40	36,33 %	
	9	198,84	0,63	0,43	69	86	17	17	19,85 %	
	10	199,09	0,63	0,16	38	31	-7	7	23,05 %	
	11	199,61	0,62	0,07	15	14	-1	1	5,80 %	
	12	200,13	0,62	0,03	6	6	0	0	5,71 %	26,06 %
2010	1	202,25	0,64	0,39	46	80	34	34	42,81 %	
	2	203,38	0,64	1,69	277	344	67	67	19,36 %	
	3	204,63	0,65	3,98	629	816	187	187	22,91 %	
	4	204,48	0,64	2,19	727	445	-282	282	63,39 %	
	5	204,28	0,63	0,68	233	138	-95	95	69,19 %	
	6	204,21	0,63	0,55	172	112	-60	60	53,25 %	
	7	204,41	0,62	0,46	118	94	-24	24	25,61 %	
	8	204,18	0,61	0,33	115	67	-48	48	71,18 %	
	9	203,58	0,60	0,18	88	36	-52	52	145,56 %	
	10	204,19	0,60	0,16	32	32	0	0	0,42 %	
	11	203,74	0,59	0,03	14	7	-7	7	105,31 %	
	12	203,62	0,58	0,02	6	4	-2	2	53,24 %	**39,49 %**

Actual FC one	Actual FC error	Actual MAD	Actual MAPE	
100	-20	20	25,00 %	
433	-89	89	25,87 %	
514	302	302	37,01 %	
529	-84	84	18,88 %	
205	-67	67	48,55 %	
188	-76	76	67,86 %	
143	-49	49	52,13 %	
116	-49	49	73,13 %	
103	-67	67	186,11 %	
38	-6	6	18,75 %	
22	-15	15	214,29 %	
10	-6	6	150,00 %	**38,16 %**

10.4 Test W1c – Article 0351890

α = **0,01**	**Test:** **W1c**	**Actual MAPE:**	**34,18 %**
β = **0,01**	**Article:** **0351890**	**Winters MAPE:**	**18,52 %**
γ = **0,99**			

Year	t	$\hat{a}$	$\hat{b}$	F	$\hat{x}$	x	Error	MAD	MAPE	
2008	1	128,62	-0,08	0,21	19	27	8	8	31,26 %	
	2	128,63	-0,08	1,60	193	206	13	13	6,41 %	
	3	128,35	-0,08	1,56	240	200	-40	40	19,81 %	
	4	128,34	-0,08	3,41	415	438	23	23	5,36 %	
	5	128,13	-0,08	1,53	219	196	-23	23	11,80 %	
	6	128,17	-0,08	1,13	133	145	12	12	8,59 %	
	7	127,98	-0,08	0,69	96	88	-8	8	9,57 %	
	8	127,79	-0,08	0,60	83	76	-7	7	9,51 %	
	9	127,77	-0,08	0,57	70	73	3	3	4,78 %	
	10	127,81	-0,08	0,38	45	49	4	4	8,47 %	
	11	127,91	-0,08	0,21	24	27	3	3	12,21 %	
	12	128,45	-0,07	0,05	4	6	2	2	32,76 %	9,73 %
2009	1	127,58	-0,08	0,08	27	10	-17	17	168,66 %	
	2	127,32	-0,08	1,38	204	176	-28	28	15,94 %	
	3	127,73	-0,08	2,14	199	274	75	75	27,49 %	
	4	127,50	-0,08	3,02	435	384	-51	51	13,39 %	
	5	127,70	-0,07	1,86	195	238	43	43	18,00 %	
	6	127,39	-0,08	0,93	144	118	-26	26	22,26 %	
	7	127,54	-0,07	0,81	88	103	15	15	14,92 %	
	8	127,69	-0,07	0,70	76	89	13	13	14,74 %	
	9	127,48	-0,07	0,51	73	65	-8	8	12,12 %	
	10	127,17	-0,08	0,32	49	40	-9	9	22,01 %	
	11	126,78	-0,08	0,16	27	20	-7	7	33,98 %	
	12	125,86	-0,09	0,02	6	2	-4	4	194,94 %	19,53 %
2010	1	128,40	-0,06	0,24	10	31	21	21	67,67 %	
	2	128,38	-0,06	1,43	178	183	5	5	2,90 %	
	3	128,25	-0,06	2,03	275	260	-15	15	5,59 %	
	4	128,15	-0,06	2,92	387	374	-13	13	3,37 %	
	5	127,45	-0,07	0,94	238	119	-119	119	100,25 %	
	6	127,56	-0,07	1,06	118	135	17	17	12,41 %	
	7	127,32	-0,07	0,70	103	89	-14	14	15,51 %	
	8	126,93	-0,07	0,52	89	66	-23	23	34,19 %	
	9	127,16	-0,07	0,63	65	80	15	15	19,05 %	
	10	127,05	-0,07	0,31	40	39	-1	1	2,72 %	
	11	126,22	-0,08	0,06	20	8	-12	12	151,25 %	
	12	124,88	-0,09	0,00	2	0	-2	2	200,00 %	**18,52 %**

Actual FC one	Actual FC error	Actual MAD	Actual MAPE	
50	-19	19	61,29 %	
323	-140	140	76,50 %	
375	-115	115	44,23 %	
246	128	128	34,22 %	
115	4	4	3,36 %	
146	-11	11	8,15 %	
113	-24	24	26,97 %	
83	-17	17	25,76 %	
76	4	4	5,00 %	
37	2	2	5,13 %	
10	-2	2	25,00 %	
7	-7	7	700,00 %	**34,18 %**

10.5 Test W1d – Article 0351882

α = **0,01**	**Test:** **W1d**	**Actual MAPE:**	**54,73 %**
β = **0,01**	**Article:** **0351882**	**Winters MAPE:**	**32,86 %**
γ = **0,99**			

Year	t	$\hat{a}$	$\hat{b}$	F	$\hat{x}$	x	Error	MAD	MAPE	
2008	1	496,37	-1,15	0,15	86	73	-13	13	18,29 %	
	2	496,80	-1,14	3,58	1350	1783	433	433	24,31 %	
	3	495,13	-1,14	2,73	1516	1351	-165	165	12,22 %	
	4	493,44	-1,15	2,19	1209	1077	-132	132	12,25 %	
	5	491,94	-1,15	0,98	518	481	-37	37	7,76 %	
	6	490,29	-1,16	0,68	368	331	-37	37	11,25 %	
	7	487,81	-1,17	0,44	295	215	-80	80	37,31 %	
	8	486,82	-1,17	0,44	205	213	8	8	3,57 %	
	9	485,61	-1,17	0,43	213	211	-2	2	0,81 %	
	10	484,66	-1,17	0,22	101	106	5	5	4,30 %	
	11	481,90	-1,18	0,05	39	26	-13	13	49,12 %	
	12	481,83	-1,17	0,05	19	23	4	4	18,86 %	15,78 %
2009	1	482,37	-1,15	0,20	71	96	25	25	26,23 %	
	2	478,86	-1,18	1,86	1723	880	-843	843	95,78 %	
	3	478,81	-1,17	3,36	1305	1613	308	308	19,10 %	
	4	478,77	-1,16	2,69	1044	1289	245	245	19,02 %	
	5	478,31	-1,15	1,12	467	535	68	68	12,64 %	
	6	478,17	-1,14	0,82	322	391	69	69	17,52 %	
	7	480,47	-1,10	0,75	211	363	152	152	41,87 %	
	8	478,96	-1,11	0,40	210	192	-18	18	9,20 %	
	9	477,86	-1,11	0,44	208	208	0	0	0,17 %	
	10	476,28	-1,11	0,20	104	94	-10	10	10,88 %	
	11	479,64	-1,07	0,10	26	50	24	24	48,48 %	
	12	476,73	-1,09	0,03	23	14	-9	9	62,87 %	30,93 %
2010	1	480,86	-1,03	0,41	94	198	104	104	52,32 %	
	2	479,27	-1,04	1,64	890	787	-103	103	13,10 %	
	3	478,50	-1,04	3,55	1608	1700	92	92	5,41 %	
	4	475,36	-1,06	1,52	1283	718	-565	565	78,70 %	
	5	471,88	-1,08	0,55	530	259	-271	271	104,58 %	
	6	470,37	-1,09	0,74	384	349	-35	35	10,12 %	
	7	467,58	-1,10	0,48	353	225	-128	128	56,92 %	
	8	465,00	-1,12	0,28	187	128	-59	59	46,22 %	
	9	461,26	-1,14	0,19	202	88	-114	114	129,45 %	
	10	459,36	-1,15	0,17	91	76	-15	15	19,62 %	
	11	460,47	-1,13	0,15	48	71	23	23	33,05 %	
	12	457,80	-1,14	0,02	14	9	-5	5	50,82 %	**32,86 %**

Actual FC one	Actual FC error	Actual MAD	Actual MAPE	
124	74	74	37,37 %	
1200	-413	413	52,48 %	
1208	492	492	28,94 %	
1579	-861	861	119,92 %	
468	-209	209	80,69 %	
449	-100	100	28,65 %	
249	-24	24	10,67 %	
256	-128	128	100,00 %	
242	-154	154	175,00 %	
88	-12	12	15,79 %	
41	30	30	42,25 %	
34	-25	25	277,78 %	**54,73 %**

10.6 Test W1e – Article 0350093

α =	0,01	Test:	W1e	Actual MAPE:	62,77 %
β =	0,01	Article:	0350093	Winters MAPE:	57,92 %
γ =	0,99				

Year	t	$\hat{a}$	$\hat{b}$	F	$\hat{x}$	x	Error	MAD	MAPE	
2008	1	74,64	0,23	0,13	16	10	-6	6	55,09 %	
	2	75,03	0,23	3,33	205	250	45	45	18,03 %	
	3	75,24	0,23	1,99	153	150	-3	3	2,25 %	
	4	75,35	0,23	2,43	219	183	-36	36	19,94 %	
	5	75,52	0,23	1,14	93	86	-7	7	7,85 %	
	6	75,68	0,23	1,02	83	77	-6	6	8,38 %	
	7	76,56	0,23	0,87	36	67	31	31	46,29 %	
	8	77,45	0,24	0,59	25	46	21	21	45,95 %	
	9	77,17	0,23	0,19	42	14	-28	28	203,44 %	
	10	77,72	0,24	0,27	15	21	6	6	29,37 %	
	11	77,53	0,23	0,08	13	6	-7	7	119,71 %	
	12	77,52	0,23	0,05	6	4	-2	2	46,26 %	21,83 %
2009	1	78,61	0,24	0,28	10	22	12	12	52,39 %	
	2	78,57	0,24	2,18	262	170	-92	92	54,26 %	
	3	78,84	0,24	2,09	157	165	8	8	4,77 %	
	4	79,39	0,24	3,38	192	269	77	77	28,46 %	
	5	79,76	0,24	1,31	91	105	14	14	13,56 %	
	6	80,13	0,24	1,18	81	95	14	14	14,26 %	
	7	79,64	0,23	0,08	70	6	-64	64	1066,85 %	
	8	79,14	0,23	0,06	47	4	-43	43	1080,59 %	
	9	82,52	0,26	0,88	15	73	58	58	79,88 %	
	10	82,29	0,25	0,11	22	9	-13	13	147,79 %	
	11	84,40	0,27	0,25	6	21	15	15	69,22 %	
	12	85,36	0,28	0,09	4	8	4	4	45,14 %	43,61 %
2010	1	86,30	0,29	0,48	24	42	18	18	43,23 %	
	2	86,39	0,28	1,69	188	146	-42	42	29,00 %	
	3	86,88	0,29	2,58	181	225	44	44	19,42 %	
	4	87,35	0,29	4,09	295	358	63	63	17,74 %	
	5	87,02	0,28	0,40	115	34	-81	81	238,89 %	
	6	86,44	0,27	0,02	103	1	-102	102	10235,87 %	
	7	96,41	0,37	0,90	7	88	81	81	91,79 %	
	8	101,71	0,42	0,32	5	33	28	28	83,59 %	
	9	101,17	0,41	0,06	90	5	-85	85	1692,68 %	
	10	100,56	0,40	0,00	11	0	-11	11	#DIV/0!	
	11	100,88	0,40	0,23	25	23	-2	2	8,48 %	
	12	101,55	0,40	0,12	9	12	3	3	21,26 %	**57,92 %**

Actual FC one	Actual FC error	Actual MAD	Actual MAPE	
70	-28	28	66,67 %	
300	-154	154	105,48 %	
278	-53	53	23,56 %	
281	77	77	21,51 %	
113	-79	79	232,35 %	
98	-97	97	9700,00 %	
78	10	10	11,36 %	
58	-25	25	75,76 %	
53	-48	48	960,00 %	
24	-24	24	#DIV/0!	
19	4	4	17,39 %	
4	8	8	66,67 %	**62,77 %**

10.7 Test W1f – Article 0350110

α = **0,01**	**Test:**	**W1f**	**Actual MAPE:**	**46,32 %**
β = **0,01**	**Article:**	**0350110**	**Winters MAPE:**	**35,37 %**
γ = **0,99**				

Year	t	$\hat{a}$	$\hat{b}$	$\hat{F}$	$\hat{x}$	x	Error	MAD	MAPE	
2008	1	42,31	0,91	0,33	15	14	-1	1	3,90 %	
	2	43,34	0,91	2,35	81	102	21	21	20,91 %	
	3	44,39	0,91	1,39	47	62	15	15	24,13 %	
	4	45,21	0,91	2,48	139	112	-27	27	24,14 %	
	5	46,15	0,91	1,60	70	74	4	4	4,81 %	
	6	46,92	0,91	0,90	59	42	-17	17	41,27 %	
	7	48,01	0,91	1,18	41	57	16	16	27,66 %	
	8	49,07	0,91	1,24	47	61	14	14	22,32 %	
	9	49,55	0,91	0,04	14	2	-12	12	611,91 %	
	10	50,82	0,91	0,31	9	16	7	7	41,41 %	
	11	51,54	0,91	0,16	13	8	-5	5	59,95 %	
	12	52,48	0,91	0,34	17	18	1	1	6,43 %	24,47 %
2009	1	53,46	0,91	0,37	18	20	2	2	11,64 %	
	2	54,17	0,91	1,49	128	80	-48	48	59,64 %	
	3	54,84	0,91	0,79	77	43	-34	34	78,49 %	
	4	56,05	0,91	3,80	138	214	76	76	35,32 %	
	5	56,93	0,91	1,53	91	87	-4	4	4,94 %	
	6	58,36	0,92	1,67	52	98	46	46	46,95 %	
	7	58,97	0,91	0,58	70	34	-36	36	106,39 %	
	8	59,63	0,91	0,74	74	44	-30	30	68,81 %	
	9	67,65	0,98	0,48	3	33	30	30	92,15 %	
	10	68,07	0,98	0,06	22	4	-18	18	437,99 %	
	11	69,76	0,98	0,31	11	22	11	11	50,99 %	
	12	70,62	0,98	0,28	24	20	-4	4	21,24 %	48,57 %
2010	1	71,93	0,98	0,54	27	39	12	12	31,40 %	
	2	72,58	0,98	0,81	108	58	-50	50	86,75 %	
	3	74,47	0,99	1,74	58	130	72	72	55,29 %	
	4	75,42	0,99	3,61	287	272	-15	15	5,54 %	
	5	76,22	0,99	1,16	117	88	-29	29	32,74 %	
	6	77,06	0,99	1,37	129	105	-24	24	22,91 %	
	7	77,99	0,99	0,54	45	42	-3	3	8,28 %	
	8	78,95	0,99	0,72	59	57	-2	2	2,92 %	
	9	80,92	1,00	1,06	39	86	47	47	55,07 %	
	10	88,27	1,06	0,49	5	44	39	39	88,59 %	
	11	88,95	1,06	0,18	28	16	-12	12	75,17 %	
	12	89,10	1,05	0,00	26	0	-26	26	#DIV/0!	**35,37 %**

Actual FC one	Actual FC error	Actual MAD	Actual MAPE	
19	20	20	51,28 %	
175	-117	117	201,72 %	
215	-85	85	65,38 %	
209	63	63	23,16 %	
87	1	1	1,14 %	
79	26	26	24,76 %	
61	-19	19	45,24 %	
40	17	17	29,82 %	
45	41	41	47,67 %	
20	24	24	54,55 %	
0	16	16	100,00 %	
5	-5	5	#DIV/0!	**46,32 %**