The Development of Supply Chain Solutions for Nailmetics

by

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Executive Summary

The project that is discussed in this document will aim to develop a structure for the implementation of collaborative planning, forecasting and replenishment (CPFR), forecasting model and inventory model for Nailmetics CC. The problem currently for Nailmetics is that they have very long lead times for the ordering and importing of products from Greece in the absence of a specialized forecasting or inventory model to support the ordering of products. This causes the company to have very high inventory levels and place inefficiently large orders due to them striving for 100% perfect order fulfilment. The collaboration in the supply chain is also not at an optimal level which also contributes to these supply chain problem areas. This project develops an implementation plan for realizing CPFR in the supply chain by implementing a basic CPFR model. In order to improve the ordering system, an optimal review period is calculated using a linear programming method and an adjustable Microsoft Excel forecasting model is developed using the Holt-Winters technique.

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List of Acronyms

AFTER - Aggregated Forecast through Exponential Re-weighting

CPFR - Collaborative planning, Forecasting and Replenishment

EOQ - Economic Order Quantity

FDA - Food and Drug Association

FY - Financial Year

IQEA - Improved Quantum Evolutionary Algorithm

LOC - Letter of Credit

LP - Linear Program

MAD - Mean Absolute Deviation

MAPE - Mean Absolute Percentage Error

SKU - Stock Keeping Unit

1. Introduction

1.1 Company Background

Nailmetics, a company that specializes in the supply and distribution of the international cosmetic brand, Coverderm, throughout Southern Africa, was established in 2007 and owns the sole distribution rights of Coverderm in Southern Africa. The essence of their business is encapsulated in their vision and mission statement:

- **Vision of Nailmetics**

"We aim to be a preferred supplier of quality skincare products, including products for skins of colour in Southern Africa."

"And That Southern African consumers, both men and women, prefer to use our cosmeceutical and colorceutical skincare product ranges through all life stages and for all lifestyles." (Nailmetics, 2010)

- **Mission of Nailmetics**

"We are committed to providing quality skincare products that offer value to our consumers and that can enhance their natural attractiveness and their image."
"We will market and distribute our products efficiently and provide world-class service to our customers (retailers and stockists)."
"We will grow our business organically." (Nailmetics, 2010)

Nailmetics, who is currently only supplying and distributing Coverderm in South Africa and Namibia, is consistently seeking opportunities to increase their market share and enlarge their business scope through continuous advertising, promotion, exhibition and sponsorship campaigns. The company is also constantly introducing new product ranges into the South African market and are currently focusing on skincare for ethnical skin types.

Nailmetics is showing steady growth in the South African cosmetics industry, competing with large, well established companies such as Nivea, Estée Lauder and Elizabeth Arden. Despite this competitive market Nailmetics showed a 27% increase in sales in the 2012 financial year. Coverderm, however, strive to be scientifically superior to any other cosmetic brand with the invention of Covermark, from which Coverderm originated, being the only make-up to receive a USA patent by the Food and Drug Association (FDA) and being the first camouflage make-up in the world. The Coverderm inventor's work is displayed at the Smithsonian Institute in the exhibition "Invention at Play" alongside other famous inventors such as Alexander Graham Bell and Thomas Edison (Nailmetics, 2010).

Coverderm is manufactured by Farmeco which is based in Athens, Greece with their manufacturing facility in Milan, Italy. Nailmetics therefore import the Coverderm range via aircraft from Greece which causes a 4 week lead time on the ordering of products from the supplier. The long lead time combined with high fixed cost on ordering and importing from Greece, cause Nailmetics to carry high levels of safety stock at present.

Nailmetics supply Coverderm products to more than 180 retail stores in al provinces of South Africa and one store in Namibia. Their biggest customer is Dischem with other stores being pharmacies, beauty salons and specialized cosmetic stores. Dischem has provided Nailmetics with a link to their SAP sales list to improve the collaborative planning, forecasting and replenishment (CPFR) link between these two companies.

1.2 Problem Statement

Coverderm is currently in the growth phase of the product life cycle and therefore decisions made in this phase can have a great influence on the maturity level that will be reached by the product.

Although Farmeco receives sales and inventory reports from Nailmetics, CPFR is not at an optimal level. Due to the fact that Farmeco and Nailmetics are situated in the Northern and Southern Hemisphere respectively, Farmeco product production and Nailmetics product sales differ during the year due to different seasons. For example, Farmeco produces Coverderm Filteray sun protection products during the Northern Hemisphere summer and the Southern Hemisphere winter and when Nailmetics order Filteray during the Southern Hemisphere summer, Farmeco needs to stop their normal production to produce Filteray.

Nailmetics currently experience the problem of very long lead times for the ordering and importing of products from Greece in the absence of a specialized forecasting or inventory model to support the ordering of products (See figures 1.1 and 1.2 for examples of the high inventory levels. . The vertical axis values are hidden for confidentiality purposes). Figure 1.3 demonstrates the forecasting inaccuracy of the current method of moving average for the previous 13 months compared to the actual sales as well as the forecasting inaccuracy of the current method for a 4 month period. This may cause Nailmetics to place unnecessarily large orders to compensate for the high fixed ordering cost and the company's aim for 100% perfect order fulfilment. However with increasing growth in sales, the continuation of the policy of very large orders and large safety stock is impractical due to limited storage space. Figures 1.1 and 1.2 indicate how large orders, due to inaccurate forecasting, can have a lasting negative effect on accurate and efficient inventory levels relative to sales.

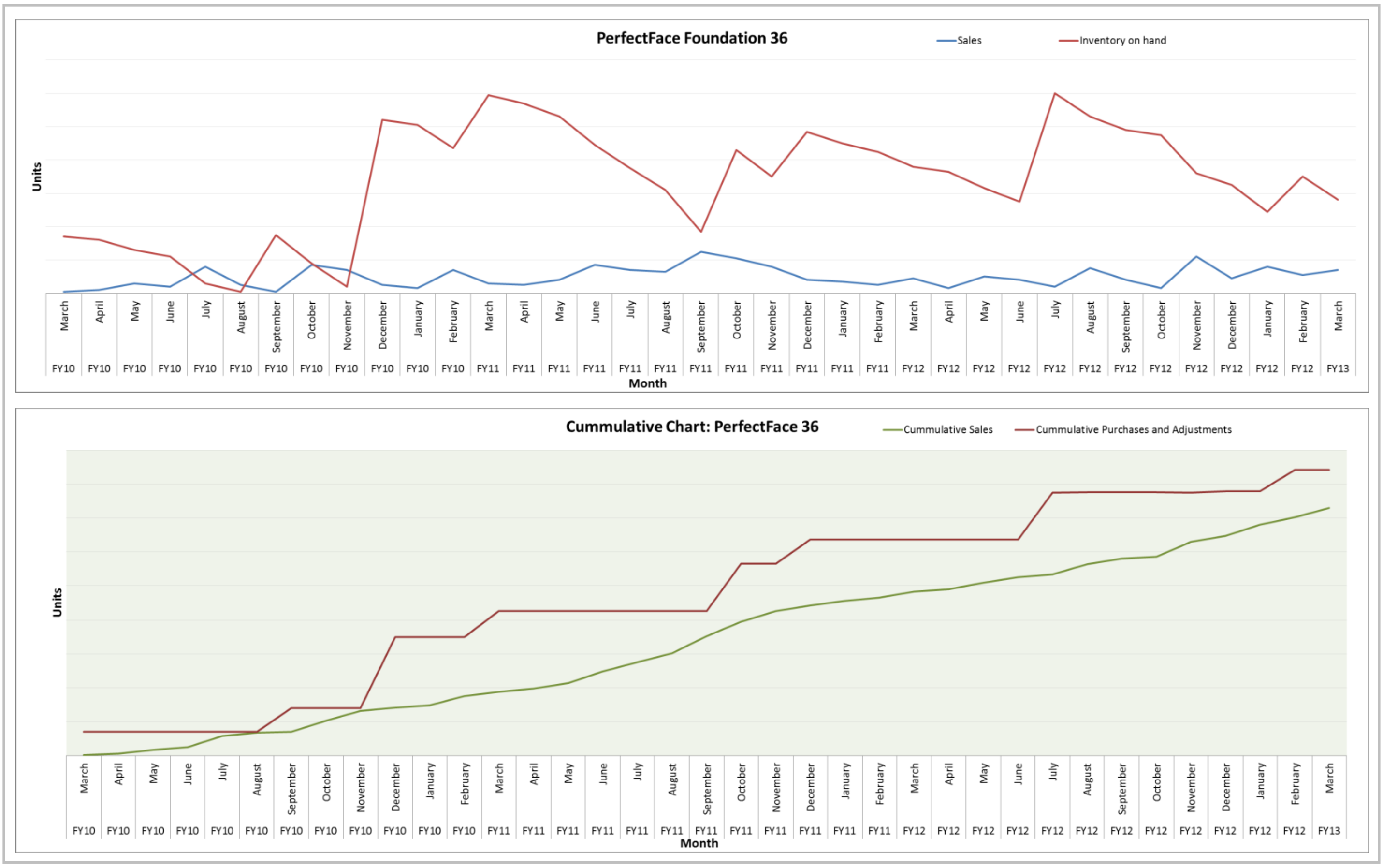

Figure 1.1: Sales and Stock-on-hand comparison for Coverderm PerfectFace 36

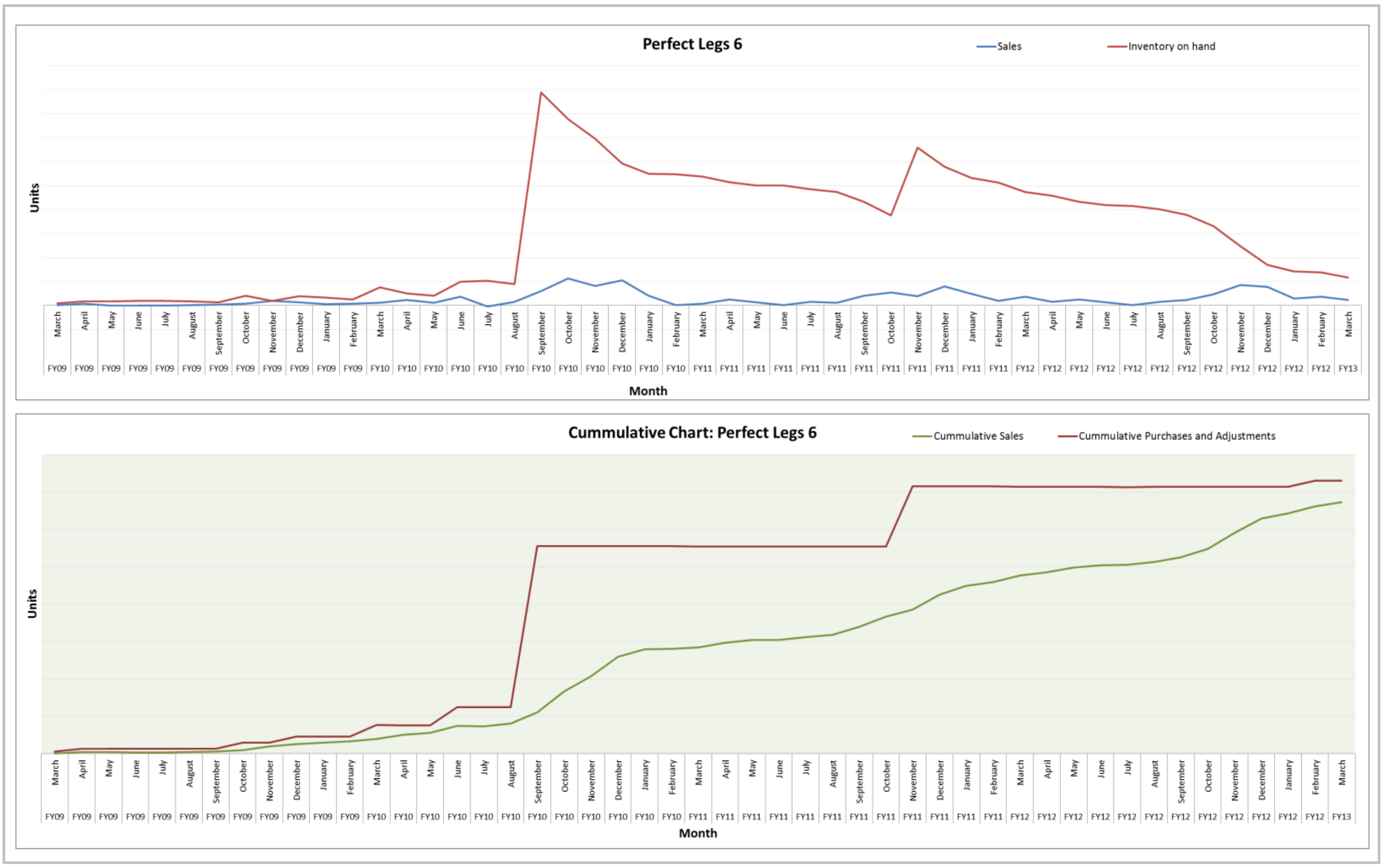

Figure 1.2: Sales and Stock-on-hand comparison for Coverderm Perfect Legs 6

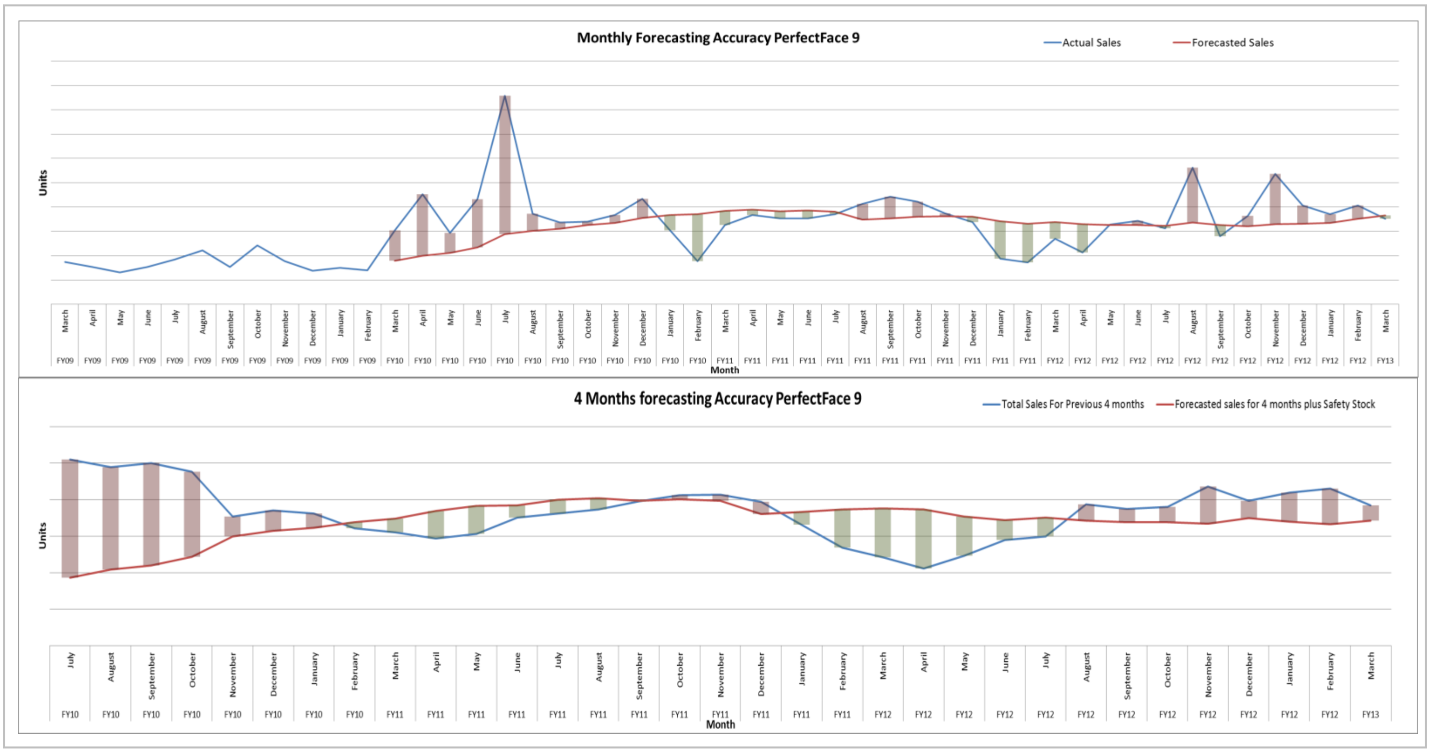

Figure 1.3: Forecasting accuracy comparison per month and for 4 month period for Coverderm PerfectFace 9

1.3 Project Aim

This project will aim to seek solutions for the implementation of a total supply chain CPFR model by studying the company's supply, inventory and demand management structures.

In implementing supply chain collaboration, the project will also aim to develop and implement a specialized forecasting and inventory model for Nailmetics' variable demand and growing market. This solution will aim to improve the cost of ordering and storing high levels of safety stock, the possible lowering of purchase cost by purchasing products in the same season that it is produced by Farmeco and to ensure that Coverderm reaches a maximum maturity level in South Africa in the long term by ensuring optimal perfect order fulfilment through accurate forecasting and ordering.

1.4 Project Scope

The forecasting model will be developed through the development of proof of concept models for single products and then implementing these forecasting models for all the products with similar historic sale tendencies. The forecasting and ordering models will be developed for the purchase of all Coverderm products that are distributed and supplied by Nailmetics and will consider both trend and seasonality. The analysis of the supply, inventory and demand management structures will be scoped to focus on the possible implementation of the supply chain wide CPFR model through the implementation of a specialized forecasting and ordering model for Nailmetics.

1.5 Conclusion

Nailmetics specializes in the supply and distribution of Coverderm throughout Southern Africa and currently have the problem of high inventory levels due to inaccurate ordering. This is caused by long lead times as well as an inaccurate forecasting and inventory model. By developing an accurate forecasting model and optimal inventory solution, the complete supply chain problem of the lack of optimal CPFR that is crucial in a supply chain between companies in the Northern and Southern Hemisphere, will be resolved.

The project will aim and be scoped to complete the following deliverables:

- An implementable and sustainable structure for the implementation of a complete CPFR model, taking into account upstream supply and downstream distribution in a complete supply chain perspective.
- Developing a specialized forecasting model that accurately forecasts the sales all products of Nailmetics' Coverderm range, taking into account trend, seasonality and factors such as advertisement and promotions.
- The development of an accurate inventory model for Nailmetics' probabilistic demand that will optimize the ordering points and ordering batch sizes for all products in the Nailmetics Coverderm range, taking into account the combined ordering of product batches.

The document will be structured by analysing and review academic literature about CPFR, inventory models and forecasting in chapter 2, before developing each of these deliverables in chapter 3, 4 and 5 respectively. The document will be concluded with an overall discussion and conclusion in chapter 6.

2. Literature Review

This literature study was conducted with the aim of supporting the need for a forecasting model, an inventory model and CPFR structure. This will include the discussion of different forecasting models as well as an in-depth study into the ideal forecasting model and method for the model's implementation. Different inventory models will also be studied and analysed which will include a comprehensive analysis of the preferred inventory model and implementation method. This literature review will also include a study and analysis of the implementation of a CPFR model.

2.1 Collaborative Planning, Forecasting and Replenishment

In today's complex supply chains, businesses need to manage supply chain activities across channel, functional, cultural and personnel boundaries. Guidelines have been developed to define business practices and technology necessary to establish collaborative supply chains between trading partners, in an aim to meet these challenges (Sherman, 1998).

A collaborative supply chain means that two or more independent companies plan and execute supply chain activities cooperatively with greater success than when acting separately. Collaboration in the supply chain can be structured vertically, horizontally or laterally. Vertical collaboration refers to the sharing of responsibility, resources and performance information between manufacturers, distributors, carriers and retailers to serve relatively similar consumers. Horizontal collaboration is when competitors share private information and resources such as joint distribution centres. Combining and sharing capabilities both vertically and horizontally with the aim of more flexibility, is defined as lateral collaboration (Simatupang & Sridharan, 2002).

Demand collaboration was characterized by Kahn, Maltz & Mentzer in 2006 as "cooperative behaviour or joint decision making between companies, and represents willingness, versus a requirement, to engage in inter-organizational efforts."

CPFR aims to develop a situation where instead of waiting for an order, the supplier delivers according to consumption (Holmström et al., 2002). However, there are some barriers to overcome in developing a CPFR model.

Simatupang (2002) notes that although collaboration is a mutual objective, it is a self- interest process with each member seeking own individual benefits. However, the focus should still be the mutual objective of joint offers to customers and the profit-making possibilities that each member cannot create alone (Simatupang, 2002). McCarthy and Golicic (2001) states that some challenges of implementing CPFR are the establishment of acceptable technology and software, difficulty of managing real time information sharing, initial lack of stability, changes in company culture in all companies involved and the time and personnel investment during the set-up phase.

2.1.1 The need for CPFR

Sherman (1998) noted that CPRF can potentially deliver “increased sales, inter-organizational streamlining and alignment, administrative and operational efficiency, improved cash flow, and improved return-on-assets performance”. The article is concluded by stating that although the challenges of implementing CPFR seems daunting at first, the benefits and competitive advantage are significant and will accrue to market leaders.

McCarthy (2001) affirmed that collaborative efforts between trading partners can improve the performance of the supply chain. This study discussed the implementation of collaborative forecasting and how it improves supply chain performance and concluded that collaborative forecasting can lead to increased responsiveness, product availability assurance, optimized inventory and associated costs and increased revenues and earnings.

When time-benefit and forecasting accuracy is used together, it demonstrates the benefit of collaborative forecasting and replenishment. A transparent supply chain also helps the supplier act more economically by having more response time through replenishment according to the customer’s inventory situation (Holmström, 2002).

In an industry example, Wal-Mart implemented CPFR and currently has a competitive advantage through competitive retail prices and a reduction in lost sales and stock-out costs. Their suppliers benefit from the CPFR by replenishing goods as they are sold, minimizing stock-outs and improved brand loyalty. Wal-Mart is a good example of close cooperation enabling supply chain members to increase the overall supply chain profitability through effective matching of demand and supply (Simatupang 2002).

Simatupang (2002) names the following benefits of effective information sharing in supply chains:

- Improved agreement on the mutual competitive advantages that can be gained on customer values, system wide performance measures, integrated policies and shared responsibilities. This improves the problem of misperception and ambiguity that often occurs in collaborative supply chain initiatives.
- Resolving of demand uncertainty that will cause improved forecasting accuracy, reduced markdown, reduced inventory and stock-outs as well as increased responsiveness.
- Improved handling of complex logistics decision making that will improve, amongst others, customer service, procurement and transportation contracts' rates, responsiveness, reliability and availability to promise as well as reduced inventory, material handling and time-to market.
- Better dealing with situations of opportunistic behaviour to protect personal interest the will improve customer service and data confidentiality while also reducing risk of underperformance, transaction costs and inventory speculation.

2.1.2 Implementing CPFR

To implement mass collaboration one needs to look at how to improve the efficiency of forecasting at the retailer, how to make replenishment more robust, how to convince prospective partners of the benefits of collaboration and finally how to set the supporting IT system (Holmström, 2002). In the channel between Farmeco and Nailmetics, Nailmetics can be seen as the retailer and thus the improvement of the efficiency of forecasting at Nailmetics is critical (this will be discussed in detail in chapter 2.3.1).

Holmström (2002) recommends that for effective mass collaboration, the supplier needs to find a solution replenishment that is easy to implement for a large number of customers. However, the article also states that it is difficult for retailers to find suppliers that are prepared to take responsibility for large-scale replenishment. In the case of Nailmetics, this is not an issue that can be changed due to Farmeco being the only manufacturer and supplier of Coverderm. Therefore, the implementation of CPFR will have to be implemented around the problem of long transportation time from Greece.

Simatupang (2002) noted that a key to the success of a collaborative supply chain is a high level commitment by the participating firms. The study concludes by proposing that the collaborative firms should consider fitting performance measures, integrated policies, information sharing and incentive alignment. This proves that a company should not stop at convincing prospective partners to collaborate, but also have all members commit and consider the aforementioned issues.

A new category of business software, Between Ware, bridges the gaps between companies by placing trading relationships at the system centre. This software exchanges and compares information and notifies users of promotions, pricing, availability, demand, authorization as well as product and service payment. Through the development of the internet and the evolving market for Between Ware, implementing the required IT support system can be affordable, widely deployable and accomplished with the minimum changes to the existing systems and company processes (Sherman, 1998).

Langley et al. (2008) also developed a business model for the implementation of CPFR and states that this implementation is based on systematic collaboration between trading partners. The steps identified by Langley (2008) is to develop a front-end agreement, create a joint business plan, create sales forecasts, identify exceptions for sales forecasts, resolve or collaborate on these exception items, create order forecast, identify exceptions for order forecast, resolve or collaborate on these exception items, generate the order and execute the delivery. The implementation of CPFR is based on the use of internet as an economical, neutral platform for the facilitation of collaboration.

2.1.3 CPFR Summary

Implementing CPFR in Nailmetics' Coverderm supply chain will not only benefit Nailmetics, but also Farmeco and all the retails stores that Nailmetics supply. The implementation of CPFR must be done in a way to ensure that all parties have common benefits and opportunities in mind and have a high level commitment. The development of fitting performance measures, integrated policies, information sharing and incentive alignment should also be considered in the developmental phase of the CPFR agreement. Although Nailmetics will not necessarily be able to implement top of the range Between Ware software, other software and procedure solutions are available for the effective implementation of CPFR.

2.2 Inventory Models

Jacobs (2009) defines inventory as "the stock of any item or resource used in an organization". Maintaining the ideal levels of inventory is therefore critical to Nailmetics as this will directly determine the level of perfect order fulfilment and order fulfilment time.

Kabak & Schiff (1986) states that inventory decisions are commonly seen as a problem of determining the correct quantity to be ordered and the timing of the order. The article also notes that inventory models have for many years been used in the planning process and are based on the principle of profit maximization. According to Jacobs (2009) inventory models stipulate the organizational structures and operating strategies for controlling and maintaining inventory to be stocked.

2.2.1 The need for an Inventory Model

Nailmetics currently has a long lead time for the ordering of Coverderm products from Greece. A combination of this factor and the aim of perfect order fulfilment have caused Nailmetics to operate with high levels of inventory and safety stock. By developing and implementing an inventory model for Nailmetics, answers such as how much to order from the supplier and when to place these orders will be answered. This will be accomplished by considering factors relating to cost and customer service requirements (Langley, 2008).

2.2.2 Inventory Management Comparison

Inventory models can either be developed using deterministic or probabilistic demand. Jacobs (2009) refers to two general types of multi-period inventory models, namely:

- The fixed-order quantity models or otherwise called the economic order quantity (EOQ) model.
- The fixed-time period models, also referred to as the periodic review system or fixed order interval system.

The fixed-time period model maintains a larger average inventory since it needs to protect against stock-out in the review period, thus a fixed- order quantity model is usually preferred for more expensive items. The fixed-order quantity model demands more time to maintain due to every addition or withdrawal having to be recorded. This monitoring makes this model more appropriate for important and critical parts (Jacobs, 2009).

There are four basic forms or combinations of these models: fixed quantity/variable interval, variable quantity/fixed interval, variable quantity/fixed interval and variable quantity/variable interval (Langley, 2008).

The model that will be considered in this project for Nailmetics would be the variable quantity/fixed interval model. This model is considered the best due to its ability to model/forecast the large range of products that Nailmetics have to consider when placing an order and the high fixed cost of ordering from Greece. By implementing any variable interval model, different products will have different re-order points which will cause high fixed cost with each order, but not a lot a products being ordered. The Multiple-Product EOQ models, as discussed in Winston (2004), will only be considered if it is found that the fixed interval model, proposed in this project, is found not to be efficient enough.

The model developed in this project will be implemented by determining the ideal time interval between orders and then calculating the optimum order size at each interval.

2.2.3 Inventory Model Development

To determine the optimal time intervals between orders or review periods, this study will categorize the historic data of Nailmetics in order to simplify the calculations. The ABC method of inventory categorization, based on the Pareto principle, is a simple and easy to use method and is one of the most commonly used techniques in organizations (Ramanathan, 2006). This technique usually classifies inventory according to the value of the item value multiplied by the annual usage of the item (Flores & Whybark, 1987). Class A inventory items are relatively few in numbers (usually 10%) but have a large amount of annual use value (70%), while group C items are a relatively large number of items (70%) but constitute for a small value of annual use value (10%). Items between the above mentioned classes constitute for group B (20% of inventory and 20% of annual use value) (Ng, 2007).

Winston (2004) recommended that the ideal review period would be equal to the time intervals between orders if a simple EOQ model were used to calculate the order size. However, since each order includes a review process, the cost per order must be set to the cost of placing an order plus the cost of reviewing the inventory levels.

The following formula is recommended by Winston (2004):

$$R = \frac{EOQ}{E(D)} \tag{1}$$

with

$$EOQ = \sqrt{\frac{2(K+J)E(D)}{h}} \tag{2}$$

$E(D)$ = mean demand during a one-year period

h = cost of holding one inventory unit for one year

R = Review Period

K = Cost of placing an order

J = Cost of reviewing inventory levels

After the review period has been determined, the on-order inventory level (S) should be calculated that will minimize annual cost. From Winston (2004) the expected cost for any given review period and on-order inventory level is given by

$$Annual\ Inventory\ cost = \sum_{i=1}^{5} x_i \tag{3}$$

with

x_1 = Annual expected purchasing cost

x_2 = Annual review cost

x_3 = Annual ordering cost

x_4 = Annual expected holding cost

x_5 = Annual expected shortage cost

Winston (2004) determines that the value of S that minimizes the annual cost will be equal to the value of S that minimizes the sum of x_4 and x_5 and will occur for the value of S satisfying the following:

For backlogging allowed:

$$P(D_{L+R} \geq S) = \frac{R.h}{c_B} \tag{4}$$

For assuming all shortages result in lost sales:

$$P(D_{L+R} \geq S) = \frac{R.h}{Rh + c_{LS}} \tag{5}$$

L = Lead time for each order (Assumed Constant)

S = On-order inventory level

D_{L+R} = Demand (Random) during time interval of length $L + R$

c_B = Cost per-unit short in backlogged case (assumed to be independent of time length until the fulfilment of the order)

C_{LS} = Cost per unit-short when assuming shortages leads to lost sales (includes shortage cost and lost profit)

The value of the required on-order inventory level will then be calculated using

$$S = E(D_{L+R}) + z\sigma_{D_{L+R}} \tag{6}$$

with z being the number of standard deviations for the probability, or, as derived from an example by Winston (2004), using the Microsoft Excel function NORMINV with:

- $Probability = P(D_{L+R} \leq S) = 1 - P(D_{L+R} \geq S)$ (7)
- $Mean\ of\ D_{L+R} = E(D_{L+R}) = (L+R)(E(D))$ (8)
- $Standard\ Deviation\ of\ D_{L+R} = \sigma_{D_{L+R}} = (L+R)\sigma_D$ (9)

The NORMINV function output is the inverse of the normal cumulative distribution for the specific mean and standard deviation. The amount of product to be ordered by Nailmetics at every review point will then be S minus the amount of stock.

Another technique that will be considered in calculating the optimal review period is a mathematical Linear Program (LP) method as this is a valuable tool for solving optimization problems. The simplex algorithm, as developed by George Dantzig in 1947, will be used to solve the LP problem (Winston & Venkataramanan, 2003). In order to calculate the optimal values for the LP variables effectively, Lingo software will be used to code and solve the LP.

2.2.4 Sensitivity Analysis

Sensitivity Analysis can be defined as the variation of input variables of a model in order to see the effects of these variations on the model's output variables. The aim of sensitivity analysis is, amongst others, to improve one's understanding of the model, to explore and form consensus as well as to guide decision making and forecasting (French, 2003).

During the development of the inventory model, sensitivity analysis will be conducted in order to better understand the influence of certain variables on the optimal review period, as well as to be able to predict possible future changes of this period.

Sensitivity analysis can on a high level be broken into local and global analysis. During local analysis, the model parameters are varied over a range which is believed to be correct or appropriate. The concept behind global analysis is to vary the parameters over the whole parameter domain space, using a probabilistic distribution to represent the values' uncertainty (French, 2003).

The sensitivity analysis of the inventory model will done using the local analysis method. This is due to the fact that most of the variation of the model's variables can be easily estimated using the company expert's experience and knowledge.

2.2.5 Inventory Model Summary

Generally there are two types of inventory models, which can either have deterministic or probabilistic demand: fixed-order quantity models and fixed-time period models. Due to the large number of SKUs to consider in the inventory model, a fixed-time period model will be developed to prevent the case of many re-order points spread over a large time period. The model will be developed by determining the optimal review periods before calculating the on-order inventory level that will minimize annual expected costs. Orders for each product will then be based on these on-order inventory levels.

2.3 Forecasting

Planning, both strategically and tactically, is an important management function in any company as it outlines and defines the way future business is done. According to Archer (1980), forecasting lies at the core of planning since "forecasting can be defined as the art of predicting the occurrence of events before they actually take place." Mentzer (2006) stated that "sales forecasting is a projection into the future of expected demand given a stated set of environmental conditions." Companies often fail to acknowledge sales forecasting as significant contributor to company success (Moon et al., 1999).

2.3.1 The need for forecasting

Through accurate demand forecasting, a high level of customer service can be achieved by keeping both channel partners as well as final customers satisfied. This is achieved by avoiding losing customers to competitors through lost sales and stock-out situations (Moon, 1999).

The company's net profit can also be increased through accurate forecasting. This is achieved by, amongst others, long-term logistical contracts rather than spot market logistical plans, more cost-effective product purchasing rather than spot market purchases as well as lower inventory levels rather than high inventory levels due to inaccurate forecasting (Moon, 1999).

Thus, Nailmetics' financial health can be improved while keeping and even improving their high level of customer service, through the development of an accurate forecasting model.

2.3.2 Forecasting Models

At a high level perspective, there are two approaches available in forecasting: A numerical approach, and the application of the instinctive, experienced and practical knowledge of an expert in the field. Often the best forecasting models take into account a combination of the two approaches (Archer, 1980).

The numerical approach to forecasting consists of time series analysis, causal methods and simulation (Jacobs, Chase & Aquilano, 2009). According to Winston (2004) extrapolation (time series) methods of forecasting is used to forecast future values of a time series by considering the past values of a time series. Winston (2004) also states that causal methods of forecasting predict the future values of a dependant variable by analysing the influence of independent variable on the dependant variable from historic data.

Thus, due to the need for the forecasting model to consider both the past values of the time series as well as independent variables that influenced the demand, a combination of extrapolation and causal forecasting models will have to be considered in forecasting the Nailmetics demand. The knowledge of the field expert will also be considered in the demand forecasting.

Di, Haitao, Sujian and Bo (2010) developed a forecasting model for the forecasting of cosmetic sales by integrating the Aggregated Forecast Through Exponential Re-weighting (AFTER) and the Improved Quantum Evolutionary Algorithm (IQEA). This model will also be considered and evaluated in this study due to its relevance to this project's problem statement and the fact that it was found to be superior to other models in accuracy and run time in forecasting cosmetic sales.

2.3.3 Quantitative Forecasting Methods

Nailmetics supplies and distributes about 340 stock keeping units (SKUs) and it is therefore critical to find a forecasting technique that won't only be accurate, but also be applicable considering the large number of different products.

When considering causal and simulation forecasting models, all the different variables that influence the demand must be identified and analysed for each of the SKUs. This technique would therefore not be used in this project due to the large amount and complexity of data needed and the difficulty and time consumption of developing the regression or simulation models.

The AFTER-IQEA technique developed by Di (2010), although it is specifically developed for the cosmetic industry, will not be used in this project due to its complexity and difficulty in developing this model for all the different products.

Time series forecasting methods includes the examination of linear and exponential trends, cyclical changes and the combination of linear and cyclical changes (Archer, 1980). This should therefore provide an accurate forecasting model for the demand of Nailmetics' sales while not being too complex to develop for all the products.

Although regression models are found to be too complex and difficult to develop for the range of products, regression techniques could possibly be considered to be used in combination with time series analysis if time series analysis proof to be inaccurate due to large variables influencing the sales. These large variables will then be identified and combined in the forecasting model.

2.3.4 Time Series Forecasting

Time series forecasting methods includes the examination of linear and exponential trends, cyclical changes and the combination of linear and cyclical changes (Archer, 1980). In the consideration of time series analysis, the Box-Jenkins technique as well as the Holt-Winters method will be analysed.

According to Jacobs (2009) the Box-Jenkins technique is very complex and difficult as well as seemingly the most accurate statistical technique available. However, Wang (2008) stated that a requirement for Box-Jenkins modelling is that the time series should be either stationary or transformed into one. The article states that a stationary time series has a constant mean and has no trend over time. Due to the fact that the sales data of Nailmetics has a trend over time, the only possibility to use the Box-Jenkins method would be to transform the time series into stationary series.

Koehler, Snyder and Ord (2001) stated that the most extensively used forecasting method for seasonal time series is the additive Holt-Winters method for additive time series and the multiplicative Holt-Winters method for multiplicative time series. Winter's method is therefore used to forecast time series where both trend and seasonality is present (Winston, 2004). Time series seasonality is multiplicative if the size of the seasonal variation increases as the mean level of the time series increases. If the seasonal effect does not depend on the current mean level, it is additive and can only be added or subtracted from a forecast that rely only on the level and trend (Koehler, 2001).

Koehler (2001) noted that although the multiplicative Holt-Winters method gives a reasonable forecast for future time periods, it does not provide a guarantee on the forecast error. Therefore, the study made by Koehler (2001) developed four models considering the variance one period ahead forecast error changes with level and season (see table 2.1 for summary of models). The article recommends that if one intends to implement one of the models without an identification procedure of the time series, one should implement model one.

	Variance of Forecast error changes with	
Model	Level	Season
1	Yes	Yes
2	Yes	No
3	No	Yes
4	No	No

Table 2.1: Variance of one-period-ahead forecast error (Koehler, 2001)

Due to the complexity and time consumption of having an identification procedure for each of the large range of products, this project will consider the use of model 1 developed by Koehler (2001) which is developed for variance of forecast error changes with both level and season.

Using model 1 for forecasting would be as follows:

Forecast function

$$y_n(h) = (l_n + hb_n)C_{n+h+jm} \tag{10}$$

where

$$j = [h/m] + 1 \tag{11}$$

Updating equations for *t* = 1,2,…, *n*

level:

$$l_t = l_{t-1} + b_{t-1} + \alpha_1 e_t / c_{t-m} \tag{12}$$

trend:

$$b_t = b_{t-1} + \alpha_2 e_t / c_{t-m} \tag{13}$$

season:

$$c_t = c_{t-m} + \alpha_3 e_t / (l_{t-1} + b_{t-1}) \tag{14}$$

where

$$e_t = y_t - y_t(1) \tag{15}$$

$$y_t(1) = (l_{t-1} + b_{t-1})c_{t-m} \tag{16}$$

with

$y_n(h)$ = Demand forecast h periods ahead at time n

m = the number of seasons in a given year

l_t = Level factor at time t

b_t = Trend factor at time t

c_t = Seasonal factor at time t

e_t = Error between actual sales and forecasted sales at time t

$\alpha_1, \alpha_2, \alpha_3$= Smoothing constants

Winston (2004) estimates the initial states for a required two years of data by using the following methods:

- Estimated trend at beginning of month 1:

$$b_0 = \frac{(Average\ monthly\ sales\ during\ year-1) - (Average\ monthly\ sales\ during\ year-2)}{12} \tag{17}$$

- Estimated level at beginning of month 1:

$$l_0 = (Average\ monthly\ sales\ during\ year-1) + (12-6.5)b_0 \tag{18}$$

- Estimated seasonality factor for a given month (To illustrate, January was used with *m* being 12 and *t* being 1):

$$Year-2\ estimated\ seasonality\ for\ January = \frac{Actual\ sales\ for\ January}{Average\ monthly\ sales\ during\ year-2} \tag{19}$$

$$Year-1\ estimated\ seasonality\ for\ January = \frac{Actual\ sales\ for\ January}{Average\ monthly\ sales\ during\ year-1} \tag{20}$$

$$s_{-11} = \frac{(Year-2\ estimated\ Jan\ seasonality) + (Year-1\ estimated\ Jan\ seasonality)}{2} \tag{21}$$

The optimum smoothing constants values will be calculated by determining the optimum values for α_1, α_2 and α_3 by maximizing the forecasting accuracy. The forecasting accuracy will be calculated using the following formulas from Di (2010), with A_t being the actual sales value at time *t*, y_t the forecasted value at time *t* and *N* the number of periods:

Mean Absolute Deviation (MAD):

$$MAD = \frac{\sum_{i=1}^{N} |A_i - y_i|}{N} \tag{22}$$

This metric will indicate the size of the mean forecasting error.

Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{\sum_{i=1}^{N} \left| {(A_i - y_i)}/{y_i} \right|}{N} \tag{23}$$

This metric will show the relative size of the forecasting error by indicating the mean percentage error.

Mean Squared Error (MSE):

$$MSE = \frac{\sum_{i=1}^{N} (A_i - y_i)^2}{N} \tag{24}$$

Another metric to indicate the relative size of the mean forecasting error

Jacobs (2009) states that usually the errors are normally distributed and that if this is the case, the MAD relates to the standard deviation in the following relationship:

$$1\ standard\ deviation = \sqrt{\frac{\pi}{2}} \times MAD \tag{25}$$

Proving that forecasting errors are normally distributed will also enable the addition of forecasting confident intervals by using the errors' standard deviation. Therefore, the residual analysis method will be used to prove whether the forecasting errors are approximately normal distributed. Either a frequency histogram or a normal probability plot of the residuals can be used to check the whether the data is approximately normal distributed (Montgomery & Runger, 2007)

The residuals will be calculated by $e_i = y_i - \bar{y}, i = 1,2 \dots n$, with e_i being the residual, y_i the actual error data point and $\bar{y}$ the average of all the errors. The number of periods (n) for which the standard deviation will be calculated, will be analysed during the data analysis as the forecast over the most recent historic data points will be more accurate and relevant to a confidence interval.

In the project, a cumulative normal probability plot will be used to evaluate whether the assumption can be made that the forecasting errors are normal distributed. The graphs will be used to approximate the normal distribution as the evaluation of the normality will only influence the use of the confidence intervals which is a guideline for the user. Unnecessary statistical procedures will therefore not be used to prove the errors' normality as the output of this evaluation does not carry enough weight to support such procedures.

2.3.5 Qualitative Forecasting

According to Archer (1980) qualitative forecasting methods uses the accumulated experience of individual expert or assembled groups of people to predict the probable outcome of events.

Nailmetics have conducted business for 5 years by using qualitative forecasting to forecast future demand and have been using a moving average method for the last year. Although the growth of the company has caused the need for a more accurate forecasting method than the current combination of the moving average technique and practical experience, the instincts, knowledge and practical experience should still be considered in the forecasting model.

2.3.6 Forecasting Model Development

The methodology followed by Di et al. (2010) in developing the AFTER-IQEA for the forecasting of cosmetics sales by combining forecasting models will be considered and revised in the development of this project's forecasting model. The model will be developed by analysing historic data using the model 1 variation of the Holt-Winters method, as developed by Koehler (2001), and determining the accuracy of this method. The algorithm will then be adjusted or combined with other forecasting models, like the regression methods, to attempt to improve the forecasting accuracy. The model will then be developed using Microsoft Excel due to cost constraints and being sufficient, implementing both the numerical as well as the qualitative forecasting techniques.

2.3.7 Forecasting Summary

Forecasting methods consists of qualitative, time series, causal and simulation techniques that are used to predict the future occurrence of events. In this project simulation and causal methods will not be used due to the large number of SKUs supplied and distributed by Nailmetics and the complexity of gathering and analysing data as well as developing these models for all the SKUs. The forecasting model developed in this project will use the model 1 variation of the Holt-Winters method, as developed by Koehler (2001), while also taking into account the knowledge and practical experience of the field experts in predicting the future sales qualitatively. However, if it is found that the forecasting accuracy is not sufficient due to a number of large independent variables influencing the sales, regression models will be considered to attempt to improve the forecasting accuracy.

2.4 Conclusion

In considering the aim of the project, the academic literature studied in this literature review provides an indication of possible solutions for the project's problem statement. The literature study of forecasting methods indicate that accurate forecasting can be beneficial for a company's financial health as well as improve their customer service which is critical for Nailmetics. The financial benefits of accurate forecasting are long-term logistical contracts, more cost effective product purchasing and lower inventory levels.

The forecasting method used for the demand of Nailmetics' Coverderm range, will have to consider both trend and seasonality for which the study indicates that the Holt-Winters method would be most accurate. The model 1 method developed by Koehler (2001) will be used while also considering a field expert's knowledge and experience. This combination of forecasting methods will be considered, analysed and tested for the solving of Nailmetics' inaccurate forecasting problem.

Academic literature recommends the development of an inventory model for determining the correct order size as well as when to place these orders. This will be considered for the solving of the problem that Nailmetics have of not placing accurate orders. This model will be developed using a fixed period / variable quantity method which will use calculations to firstly determine the optimal review periods according to the EOQ order quantities and then determine the on-order inventory level to minimize cost.

CPFR, according to the literature reviewed in this study, will give the whole Southern African Coverderm supply chain a competitive advantage through a reduction in lost sales and stock-out costs, improved supply chain communication, increased responsiveness and increased revenues and earnings. This will be considered with regard to the aim of developing a CPFR structure for complete supply chain CPFR. This will include the consideration of the appropriate performance measures, integrated policies, information sharing and incentive alignment needed to ensure common benefits and opportunities are gained. Additionally, the project will also have to analyse different software and information sharing procedures that will be ideal for this specific supply chain.

3. CPFR Development

This chapter will look at the development of a CPFR implementation plan for Nailmetics by analysing the current supply chain collaboration of Nailmetics, the CPFR model to be implemented, the CPFR implementation and future CPFR possibilities.

3.1 Current Collaboration Analysis

Nailmetics is in the centre of a supply chain with Famerco being their only supplier of Coverdem and Dischem responsible for about 80% of their demand. Therefore, the supply chain between Farmeco, Nailmetics and Dischem is the main objective for implementing CPFR.

3.1.1 Farmeco – Nailmetics Collaboration

Farmeco is a company based in Greece and therefore personal interaction with Nailmetics is limited. The two companies do however communicate a lot through emails and telephone calls. This is due to Farmeco being very involved and concerned with the sales of Coverderm and supporting Nailmetics to establish Coverderm as a leading cosmetic brand in the South African cosmetic market.

Nailmetics currently provides Farmeco with monthly units sales reports in order to give Farmeco an idea of the size of the following order that will be placed and when they will place their next order. However, there is still a gap in the effective order forecasting system between Nailmetics and Farmeco. This is a concern due to the fact that Farmeco produces summer cosmetic products in the South African winter and the other way round. This causes Farmeco to sometimes stop their usual production in order to produce the products needed for the Nailmetics' order.

Nailmetics do try and provide Farmeco with an estimation of the seasonal products that they will order, however without an accurate forecasting system, this will only be a guess between the Nailmetics and Farmeco experts.

3.1.2 Nailmetics – Dischem Collaboration

Dischem is a large South African pharmaceutical company, with Nailmetics being only one of their smaller suppliers. This makes the collaboration from Nailmetics side more challenging as they are not always at the top of Dischem's priorities.

In an attempt to increase the supply chain visibility, Dischem supplied Nailmetics with an application, QlikView, to be able to access their SAP sales data of Coverderm. Although Nailmetics do not use this application as effectively as they should, this enables them to see the units sold or total value of sales per period for any or all stores and regions. Nailmetics can see the gross profit, different prices at different stores and all relevant financial information.

The problem with this information is that it is manually confirmed on the SAP system through stock takes and not always accurate. This problem can be solved by having Nailmetics' representatives monitor the SAP data on their visits to the Dischem stores.

Although the QlikView application is in place, the ordering between Dischem and Nailmetics is done by the Nailmetics representative placing an order for the specific store. Incorrect orders can lead to Nailmetics having to buy back any additional stock from Dischem.

3.2 CPFR Model

The implementation of CPFR was analysed and areas of possible implementation was identified. The implementation of CPFR in the Farmeco, Nailmetics and Dischem supply chain would be a basic model due to the following factors:

- Companies are only ready for limited collaboration
- Nailmetics does not have the financial capabilities of implementing complete, advanced collaboration with shared software.
- It provides an ideal opportunity for learning the CPFR business practices before implementing further advanced CPFR

The implementation of this basic CPFR model will aim to provide the supply chain with the framework of implementing further collaboration once the companies see the advantages of collaboration first hand.

3.3 CPFR Implementation

After analysing the implementation of a basic CPFR model, the collaboration opportunities for Nailmetics were narrowed down to the following main areas:

- Demand forecasting and the sharing of this information are crucial to the implementation of CPFR. The development of an accurate forecasting model for Nailmetics will be central in the implementation of CPFR throughout the supply chain, due to the fact that Nailmetics can also estimate the Dischem sales through the SAP data. This model should be generic and adaptive in order to add products for forecasting as needed.
- The calculation and development of an inventory policy with the aim of identifying the optimal review period. This will allow the development of order forecasts using the review period and demand forecast to be able to share with Farmeco the forecasted order size in advance.
- Nailmetics can aim to control the Dischem SAP data more meticulously through their Dischem representatives. The purpose of this will be to move to a replenishment system of restocking the Dischem stores according to their SAP sales data.
- Improved sharing of promotional information throughout the supply chain, with Nailmetics being at the centre of this communication.
- The sharing of not only sales data, but also stock-on-hand data with Farmeco. Reports can consist of sales, stock-on-hand, forecasted sales and forecasted order size.

After discussing the CPFR implementation opportunities with Nailmetics, the opportunity of replenishing Dischem stock using the SAP data was rejected. The reason for this rejection is the need for Nailmetics to have their representatives in touch with what actually happens in the Dischem stores. It is also important for the representatives to have a relationship with the Dischem stores and keep that relationship in tact by visiting the stores regularly. This will also ensure that the relationship between Nailmetics and

Dischem does not fade away to a situation where Coverderm becomes only a SKU number.

This replenishment implementation opportunity will therefore be adjusted to a system where Nailmetics use the SAP data to monitor unusual and special orders. Nailmetics will also be able to advise their representative on ordering more effectively.

Nailmetics also rejected the idea of sharing stock-on hand information with Farmeco as they do not see it as a necessity on a report basis. Farmeco does have the ability to have an indication of the stock-on hand through the order sizes and Nailmetics' sales reports. Farmeco also do not find the need for continuous updates on stock-on hand and Nailmetics are willing to send this information to Farmeco if they ever need it.

Before implementing CPFR, Nailmetics and specifically Farmeco should commit to the collaboration and agree on reporting periods, communication methods and communication formats.

The implementation opportunities will be realized in the following ways:

- The forecasting model developed in chapter 5 will provide Nailmetics with the capability to accurately forecast demand.
- The inventory model will be developed in chapter 4 with the forecasting model developed to forecast for the review and lead time period.
- Nailmetics will be advised to control the SAP data more meticulously through their representatives and monitor unusual and special orders.
- Nailmetics will be advised to add Dischem SAP data to forecasting model in order to forecast Coverderm sales for specific Dischem branches.
- A template will be developed for the communication of sales, forecasting data and approximate order forecasts with Farmeco. The template will also provide information about any upcoming promotional events.

Due to the availability and low financial implications, all communication for this basic collaboration can be done by email and using Microsoft Excel datasheets.

3.4 CPFR Report Template

During the development of the CPFR communications template, the decision was made by Nailmetics to send the sales and forecast report to Farmeco on a monthly basis. The template was developed in order to provide Nailmetics with an indication of the data required on the report as well as act as a reminder of these requirements (See appendix A, figure 1).

The monthly report template provides Nailmetics the opportunity to input next planned order date according to the review period calculated in chapter 4 as well as the current date. The days until the next planned order is calculated to give both Nailmetics and Farmeco an idea of how relevant the sales and forecast data is with regards to the next order. Space is also available on the sheet to input the date, description and related product ranges of any upcoming promotions. Although most of this promotional information is communicated throughout most months, this can act as a reminder and official confirmation of the promotions.

For each product, Nailmetics will be required to insert the month's sales data, the forecasted sales for the next 5 months and the projected order size. Although it will not be absolutely necessary to input the projected order size for each product right after the arrival of a previous order, Farmeco may request an indication of certain products' orders a few months ahead. It will be advised that Nailmetics input projected order data at least 2 months before the next planned order date. These projected order sizes will be according to the forecasted sales data, the stock-on hand as well as the Nailmetics' experience. The projected order value in € will automatically be calculated, while all the sales, 5 month forecast and projected ordering data will be summed according to product ranges and totals for all products.

The user will then be able to email this report to all relevant parties by clicking on the <Email> button.

3.5 Future CPFR Opportunities

After the successful implementation of the basic CPFR recommended in this document, Nailmetics can look to implement the following in the future:

- Between Ware software to automatically provide all trading partners with access to needed information.
- An automatic order system between Nailmetics and Farmeco.
- A continuous replenishment system between Nailmetics and Dischem once Coverderm is a well-established brand and all communication and relationships are in place. In this system it will still be crucial for Nailmetics to have representatives in place at the Dischem branches, but only to promote the products and not placing orders.

3.6 Conclusion

The aim of implementing CPFR in the supply chain between Farmeco, Nailmetics and Dischem was to increase the supply chain efficiency in terms of increased customer service and perfect order fulfilment. After analysing the implementation of a basic CPFR model and discussing it with the project sponsor, it was decided to focus on improved forecasting and order review period, monitoring of Dischem orders using QlikView, sharing of forecasted data with Farmeco as well as promotional information.

A monthly sales and forecast report template was developed to assists Nailmetics with the reporting of sales and sales forecast to Farmeco. The monitoring of Dischem order and the future CPFR opportunities will be discussed with Nailmetics.

4. Inventory Model Development

The inventory model that will be developed in this section will only be used for the purpose of finding the optimal review period for ordering products. This is due to it not being feasible to order according to an EOQ value in terms of allowing for seasonality when ordering. The inventory model will therefore be developed to find the best ordering period and then order according to the forecasting model's forecasted demand and stock-on-hand. This review period will also be communicated to Farmeco with the aim of providing them ordering information to improve their production planning.

This chapter will consider the data analysis, method analysis, linear program development as well as the validation and evaluation in developing the optimal order policy.

4.1 Data Analysis

Nailmetics provided the total sales of all SKUs for the period March 2011 to March 2012. This data was narrowed down to only the products, excluding testers, poster and other promotional materials. The data will be used to determine the average demand for all the products, while Farmeco's order sheet was provided with the purpose of providing these products' price and batch size.

In standardizing the data analysis, a fixed Euro/Rand exchange rate has to be determined. Using the historic daily Euro/Rand exchange rate for the previous 3 years, as on 2012/10/05, the average daily exchange rate was calculated to be R10.75 for one €1 (The Standard Bank of South Africa Limited, 2012).

With the aim of standardizing the historic sales data of all the products, the products had to be categorized. The ABC method of inventory categorization was not used as this would have forced the calculation of average product prices per category over a large range of prices. It was decided to rather categorize the data into 8 categories according the price per box. The weighted average price was still calculated for each product category, but this is more accurate as it is the average of a constricted group of values. The demand was calculated in boxes rather than in units, as the airfreight ordering cost is calculated according to the weight. It was therefore necessary to measure all the products' box weight and calculated a weighted average weight for each product category. See table 4.1 for the product category data.

Category	Price per box in €	Total Demand/ month	Weighted avg. price (€)	Weighted avg. weight (kg)
1	≤ 100	10.18	63.43	3.11
2	100 < x ≤ 150	17.45	127.21	3.12
3	150 < x ≤ 200	19.84	163.18	3.28
4	200 < x ≤ 250	49.96	218.68	2.26
5	250 < x ≤ 300	5.51	275.18	3.33
6	300 < x ≤ 350	1.75	323.49	4.22
7	350 < x ≤ 400	1.22	365.54	4.40
8	> 400	1.28	458.91	3.44

Table 4.1: Product Categories

The following set-up cost data was given in order to be able to calculate the EOQ:

- Holding cost is given as R4.20 per box per year.
- Bank commission for the Letter of Credit (LOC) is approximately 0.35% of the value of the invoice for that day's foreign exchange rate. With the addition of R200 for two swifts per LOC and R700 for overseas bank fees.

Using the elevation freight and airfreight invoices of all orders during FY11 until FY13, the following costs were calculated using the linear trend line function on Microsoft Excel in order to calculate the fixed and variable cost according to the order weight (This function calculates the linear trend line using the least square method):

- Elevation freight cost includes insurance, import tax, airline storage and handling, documentation, inspection, customs, road transport as well as agent fees. The elevation freight cost is calculated as (see figure 4.1):

$$Elevation\ Freight\ Cost\ (y) = 46.453w + 1339.5$$

with

w = Total order weight in kg

- The airfreight cost includes the airfreight as well as the export expenses and is calculated as (see figure 4.2):

$$Airfreight\ \ Cost\ (a) = 22.381w + 3164$$

with

w = Total order weight in kg

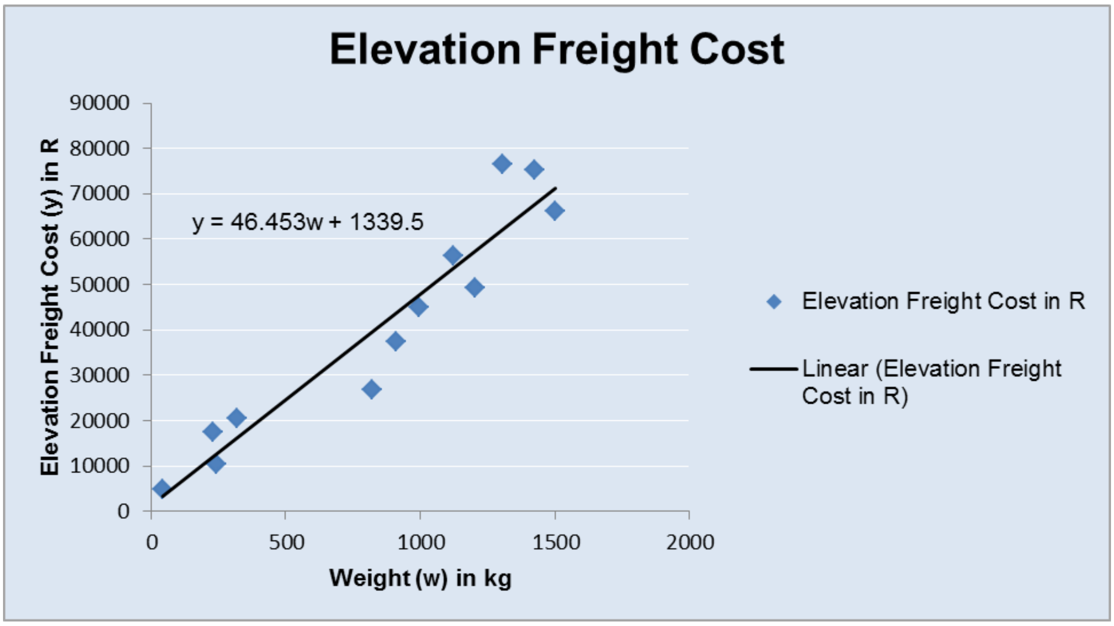

Figure 4.1: Elevation Freight Cost Calculation

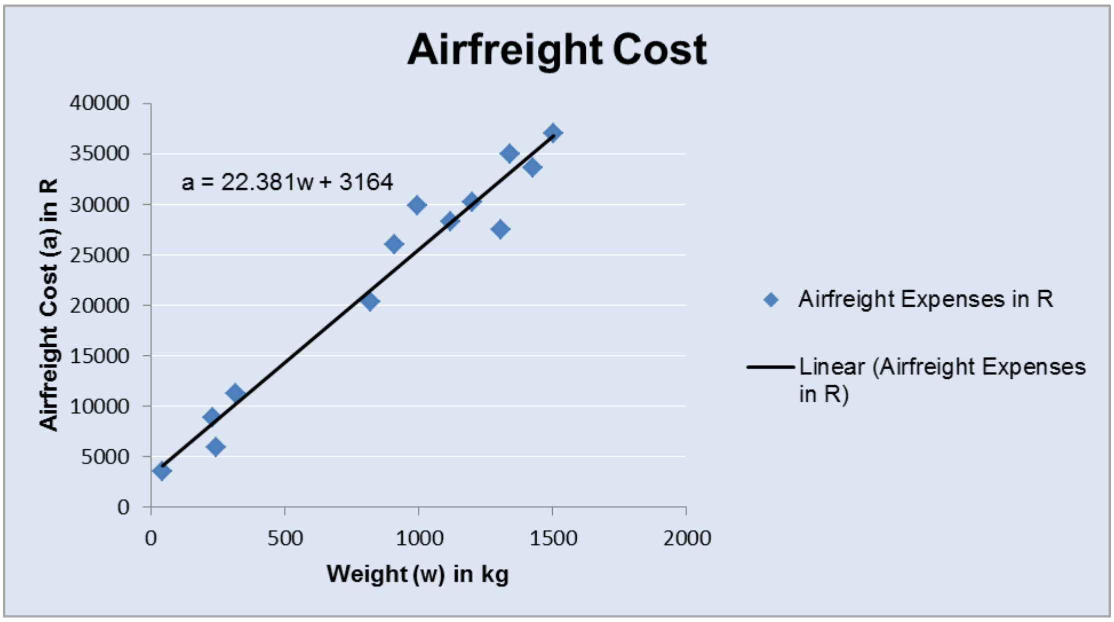

Figure 4.2: Airfreight Cost Calculation

Nailmetics do have certain financial and logistical constraints relevant to the possible order size. The financial constraints include a LOC size limit, credit facility limit and overdraft facility limit*. Nailmetics also need be able to sell a third of the ordered products within 90 days in order to be able to pay for the order.

The review period and the validity thereof can be seen as a logistical constraint. It would not be possible or logical to have a too long review period with different products ranges and upgrades available every few months.

* All financial constraints are confidential and will not be visible in this document as it will not have an influence on the calculations' feasibility

4.2 Method Analysis

In the development of an EOQ inventory model, the set-up cost is a fixed cost of placing an order. The ordering cost of Nailmetics, however, consists of fixed values as well as quite a number of variable costs. In the instance of the airfreight cost (excluding export expenses), the ordering can be seen as a price-break where the price decreases as the order weight increases. To calculate this using an EOQ method would be extremely tedious as it will require the calculation of the EOQ using each increase in order size as a discounted price.

Due to this factor, the numerous constraints and the difficulty in implementing the constraints in an EOQ model, it was decided to rather make use of a mathematical method in order to find the optimal review period. The decision was made to make use of an LP that will be coded in Lingo. This method will enable the implementation of all constraints and variables while calculating optimal review period by minimizing the cost.

4.3 Linear Program Development

The following LP was developed for the calculation of the optimal order size:

$\bar{I} \; = \{1,..,8\}$

$d_i \triangleq The\ monthly\ demand\ for\ product\ categaory\ i \in \bar{I}\ in\ number\ of\ boxes$

$p_i \triangleq The\ price\ per\ box\ for\ product\ category\ i \in \bar{I}\ in\ €$

$x_i \triangleq The\ number\ of\ boxes\ of\ product\ i \in \bar{I}\ to\ be\ ordered\ at\ re-order\ point$

$w_i \triangleq The\ weight\ per\ box\ for\ product\ category\ i \in \bar{I}\ in\ kg$

$q \triangleq The\ total\ order\ quantity\ in\ boxes$

$r \triangleq The\ review\ period\ in\ months$

$e \triangleq The\ price\ of\ one\ €\ in\ Rand$

$f \triangleq The\ value\ of\ the\ order\ quote\ in\ Rand$

$l \triangleq The\ financial\ limit\ of\ an\ order\ in\ Rand$

$y \triangleq The\ elevation\ freight\ cost\ per\ order\ in\ Rand$

$b \triangleq The\ banking\ cost\ per\ order\ in\ Rand$

$a \triangleq The\ airfreight\ cost\ per\ order\ in\ Rand$

$$\min = (0.5)(4.2) \times q + \frac{12(y+b+a)}{r}$$

$\boldsymbol{s.t.}$

$x_i \geq (r+1)d_i$ (Order should meet demand for review period plus lead time)

$\sum_{i=1}^{8} 3d_i \geq \sum_{i=1}^{8} \frac{x_i}{3}$ (A third of the order should be less or equal to three months demand)

$q = \sum_{i=1}^{8} x_i$ (Total order quantity calculation)

$f = e \times \sum_{i=1}^{8} p_i x_i$ (The quote value)

$f \leq l$ (The quote value's financial limit)

$b = 0.0035f + 900$ (Calculation of banking cost)

$y = 1339.5 + 46.453 \sum_{i=1}^{8} x_i w_i$ (Calculation of elevation freight cost)

$a = 3164 + 22.381 \sum_{i=1}^{8} x_i w_i$ (Calculation of airfreight cost)

$r \leq \frac{q}{\sum_{i=1}^{8} d_i}$ (Review period should be less or equal to order quantity divided by total demand)

$e = 10.75$ (Rand/Euro exchange rate)

$x_i \geq 0 \quad \forall\, i \in \bar{I}$ (Order can't be less than 0)

$x_i = integer \quad \forall\, i \in \bar{I}$ (Number of boxes ordered should be an integer)

The LP was then coded in Lingo and resulted in the calculation of an initial optimal review period of 4.44 months. (See appendix B for the Lingo code of this LP).

4.4 LP Result and Sensitivity

The LP resulted in an optimal review period of 4.44 months which will be rounded to 4 months. This will allow for a period of approximately 2 weeks for Nailmetics to finalize and place the order and fix the LOC on the best possible exchange rate. The forecasting model will be adjusted to forecast for 5 months which includes the review period and the 4 week lead time.

The sensitivity analyses was conducted by adjusting the financial limit, the order pay-back credit period and the Rand/Euro exchange rate to their maximum and minimum level according to experience and with a realistic range. The fixed and variable portion of the elevation freight, airfreight and banking cost was also analysed, however these parameters showed no change in the review period. This indicates that the review period is not currently constrained these costs. (Figures 4.3, 4.4 and 4.5 indicates the change in review period as the parameters changes over a realistic domain)

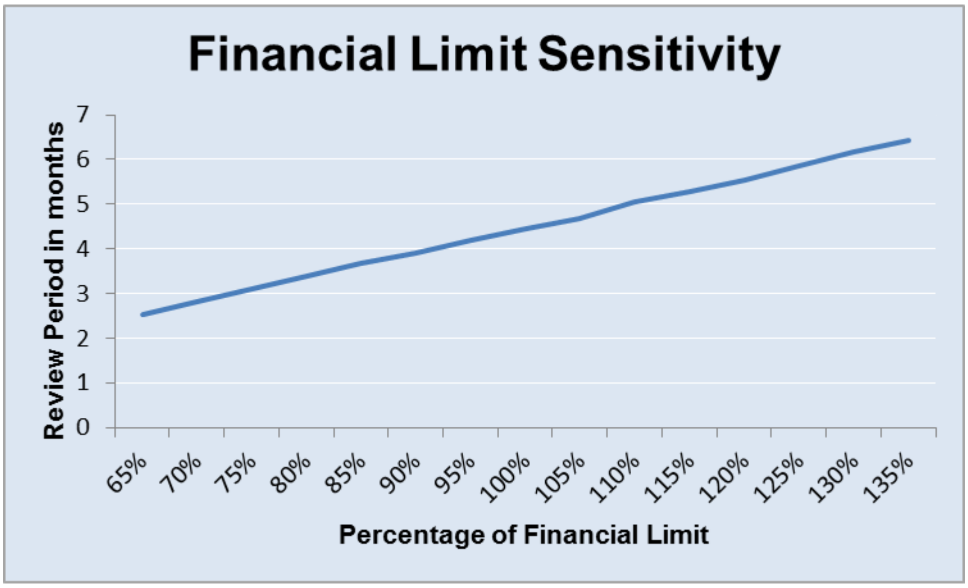

Figure 4.3: Financial Limit Sensitivity

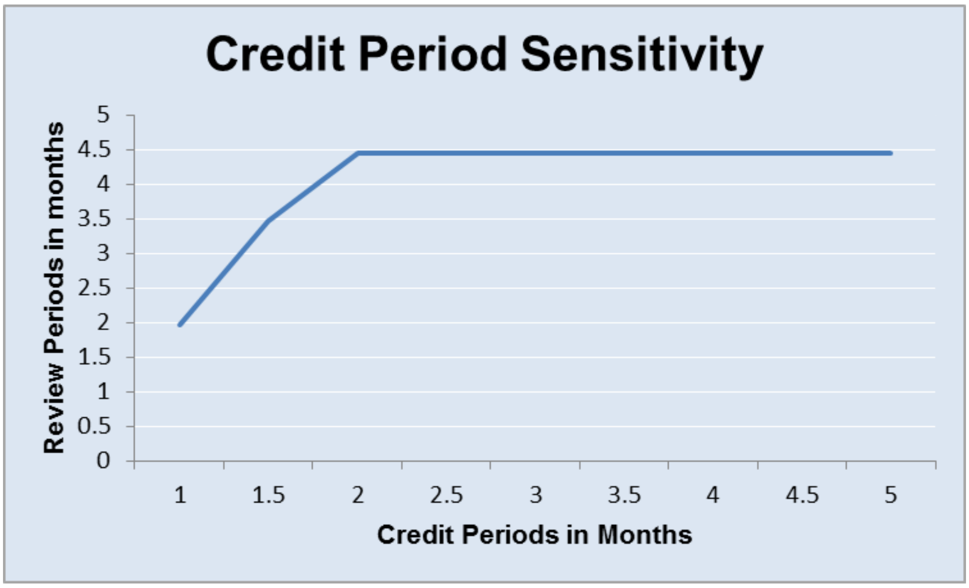

Figure 4.4: Credit Period Sensitivity

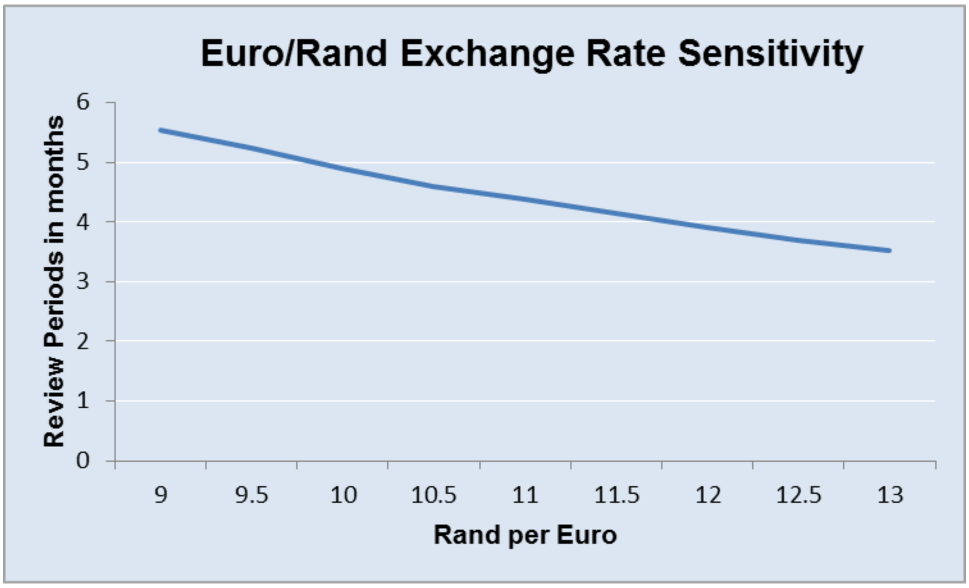

Figure 4.5: Euro/Rand Exchange Rate Sensitivity

Tornado diagrams were also developed in order to analyse the absolute deviation (figure 4.6) and the percentage deviation (figure 4.7) of the review period with regards to changes in the parameters. The parameters were varied as follows:

- Financial limit: Maximum of 1.33 times the current limit and a minimum of 0.667 times the current limit.
- Pay-back period: Maximum of 5 months and minimum of 1 month. This is a crucial sensitivity analysis parameter as a decrease in the

payback period is a realistic possibility as Nailmetics are settled now and Farmeco may possibly decrease the credit period.

- Euro/Rand exchange rate: Maximum of R13 for €1 and a minimum of R9 per €1. These graphs were adjusted as a higher exchange rate cause a decrease in the review period, which does not relate to the other parameters (as seen in figure 4.5). In order to indicate the sensitivity more accurately, the maximum value was seen as R9 and the minimum as R13.

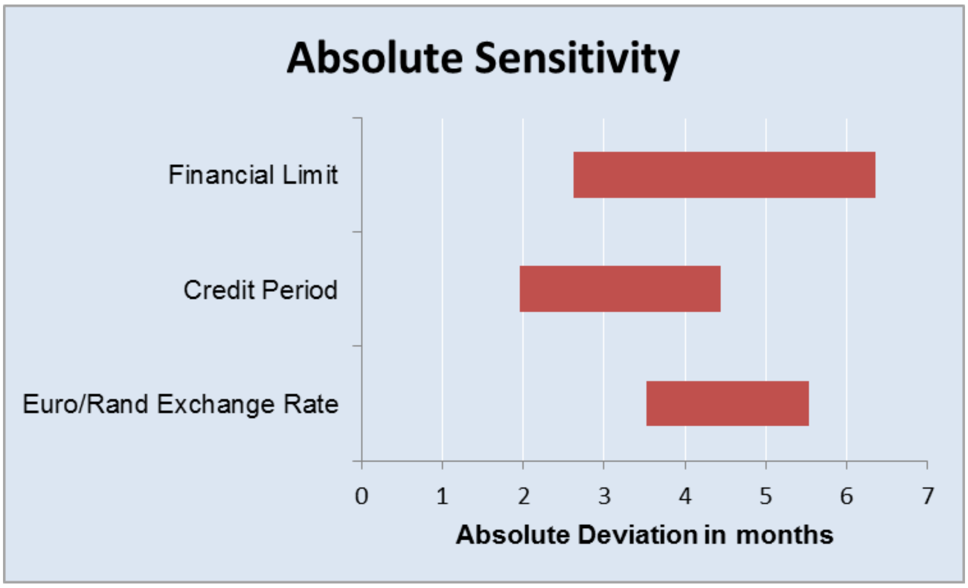

Figure 4.6: Absolute Sensitivity

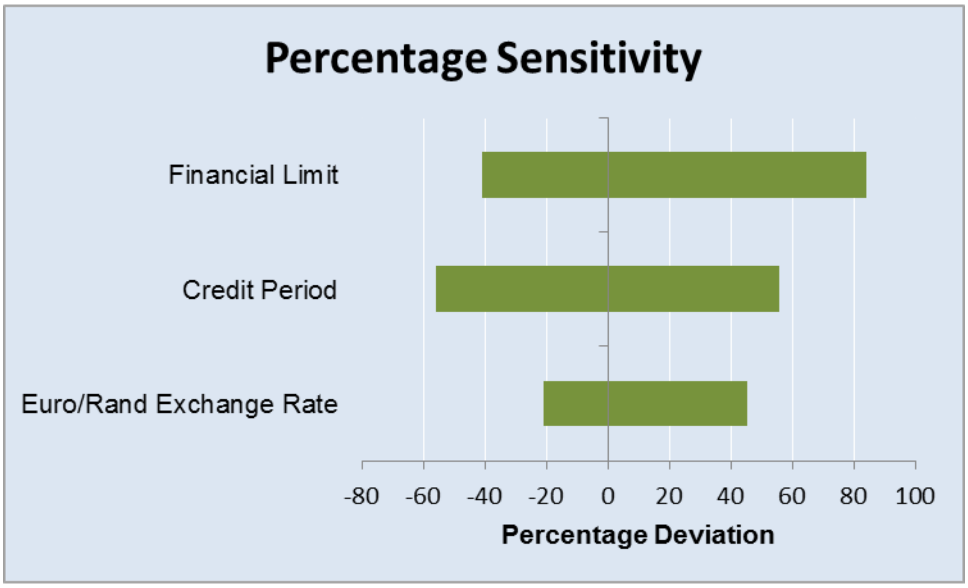

Figure 4.7: Percentage Sensitivity

The financial limit has the greatest effect on the final review period with an absolute variation between a minimum of 2.6 months to a maximum of 6.4

months. Although the credit period can possibly push the review period to its lowest, it is seen through the maximum, which is the same as the current review period, that the credit period only constraint the model up to a certain point. After analysing figure 4.8 one can see that the credit period is a constraint only when the credit period is less than approximately 1.9. This indicates that once the credit period is decreased to less than 2 months, Nailmetics will have to place smaller, less frequent orders and that the credit period do not currently constrain the review period.

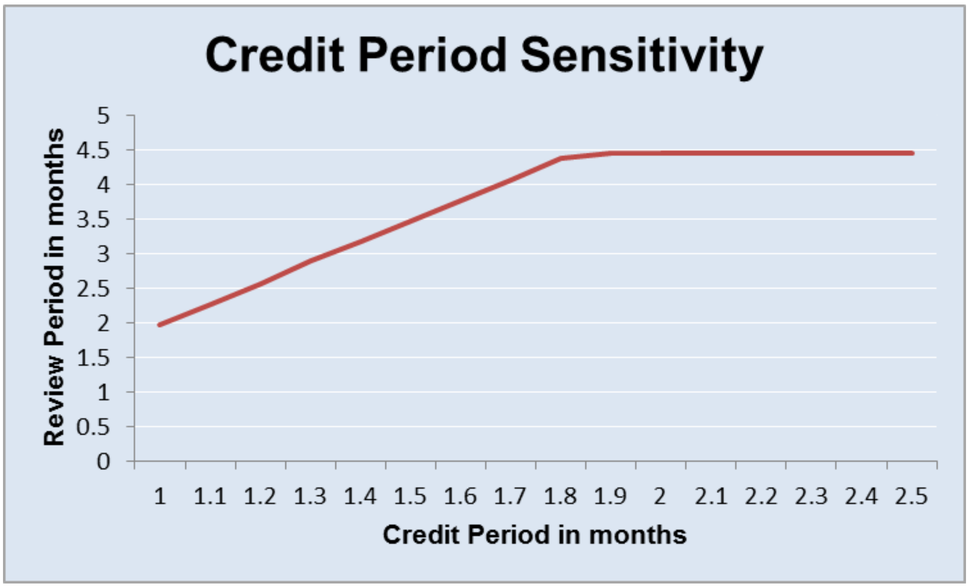

Figure 4.8: Detailed Credit Period Sensitivity Plato

4.5 Conclusion

The inventory model was planned to make use of an EOQ technique in order to calculate the optimal review period to be used in conjunction with the forecast model to improve Nailmetics' order policy. However, due to numerous constraints and the variety of ordering cost, it was decided to develop a LP to calculate this review period. The LP model that was developed calculated an optimal review period of 4 months, which will be used in developing the forecasting model. This review period will be used in conjunction with the forecasting model to assist Nailmetics in ordering products from Greece, by ordering the forecasted sales amount minus the stock-on hand. The sensitivity analysis demonstrated that the decrease in credit period, which is a real possibility, can have the major effect on the optimal review period which can decrease 2 months.

5. Forecasting Model Development

This chapter will look at the development on the forecasting model for Nailmetics and all the steps completed in completing this deliverable. The structure will consist of data analysis, forecasting method analysis, forecasting model requirements, forecasting model prototype, prototype evaluation and final forecasting model development.

5.1 Data analysis

In the development of the forecasting model, historic data needs to be analysed in order to determine and validate the most appropriate forecasting technique.

Nailmetics provided the historic sales and inventory data of PerfectFace 1 to 9, 30, 36 and Perfect Legs 1 to 9 as a representation of their product ranges. This data indicates the trends of slow moving and fast moving products as well as the different seasonal trends. Figure 5.1 shows the sales of PerfectFace and Perfect Legs for the financial years (FY) of 2009 to 2012. (Both graphs have the same vertical axis values to enable the comparison of PerfectFace and Perfect Legs' sales. The vertical axis values are hidden for confidentiality purposes.)

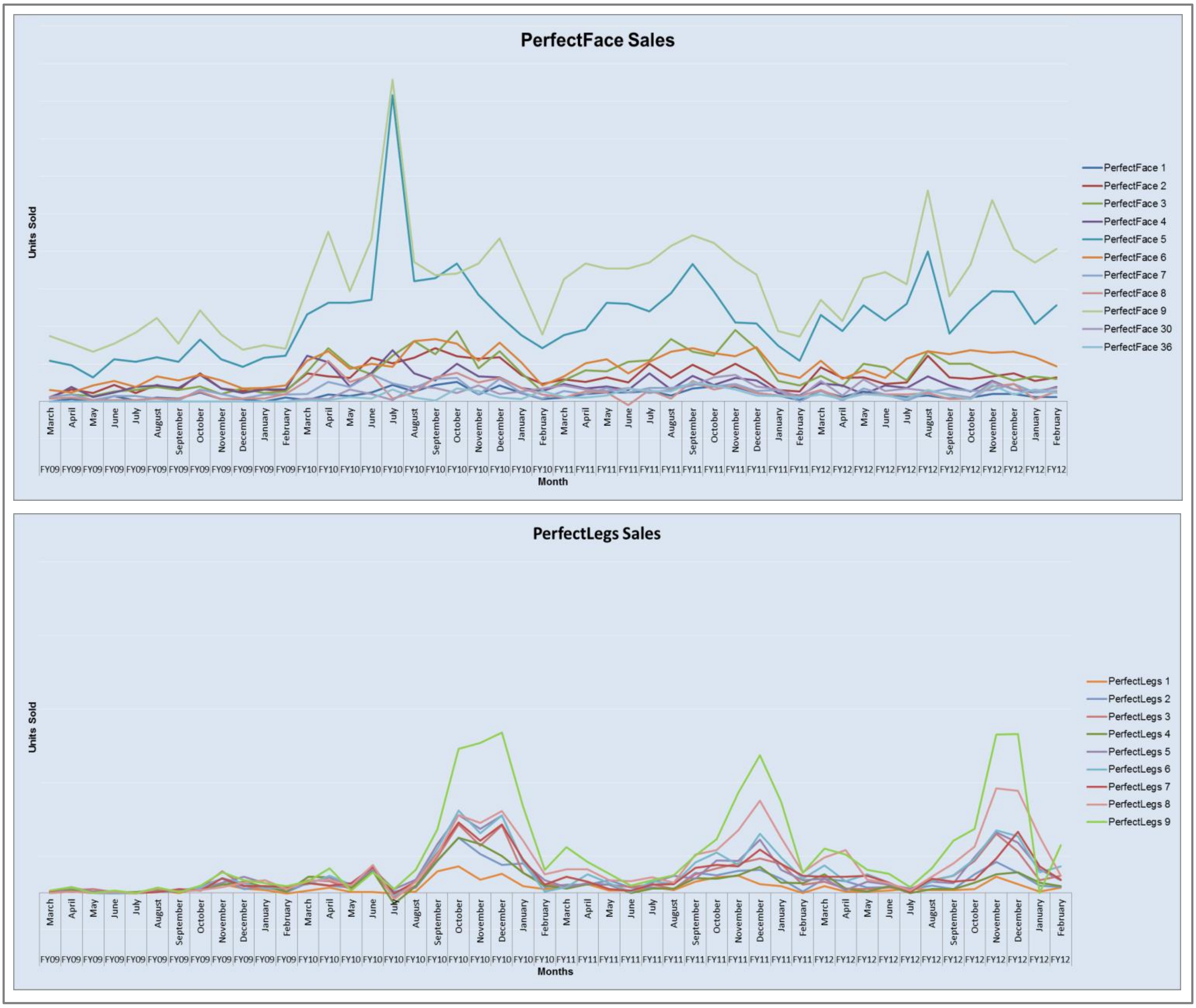

Figure 5.1: Sales of PerfectFace and Perfect Legs product ranges

In both graphs of figure 5.1, the data exhibits the following trends:

- A positive trend from FY09 to FY10
- A negative trend from FY10 to FY11
- A positive trend from FY11 to FY12

The trends for example for PerfectFace 9 are 9.2, -1.9 and 0.94 for FY09 to FY 10, FY10 to FY11 and FY11 to FY12 respectively. These trends can be explained as the result of Nailmetics starting to distribute to Dischem in FY10. Dischem then bought a lot of product from Nailmetics, but this positive trend can be seen as artificially enlarged. The negative trend between FY10 and FY11 was due to the demand from Dischem stabilizing and becoming a true representation of the consumer demand. The growth from FY11 to FY12 is a positive sign and is perceived as a representation of the total positive trend over time.

Seasonality is also visible in the graphs of figure 5.1 especially for Perfect Legs. Table 5.1 indicates that seasonality can also apply to the demand of PerfectFace although it is not as apparent as that of Perfect Legs. Table 5.1 displays that PerfectFace has higher sales from August to December while Perfect Legs have a large increase in demand during the summer periods (October to January).

	PerfectFace	Perfect Legs
March	0.781	0.571
April	0.795	0.685
May	0.824	0.327
June	0.892	0.381
July	0.997	0.167
August	1.102	0.494
September	1.079	0.947
October	1.325	1.700
November	1.179	2.467
December	1.013	2.349
January	0.734	1.297
February	0.733	0.616

Table 5.1: Seasonal Factors of PerfectFace and Perfect Legs

Due to the existence of trend and seasonality in the historic sales data of both PerfectFace and Perfect Legs, as a representation of the whole Coverderm range, the Holt-Winters forecasting method will be a valid forecasting approach.

5.2 Forecasting Method analysis

The Holt-Winters forecasting method, as developed by Koehler (2001), was used as the start point for the development of the forecasting algorithm to be used. Using the PerfectFace and Perfect Legs data provided by Nailmetics, this forecasting technique was tested in order to investigate and analyse the forecasting error using Microsoft Excel.

The testing of the method was done on PerfectFace 9, Perfect Legs 5 and Perfect Legs 9 as these products are in high and medium demand and the Perfect Legs products have visible seasonality.

After evaluating the forecasting error and the method of calculating the initial values, as stated in chapter 2.1.4, it became visible that it will be possible to decrease the forecasting error by adjusting the initial values calculations. The following was done to decrease the forecasting error:

- The trend was calculated as the linear trend of all the historic data points using the least squares method. This was done by using the LINEST Microsoft Excel function.
- The initial level was calculated as:

  $$l_0 = (y\ axis\ intercept) + m \times b_0 \tag{25}$$

  with

  m = the number of seasons in a given year

  b_0 = the initial trend value

  The y axis intercept was calculated using the INDEX and LINEST functions in Microsoft Excel
- The seasonal factors was calculated using the same method as stated in chapter 2.1.4, but using all the historic data points instead of only 2 years.
- The calculations of the fitted forecasting line (one-period forecasts calculated at the previous periods) also started from

  $$t = m + 1$$

  using time periods (t) $\{0, .., m\}$ to calculate the seasonal factors.

- The addition to a holdout variable as a period set aside at the end of the historic data as a stand-in for the future.
- Due to the calculations dividing by the seasonal factor, the model was developed to adjust the seasonal factor to 0.001 when the initial seasonal factor calculated to be 0.

As seen in table 5.2, the changes in calculating the initial values as well as starting the calculation of the fitted forecasting line earlier improved the MAD with an average of 42.29%.

	Initial MAD	Improved MAD	Improvement	% Improvement
PerfectFace 9	46.65	39.44	7.21	15.45
Perfect Legs 5	24.58	13.05	11.53	46.92
Perfect Legs 9	69.23	24.58	44.65	64.50

Table 5.2: Analysis of forecasting error

The forecasting model will therefore be developed using the Holt-Winters method, as developed by Koehler (2001), with the improved technique of calculating the initial values and the fitted forecasting line.

5.3 Forecasting Model Requirements

The following requirements were established for the forecasting model:

- The model must be user friendly
- The model must be adaptable in order to add new products with ease
- All the important information should be available on a one page interface
- The addition of data should be done manually and not through the use of an interface to be able to check the data and be able to add data faster
- The forecasting should be done for the review period plus 4 weeks (1 month) lead time.

5.4 Forecasting Model Prototype

A prototype of the forecasting model was developed to test the model's feasibility according to the requirements, using the available PerfectFace and Perfect Legs data. The prototype was developed in Microsoft Excel, using the following five sheets:

- Forecast Interface
- SKUs
- Data
- Calculations

- Graph Calculations

The ‘Calculations’ and ‘Graph Calculations’ sheets will be hidden in order to prevent the system user form changing any of the calculations.

5.4.1 ‘Forecast Interface’ Sheet

On the forecast interface sheet (see appendix C, figure 1), the system user is able to select a product from a dropdown list and then click on the <Forecast> button in order to forecast the demand for the selected product. The following Visual Basic (VB) code was written to enable this function:

```
Worksheets("Calculations").Range("D17:D160").Formula =
Worksheets("Data").Range("C4:C147").Offset(0, Range("ProductNr").Value).Value
```

This function is executed by the dropdown list linking with the cell ‘ProductNr’ that has the same product number as on the ‘SKUs’ sheet.

The forecasting parameters and variables can also be adjusted on the interface by selecting the appropriate checkboxes and adjusting the values with the respective spin buttons (see appendix D figure 1 for the VB code of the seasonal checkbox). By adjusting the values, the graph and forecasting error will change to enable the user to adjust the value that has the minimum error and the closest fitting fitted line. The user will then be able to see the forecasted sales the length of the order review period plus the lead time (the prototype was developed for the forecasting requirement of 4 months).

An upper and lower forecasting interval is also calculated and displayed in the graph using ±3 standard deviations of the previous 24 months to ensure a probability of 99.7% that the demand will be between the upper and lower interval. This will be evaluated and validated once the final model is developed and all product ranges can be used.

5.4.2 ‘SKUs’ Sheet

The ‘SKUs’ datasheet is the list of the products in the forecasting model and is the ‘ListFillRange’ property of the product drop down box on the interface sheet. This list also has a product number (n) for every product which is the same as the column of the specified product in the ‘Data’ sheet (see appendix C, figure 2). These product numbers enable the forecasting button function on the forecast interface to be able to select the correct column’s data to forecast. It is thus crucial that the SKU list be kept in the same order as the data columns.

5.4.3 ‘Data’ Sheet

This sheet stores all the historic sales data of the product in the column corresponding with the product number on the ‘SKUs’ sheet (see appendix C, figure 3). This data is copied into the calculations sheet when a product is selected and forecasted on the ‘Forecast Interface’ sheet. The ‘FY’ and ‘Month’ columns are filled until the end on the 2020 financial year, which will enable the system user to simply add the sales data of each product at the end of each month. The sheet is set-up to make the addition of data more user friendly by having the row and column headings fixed.

The requirement of being able to fill the data manually is therefore fulfilled and will enable the user to add sales data faster and more accurately.

5.4.4 ‘Calculations’ Sheet

When a product is selected and the <Forecast> button is clicked on the ‘Forecast Interface’ sheet, the selected product’s historic data is copied to the ‘Calculations’ sheet’s ‘Data’ column (see appendix C, figure 6 and figure 4 for overview). This data is then used to calculate all the required forecasting calculations. The ‘Alpha’, ‘Beta’, ‘Gamma’, ‘Holdout’ and ‘Season’ variable is also updated as these variables are adjusted on the interface. In the case where there is no seasonal effect present, the season variable will be 0 (appendix C, figure 5). The data periods is counted, with the warm-up periods being equal to the data periods minus the holdout periods.

The ‘Warmup’ column is the historic data point if n is smaller than the number of warm-up periods. If n is greater than the warm-up period and smaller or equal to the data periods, the ‘Holdout’ column will be the historic data point (appendix C, figure 7).

The initial values of the trend and level are calculated in the row of n equal to the number of seasons, while the initial season factors are calculated in rows n smaller than the number of seasons (appendix C, figure 8). These factors are calculated by a VB developed function with the historic data, number of seasons (season length) and n as input (appendix D, figure 2).

The ‘Fitted’ column is filled with the ‘F’ column values where n is smaller or equal to the warm-up period. The ‘Forecast’ column is dependent on the ‘F’ column for n greater than the warm-up periods (appendix C, figure 9).

The warm-up and holdout errors are calculated using the respective ‘MAD’, ‘MAPE’ and ‘MSE’ columns, with the ‘ControlMAD’ column for the calculation of the MAD error of the previous 24 months (appendix C, figure 10).

5.4.4 ‘Graph Calculations’ Sheet

The ‘Graph Calculations’ sheet is the data used for the graph on the ‘Forecast Interface’ sheet. This data is the respective graph calculations for the previous 24 months and the future 12 months (see appendix C, figure 11). The standard deviation of the previous 24 months is also calculated on this sheet and used to calculate the upper and lower forecasting intervals.

5.5 Prototype evaluation

The prototype of the forecasting model was evaluated by comparing the forecast of the months March, April, May and June with the actual sales for these months. As seen in this comparison of 5 products (see figure 5.9), the forecasts was acceptably accurate and approved by Nailmetics.

	PerfectFace 1			PerfectFace 9			PerfectFace 30			Perfect Legs 1			Perfect Legs 7		
	Forecasted	Actual	Absolute Deviation	Forecasted	Actual	Absolute Deviation	Forecasted	Actual	Absolute Deviation	Forecasted	Actual	Absolute Deviation	Forecasted	Actual	Absolute Deviation
March	6.7	9.0	2.3	182.9	181.0	1.9	17.6	34.0	16.4	6.2	7.0	0.8	29.3	27.0	2.3
April	9.0	4.0	5.0	196.9	143.0	53.9	9.2	7.0	2.2	7.6	3.0	4.6	13.3	18.0	4.7
May	9.3	8.0	1.3	184.6	197.0	12.4	22.7	19.0	3.7	1.9	0.0	1.9	16.8	11.0	5.8
June	14.4	19.0	4.6	214.9	247.0	32.1	15.9	29.0	13.1	2.3	1.0	1.3	4.4	5.0	0.6
MAD			3.33			25.06			8.85			2.15			3.34

Figure 5.2: Prototype Evaluation

The interface and functions of the prototype was also tested and approved by the project sponsor at Nailmetics. The company acknowledge the use of the forecasting model and permitted the development of a final forecasting model for all SKUs.

5.6 Final Forecasting Model Development

The forecasting model prototype was developed into a final forecasting model by adding the remaining SKUs, adding their historic sales data, analysing the normal distribution of the forecasting errors and adjusting the model to forecast according to the review period calculated in chapter 4. An example will also be given of the forecasting result of a selected product.

5.6.1 SKU and Historic Data Addition

The remaining SKUs were added to the forecasting model by adding them to the list of SKUs as well as adjusting the product drop-down box to include them. Their historic sales data was added and the sales data of the prototype products was also updated up to September of FY 13. The total number of products, which has historic sales data of more than 1 year and can therefore be forecasted using the forecasting model, add up to 143.

In certain instances when Nailmetics had had to either adjust or buy back product from Dischem, that month's sales was given to be negative. In order to have valid historic sales data, all these values were adjusted to 0.

During the addition of the remaining SKUs' historic sales data, the observation was made that most of the slower moving products had an extremely high sales month. This is obvious as sales before this data point would have a low average monthly sales, then the extreme outlier followed by a higher average (see table 5.3 as an example of the occurrence in a few products' historic sales).

	Luminous Compact Powder 3	Peptumax Concealer Plus 4	Superfection 2
Early sales average	0.94	3.1	1.59
Extreme Outlier	112	112	133
Average Sales After Outlier	10.77	17.54	22.61

Table 5.3: Historic Data Outliers

On examination, it was found that these outliers occurred on the months that these products were released in Dischem. A certain number of products were distributed to all Dischem stores before the sales steadied again with an increase due to the Dischem sales. As this occurrence is a once-off situation which will not specifically be repeated for the specific months, it was decided to manipulate the date with the aim of steadying the seasonal effect of this outliers. This manipulation was done by either using the average of the same month's sales after the outlier (for example if the outlier is on an April using the average of all the April sales thereafter) or if there is not sufficient amount of months after the outlier, using the monthly average sales for the increased period. The product specialist at Nailmetics also advised on realistic sales information. This will still indicate an increase in sales while not having a negative effect on the forecasts' and forecasting errors' integrity. The seasonal factor and the specific month's forecast could not have been used for the manipulation, as these values would have been influenced by the outlier during the calculation of the initial values. There will however still be enough periods to calculate an accurate seasonal factor for the outlier month and this factor's accuracy will increase in future as more historic data will be available.

5.6.2 Forecasting Error Distribution Analysis

The analysis of the distribution of the forecasting error is done to validate the use of the standard deviation equation ($1\ standard\ deviation = \sqrt{\frac{\pi}{2}} \times MAD$), as well as to verify whether a confidence interval of 99.7% is represented by ±3 standard deviations, as is the case with normal distribution. Using the residual analysis method and cumulative normal probability plots, a sample of 15 products out of the total of 143 products was selected. The following table

5.4 indicates the randomly selected products, according to their number in the forecasting model, in the sample:

	Product Number		Product Number
1	10	**9**	48
2	11	**10**	65
3	43	**11**	138
4	18	**12**	54
5	9	**13**	47
6	52	**14**	96
7	28	**15**	120
8	98		

Table 5.4: Product Sample

The forecasting errors for the 24 months prior to the current date, of all the sample products, was used to complete the residual analysis study as only these 24 months' standard deviation will be used in the model. As seen in Appendix E, all the product's residual points on the cumulative normal probability plots are approximately on the linear cumulative normal probability line which is an indication of normal distribution. As the output of this procedure is only to verify the use of the standard deviation equation and the forecasting confidence interval, which does not carry so much weight in terms of the effectiveness of the forecasting model, it will be assumed that all the products' forecasting errors for the last 24 months are normal distributed. As the forecasting model is continually used and updated over time, one can also assume that these forecasting errors will decrease, stabilize and continue to be normal distributed.

The standard deviation equation used in the forecasting model as well as the calculation of the confidence interval using the standard deviation is therefore valid and accurate. This will be used to give the user an indication of future errors to ensure safe forecasting intervals.

5.6.3 Forecasting Period Adjustment

The LP, developed in chapter 4, calculated the optimal review period to be 4 months. Due to the lead time of product arriving from Greece being 4 weeks, the forecasting model has been modified to indicate the sales forecast of 5 months on the forecasting interface sheet (see Appendix F for figure of final forecasting interface).

5.6.4 Forecasting Result Example

PerfectFace 9 is one of Nailmetics' best selling products and although seasonal trend are not obvious, seasonality and trend exists, as discussed in chapter 5.1. When using the forecasting model to forecast the sales of any of the products (in this case PerfectFace 9), the graph (figure 5.3) and forecasted data (figure 5.5) will be the output after changing the relevant forecasting parameters and analysing the forecasting errors with the aim of minimizing the error. As seen in figure 5.3, the graph indicates that the fitted line was reasonable close to the warmup line over the historic data periods, which is a good indication of the forecast line's accuracy. The forecast and interval lines give the user a much more accurate representation of the future sales and the appropriate amount to order, than what the current forecasting method (see figure 5.4 and discussion in chapter 1.2). The forecasting model indicates monthly seasonal factors and trends where the previous method only considered moving average.

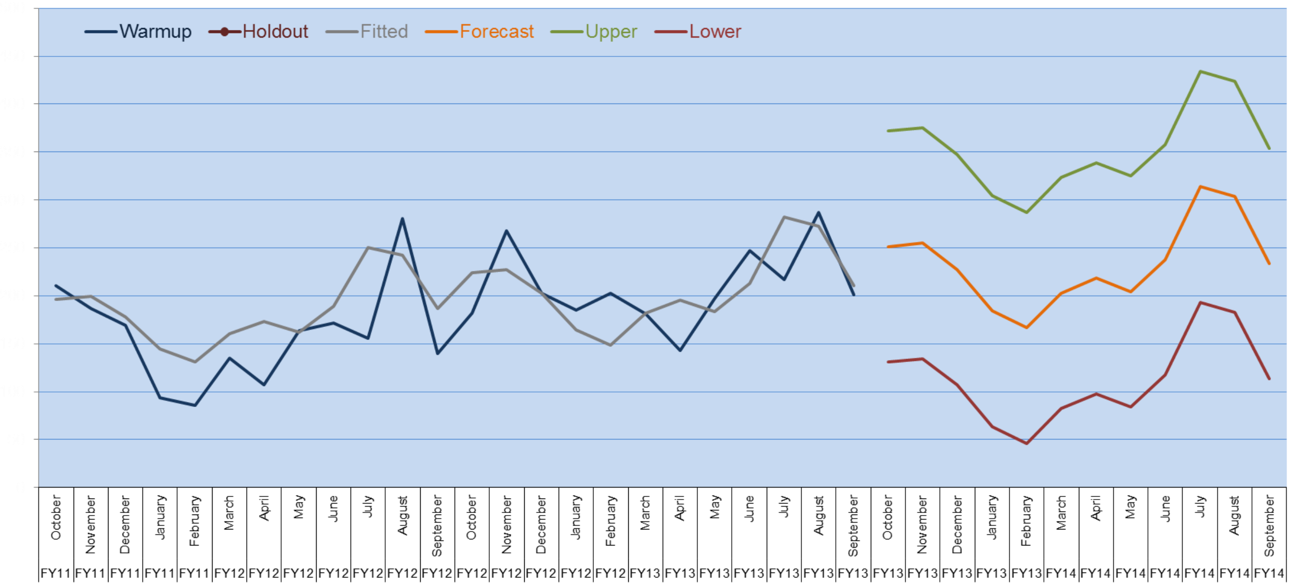

Figure 5.3: Forecast Graph

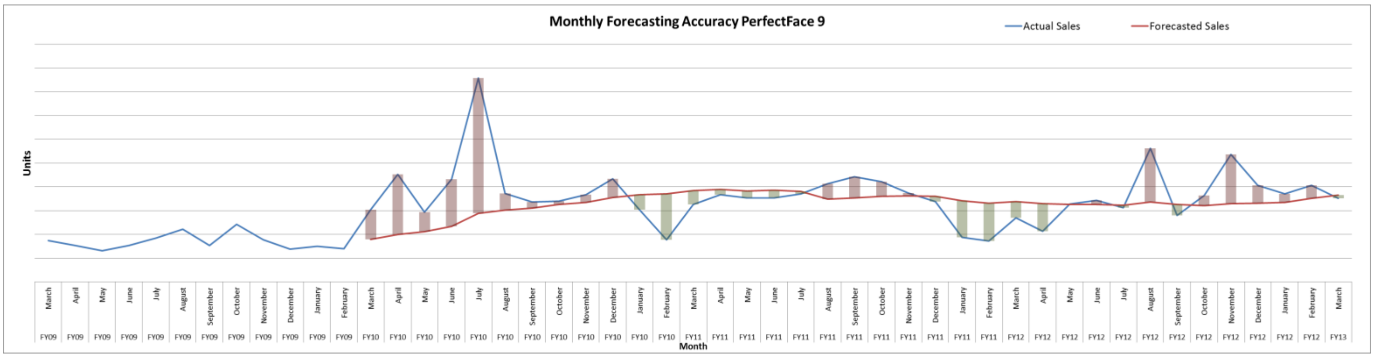

Figure 5.4: Previous Forecast Method

The table seen in figure 5.5 can therefore now be used in the collaboration of information with Farmeco as well as placement of more accurate orders. This table gives the user the values of the 5 months forecast data including the upper and lower 99.7% intervals.

Forecasted data

FY	Month	Forecasted Sales	Lower	Upper
FY13	October	251.39	130.99	371.79
FY13	November	254.93	134.53	375.34
FY13	December	227.43	107.03	347.83
FY13	January	184.02	63.62	304.42
FY13	February	166.61	46.21	287.02
	5 month sum =	917.8	436.17	1399.38

Figure 5.5: 5 Month Sales Forecast

5.7 Conclusion

The forecasting model was developed in order to improve Nailmetics' order system and to enable the collaboration of forecasted demand information between Nailmetics and Farmeco. The Holt-Winters method was used to be able to forecast data with both trend and seasonal factors. The model was also designed to be adaptive and generic to be able to add and forecast new products while providing a user friendly forecast interface. A forecasting model prototype was developed and accepted before being modified into the final forecast model for all Nailmetics' products and combined with the review period calculated in the inventory model chapter in order to forecast accurate order sizes to be placed.

6. Discussion of Results and Conclusion

6.1 Discussion of Results

The results generated in this project lead to the following supply chain management method changes advised for Nailmetics:

- Nailmetics should aim to improve CPFR especially in the supply chain between them and Farmeco. Using the monthly sales and forecasting template developed, Nailmetics should report monthly sales, 5 month forecast as well as projected order sizes to Farmeco in order to improve the final ordering efficiency. This will be done by Farmeco having a realistic projection of the final order which will improve the hemisphere synchronization. Nailmetics will also be advised to monitor the Dischem orders, especially unusual size orders, using the Qlikview application.
- The new order policy that Nailmetics are advised to implement, would be to place an order every four months. Using the forecasting model to generate sales forecasts for 5 months, the order size can be calculated using the forecasted sales for the 5 month period, minus the stock-on hand. Nailmetics will also be advised to use their experience when placing the orders as the forecasting model is only a more accurate estimation, but not a necessarily correct.
- Nailmetics will be advised to add Dischem sales data to the forecasting model with the aim of tracking and controlling the sales in Dischem stores as well as monitoring the orders placed by the Dischem representatives.

6.2 Conclusion

This project was aimed at seeking solutions for the improvement of Nailmetics' supply chain by developing a structure for the implementation of CPFR while developing an accurate forecasting model and finding an optimal ordering policy. The CPFR implementation structure was developed for a basic CPFR model in which supply chain partners share sales forecasts, promotion plans and order forecasts.

In providing Nailmetics with an accurate forecasting model, relevant to the CPFR implementation, an optimal inventory review period had to be calculated in order to improve the ordering policy. This was developed using a LP to calculate the optimal ordering period while minimizing the cost involved.

An adaptable Microsoft Excel forecasting model for all Nailmetics' products was developed using the Holt-Winters method. Historic Sales data are inserted into the model which provides a user-friendly way to select between the different products and provide an accurate sales forecast.

All the deliverables developed in this project was validated by Nailmetics. They buy into the CPFR principles and verified the effectiveness of the monthly sales and forecasting report template. Nailmetics also evaluated and validated the efficiency and feasibility of the forecasting model with the optimally calculated review period. They are committed to the newly developed ordering policy and for the ordering periods. The project, as a whole, will be presented to them, including training on the forecasting model, advised implementation methods and discussions on supply chain improvement possibilities.

In the future, as Nailmetics aims to grow Coverderm into a large competitive Cosmetic brand in the South African market, they can start looking at the implementation of more advanced CPFR through Between Ware software, automatic ordering from suppliers and continuous replenishment of customers. The LP developed in this project can also be used to calculate the optimal review period as parameters such as the financial limits, credit period and exchange rate change.

Using the supply chain solutions developed in the project, Nailmetics will be able to improve the inventory levels and ordering policy, while maintaining their high customer service standards and reducing cost.

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Appendix A

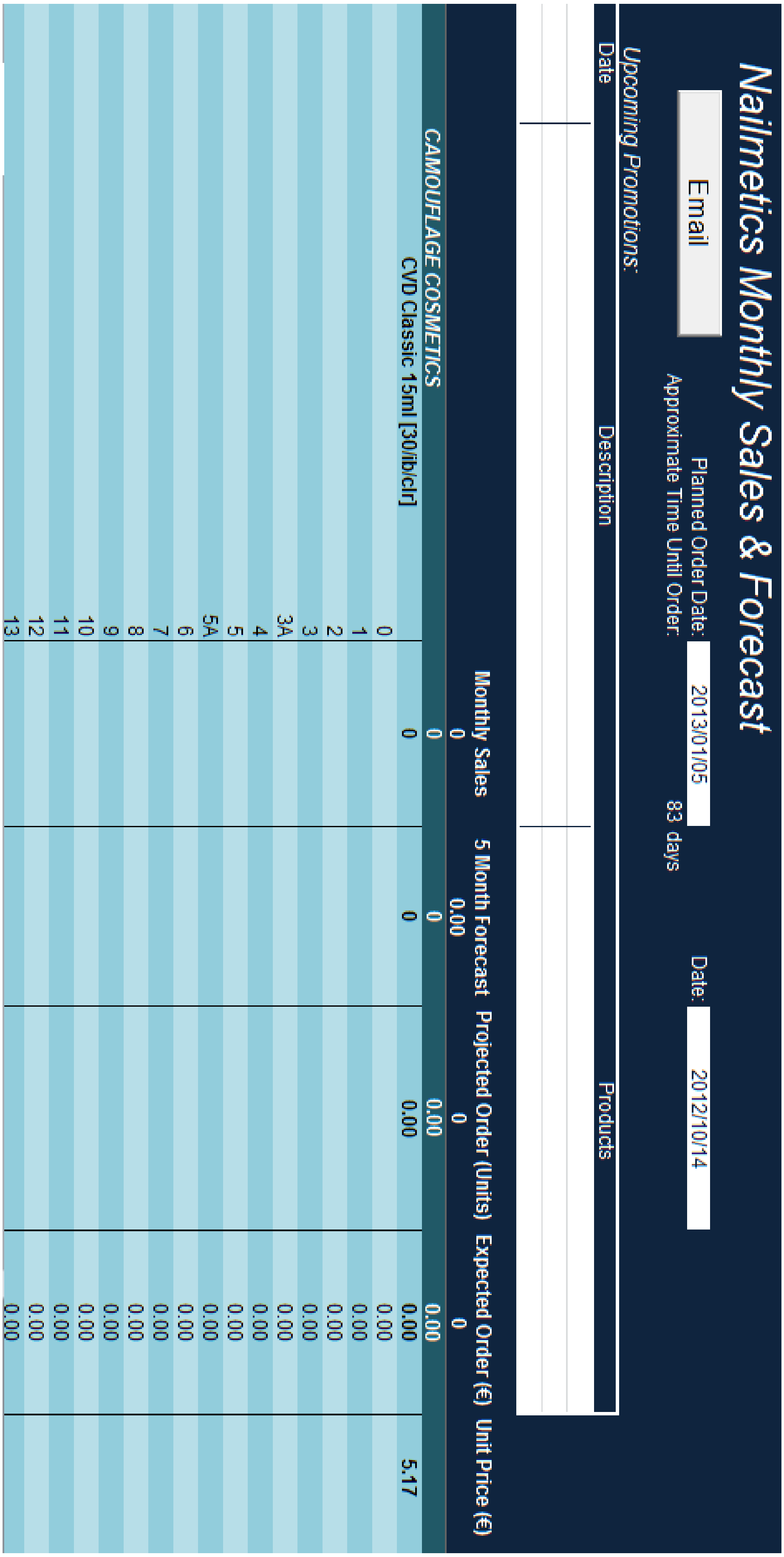

Figure 1: Monthly Sales Report Template

Appendix B

LP coded in Lingo:

```
Model:
sets:
Product / P1..P8/ : Demand, Price, Order, Weight;
endsets
Data:
Demand = 10.18 17.45 19.84 49.96 5.51 1.75 1.22 1.28;
Price = 63.43 127.21 163.18 218.68 275.18 323.49 365.54 458.91;
weight = 3.11 3.12 3.28 2.26 3.33 4.22 4.40 3.44;
Euro = 10.75;
Limit = L*;
enddata
min = (0.5)*(4.2)*Quantity + (1/(Period/12))*(y + a + b);
@For ( Product(I) : Order(I) >= (Period + 1)*Demand(I));
@sum( Product(J) : 3*Demand(J)) >= @sum(Product(K) : (1/3)*Order(K));
Quantity = @sum(Product(I): Order(I));
M = Euro*@sum(Product(I): Price(I)*Order(I));
M <= Limit;
b = 900 + 0.0035*M;
a = 3164 + 22.381*@sum(Product(I): Order(I)*weight(I));
y = 1339.5 + 46.453*@sum(Product(I): Order(I)*weight(I));
Period <= Quantity / (@sum(Product(J): Demand(J)));
@for(Product(I):Order(I)>=0);
@for(Product(I):@gin(Order(I)));
```

*Financial limit is confidential and will not be visible in this document as it will not have an influence on the calculations' feasibility

Appendix C

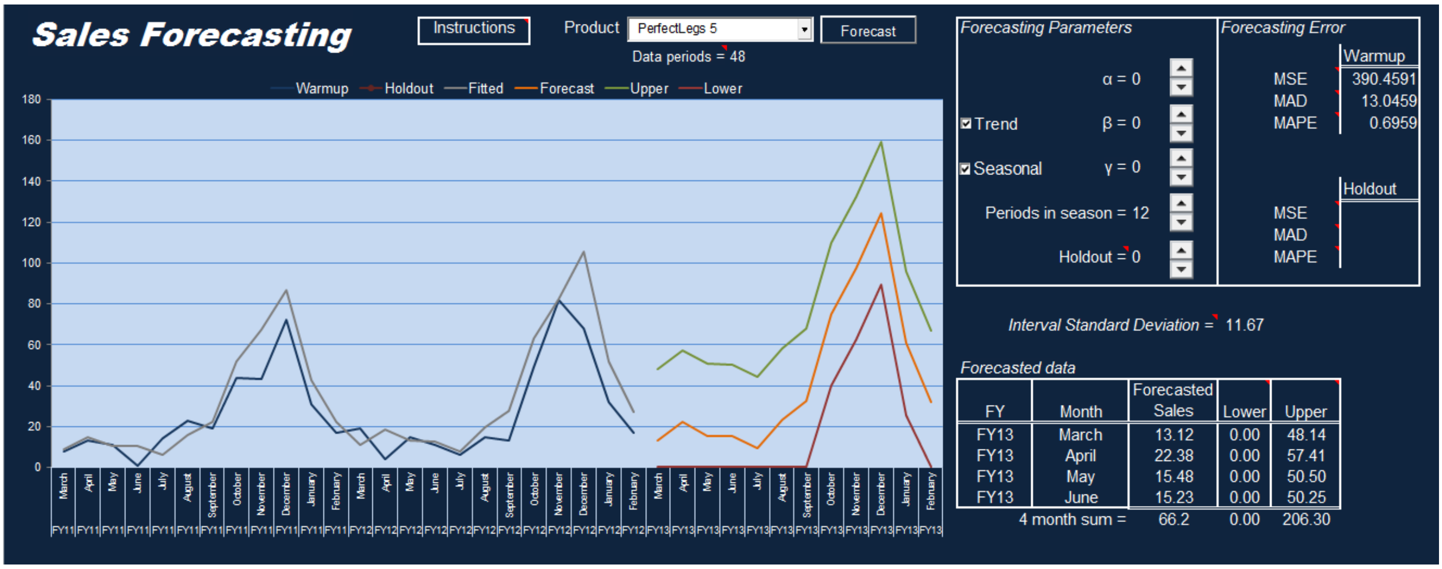

Figure 1: Forecast Interface

n	ProductName
1	PerfectFace 1
2	PerfectFace 2
3	PerfectFace 3
4	PerfectFace 4
5	PerfectFace 5
6	PerfectFace 6
7	PerfectFace 7
8	PerfectFace 8
9	PerfectFace 9
10	PerfectFace 30
11	PerfectFace 36
12	PerfectLegs 1
13	PerfectLegs 2
14	PerfectLegs 3
15	PerfectLegs 4
16	PerfectLegs 5
17	PerfectLegs 6
18	PerfectLegs 7
19	PerfectLegs 8
20	PerfectLegs 9

Figure 2: SKUs Sheet

n	FY	Month	PerfectFace 1	PerfectFace 2	PerfectFace 3
1	FY09	March	0	6	6
2	FY09	April	3	16	9
3	FY09	May	0	11	7
4	FY09	June	7	22	13
5	FY09	July	1	11	15
6	FY09	August	5	22	19
7	FY09	September	4	15	15
8	FY09	October	12	37	20
9	FY09	November	3	17	10
10	FY09	December	3	14	17
11	FY09	January	0	16	11
12	FY09	February	5	14	13
13	FY10	March	2	37	39
14	FY10	April	9	33	71
15	FY10	May	7	31	47
16	FY10	June	12	58	36
17	FY10	July	22	51	61
18	FY10	August	13	58	80
19	FY10	September	22	71	63
20	FY10	October	26	60	94
21	FY10	November	9	57	44
22	FY10	December	21	59	67

Figure 3: Data Sheet

Periods	
Data Periods	48
Holdout	0
Warmup	48
Total Periods	60

Season	12
Alpha	0
Beta	0
Gamma	0

MAD	39.43905116
MAPE	0.218555409
MSE	3324.613577
MAD Holdout	
MAPE Holdout	
MSE Holdout	

														Warmup				Holdout		
n	FY	Month	Data	Warmu	Holdou	Data	Tren	Level	Season Fac	Error	F	Fitte	Forec	MAD	MAPI	MSE	ControlMAI	MAD2	MAPE2	MSE2
							#N/A	#N/A												
1	FY09	March	87	87	#N/A	87	#N/A	#N/A	0.875055432	#N/A	#N/A	#N/A	#N/A							
2	FY09	April	77	77	#N/A	77	#N/A	#N/A	0.932732344	#N/A	#N/A	#N/A	#N/A							
3	FY09	May	66	66	#N/A	66	#N/A	#N/A	0.866315603	#N/A	#N/A	#N/A	#N/A							
4	FY09	June	77	77	#N/A	77	#N/A	#N/A	0.998498499	#N/A	#N/A	#N/A	#N/A							
5	FY09	July	92	92	#N/A	92	#N/A	#N/A	1.306340337	#N/A	#N/A	#N/A	#N/A							
6	FY09	August	111	111	#N/A	111	#N/A	#N/A	1.253436565	#N/A	#N/A	#N/A	#N/A							
7	FY09	Septembe	77	77	#N/A	77	#N/A	#N/A	0.957185388	#N/A	#N/A	#N/A	#N/A							
8	FY09	October	121	121	#N/A	121	#N/A	#N/A	1.133138776	#N/A	#N/A	#N/A	#N/A							
9	FY09	November	89	89	#N/A	89	#N/A	#N/A	1.138714433	#N/A	#N/A	#N/A	#N/A							
10	FY09	December	69	69	#N/A	69	#N/A	#N/A	1.006748796	#N/A	#N/A	#N/A	#N/A							
11	FY09	January	75	75	#N/A	75	#N/A	#N/A	0.807316363	#N/A	#N/A	#N/A	#N/A							
12	FY09	February	70	70	#N/A	70	2.0644	132.6120097	0.724517405	#N/A	#N/A	#N/A	#N/A							
13	FY10	March	152	152	#N/A	152	2.0644	134.6763823	0.875055432	34.151	117.85	117.85	#N/A	34.151	0.2247	1166.3				
14	FY10	April	226	226	#N/A	226	2.0644	136.7407548	0.932732344	98.457	127.54	127.54	#N/A	98.457	0.4357	9693.9				
15	FY10	May	147	147	#N/A	147	2.0644	138.8051274	0.866315603	26.751	120.25	120.25	#N/A	26.751	0.182	715.61				
16	FY10	June	216	216	#N/A	216	2.0644	140.8694999	0.998498499	75.342	140.66	140.66	#N/A	75.342	0.3488	5676.4				
17	FY10	July	429	429	#N/A	429	2.0644	142.9338725	1.306340337	242.28	186.72	186.72	#N/A	242.28	0.5648	58699				
18	FY10	August	186	186	#N/A	186	2.0644	144.998245	1.253436565	4.2539	181.75	181.75	#N/A	4.2539	0.0229	18.096				
19	FY10	Septembe	168	168	#N/A	168	2.0644	147.0626176	0.957185388	27.234	140.77	140.77	#N/A	27.234	0.1621	741.68				
20	FY10	October	170	170	#N/A	170	2.0644	149.1269902	1.133138776	1.0184	168.98	168.98	#N/A	1.0184	0.006	1.0372				

Figure 4: Calculations Sheet Overview

Periods	
Data Periods	48
Holdout	0
Warmup	48
Total Periods	60

Season	12
Alpha	0
Beta	0
Gamma	0

MAD	39.43905116
MAPE	0.218555409
MSE	3324.613577
MAD Holdout	
MAPE Holdout	
MSE Holdout	

Figure 5: Top section of Calculations Sheet

n	FY	Month	Data
1	FY09	March	87
2	FY09	April	77
3	FY09	May	66
4	FY09	June	77
5	FY09	July	92
6	FY09	August	111
7	FY09	September	77
8	FY09	October	121
9	FY09	November	89
10	FY09	December	69
11	FY09	January	75
12	FY09	February	70
13	FY10	March	152
14	FY10	April	226
15	FY10	May	147
16	FY10	June	216
17	FY10	July	429
18	FY10	August	186
19	FY10	September	168
20	FY10	October	170
21	FY10	November	184
22	FY10	December	217
23	FY10	January	152
24	FY10	February	89

Figure 6: Data section of Calculations Sheet

Warmup	Holdout
87	#N/A
77	#N/A
66	#N/A
77	#N/A
92	#N/A
111	#N/A
77	#N/A
121	#N/A
89	#N/A
69	#N/A
75	#N/A
70	#N/A
152	#N/A
226	#N/A
147	#N/A
216	#N/A
429	#N/A
186	#N/A
168	#N/A
170	#N/A
184	#N/A
217	#N/A
152	#N/A
89	#N/A

Figure 7: Warmup and holdout section of Calculations Sheet for periods 1 to 24

Data	Trend	Level	Season Factor	Error	F
	#N/A	#N/A			
87	#N/A	#N/A	0.875055432	#N/A	#N/A
77	#N/A	#N/A	0.932732344	#N/A	#N/A
66	#N/A	#N/A	0.866315603	#N/A	#N/A
77	#N/A	#N/A	0.998498499	#N/A	#N/A
92	#N/A	#N/A	1.306340337	#N/A	#N/A
111	#N/A	#N/A	1.253436565	#N/A	#N/A
77	#N/A	#N/A	0.957185388	#N/A	#N/A
121	#N/A	#N/A	1.133138776	#N/A	#N/A
89	#N/A	#N/A	1.138714433	#N/A	#N/A
69	#N/A	#N/A	1.006748796	#N/A	#N/A
75	#N/A	#N/A	0.807316363	#N/A	#N/A
70	2.064373	132.6120097	0.724517405	#N/A	#N/A
152	2.064373	134.6763823	0.875055432	34.1507	117.8493
226	2.064373	136.7407548	0.932732344	98.45748	127.5425
147	2.064373	138.8051274	0.866315603	26.75095	120.249
216	2.064373	140.8694999	0.998498499	75.34202	140.658
429	2.064373	142.9338725	1.306340337	242.2797	186.7203
186	2.064373	144.998245	1.253436565	4.253898	181.7461
168	2.064373	147.0626176	0.957185388	27.23381	140.7662
170	2.064373	149.1269902	1.133138776	1.018425	168.9816
184	2.064373	151.1913627	1.138714433	11.83621	172.1638

Figure 8: Forecasting calculations section of Calculations Sheet for periods 1 to 21

Fitted	Forecast
#N/A	#N/A
#N/A	#N/A
#N/A	#N/A
#N/A	#N/A
#N/A	#N/A
#N/A	#N/A
#N/A	#N/A
#N/A	#N/A
#N/A	#N/A
#N/A	#N/A
#N/A	#N/A
#N/A	#N/A
117.8493	#N/A
127.5425	#N/A
120.249	#N/A
140.658	#N/A
186.7203	#N/A
181.7461	#N/A
140.7662	#N/A
168.9816	#N/A
172.1638	#N/A

Figure 9: Fitted and forecast section of Calculations Sheet for periods 1 to 21

Warmup				Holdout		
MAD	MAPE	MSE	ControlMAD	MAD2	MAPE2	MSE2
34.1507	0.224676	1166.27				
98.45748	0.435653	9693.874				
26.75095	0.181979	715.6135				
75.34202	0.348806	5676.419				
242.2797	0.564755	58699.46				
4.253898	0.02287	18.09565				
27.23381	0.162106	741.6805				
1.018425	0.005991	1.037189				
11.83621	0.064327	140.0959				

Figure 10: Error calculations section of Calculations Sheet for periods 1 to 21

							StDev	11.6742		
	n	FY	Month	Warmup	Holdout	Fitted	Forecast	MAD	Upper	Lower
-23	25	FY11	March	8	#N/A	8.62115	#N/A	0.62115	#N/A	#N/A
-22	26	FY11	April	13	#N/A	14.8184	#N/A	1.81844	#N/A	#N/A
-21	27	FY11	May	11	#N/A	10.3208	#N/A	0.67923	#N/A	#N/A
-20	28	FY11	June	1	#N/A	10.2216	#N/A	9.22165	#N/A	#N/A
-19	29	FY11	July	14	#N/A	6.31898	#N/A	7.68102	#N/A	#N/A
-18	30	FY11	August	23	#N/A	15.7652	#N/A	7.23479	#N/A	#N/A
-17	31	FY11	September	19	#N/A	22.4039	#N/A	3.40392	#N/A	#N/A
-16	32	FY11	October	44	#N/A	51.5665	#N/A	7.56648	#N/A	#N/A
-15	33	FY11	November	43	#N/A	67.4548	#N/A	24.4548	#N/A	#N/A
-14	34	FY11	December	72	#N/A	86.6859	#N/A	14.6859	#N/A	#N/A
-13	35	FY11	January	31	#N/A	42.523	#N/A	11.523	#N/A	#N/A
-12	36	FY11	February	17	#N/A	22.3072	#N/A	5.30722	#N/A	#N/A
-11	37	FY12	March	19	#N/A	10.8697	#N/A	8.13025	#N/A	#N/A
-10	38	FY12	April	4	#N/A	18.6012	#N/A	14.6012	#N/A	#N/A
-9	39	FY12	May	15	#N/A	12.9005	#N/A	2.09947	#N/A	#N/A
-8	40	FY12	June	11	#N/A	12.7245	#N/A	1.72449	#N/A	#N/A
-7	41	FY12	July	6	#N/A	7.83529	#N/A	1.83529	#N/A	#N/A
-6	42	FY12	August	15	#N/A	19.4741	#N/A	4.47408	#N/A	#N/A
-5	43	FY12	September	13	#N/A	27.5733	#N/A	14.5733	#N/A	#N/A
-4	44	FY12	October	49	#N/A	63.2401	#N/A	14.2401	#N/A	#N/A
-3	45	FY12	November	82	#N/A	82.4425	#N/A	0.44251	#N/A	#N/A
-2	46	FY12	December	68	#N/A	105.596	#N/A	37.5964	#N/A	#N/A
-1	47	FY12	January	32	#N/A	51.6337	#N/A	19.6337	#N/A	#N/A
0	48	FY12	February	17	#N/A	27.0028	#N/A	10.0028	#N/A	#N/A
1	49	FY13	March	#N/A	#N/A	#N/A	13.1183		48.1408	0
2	50	FY13	April	#N/A	#N/A	#N/A	22.384		57.4065	0

Figure 11: Graph Calculations Sheet

Appendix D

```
Private Sub CheckBox1_Click()
If CheckBox1.Value = False Then
    SpinButton4.Visible = False
    SpinButton3.Visible = False
    Range("PeriodsLabel").Value = ""
    Range("Season1").Value = ""
    Range("Season2").Value = 0
    Range("GammaLabel").Value = ""
    Range("Gamma1").Value = ""
    Range("AN4").Value = 0
End If
If CheckBox1.Value = True Then
    Range("GammaLabel").Value = Range("AL4").Value
    Range("Gamma1").Formula = "=Gamma2"
    Range("PeriodsLabel").Value = Range("AL5").Value
    Range("Season1").Formula = "=Season2"
    SpinButton4.Visible = True
    SpinButton3.Visible = True
End If
End Sub
```

Figure 1: VB code for seasonal checkbox

```
Function Seasonality(Datapoints As Range, Seasonlength As Long, n As Long)
Dim Factor As Single
Dim Totals() As Single
Dim NoFullSeasons As Long
Dim i, j, k
NoFullSeasons = Int(Datapoints.Count / Seasonlength)
ReDim Totals(NoFullSeasons)
    For i = 1 To NoFullSeasons
        For j = 1 To Seasonlength
            Totals(i) = Totals(i) + Datapoints.Cells((i - 1) * Seasonlength + j)
        Next j
    Next i
Factor = 0
For i = 1 To NoFullSeasons
    If Totals(i) <> 0 Then
        Factor = Factor + Datapoints.Cells((i - 1) * Seasonlength + n) / (Totals(i) / Seasonlength)
    End If
Next i
Seasonality = Factor / NoFullSeasons
End Function
```

Figure 2: Seasonality Function

Appendix E

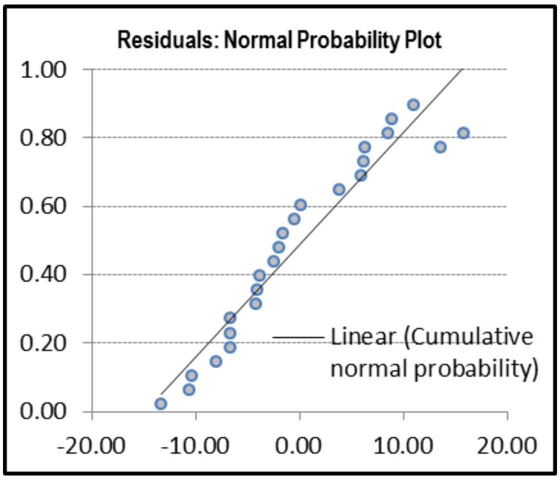

Figure 1: Product 10

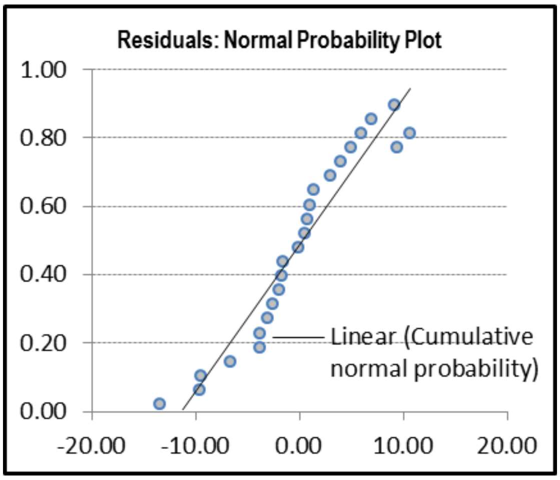

Figure 2: Product 11

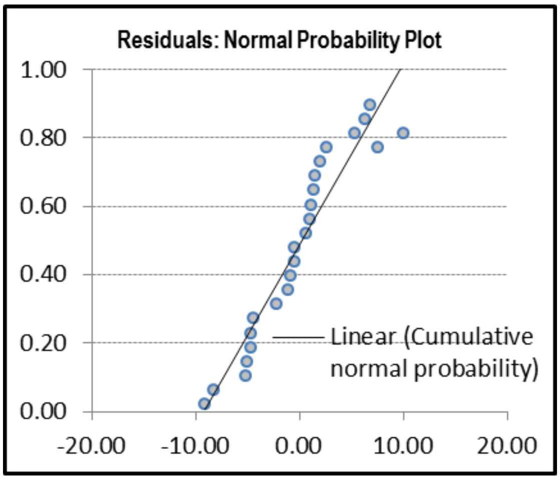

Figure 3: Product 43

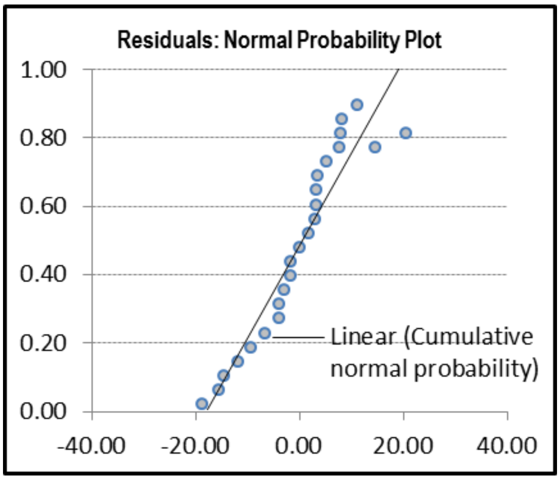

Figure 4: Product 18

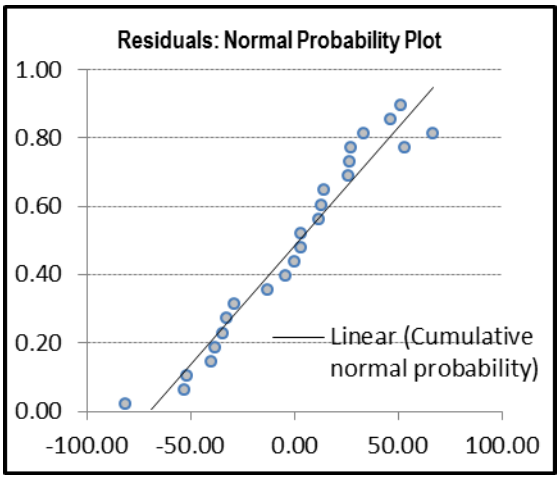

Figure 5: Product 9

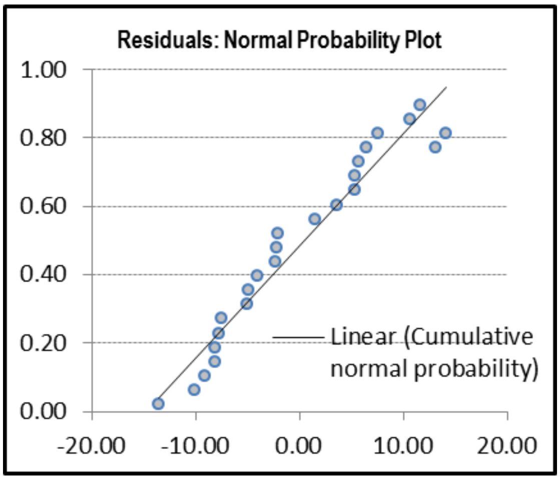

Figure 6: Product 52

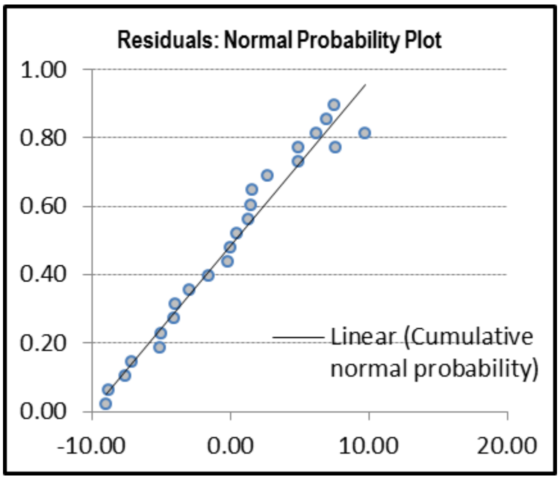

Figure 7: Product 28

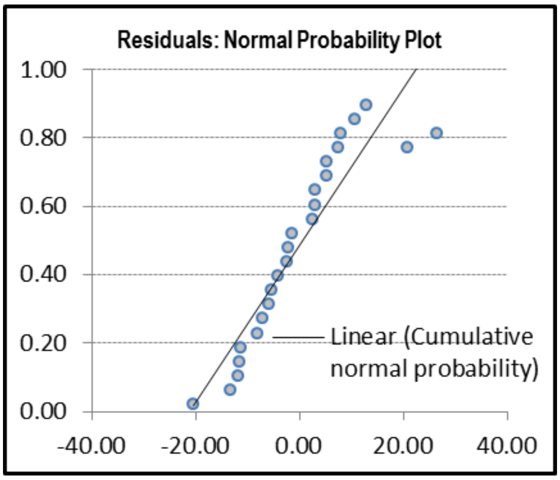

Figure 8: Product 98

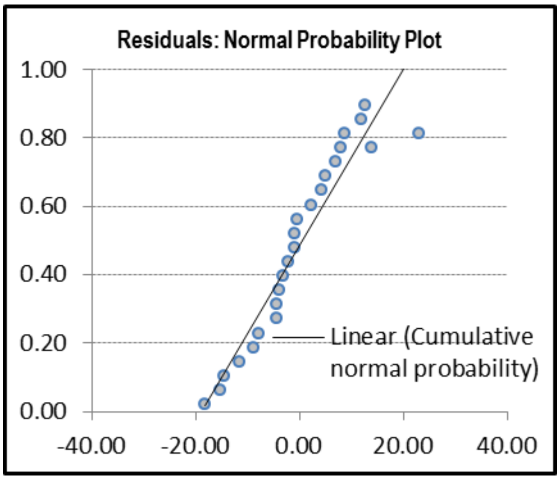

Figure 9: Product 48

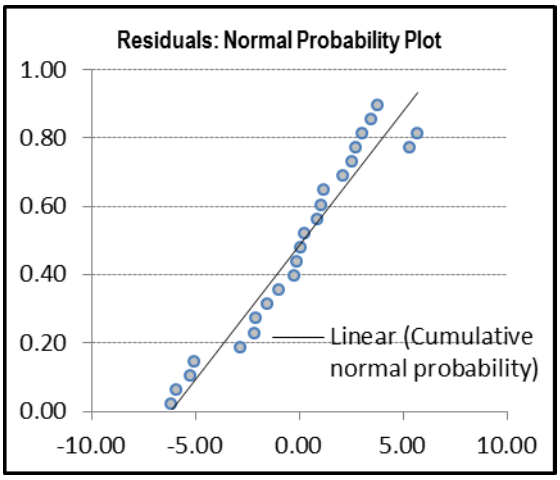

Figure 10: Product 65

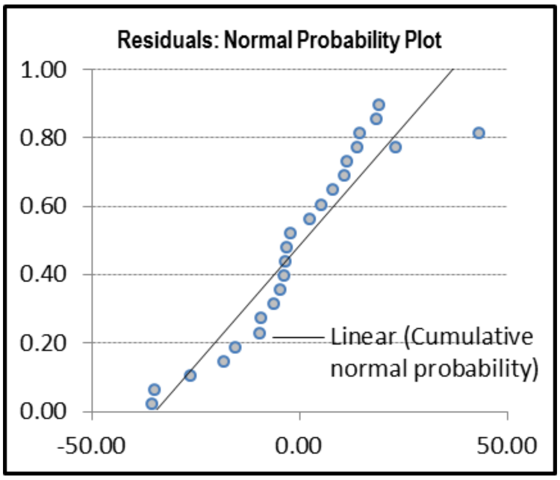

Figure 11: Product 138

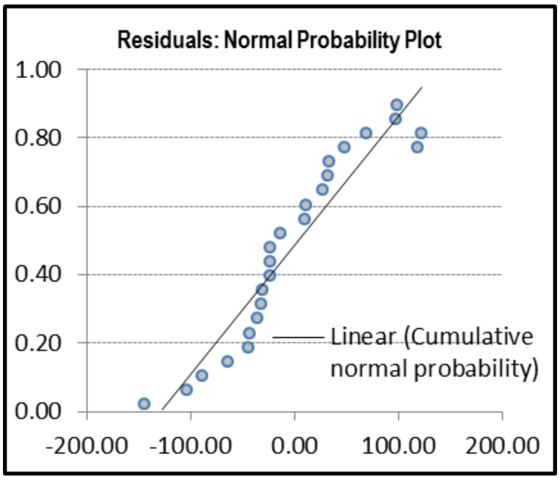

Figure 12: Product 54

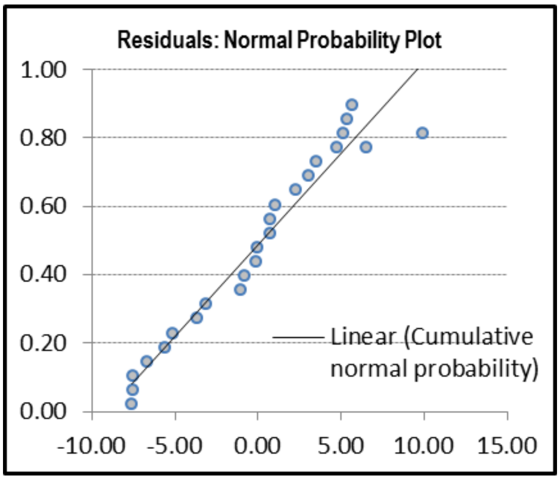

Figure 13: Product 47

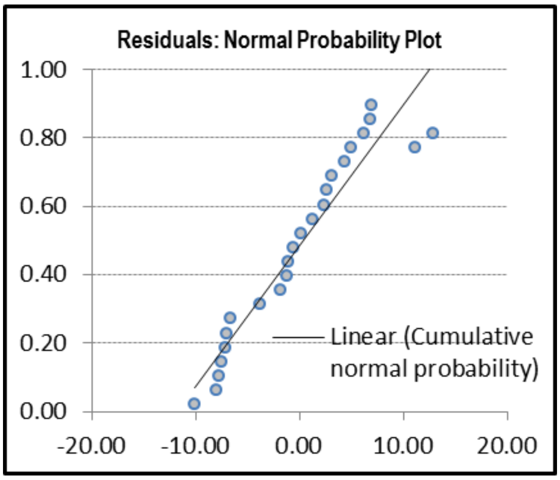

Figure 14: Product 96

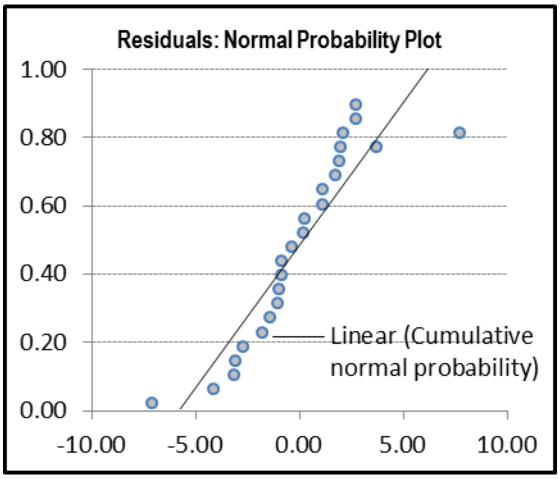

Figure 15: Product 120

Appendix F

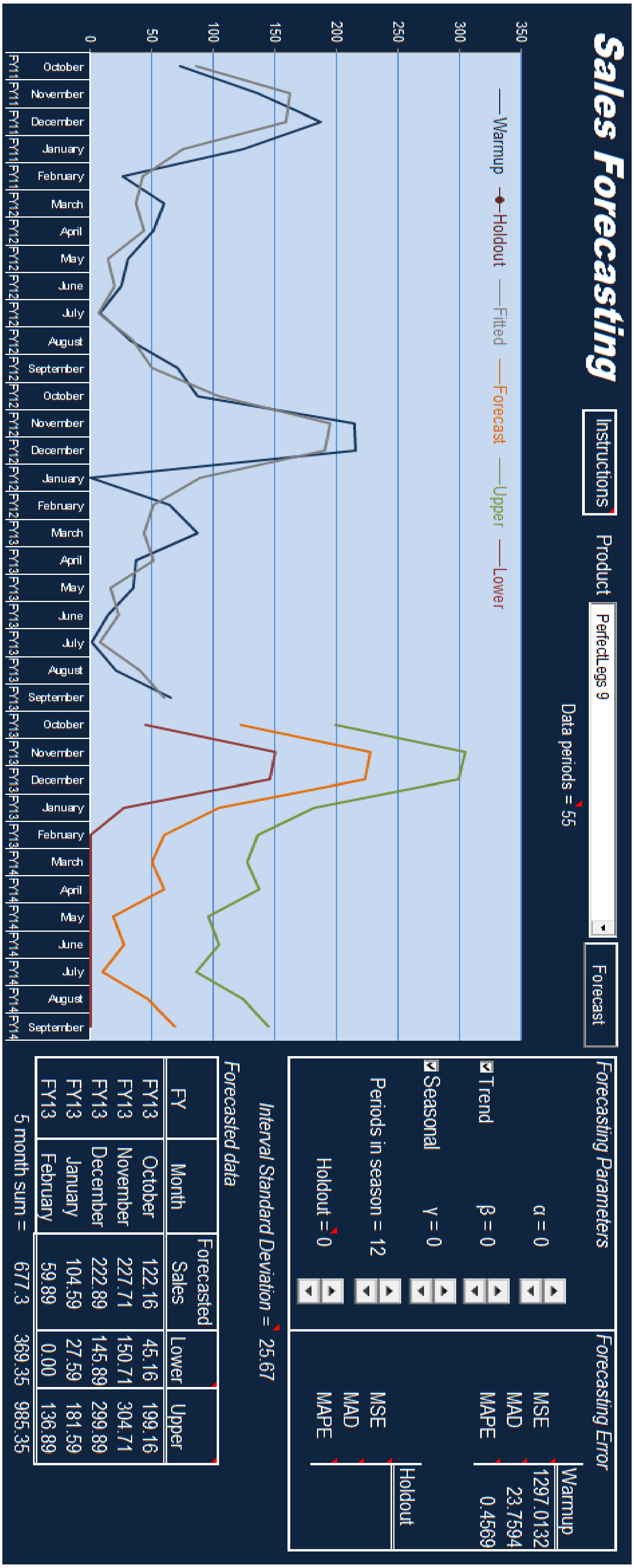

Figure 1: Image of Final Forecasting Model Interface