Integrated Forecasting and Inventory Management in a Wholesale Company at Tescoma s.r.o

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Ao meu avô, António Gouveia Lopes

Resumo

Atualmente, em todas as áreas de negócio com qualquer grau de complexidade e de dimensão, as empresas são confrontadas com necessidades de planeamento e previsão. Em particular, estas necessidades prendem-se muitas vezes com a previsão de vendas e o planeamento, seja de produção, seja de ordem de produção, que no fundo e em perspectivas diferentes pretendem analisar a gestão de inventários.

Neste trabalho foram exploradas estas necessidades, na dimensão de uma empresa multi nacional de artigos de *kitchen and houseware*, com um centro logístico de distribuição global.

Numa primeira fase será abordada a temática dos métodos de previsão, onde serão propostos os diferentes modelos e processos, procurando assim os que melhor se adequem à realidade do projeto. Serão contrastados diferentes níveis de agregação dos dados, permitindo incluir uma avaliação mais pormenorizada de como tratar dados numa empresa de venda a grosso e as razões inerentes.

Numa segunda fase, os métodos de previsão foram integrados com um sistema de reabastecimento de inventário, onde várias metodologias atuais de gestão de inventário serão alvo de estudo e debate. Surgirá uma revisão relativa ao stock de segurança, as suas diversas abordagens e limites, e onde a escolha residirá suportada por dados estatisticos.

Esta integração será feita por meio de um algoritmo, testado sobre o ano de 2012 com os dados reais de vendas e stocks do período de Janeiro a Agosto.

Abstract

Nowadays, in every business area with any degree of complexity and magnitude, companies face the need of planning and forecast. In particular, these needs often relate with sales forecasting and planning, either production planning, or production order, which at the end, and in different perpectives intend to analyse inventory management.

In this work these needs are explored, in the dimension of a multi national company of kitchen and houseware articles, with a main logistics center of global distribution.

In a first phase, an approach to the forecasting methods thematics will be made, where different models and processes will be proposed, in order to find the ones that better suit the project reality. Different levels of data agreggation will be compared, allowing a deeper analysis of how to process data in a wholesale company and the inherent reasons.

In a second phase, the forecasting method will be integrated with the inventory replenishment policy, where different inventory management policies will be studied and debated. Naturaly in this context a review of safety stock is required, with its approches and constraints, and the choice suported by statistic data.

This integration will be made by an algorithm, tested with 2012 data, with real sales and stocks data from January to August.

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1 Introduction

The practical experience of Tescoma, associated with a perspective of the current methodologies used in the business will lead the way in the development of this work.

Facing a continuous growth, and due to its national and subsequent international expansion, Tescoma recently felt the need to incorporate new models in distinct areas that could outperform the old ones, thus helping to boost this growth.

Developments were made in the past few years in logistics, with a complete remodelling of the warehouse and distribution system, with the development of native software integrated with the ERP (Enterprise Resource Planning), (SAP).

With this work we pursue to continue this evolution, emphasising efforts in performance improvements using several tools and techniques applied in inventory management. A selection of protocols and methods regarding forecasting, replenishment policies and safety stock literature will be reviewed, so a effective selection of the appropriate system can be achieved.

Further, all these preceding ideas will be aggregated to obtain a robust algorithm that can retrieve an "Order planning" interface.

1.1 Tescoma Presentation

Tescoma s.r.o is a company without foreign capital seat in Zlín, Czech Republic, focusing its main business in design, research and development of all kinds of kitchen and houseware.

Tescoma is devoted to the following three principles:

"1.Offer a wide range of products of excellent quality with favorable prices"

"2.Apply and develop own original designs of Kitchen utensils"

"3.Promote the brand and the reputation of the Czech Republic abroad"

Tescoma Worldwide

With a leading position on the global market of kitchenware, a range of over 2,000 SKU (Stock Keeping Unit), and average of 17 new utensils per month, Tescoma sells in over 100 countries worldwide.

As a consequence of this worldwide growth Tescoma completed in 2008 his second stage of "Tescoma World Logistics Centre", with an actual capacity of 30,000 pallets in Zlín headquarters. However, this reveals not to be enough in years to come, and so, a third stage is already in progress to rise the total capacity of the main warehouse in 16,000 pallets.

Tescoma Team and Amenities

The success of Tescoma s.r.o is, allied with all the principles, based in its 250 workers in Zlín Headquarters, the teamwork between all company departments, and the environment created by the relationships between employees and the company itself.

Adopting a policy of added value to its products turned to work right for Tescoma, and it wasn’t surprisingly that based on this experience the same philosophy was applied to the workers. Every Tescoma employee can apply for skills courses, such as language courses, lectures, or even salesman training, free of charge. This investment encourages the workers to evolve, developing new skills and consequently become better assets to the business.

Still, sports and leisure turn to be company’s concern as well, for it can directly affect employee’s physical and mental health. To reward the work developed by the whole team, to aggregate the Tescoma family in leisure time, and to strength even more the bounds between workers, Sport and Relaxation Centre opened in 2006.

Equipped with swimming pool, playground, tennis course, mini-golf course, beach volleyball field and other features and possible activities, it makes the perfect place for employees to have a good time after work with their relatives and family.

Quality Control

The control of standards regulations, and the guarantee of the finest products, has led the company to open the “Laboratory for the Development and Quality Inspection of Kitchen

Utensils” in 2005. With a quality management system under ISO 9000:2001 and environmental management under ISO14001:2005, Tescoma pursues excellence and certificates in all its products and processes, so it can ensure costumer satisfaction.

1.2 Tescoma Project Scope

Companies are often faced with the question of “What to buy?” “When to buy?” and “How many to buy?”.

To face these difficulties many authors started do develop methodologies that could help management with the answers.

Such studies focused in specific aspects of these broad questions.

In this project knowledge was aggregate, gathering information of different fields and authors methodologies, which are directly linked with the project concern.

The three main fields of study in this project will be:

-Forecasting Methods

-Inventory Management

-Safety Stock Methods

Forecasting

According with The American Heritage® Dictionary of the English Language, Fourth Edition copyright ©2000 by Houghton Mifflin Company. Updated in 2009. Published by Houghton Mifflin Company, forecasting is “to estimate or calculate in advance, especially to predict by analysis of data”. This is a dictionary definition of something that is much more complicated than two lines of text.

Forecasting has become over time the consequence of our need to plan and not the other way around.

The time lag between our decisions and their actual occurrence, lead-time, can be of 1 millisecond, when we decide to talk, or 10 years when it comes to building an airplane. The range of this lead-time can take multiple proportions, and so can a forecasting method or a planning horizon.

A forecasting aim is taking the right decision in an uncertainty environment and it plays a high role predicting how these variables will behave in the future, minimizing the risks of our decisions, and improving the final result.

"An unsophisticated forecaster uses statistics as a drunken man uses lamp-posts - for support rather than for illumination. ". Andrew Lang

The choice and collection of the right data, the control of its quality, and the right analysis of all current processes are the first steps in our model development, and they are as important as implementing the right forecasting method.

However, forecasting is not “futurology”, and the first thing that we can be sure, is that “all forecasts will be wrong” (2nd Law of Forecasting, Lobo, B. A., 2011). We can then conclude that we will over-forecast, causing excess of inventory costs, inventory holding costs, and costs of obsolescence, or we will under-forecast, causing losses due to missed sales, decrease product availability, (resulting is consumers dissatisfaction), and increase products cost. (Almada Lobo, 2011a)

Inventory Management

Inventory level changes over time as consequence of goods consumption and, somewhere in time, this level reaches a point where a new order needs to be placed. But when to order? How many? Covering how many days, months, years? The main issue in inventory management is answering all these questions while guarantying the availability of the products to costumers and minimizing costs.

Many methodologies have been developed in order to fulfill this need.

Models that can minimize costs were developed to different demands patterns, being EOQ (economic order quantity) one of the most well known methodologies that fits a steady-state demand. Other models that handle dynamic demand will be studied in chapter 2 where the costs of ordering, holding costs, and all kind of constraints will be balanced to achieve the minimum total cost.

Safety Stock

Demand seasonality and demand uncertainties are two concerns when it comes to planning. Despite the efforts and the accuracy of our forecasting models, as in our replenishment order planning, there will always be some deviation between our estimated values and real values in demand as well as in lead-time.

To deal with these uncertainties, and to accommodate periods of higher demand and/or lead-time than expected, safety stocks are kept in warehouse to minimize the occurrence of stock out.

The calculation of this safety stock level will depend on forecasted demand, the variability of this demand, and also on the variability of the lead-time.

Scientific methods and different approaches to the subject will also be discussed in chapter 2.

1.3 Objectives

Centered in theoretical thinking, but always focused in the real business constraints of the company, this project proposes the evolution to new and better procedures that can improve the actual results of Tescoma s.r.o.

Our main target of this project is the selection of more accurate forecasting and inventory management, methods, allied with an algorithm that can integrate purchasing processes and logistics management.

To attain this, the study will be focused in the supply chain variables that can be directly managed by the company, and with all background data, develop an algorithm that can help the company to improve their decisions in areas such as purchasing orders processes and stock keeping policies.

By the end of this work the following results are expected to be achieved:

-Reduce Stock Keeping Costs

-Reduce Product Investment in Warehouse

-Decrease Average Volume Occupied P/Product

-Decrease Backorders Rate

-Increase Products Turnover

-Increase the Liquidity

1.4 Dissertation Structure

This dissertation is divided in 5 chapters.

In this first chapter the problem scope, the organization context and the project targets have been introduced.

Chapter 2 leans in the theoretical and scientific study of the project scope subjects, framing our problematic with the state of art of forecasting methods, inventory management policies and safety stock approaches.

In the third chapter an overview of the current practices of the company, its departments and synergies, along with problems and fields where we believe improvements can be made will be given.

Chapter 4 displays the implementation methods, describing step by step procedures, arguing between the previous options, and supporting the final methodology by theoretical or statistics facts.

Chapter 5 presents the results, and compares them with actual data from the company's current practices.

Finally, in chapter 6 all the work is reviewed, conclusions are introduced and suggestions for future work are made.

2 State of Art

In order to improve and support the decision on the methodology, this entire chapter is dedicated to the study and analysis of different approaches related with the project scope.

Research has been made in the main subjects that this work carries, improving knowledge and relating the actual problematic with solutions supported by recognized authors and scientific articles.

These researched literature deals with strategic and tactical decisions opposing distinct models.

Leaning in topics such as, safety stock policies, forecasting methodologies and inventory management, this chapter will present and carefully debate the current state of art of these subjects, combining multiple procedures so that the best solution of methods may be achieved.

2.1 Forecasting

Clearly revealing a plan to stock policy, Tescoma has to plan in advance all the production of its products.

Different techniques are applied in forecasting procedures and we can divide them in:

-Quantitative methods

-Qualitative methods

Qualitative methods are only used when there is no relevant data available, so we will focus in quantitative methodologies. (Almada Lobo, 2011a)

Quantitative methods, or time series methods as they are also called, use historical data to predict future demand.

As our demand reveals a partially random distribution, we will focus our research in the stochastic times series, and particularly in exponential smoothing methods.

The choice of exponential smoothing is supported by the popularity and success achieved with this methodology, that has proved to have very good accuracy, with minimal effort in model identification.(E. Gardner, 1985)

The comparison between these models and other solutions will also be discussed along the chapter corroborating the methodology choice when necessary.

Exponential smoothing

Exponential smoothing was originally developed by Robert G. Brown for the US Navy during World War II (E. Gardner, 2006). These developments started with a tracking model for fire-control information on the location of submarines in Second World War, using a basic simple exponential smoothing of continuous data, and later in the 50’s with the extension of SES to discrete data and the development of methods that could handle trend and seasonality.

The first application was to forecast demand for spare parts in the US Navy inventory system. This latter work was presented at a meeting of the Operations Research Society of America in 1956 and formed the basis of Brown’s first book on inventory control (Brown 1959) (R. Hyndman, Koehler, Ord, & Snyder, 2008).

At the same time, and working for the US Office of Naval Research, Holt developed exponential smoothing methods, quite different of Brown's methodology concerning trend and seasonal components. Later on, his student Peter Winters (1960), made empirical tests achieving what is call Holt-Winter's methods.

In the following years extensions of the methods were made by other researchers such as Pegels (1969), Gardner and Mckenzie(1985) and Taylor(2003a).

According with R. Hyndman et al. (2008) we can describe a time series as the combination of the following components:

Trend (T): the long-term direction of the series;

Seasonal (S): A pattern that repeats with a known periodicity;

Cycle (C): A pattern that repeats with some regularity, but with unknown and changing periodicity;

Error (E): The unpredictable component of the series.

Table 1 presents the equations for the standard methods of exponential smoothing, all of which are extensions of the work of Brown (1959, 1963), Holt (1957), and Winters (1960)(E. Gardner, 2006).

Two formulas are presented for each method, one refers to the recurrence forms, and the second is related with error-correction forms.

Both can and are used till today, being the use of error-correction forms much more simple, and still they have proved to come up with similar forecast.

The taxonomy is based on Hyndmans et al.'s (2002) with Taylor (2003) extension, where each method trend is described by one or two letters (row heading), and the seasonality of the methods is described by one letter (column heading); as an example, if we have A-N, it means additive trend with no seasonality.

The following methods are in Table 1:

N-N Simple exponential smoothing (Brown, 1959)

A-N Additive trends (Holt, 1957)

DA-N Damped additive trend (Gardner and Mckenzie, 1985)

M-N Multiplicative trend (Pegel, 1969)

DM-N Damped multiplicative trend (Taylor, 2003)

Table 1- Standard exponential smoothing methods (Source: Gardner, 2006)

Trend	Seasonality: N None	Seasonality: A Additive	Seasonality: M Multiplicative
N None	$S_t = \alpha X_t + (1-\alpha)S_{t-1}$ $\hat{X}_t(m) = S_t$	$S_t = \alpha(X_t - I_{t-p}) + (1-\alpha)S_{t-1}$ $I_t = \delta(X_t - S_t) + (1-\delta)I_{t-p}$ $\hat{X}_t(m) = S_t + I_{t-p+m}$	$S_t = \alpha(X_t / I_{t-p}) + (1-\alpha)S_{t-1}$ $I_t = \delta(X_t / S_t) + (1-\delta)I_{t-p}$ $\hat{X}_t(m) = S_t I_{t-p+m}$
	$S_t = S_{t-1} + \alpha e_t$ $\hat{X}_t(m) = S_t$	$S_t = S_{t-1} + \alpha e_t$ $I_t = I_{t-p} + \delta(1-\alpha)e_t$ $\hat{X}_t(m) = S_t + I_{t-p+m}$	$S_t = S_{t-1} + \alpha e_t / I_{t-p}$ $I_t = I_{t-p} + \delta(1-\alpha)e_t / S_t$ $\hat{X}_t(m) = S_t I_{t-p+m}$
A Additive	$S_t = \alpha X_t + (1-\alpha)(S_{t-1} + T_{t-1})$ $T_t = \gamma(S_t - S_{t-1}) + (1-\gamma)T_{t-1}$ $\hat{X}_t(m) = S_t + mT_t$	$S_t = \alpha(X_t - I_{t-p}) + (1-\alpha)(S_{t-1} + T_{t-1})$ $T_t = \gamma(S_t - S_{t-1}) + (1-\gamma)T_{t-1}$ $I_t = \delta(X_t - S_t) + (1-\delta)I_{t-p}$ $\hat{X}_t(m) = S_t + mT_t + I_{t-p+m}$	$S_t = \alpha(X_t / I_{t-p}) + (1-\alpha)(S_{t-1} + T_{t-1})$ $T_t = \gamma(S_t - S_{t-1}) + (1-\gamma)T_{t-1}$ $I_t = \delta(X_t / S_t) + (1-\delta)I_{t-p}$ $\hat{X}_t(m) = (S_t + mT_t)I_{t-p+m}$
	$S_t = S_{t-1} + T_{t-1} + \alpha e_t$ $T_t = T_{t-1} + \alpha\gamma e_t$ $\hat{X}_t(m) = S_t + mT_t$	$S_t = S_{t-1} + T_{t-1} + \alpha e_t$ $T_t = T_{t-1} + \alpha\gamma e_t$ $I_t = I_{t-p} + \delta(1-\alpha)e_t$ $\hat{X}_t(m) = S_t + mT_t + I_{t-p+m}$	$S_t = S_{t-1} + T_{t-1} + \alpha e_t / I_{t-p}$ $T_t = T_{t-1} + \alpha\gamma e_t / I_{t-p}$ $I_t = I_{t-p} + \delta(1-\alpha)e_t / S_t$ $\hat{X}_t(m) = (S_t + mT_t)I_{t-p+m}$
DA Damped Additive	$S_t = \alpha X_t + (1-\alpha)(S_{t-1} + \phi T_{t-1})$ $T_t = \gamma(S_t - S_{t-1}) + (1-\gamma)\phi T_{t-1}$ $\hat{X}_t(m) = S_t + \sum_{i=1}^{m} \phi^i T_t$	$S_t = \alpha(X_t - I_{t-p}) + (1-\alpha)(S_{t-1} + \phi T_{t-1})$ $T_t = \gamma(S_t - S_{t-1}) + (1-\gamma)\phi T_{t-1}$ $I_t = \delta(X_t - S_t) + (1-\delta)I_{t-p}$ $\hat{X}_t(m) = S_t + \sum_{i=1}^{m} \phi^i T_t + I_{t-p+m}$	$S_t = \alpha(X_t / I_{t-p}) + (1-\alpha)(S_{t-1} + \phi T_{t-1})$ $T_t = \gamma(S_t - S_{t-1}) + (1-\gamma)\phi T_{t-1}$ $I_t = \delta(X_t / S_t) + (1-\delta)I_{t-p}$ $\hat{X}_t(m) = (S_t + \sum_{i=1}^{m} \phi^i T_t)I_{t-p+m}$
	$S_t = S_{t-1} + \phi T_{t-1} + \alpha e_t$ $T_t = \phi T_{t-1} + \alpha\gamma e_t$ $\hat{X}_t(m) = S_t + \sum_{i=1}^{m} \phi^i T_t$	$S_t = S_{t-1} + \phi T_{t-1} + \alpha e_t$ $T_t = \phi T_{t-1} + \alpha\gamma e_t$ $I_t = I_{t-p} + \delta(1-\alpha)e_t$ $\hat{X}_t(m) = S_t + \sum_{i=1}^{m} \phi^i T_t + I_{t-p+m}$	$S_t = S_{t-1} + \phi T_{t-1} + \alpha e_t / I_{t-p}$ $T_t = \phi T_{t-1} + \alpha\gamma e_t / I_{t-p}$ $I_t = I_{t-p} + \delta(1-\alpha)e_t / S_t$ $\hat{X}_t(m) = (S_t + \sum_{i=1}^{m} \phi^i T_t)I_{t-p+m}$
M Multiplicative	$S_t = \alpha X_t + (1-\alpha)(S_{t-1}R_{t-1})$ $R_t = \gamma(S_t / S_{t-1}) + (1-\gamma)R_{t-1}$ $\hat{X}_t(m) = S_t R_t^m$	$S_t = \alpha(X_t - I_{t-p}) + (1-\alpha)S_{t-1}R_{t-1}$ $R_t = \gamma(S_t / S_{t-1}) + (1-\gamma)R_{t-1}$ $I_t = \delta(X_t - S_t) + (1-\delta)I_{t-p}$ $\hat{X}_t(m) = S_t R_t^m + I_{t-p+m}$	$S_t = \alpha(X_t / I_{t-p}) + (1-\alpha)S_{t-1}R_{t-1}$ $R_t = \gamma(S_t / S_{t-1}) + (1-\gamma)R_{t-1}$ $I_t = \delta(X_t / S_t) + (1-\delta)I_{t-p}$ $\hat{X}_t(m) = (S_t R_t^m)I_{t-p+m}$
	$S_t = S_{t-1}R_{t-1} + \alpha e_t$ $R_t = R_{t-1} + \alpha\gamma e_t / S_{t-1}$ $\hat{X}_t(m) = S_t R_t^m$	$S_t = S_{t-1}R_{t-1} + \alpha e_t$ $R_t = R_{t+1} + \alpha\gamma e_t / S_{t-1}$ $I_t = I_{t-p} + \delta(1-\alpha)e_t$ $\hat{X}_t(m) = S_t R_t^m + I_{t-p+m}$	$S_t = S_{t-1}R_{t-1} + \alpha e_t / I_{t-p}$ $R_t = R_{t-1} + (\alpha\gamma e_t / S_{t-1}) / I_{t-p}$ $I_t = I_{t-p} + \delta(1-\alpha)e_t / S_t$ $\hat{X}_t(m) = (S_t R_t^m)I_{t-p+m}$
DM Damped Multiplicative	$S_t = \alpha X_t + (1-\alpha)(S_{t-1}R_{t-1}^{\phi})$ $R_t = \gamma(S_t / S_{t-1}) + (1-\gamma)R_{t-1}^{\phi}$ $\hat{X}_t(m) = S_t R_t^{\sum_{i=1}^{m} \phi^i}$	$S_t = \alpha(X_t - I_{t-p}) + (1-\alpha)S_{t-1}R_{t-1}^{\phi}$ $R_t = \gamma(S_t / S_{t-1}) + (1-\gamma)R_{t-1}^{\phi}$ $I_t = \delta(X_t - S_t) + (1-\delta)I_{t-p}$ $\hat{X}_t(m) = S_t R_t^{\sum_{i=1}^{m} \phi^i} + I_{t-p+m}$	$S_t = \alpha(X_t / I_{t-p}) + (1-\alpha)(S_{t-1}R_{t-1}^{\phi})$ $R_t = \gamma(S_t / S_{t-1}) + (1-\gamma)R_{t-1}^{\phi}$ $I_t = \delta(X_t / S_t) + (1-\delta)I_{t-1}$ $\hat{X}_t(m) = (S_t R_t^{\sum_{i=1}^{m} \phi^i})I_{t-p+m}$
	$S_t = S_{t-1}R_{t-1}^{\phi} + \alpha e_t$ $R_t = R_{t-1}^{\phi} + \alpha\gamma e_t / S_{t-1}$ $\hat{X}_t(m) = S_t R_t^{\sum_{i=1}^{m} \phi^i}$	$S_t = S_{t-1}R_{t-1}^{\phi} + \alpha e_t$ $R_t = R_{t-1}^{\phi} + \alpha\gamma e_t / S_{t-1}$ $I_t = I_{t-p} + \delta(1-\alpha)e_t$ $\hat{X}_t(m) = S_t R_t^{\sum_{i=1}^{m} \phi^i} + I_{t-p+m}$	$S_t = S_{t-1}R_{t-1}^{\phi} + \alpha e_t / I_{t-p}$ $R_t = R_{t-1}^{\phi} + (\alpha\gamma e_t / S_{t-1}) / I_{t-p}$ $I_t = I_{t-p} + \delta(1-\alpha)e_t / S_t$ $\hat{X}_t(m) = (S_t R_t^{\sum_{i=1}^{m} \phi^i})I_{t-p+m}$

Despite the lack of agreement on notation concerning exponential smoothing, Gardner (1985) notation will be followed, as it is the most used notation in the researched articles.

Table 2- Notation for exponential smoothing (Source: Gardner, 2006)

Symbol	Definition
α	Smoothing parameter for the level of the series
γ	Smoothing parameter for the trend
δ	Smoothing parameter for seasonal indices
ϕ	Autoregressive or damping parameter
β	Discount factor, $0 \le \beta \le 1$
S_t	Smoothed level of the series, computed after X_t is observed. Also the expected value of the data at the end of period t in some models
T_t	Smoothed additive trend at the end of period t
R_t	Smoothed multiplicative trend at the end of period t
I_t	Smoothed seasonal index at the end of period t. Can be additive or multiplicative
X_t	Observed value of the time series in period t
m	Number of periods in the forecast lead-time
p	Number of periods in the seasonal cycle
$\hat{X}_t(m)$	Forecast for m periods ahead from origin t
e_t	One-step-ahead forecast error, $e_t = X_t - \hat{X}_{t-1}(1)$. Note that $e_t(m)$ should be used for other forecast origins
C_t	Cumulative renormalization factor for seasonal indices. Can be additive or multiplicative
V_t	Transition variable in smooth transition exponential smoothing
D_t	Observed value of nonzero demand in the Croston method
Q_t	Observed inter-arrival time of transactions in the Croston method
Z_t	Smoothed nonzero demand in the Croston method
P_t	Smoothed inter-arrival time in the Croston method
Y_t	Estimated demand per unit time in the Croston method (Z_t/P_t)

Regarding exponential smoothing study, some basic definitions to acknowledge the methods differences are presented.

Additive and Multiplicative Seasonality

Sales behavior during a year can be sometimes seasonal. As an example we may refer umbrellas sales where every year during winter sales will increase. Considering only one “raining month” the seasonality period will be 12 months. The seasonal length can be days, weeks, months etc., but they will always have the same general pattern (Kalekar, 2004).

Seasonality can be for instance the increase of 10000 umbrellas sale in this seasonal months; so, every year we know there will be 10000 umbrella difference between the average sale and the seasonal period. This is additive seasonality (Kalekar, 2004).

When the increase is a percentage of the average sale (50% as example), either has been the worst year of sale or the best one in the company history, we have a multiplicative seasonality (Kalekar, 2004).

Additive, Multiplicative and Damped Trend

As in seasonality, the same theory can be applied to trend.

When we have a linear increase in sales every year, we have an additive trend. Multiplicative trend, just as multiplicative seasonality, is the increase of sales every year revealing a factor in this growth (Kalekar, 2004).

Finally, damped trend has a different behavior, related with sales that increase with a decadent factor, i.e. sales growth in the second year will be 80% of the first year factor, in the third will be 80% of previous year factor, and so on (Kalekar, 2004) .

Method Selection

Many studies have been made in method selection. Meade (2000) proposed an experimental study where time series with known properties, and consequently, with the best suitable forecasting method identified, were analyzed.

This analysis relates the data during the estimation period with its usability in predicting forecasting method.

Meade's study included, three naïve methods, 3 exponential smoothing methods, Robust trend, a non-parametric version of Holt's linear trend method, and a third group, compromising ARMA (autoregressive moving average) based methods (Meade, 2000).

The final conclusion revealed that summary statistics do contain sufficient information to select a method or a set of methods that will perform well (Meade, 2000).

Concerning exponential smoothing methods, Tashman & Kruk, (1996) considered variance protocol, which was already considered by Gardner and McKenzie, (1988)

Still according with Tashman & Kruk, (1996), the protocol consisted in the transformation of first and second differences of the series, identifying the minimum variance between these two and the original series; if the original series presents the least variance then a single exponential smoothing should be the chosen method, if the minimum was obtained with the first differenced series then Holt's damped exponential smoothing should be applied, and finally, if second differencing had reached the minimum between the three, Holt's linear or multiplicative trend is suggested.

Gardner (2006) has applied these methodology with an extension to other exponential smoothing methods, (according with these notation) , which are presented in Table 3.

Table 3- Method Selection Rules

(Source: Gardner, 2006)

Method selection rules

Case	Series yielding minimum variance	Method
A	X_t	N-N
B	$(1-B)X_t$	DA-N
C	$(1-B)^2X_t$	A-N
D	$(1-B^p)X_t$	N-M
E	$(1-B)(1-B^p)X_t$	DA-M
F	$(1-B^2)(1-B^p)X_t$	A-M

Variances and prediction intervals

Prediction intervals for exponential smoothing were believed to be impossible to calculate in the past. The first analytical approach to this problem was to assume that the series were generated by deterministic function of time plus white noise (Brown, (1963); Gardner, 1985; McKenzie, (1986); Sweet, (1985)) (De Gooijer & Hyndman, 2006).

Regression model would be more reliable if this was to be truth (De Gooijer & Hyndman, 2006).

However, Johnston and Harrison (1986) calculated prediction intervals, by the equivalence of exponential smoothing methods and statistical models, finding forecast variances for the simple and Holt's exponential smoothing for the state space models.

Other authors later developed models to obtain prediction intervals for all the main exponential smoothing methods, having R. J. Hyndman, Koehler, Ord, & Snyder, (2005) accomplished to develop models for all the most common methods of the state space models.

Fixed Parameters

The use of arbitrary parameter in exponential smoothing has become worthless nowadays, once the existence of common search algorithms software (e.g. Microsoft Excel Solver may quickly calculate the parameters by minimizing the MSE (Mean square root).

The use of adaptive parameters has been found to have no credible evidence of forecasting improvement Gardner (1985), so this section will not be reviewed.

Initial values and parameters optimization

The effect of initial values and loss function in the post-sample forecasting accuracy has been widely studied along the years. Makridakis and Hibon (1991) measured the effect of different initial values in N-N, A-N, and DA-N methods (E. Gardner, 2006).

In this study, the most common initialization methods have been applied, such as Least Square Estimates, Backcasting, Training Set, Convenient Initial Values and Zero values.

Various loss functions such as linear, quadratic and higher order functions have been used, penalizing bigger errors. The rationale behind such choice is that the negative consequence of forecasting error are not necessarily proportional (Makridakis & Hibon, 1991).

To attain the purpose, MAD (Mean absolut error), MAPE (Mean absolut percentage error), Median and MSE were used as loss function in the study. Despite they are never utilized, cubic, 1.5, 2.5, and fourth power function were also included in these studies, so all theoretical and actually used alternatives could be compared.

As a conclusion, it has been revealed that from a practical point of view the most used methodology (MSE) as a loss function and least square estimates to initialize the starting values are as good as all other alternatives as differences are statistically non-significant.

2.2 Inventory Management

Inventory management seeks to answer three questions (Silver, 1981):

1) How often should we review our inventory?

2) When should a replenishment order be placed?

3) How large should the replenishment order be?

The main objectives of a manager implementing inventory management are (Silver, 1981):

1) Maximize profit, rate of return on stock investment

2) Minimize total cost

3) Determine feasible solutions

4) Ensure flexibility of operation

Developed by Ford Harris in 1915, Economical Order Quantity was the first theoretical approach to solve the problem of determining what quantity to buy or produce at a given time assuming constant rate demand with a single-item mode(Erlenkotter, 1990).

Despite it has been published, Harris original EOQ paper was lost for many years, being rediscovered in 1988 (Erlenkotter, 1990).

The simple square-root formula for the optimal order quantity for constant demand rate is now taken as common sense inside the scientific and practitioner's community.

Equation 1- EOQ Formula

$$EOQ = \sqrt{\frac{2DA}{H}}$$

Where:

D- Annual Demand

A-Fixed Cost per Order

H- Holding Cost per Unity

Later models that could handle all kind of constraints and variables were developed. The most important and handled constraints are (Silver, 1981):

-Supplier constraints: minimum order sizes, maximum order quantities

-Marketing constraints: minimum service levels

-Internal constraints: storage space limitations, maximum budget for purchases in each period

As in terms of variable models reviewed, we can distinguish between:

Single vs. Multi-item

Deterministic vs. Probabilistic Demand

Single Period vs. Multi period

Stationary vs. Time-Varying Parameters (demand, costs..)

Single vs. Multiple Stocking Points

Costs have been considered in literature to decision-making purposes. This has led to the disaggregation of costs into categories that can be more easily measured.

The relevant cost categories are (Silver, 1981):

Replenishment Costs: The costs incurred when a replenishment action is taken. They can be divided into fixed part of the cost, due to the order itself, such as setup costs or transportation costs, and a variable part that can include cost of materials or products.

Carrying Costs: These are the in stock products multiple costs, as the cost of borrowing capital invested, warehouse costs, insurance, taxes, and obsolescence.

Insufficient Inventory Costs: When customers demand is not satisfied, due to stock out, backordering or lost sales are costs incurred by the company, as well as company image, that can affect future sales.

The evolution of Harris method was a natural path, for practical industrial environment deals with variable demand along the time, finite capacity along with many other variables and constraints cited before. Harris method takes assumptions that would mislead our decisions by not considering serious and significant information (Okhrin & Richter, 2011).

Most recent works deal with the dynamic version of the economic lot size model.

In Wagner & Whitin, 2004 work, single item replenishment is studied handling inventory holding changes and variable setup costs over time, thus minimizing the total cost and satisfying the time-varying demand in every period.

P.Dixon (1981) considers a multi-item replenishment model for a single work centre, considering setup cost at each time, production costs, and finite capacity.

Single item with stationary, probabilistic demand and known distribution is a common inventory management variant, which uses different control procedures.

The four most well known replenishment systems schemes for single item are the time based (R,S), the quantity time based (s,Q) and (s,S) , and a hybrid approach, that is the time-and-quantity based (R,s,S). Figure 1, 2 and 3 (Esteves, 2011) will support each model understanding.

L= Delivery time

R= Review interval

(R,S) Control System

This policy is a time-based policy with a predetermined R period review.

The procedure in this scheme is: in each R period inventory level is compared with the predetermined S level, the difference between the current stock, and S is calculated, obtaining the replenishment quantity to order.

This is a common method for multi-item with single supplier cases, for it's a simple and static solution for replenishment planning. However it is characterized by having big holding costs (Smits, 2003).

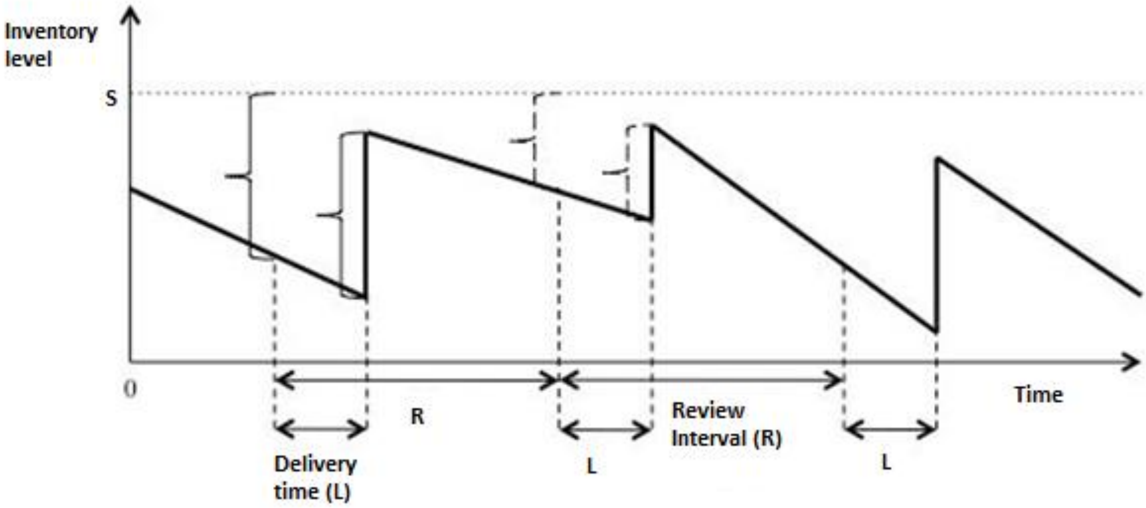

Figure 1- (R,S) Graphic Model (Source: Esteves, 2011)

(s,Q) Control System

Continuous review is the primary positioning of this scheme.

A minimum quantity level is designated as s and every time the on-hand inventory falls below this s level it triggers the process indicating the need of re-supply.

The replenishment order is then placed to the supplier with Q quantity size.

The risk of this scheme is to potentially run out of stock, in the short term, if the s quantity is not enough to cover the lead-time of the new order, and also in the long term, with the continuous decrease of the inventory level (Smits, 2003).

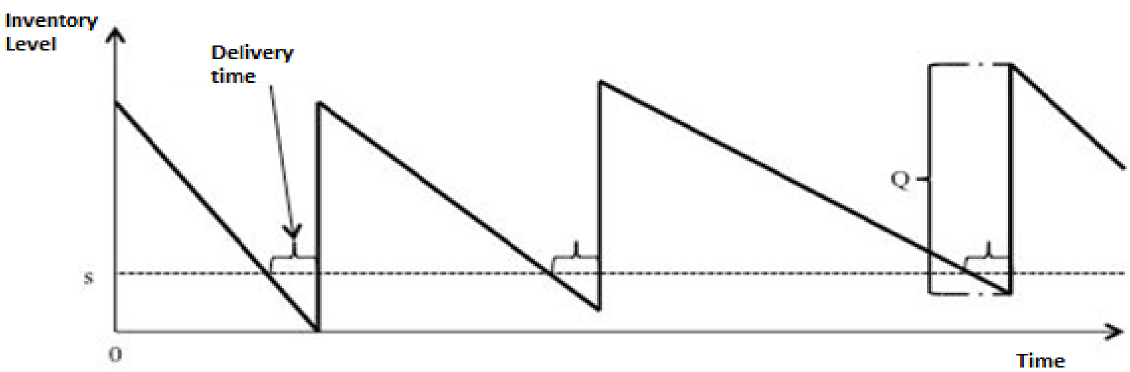

Figure 2- (s,Q) Graphic Model (Source: Esteves, 2011)

(s,S) Control System

Similar to the s,Q policy, this policy is a small variant, where the order quantity after process triggering will not be a Q fixed quantity. Instead, this lot size will be the difference between the current stock at triggering time and an S level (Smits, 2003).

Usually this method outperforms the previous one, as it prevents stock run out in the long-term.

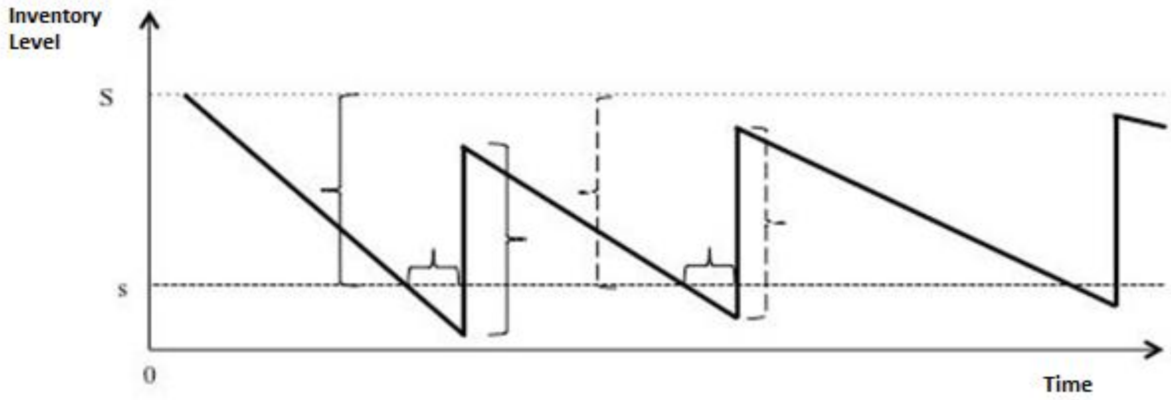

Figure 3- (s,S) Graphic Model (Source: Esteves, 2011)

(R,s,S) Control System

With an R periodic review, this hybrid approach combines advantages of both continuous and periodic policies.

In every cycle the current stock level is compared with a predetermined s quantity. If this level is above s, the order doesn't take place. However, if this level is below s an order is placed. The batch size is equal to the quantity needed to refill the inventory to the predetermined S level (Smits, 2003).

2.3 Safety Stock and Safety Lead time

In order to deal with the uncertainties in demand and supply, companies usually keep a buffer to prevent stock-out. This buffer is usually called safety stock when it means extra inventory kept, or safety lead-time when "extra time" is used.

"Safety stock is defined as the average amount of inventory kept in hand to accommodate short-term uncertainty in demand and variability in supply, and safety lead-time as the difference between release time and the due date, minus the supply lead-time of the product" (Van Kampen, Van Donk, & Van der Zee, 2010).

The comparisons between both approaches were made by Kampen et.al (2009) considering different combinations of lead-time variability, demand variability, product type changes among with others.

Concerning both lead-time variability and stochastic demand, (where this is the relevant case in this study), some conclusions have been acknowledge:

- In case of demand uncertainties, safety lead-time results in lower average inventory levels at low levels of uncertainty, but when in the presence of high uncertainty level, the required inventory level increases drastically (Kampen et.al, 2009).
- Kampen explains this rapid increase by the fact that in the presence of excess inventory using safety stock, the next supplying order is made later, while using safety lead time the order has already been made, resulting in even more stock (Kampen et.al, 2009).
- The results also showed that as the number of SKU increased the inventory levels of safety lead-time time also reveal worst results than safety stock (Kampen et.al ,2009).

Because demand variability is a high and real fact in the current project, and because all suppliers and orders by the company effectively present more than one SKU, the rest of the analysis deeps in the safety stock approach.

Talluri, Cetin, & Gardner (2004) described the four well-established models of safety stock and applied both demand and lead-time variability model on a made-to-stock pharmaceutical company thus comparing it with the current model.

Plus they have done a sensitivity analysis using demand and lead-time variability.

The conclusion of this paper provided the idea that an extra effort in the accuracy of forecasting models, along with the lead-time variability estimation, should be done as they have a significant impact on stock levels (Talluri, Cetin, & Gardner, 2004).

Figure 4 presents the four models:

		Lead-Time	
		Constant	Variable
Demand	Constant	No Safety Stock	$R_L = RL$ $\sigma_L = \sqrt{R^2 s_L^2}$ $SS = F_s^{-1}(CSL)\sigma_L$
	Variable	$R_L = RL$ $\sigma_L = \sqrt{\sigma_R^2 L}$ $SS = F_s^{-1}(CSL)\sigma_L$	$R_L = RL$ $\sigma_L = \sqrt{\sigma_R^2 L + R^2 s_L^2}$ $SS = F_s^{-1}(CSL)\sigma_L$

Figure 4- Safety Stock Models (Source: Talluri, 2004)

Eppen & Martin, (1988) considered a problem of setting safety stock in the presence of both lead-time and demand variability.

They developed two procedures, one considering the knowledge of demand lead-time distributions, and a second where they were unknown and had to be estimated.

Again the analysis will be focused on the second procedure because that is the project scope.

Eppen & Martin (1988) made some important steps in safety stock analysis by distinguishing demand variation and forecast error variation, and showing how to calculate the variance of forecast error over lead-time with non normal distribution of forecasted errors. This is the right approach to this project as the deviation in the forecasted demand reveals much more importance in what safety stock concerns, than the demand variability.

Zinn & Marmorstein (1990) actually compared these methods, where the variance of demand in the formula was replaced by the variance of forecast error.

The improvements in the safety stock level were confirmed by the analysis, that were already predicted by the fact that the standard deviation of the forecast errors was smaller than the standard deviation of average demand.

This decrease revealed not to have a negative impact in customer service level.

Also, sensitivity analysis suggested that the greater the variability of demand, the greater the stock level reduction.

Finally, the impact of forecast quality was also measured, and as expected, quality improvement translated into a safety stock reduction.

3 Structure and Competencies of Relevant Departments

Firstly it should be point out which are the main and relevant departments in the sphere of this project and followed by a description of their structure and competencies.

The Purchasing and the Logistics department are the key departments and directly concerned with this project scope. These two departments are responsible for all matters issued along the study and is co-working with them that analysis will be made, processes will be studied, problems will be investigated and furthermore a solution will be provided based in scientific results.

In the next sections their competencies will be described.

3.1 Purchasing

Politics and Negotiation

The main objective of the purchasing department is to provide and schedule all supplying orders of the company, ensuring the supply of goods for Tescoma worldwide and having a special concern on keeping the inventory at a reasonable level at the same time.

However there is more in the scope of purchasing department than to schedule orders.

Constituted by 3 teams, they manage to continuously negotiate supplier contracts in order to maximize profitability.

This can be challenging and the pros and cons are very difficult to balance; in one side they have to consider discount prices for large size orders, a target of service level, etc., but at the same time they have to worry about the capital investment, the obsolescence of products and storage capacity problems.

Evaluating price is also an important matter for the department, as raw materials prices varie in the world market along the year. This implies a variation in the final product price that has to be analyzed with the supplier and negotiated several times during the year.

Forecasting and Lead Time

Forecasting is a critical process in such a company, where a make-to-stock policy is followed for every product. The Purchasing department is also responsible for this theme and a good performance in this field can be an answer for many of the current problems.

Current forecasting processes are revealing inaccurate results. They are based in non scientific methods, mainly centered in workers past experience, and simplistic models, comparable some way to focus forecasting models, which include:

-Average yearly sales;

-Average monthly sale;

-Last 3 months average sale;

-Last year monthly sale.

Orders lead-time is also measured based in past experience and simplistic assumptions, where orders are placed to suppliers based in the available stocks, expected consumption and past experienced lead-time.

Thereby other scientific methods should be taken in this analysis to prevent problems such as:

-Variability in the lead-time;

-Variability by supplier and by each product lead-time;

-Variability in transportation lead-time.

Revealing lack of appropriate scientific methodology it may be said that this is a critical subject where this study must dwell.

Purchase Orders

The Purchasing department is also assigned to check every branch order and to assign products asked according to stock availability. This means that when headquarters stock is low the Purchasing department will distribute ordered pieces by a set of rules, based in other branches orders and the importance of the product to that specific branch market.

Preventive ordering is typically used to better perform and avoid stock out in promotions carried by branches.

A “booking board” was created so branches can book certain products in the future. This is a good practice for promotions, so company can predict extra and abnormal sales and assign these products as “extra ordering stock”.

Orders constraints

Outsourced production has advantages but also some disadvantages, one of which consists on the supplier requirements.

Main suppliers keep to the standard international commercial policies as they produce a lot of SKU and have close relations and interests with the company.

Additionally many Asian suppliers produce only 4, 5 or 6 SKU, leaving the company with serious constraints and requests.

It is inevitable to, at least, make an order that can fill a full container; otherwise it will not be economically sustainable.

Another frequent case is handling with big factories, which also produce to large key-chains, and where is particularly difficult to get into the production plan.

Briefly, we can acknowledge that regular order request would have to be in huge quantities, in some cases for a year consumption, sometimes, even more.

We can then conclude that purchasing department has a wide spectrum of competencies with a lot of constraints for theoretical procedures. Nevertheless it’s believed that significant improvements can be done in this department.

3.2 Logistics

Warehouse and stock keeping are directly linked with the objective of this project methodologies, and the control of all variables is crucial for the correct analysis of market behavior. The right and on time information can only be delivered to management and purchasing department if appropriate procedures are followed.

ABC Concept and Warehouse disposal

The concept of ABC analysis comes from Pareto principle, developed by Joseph M.Juran. It was named Pareto due to Vilfredo Pareto's observation as an economist, in which he realized that 80% of Italy's richness was owned by 20% of the population.

Deeper analyses later on have come to corroborate that this thesis could be applied in all kinds of distributions and turn to be used on business environment worldwide (Chen, Li, & Liu, 2008).

The ABC analysis is used in the warehouse as an inventory classification, helping each product treatment and logistics organization.

Tescoma organizes the warehouse disposal based on this principle, in order to help improve the order lead-time, to ease access to goods and minimize waste.

High rotation (A) products are stored in pallets and boxes, located near to the loading point, so they can be quickly picked up reducing the order lead time.

Medium rotation (B) products are stored in pallets and boxes further from this point as they are not as much ordered as high rotation (A) products, thus the location of these products will not affect so considerably the orders lead time.

Regarding C products, they are stored at the end of the warehouse far away from the loading point, obviously due to their very low rotation, and justified by the same reason as B to A products relation.

Finally there is a Picking Area at the warehouse, where workers can pick individual products directly from boxes. This area works in a light-to-worker basis where, according to the product in the order, a light indicates the product location so the worker can pick it up. Further along products of picking area are placed in a box that goes in a conveyor to the loading area.

Order assignment

Orders are transmitted to workers personal interface, where every picking sequence is described, and must be followed and checked in the system via bar coding in check-points, pallets and boxes.

The Business Warehouse (SAP) software manages the disposal of the products in the warehouse as well as trace the best picking sequence. The outcome is to take the least time possible while minimizing steps.

All these calculations and methodologies made by logistics software will not be part of this project.

Safety Stock

Logistics department runs a Safety Stock policy at Tescoma.

Data is kept and stored according with actual demand, by week, and then aggregated properly so analysis can be made in what safety stock level is concerned.

Revealing the use of scientific knowledge and application, variability either in terms of lead-time or in terms of demand is taking into account when calculating safety stock level for each product.

Product consumption is examined, turnover is identified, safety stock level and minimum stock quantities are compared and average turnover of all products is calculated.

According with data observed, low rotation products are identified as well as products with excess of stock in all year round.

This seems quite good at a first glance. However, despite the theoretical good practices and analysis in what safety stock concerns by the logistics department, its not being shared and used by the purchasing department, for forecasting demand, and purchasing planning, thereby it reveals to be pretty much useless.

Considering this kind of information and analysis, in other words, the integration between the two departments can be of great interest for the company.

Stock Keeping Costs

The complete range of costs in the supplying chain has already been made by the logistics department and is integrated in the native software.

Distribution costs to client and branches are also considered, but the study will not focus on these subjects, as the scope of the project does not cover these matters.

Regarding the project interests, stock-keeping costs that reveal particular importance are the ones such as warehouse keeping costs, supplier-to-warehouse transportation costs, along with all costs from the supplier to the exit dock of the warehouse.

Stock Control System

The Stock Control System can trace in each moment the actual stock quantity of all products, the stock in hand and the available stock. In other words, the system can retrieve the stock in the warehouse, but it can also retrieve the stock in the warehouse minus the products in active orders.

Data about products replenishment arrival is also available, shared with the purchasing department so they can manage the purchasing orders, and allowing the logistics department to organize warehouse disposal.

3.3 Trading

When we talk about trading at a company, we talk about transfer of goods or services.

In this project we will divide it into three major issues:

-Products

-Suppliers

-Customers

Products

As mentioned before, Tescoma sells more than 2000 SKU. Products are distributed in their own families and categorized according with their use and their line. Tescoma has a wide range of products, varying from basic glasses of wine to pressure cookers, apple peelers or silicone pans.

The development of their own products is a key factor to Tescoma, being recognized as one of the core differentiation skills against his major competitors.

With a young and dynamic team in the design and development departments, Tescoma launches an average of 17 new products per month.

Whether completing already existing product families or building up new ones, the range of products is getting wider to fulfill all costumers needs.

Suppliers

Tescoma does not produce its own products, the key and core business is their development and design. Outsourcing the production allows Tescoma to focus all efforts and human resources in what they know to do best.

Because of its wide range of products, so are the raw materials required and the production techniques needed. This means the need of different factories, which may fit every product need. Factories specialized in each kind of product, each kind of material, and each kind of technique so that Tescoma quality standards are achieved.

A team of workers has the skills to fulfill this objective at the company. Ther task is to search and target all factories that can better suit Tescoma products previously developed in headquarters.

Product prices and specialized tooling, along with all other variables in the contract are negotiated directly by the department with the potential suppliers. Nowadays Tescoma works with over 150 suppliers, 70%, which are based in Asia, and 30% in Europe.

As a direct consequence of their location, European suppliers are only a few hours away from Tescoma headquarters, providing a better control of all stages of the process, whether considering the initial negotiation process, as the re-negotiation of raw material prices and production info.

Uncertainty and average lead-time are lower among European suppliers than Asian suppliers. Also breakdowns vulnerability is decreased by the quicker response available.

The shorter lead-time of European suppliers has another planning advantage, as it provides the company to save investment and volume in the warehouse by the reduction of cycle and safety stock required.

Asian suppliers on the other hand are far away and for many years when something went wrong there was no way to catch up the delivery date or to pressure the suppliers to solve problems on time.

To fix these kinds of problems, or to at least decrease its occurrence and effect in the business, Tescoma has created a team of native people divided in two offices in Asia. Their only concern is, beyond cooperating in the search of new suppliers, to monitor every factory, check every single stage and process of production and push the factories so they are not late in their deliveries.

This strategy and investment has become of major importance for Tescoma as monitoring and checking all the processes increases the probability of quality to be according with standards, decreasing the probability of the lot to be turn down by the quality department in Europe headquarters.

The relationships with factories also turn to be closer, prioritizing Tescoma orders, performing a greater capability to deliver goods on time and with quality to costumers.

Customers

Tescoma costumers may be divided in three categories:

-National

-Stores

-Market

-Branch

-International

National

National customers are Czech customers, divided in two subcategories:

-Stores

Despite not being the biggest customer group, stores are a key and strategic customer, as they can give direct feedback to the company, in term of sales as well as customers feeling about Tescoma products and needs. Stores may be owned by Tescoma or franchised.

Stores are important under Tescoma strategy as the full range of products can be presented to customers and chain is shortened one step, profit margin gets higher and retail price is lower and more competitive.

At the moment Tescoma has 80 stores all over Czech Republic, and strategically plans to reach 100 stores in 2014.

-Market

“Market” customers are national customers with whom Tescoma built a relation over the years. Convenience stores, big-chains and supermarkets as Tesco, Globus are examples.

Branch

Selling for more than 100 countries gave more visibility to Tescoma and with internationalization came the necessity to expand and build some infrastructure to support the business in some of those markets.

Tescoma has branches in, Slovakia, Italy, Russia, Poland, Spain, Portugal and Ukraine.

Tescoma headquarters manages branches. However branches have their own strategy and a low rate of integration, in order to be better suit each market.

Branches buy from Tescoma headquarters like common costumers, placing orders and receiving information without integrated software. This has some disadvantages in terms of information to headquarters and even to branches, resulting in a lack of knowledge of branches detailed selling, stock, and updated abroad market behavior.

To minimize this lack of information several meetings are held during the year to discuss new products, market analysis and strategy, and gathering of information.

International

"International" costumers are all costumers outside Czech Republic that are not branches.

Despite headquarters is based in Czech Republic, international sales is responsibility of Tescoma Spa (Italy), on account of their better geographic positioning and infrastructures for export.

4 Implementation

4.1 Products Selection

The product selection began with a statistical analysis, based on the development of an algorithm which could apply a multi criteria ABC classification (Chen et al., 2008).

This multi criteria ABC analysis has considered three factors: underlying sales volume, average investment and average volume occupied.

Table 4 presents a matrix representation of this approach obtained by a sales-investment relation, and the same philosophy was conducted for a sales-volume relation (Table 5). A last category was created by the integration of both schemes, thereby showing a CACA category. This CACA group possesses the most economically unfeasible products, which were considered to be the most important and where greater improvements are expected in all KPIs (Key performance indicator).

Table 4- Multi Criteria Sales/Investment ABC Analysis

ABC Sales-Investment		**Investment**		
		A	B	C
Sales	A	AA	AB	AC
	B	BA	BB	BC
	C	CA	CB	CC

Table 5- Multi Criteria Sales/Volume ABC Analysis

ABC Sales-Volume		**Volume**		
		A	B	C
Sales	A	AA	AB	AC
	B	BA	BB	BC
	C	CA	CB	CC

In order to corroborate this classification, a further ABC analysis has been made upon a sales per investment factor and sales per volume factor (Table 6). An integration algorithm was applied, thereby determining AA as the critical criterion (Factor sorted from lowest to highest value).

It must be noted that there would be cases of wrongly assigned A products due to the existence of articles at the end of their life-cycle, or with very low sales, thus revealing high factors that clearly mislead this classification.

To prevent such cases a filter with a minimum sales volume was proposed, which should remove the occurrence of this situation.

Table 6- Multi Criteria (Sales/Volume)/(Sales/investment) Factor ABC Analysis

<table>
<tr><td colspan="2" rowspan="2">ABC
Sales/Volume-Sales/Investment</td><td colspan="3">Sales/Investment</td></tr>
<tr><td>A</td><td>B</td><td>C</td></tr>
<tr><td rowspan="3">Sales/Volume</td><td>A</td><td>AA</td><td>AB</td><td>AC</td></tr>
<tr><td>B</td><td>BA</td><td>BB</td><td>BC</td></tr>
<tr><td>C</td><td>CA</td><td>CB</td><td>CC</td></tr>
</table>

Results turn to be significantly satisfying, confirming that these different approaches produced overall similar classification, with an 87% correspondence.

The 13% of non correspondence articles may be explained by C sales products that have been removed by the filter and in some other cases attributed to the B or even A sales products in some of the criterias that have high factors but that were not considered by the first approach.

From the aforementioned list a random selection of 3 products was made, considering products from the same supplier. In other words a random selection was made in the universe of products which the supplier had at least 3 articles in the “critical list”.

Justification for this approach will be discussed later on.

A second analysis was performed after the presentation of the first results to the top management.

Acknowledging the potential of the method equivalent study was assigned by management to 18 other products, replacing the previous selection for an ABC analysis using sales as main criteria, thereby considering and characterizing products in a financial importance distribution.

The sample of series examined should then include all kind of behaviors, in order to project the benefits in a wider range of products.

Combinations of 6 products was made for each category, namely A, B and C. In each level two sub-groups were decomposed into “stable” and “unstable” sales for A and B products, and “parasite” and “slow movers” to C products.

It is quite intuitive to understand that “sales stability” in C products does not affect inventory planning. On the other hand it is quite important to correctly understand parasite products behavior.

Parasite products are defined as products that are not economically interesting to the company but play a high role in marketing and products benchmarking, by completing ranges.

Data Collection

Data was gathered and provided by the company, in a weekly basis, for every product life.

Such a disaggregated data gave the possibility to make considerable analysis, successfully evaluating the best aggregation level, according with the most accurate forecast model, thereby, weekly, monthly and tertile aggregated data were submitted to the forecasting model.

Numerous variations of the original data have been proposed. However tertile aggregation was recommended as an alternative for the quarterly evaluation, as products clearly denote 3 different seasons along the year and also due to the considerable amount of suppliers with 4 months lead time.

Commonly used in retail, a 4-5-4 Calendar was used to aggregate the monthly data, allowing a more consistent month flow, providing the same number of weekends for each month.

Tertile aggregation on the other hand was divided in a 17-17-18 weeks respectively, essentially owing to the (statistical non-important) last week sale of the year. Looking back this could sound odd but observations presented average sales of 9% compared with the weekly sales in the same month, in other words, an expected 2.25% increase on overall tertile sale. Further research involving management suggests that this can be supported by the existence of national holidays and Christmas time, decreasing labor days and general work in the warehouse.

4.2 Forecasting methods

Although there are several models underlying exponential smoothing, we proposed the ones that could eventually achieve better results according to the following studies.

Gardner & Anderson, (1997) and E. Gardner, (2001) bend their study in a cookware company manufacturer, comparing focus forecasting to damped-trend, seasonal exponential smoothing, and conclude that exponential smoothing proved to be more accurate, thereby, relating the equivalent situation, is worth emphasizing our study in the DA-M method.

Equation 2- DA-M Exponential Smoothing Method (Source: Gardner, 2006)

$$S_t = \alpha(X_t / I_{t-p}) + (1-\alpha)(S_{t-1} + \phi T_{t-1})$$
$$T_t = \gamma(S_t - S_{t-1}) + (1-\gamma)\phi T_{t-1}$$
$$I_t = \delta(X_t / S_t) + (1-\delta)I_{t-p}$$
$$\hat{X}_t(m) = (S_t + \sum_{i=1}^{m} \phi^i T_t) I_{t-p+m}$$

A standard autocorrelation test was programmed, conducting to non-seasonal times series identification.

This procedure ensured the correct use of the non-seasonal version of the damped-trend model for time-series that showed to be non-seasonal.

Equation 3- DA-N Exponential Smoothing Model (Source: Gardner, 2006)

$$S_t = \alpha X_t + (1-\alpha)(S_{t-1} + \phi T_{t-1})$$
$$T_t = \gamma(S_t - S_{t-1}) + (1-\gamma)\phi T_{t-1}$$
$$\hat{X}_t(m) = S_t + \sum_{i=1}^{m} \phi^i T_t$$

To avoid fitting a model that handles trend and/or seasonality, and yet increasing variance, the N-N method was suggested for reasons of robustness as a naïve method.

Equation 4- N-N Exponential Smoothing (Source: Gardner, 2006)

$$S_t = \alpha X_t + (1-\alpha)S_{t-1}$$
$$\hat{X}_t(m) = S_t$$

Initial values and loss functions

Within each time series one of several alternatives for initial values and loss functions mentioned in the state of art chapter was used.

Although it seems an unreasonable alternative "Zero Values" was chosen as it provides an advantage in terms of large initial error which force the estimated values to approach the actual ones much faster than alternative initialization procedures (Makridakis & Hibon, 1991).

Equation 5- Zero Values Formula (Source: Makridakis & Hibon, 2006)

$$S_1 = \frac{\sum_{t=1}^{n} X_t}{n} - T_1 \frac{\sum_{t=1}^{n} t}{n}$$

S1=Least Square estimate

T1=0

The error using the two-step-ahead forecast was measured, and smoothing parameters alpha, beta, gamma and theta were chosen as to minimize the Mean Square Error (MSE):

Equation 6- MSE Formula

$$MSE = \frac{\sum_{t=1}^{n} {e_t}^2}{n}$$

Further along, forecast comparisons for the time series are summarized.

Performance evaluation began with each level of time series aggregation comparisons divided in three groups (weekly, monthly an tertile aggregation), selecting the procedure with the lowest value.

Following the same reasoning, the selected methods were compared, and the one revealing the best accuracy was chosen.

The measure of equivalent levels of aggregation accuracy was defined by the MSE, therefore penalizing the errors with bigger magnitude. On the other hand, and due to the inappropriate application of the MSE in values with different degrees, the MAPE was chosen as reference for different level of aggregation comparisons.

4.3 Safety Stock

The proposed safety stock policy is based in the concept that the business runs with a stochastic demand and lead-time, thus a model that allows the incorporation of demand and lead time variability as follows is indicated.

Equation 7- Safety Stock Formula (Source: Talluri, 2004)

$$R_L = RL$$

$$\sigma_L = \sqrt{\sigma_R^2 L + R^2 s_L^2}$$

$$SS = F_s^{-1}(CSL)\sigma_L$$

As abovementioned, Zinn & Marmorstein (1990) applied the same formula but, unlike the standard approach, they recommended the use of forecasted error in variance calculation. This procedure will be applied, and further along, the improvements with such a technique will be presented.

This approach is easily generalized and simplified by assuming the normal distribution of the errors and, in fact, such assumption is reasonable to be taken once the required tests to the expected value and the correlation between errors procedures were both consistent (Almada Lobo, 2011b).

Equation 8- Test to the Expected Value (Source: Lobo, 2011)

$$\overline{X} = \hat{\mu}_{E_t} = \frac{1}{N}\sum_{t=1}^{N} E_t$$

$$s_{\overline{X}} = \hat{\sigma}_{\hat{\mu}_{E_t}} = \frac{s_X}{\sqrt{N}} = \frac{1}{\sqrt{N}} \cdot \sqrt{\left[\frac{1}{N-1}\sum_{t=1}^{N}\left(E_t - \hat{\mu}_{E_t}\right)^2\right]}$$

$$\begin{array}{ll} H_0 : \mu = 0 & \\ H_1 : \mu \neq 0 & \end{array} \qquad ET = \frac{\hat{\mu}_{E_t} - 0}{\hat{\sigma}_{\hat{\mu}_{E_t}}}$$

$$\text{Se } H_0 \text{verd.} \Rightarrow ET \rightarrow t_{N-1}(\alpha)$$

Equation 9- Autocorrelation Coefficient of The Error (Source: Lobo, 2011)

$$r_1 = \frac{\sum_{t=2}^{N} (E_t - \hat{\mu}_{E_t})(E_{t-1} - \hat{\mu}_{E_t})}{\sum_{t=1}^{N} (E_t - \hat{\mu}_{E_t})^2} \qquad \pm 1.96 \times \frac{1}{\sqrt{n}}$$

Despite this normal distribution assumption, further research showed that we are still in the presence of bias, and that this forecasting bias directly affects safety stock level.

In fact, forecasts revealing an over forecasting tendency required a SS level superior than the maximum under forecast value that SKU had ever experienced.

The following picture helps understanding this case scenario, where a Normal (0,1,000) and a Normal (1,000, 1,000) distribution are set to a service level of 95%.(Manary & Willems, 2008)

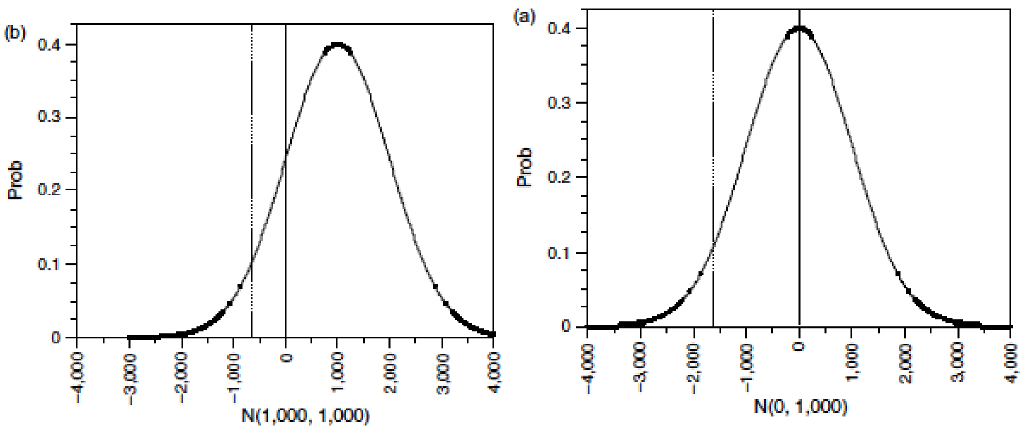

Figure 5- Normal(0, 1,000) and Normal(1,000 , 1,000) Distribution Graphic

(Source: Manary & Willems, 2008)

The picture clearly validates our theory, reinforcing the need to statistically eliminate the bias; for a 95% service level, a Normal (0, 1,000) cumulative distribution function corresponds to -1,645 factor, while for a Normal (1,000, 1,000) this value is found to be -.645.

Therefore, and to eliminate the bias with a feasible process, a new and modified estimate of the standard deviation of the forecast error was calculated according to Manary (2008).

Equation 10- Modified Standard Deviation Formula (Source: Manary, 2008)

$$\sigma^{Modified} = \frac{\mu}{F^{-1}(1-\alpha)} + \sigma,$$

4.4 Inventory Management

Standard lot sizing formulation assumes setup and holding costs. Tescoma business, however, suggests the use of minimum order restriction instead of the setup cost, for it better suits the current constraints.

Due to the many particularities and restrictions of our case scenario, an adapted and dynamic model of the (R,s,S) was developed for inventory management strategy.

The concept of our method and the adaptation extension rests upon the following facts:

-Forecasting is made for k+2 periods, therefore the use of R periodic reviews makes more sense than the continuous review, once there is always an “on process order”.

-Constraints such as MOQ (Minimum order quantity) must be considered.

-Since the demand is variable and stochastic, a constant value of S implies significant loss of space in the warehouse, and excess of stock. Hence, the use of a dynamic S value will outperform the original model.

-Consequently we also compute a dynamic s value.

Formulation of these values will be explained in chapter 5.

-Algorithm

A program able to run an “Order planning” according with each product need and supplier constraint has been developed, considering each supplier separately and evaluating all articles forecasted demand, constraints, and stock levels, thus placing an order that can handle and satisfy all these parameters.

The algorithm considers the best policy in terms of capacity constraints while minimizing costs for the company, which means planning according to the lowest average stock per item possible.

It has been assumed that for a feasible order the container must be full, but at the same time the least amount possible regarding all constraints is ordered.

Figures 6 and 7 illustrate the algorithm flowchart. (F(i)= Forecasting in period i)

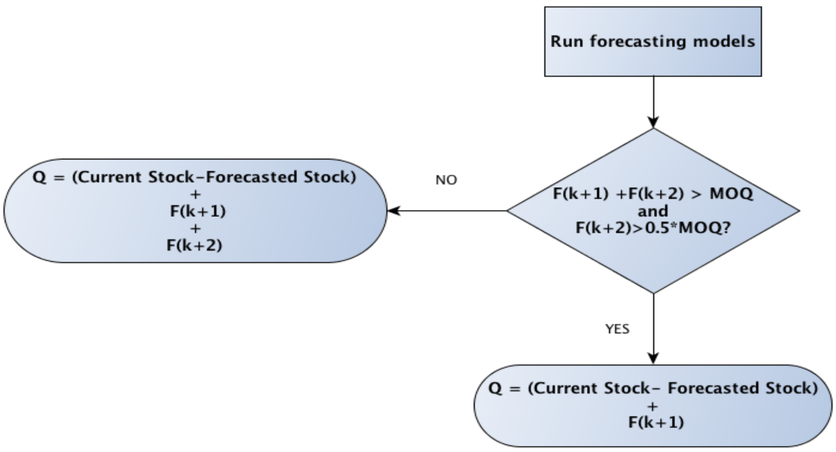

Figure 6- Theoretical order quantity flowchart (Q)

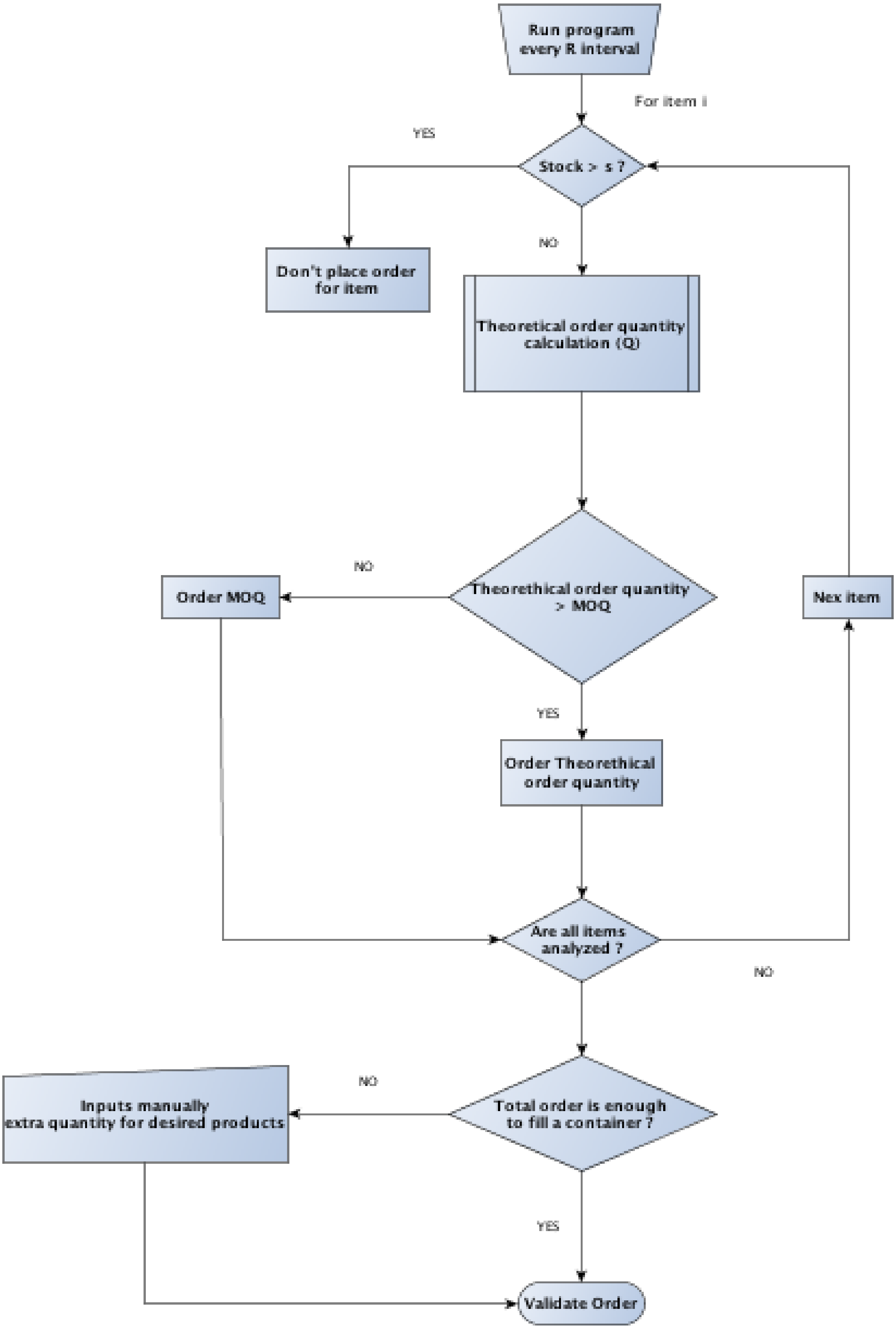

Figure 7- Algorithm Flowchart

5 Results

5.1 Safety Stock Reform

Inventory management and planning can reduce inventory costs, while raising the overall service level. However a wrong approach may lead to unnecessary stock level, increasing investment and costs.

Traditionally, in a stochastic demand and lead-time approach, the sales standard deviation is used to safety stock calculation, has seen in Talluri's formula, mentioned in the previous chapter.

In this chapter it is determine the impact of Zinn & Marmorstein (1990) methodology, using the standard deviation of forecast error, instead of sales.

Finally, for a given service level (95%), we will statistically remove the bias, compare both approaches expected safety stock, and conclude whether the impact was more or less appealing than the traditional method.

Table 7 and 8, exhibits the impact on all articles subject to study.

For all products it has been assumed:

Lead time = 2 Periods

Lead time Standard Deviation = 2 weeks (given by management)

Table 7- Safety Stock Level Variation for Management Products

Art	Safety Stock Forecast Error	Safety Stock Forecast Error Unbiased	Art	Safety Stock Forecast Error3	Safety Stock Forecast Error Unbiased	Art	Safety Stock Forecast Error6	Safety Stock Forecast Error Unbiased
1	-53.68%	-48.17%	7	-42.88%	-43.39%	13	-41.69%	-41.58%
2	-41.95%	-52.56%	8	-37.93%	-17.33%	14	-14.61%	-11.84%
3	-69.54%	-66.14%	9	-6.61%	8.06%	15	-67.57%	-70.86%
4	-16.34%	-37.03%	10	-49.20%	-58.91%	16	-66.11%	-70.39%
5	-9.72%	5.91%	11	-20.98%	-32.37%	17	-50.14%	-76.79%
6	-15.11%	-25.22%	12	-33.58%	-40.91%	18	-39.22%	-69.24%
Aver. Safety Stock Forecast Error Impact				-37.60%	Aver. Unbiased Safety Stock Forecast Error Impact			-41.60%

Table 8- Safety Stock Variation for Multi-criteria ABC Products

Art	Safety stock Forecast Error	Safety stock Forecast Error Unbiased
A	-32.77%	-37.37%
B	0.03%	-18.27%
C	-56.76%	-65.60%
Average	-29.83%	-40.41%

The two preceding approaches performed better results than the traditional method, with an average of 37.6% decrease of the average stock, for the standard safety stock (by forecast error calculation), and 41.6% decrease for the unbiased safety stock.

All products consistently support this conclusion, with the exception of product 5 and 9 that contradict overall results.

The report clearly states the cause of this phenomenon. As with all other products, carrying the safety stock by forecast error decreased the safety stock level. However, when removing the bias of this procedure the level was increased.

Such an impact when unbiasing data, diagnoses a under forecast, that raises the SS level when the refined method is applied.

5.2 Multi-Criteria ABC products

The first tests include 3 products from the same supplier (x), selected by our first multi criteria ABC classification.

For all time series, the tertile aggregation performed better accuracy than weekly and monthly aggregation, an expected result since branch orders can be smoothed on longer period analysis, reducing the variability and denoting a more clear seasonality pattern.

Although 3 products were not enough to fill the entire container in every order, our choice (3 products, same supplier) was driven to simulate a standard process of “order planning”.

Still, it was reasonable to believe that 4 or 5 products should be enough to fill the entire container in every order, since these 3 products are of very low rotation and, therefore, they are not ordered in every period. Also, this algorithm was meant to be applied to major suppliers which produce dozens or even hundreds of products, thus the combination of products would not be a problem.

Table 9 summarizes these 3 products results, from January till August of 2012, while the stock and replenishment behavior is shown in figures 8, 9 and 10.

Table 9- Multi-Criteria ABC Products Resume

	Sales Deviation							
Product	1º Tertile	2ºTertile	Average	ABS Average	EPAM F/Model	Stock Variation	Abs Err	Service Level
A	-34%	8%	-13%	21%	24%	4%	13%	100%
B	-104%	-1%	-52%	52%	14%	-2%	52%	100%
C	-40%	5%	-18%	23%	17%	-25%	18%	100%
					Average	-8%	28%	100%

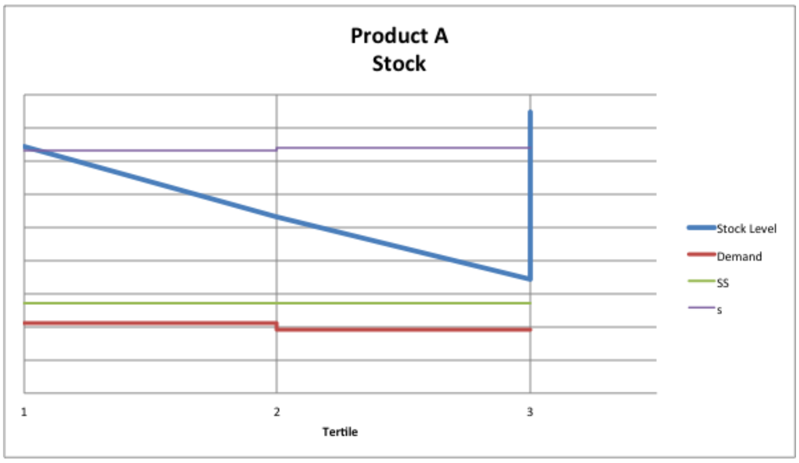

Figure 8- Product A Chart

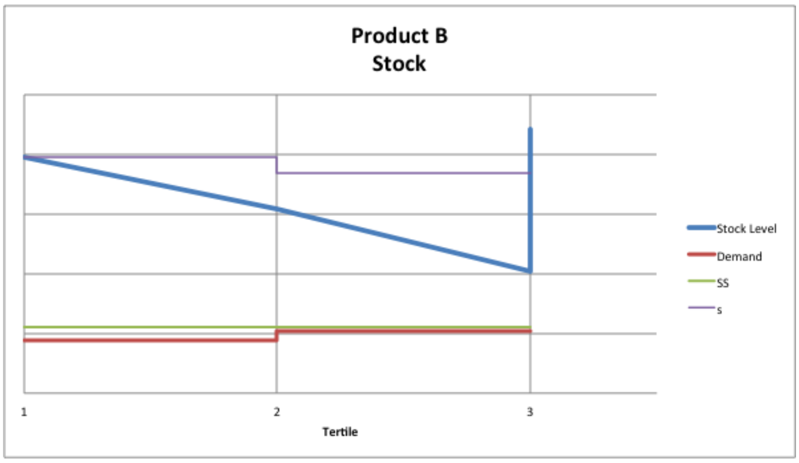

Figure 9- Product B Chart

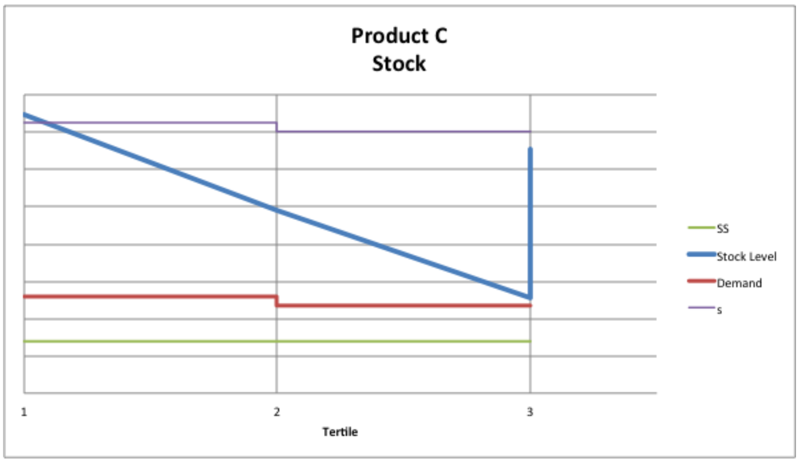

Figure 10- Product C Chart

Despite the more or less close values of sales deviation and the model sample EPAM, the stock variation does not attain great results, with a overall 8% decrease and an increase of 4% in the average stock of product A, suggesting that the model improvements were not so obvious and worth of implementation.

However, a deeper analysis and detailed review of stock behavior, SS, s and demand values shown in figures 8, 9 and 10 can contribute to a very consistent explanation of this low improvement. In fact, Figure 8 shows that product A requires a safety stock clearly higher than the demand for both periods. This will naturally result in very high average stock.

But why is this SS level higher than the demand for the period, if the average deviation of forecast vs. demand is 24%? The explanation relies on the standard deviation value, which is the only that varies between articles.

This could be quite confusing, since if we had a low EPAM, this would theoretically drive us to the idea that the errors were low, and thereby, the standard deviation and the SS (Safety stock) would be also low.

However, when presenting a product that is in the descendent part of his life cycle, considering all the time series for standard deviation calculation will significantly increase the SS required. Though the percentage error is the same, the order of magnitude is quite superior. This is the case of products A and B and it has been possible to marginally decrease the average stock of product B and as abovementioned, increase in only 4% product A average stock, what gives us good perspectives if we consider to correct the calculation of the standard deviation.

A second implication undermining the model is the fact that low rotation products require only 1 or maximum 2 replenishment orders a year, very much conditioned by the MOQ, therefore decreasing the potential improvement. Although we have reasons to believe that in high rotation products, our improvement will be higher than 8%.

5.3 Management Products

Following the same reasoning as for the Multi-Criteria ABC products, the 18 management products were submitted to test. As these products come from random suppliers, adjustments had to be made.

In order to estimate the order planning, for all given SKU it has been assumed that the placed order can full a container, therefore, for a major or small supplier, the combination of products can always meet a feasible order.

Table 10 presents the results for management chosen products (where the red rows are not considered to stock variation improvements due to article sold out, and yellow rows are also not considered due to data unavailability by the company).

Table 10- Management Products Resume

		Sales Deviation								
	Art	1º Tertile	2º Tertile	Average	ABS Aver.	EPAM F/ Model	Stock Variation	Abs Err	Aver. Error	Servic e Level
A Stable	1	9%	-29%	-10%	19%	24%	-55%	10%	18%	100%
	2	36%	17%	27%	27%	14%	-	27%		92%
	3	34%	4%	19%	19%	17%	-	19%		87%
A Unstable	4	43%	51%	47%	47%	10%	-	47%	33%	62%
	5	-121%	41%	-40%	81%	16%	-	40%		100%
	6	-26%	3%	-12%	14%	46%	-	12%		100%
B Stable	7	-22%	4%	-9%	13%	9%	-36%	9%	15%	100%
	8	-2%	24%	11%	13%	13%	-32%	11%		100%
	9	14%	33%	24%	24%	20%	-39%	24%		100%
B Unstable	10	30%	53%	41%	41%	27%	-64%	41%	27%	100%
	11	-17%	-13%	-15%	15%	20%	-59%	15%		100%
	12	17%	32%	24%	24%	31%	-43%	24%		100%
C Parasite	13	-29%	49%	10%	39%	28%	-55%	10%	62%	100%
	14	-38%	-87%	-62%	62%	34%	-94%	62%		100%
	15	-255%	28%	-113%	142%	14%	56%	113%		100%
C Slow	16	-27%	-2%	-14%	14%	26%	15%	14%	45%	100%
	17	-90%	-71%	-80%	80%	44%	-72%	80%		100%
	18	6%	-85%	-40%	46%	26%	-84%	40%		100%
Average							-43%		33%	97%

The forecasting potential, as opposed to the previous test, produced great impact in average stock level. The comparison between the "order planning" and actual data results from January 2012 to August 2012, confirmed our previous correlation between high rotation products and the potential of the program.

The overall data contributed for a 43% average decrease in the average stock, along with a 97% of service level.

Compelling evidence led us to recommend this model as it outperforms the current one. However, some inefficiencies must be considered as subject of deeper study.

Considerable inefficiency was observed in articles 2, 3 and 4, underlying service level, and articles 15 and 16 regarding stock variation, therefore a review can conveniently evidence any problems arising from this model.

The development of the model was adjusted and there was no considerable suspicious that this inefficiency could come from some error of the process, even though a complete review of all processes was made and proved there was no evidence of such a hypothesis.

The link between some of these errors was discovered after a meeting with the management, and each case was properly investigated.

The most alarming article is no. 4, an A sales article, with a availability of only 67% during the first 2 tertile. The first impression was that the accuracy of the method performed badly. The truth, however, was far from any statistical method.

Management examination indicated that for the first two years this article was produced by an Asian supplier, which together with business relation problems had successive delays in deliveries and quality problems. In 2012, a new supplier was assigned to this article boosting the sales of the product. This fact explains the inaccurate forecasting.

The service level of Article 2, is not as severe as article’s 4, and presents no evidence of abnormal situation during the year, therefore was considered part of the variability of the series and the statistical hypothesis of missing the forecast.

Article 3 is an article with an exponential sales growth, which caused some out of stock problems in the past 2 years. In the beginning of 2012 a bigger order has arrived, for it was perceived by the company that more quantity was needed to fulfill the market need. The stored data however only relates to actual sales, and this practice misleads the general model.

Nevertheless, the model uses actual sales rather then “actual sales + missed sales due to out of stock”, which caused the model to under forecast.

Article 16, follows the same reasoning as multi-criteria ABC products, as the accuracy of the forecasting is according to the model, which leaves us with the supposition that the safety stock is higher than expected due to the life-cycle of the product. Further observations confirmed this theory.

Despite the generalized 100% service level, each product could incur in delays in the lead-time, which are not taken into account in this study.

It is advisable to evaluate the model robustness to handle these possible delays and quantify these delays feasible range in order to keep such a service level.

Table 11 shows us the remaining weeks of stock for each product, (assuming a constant demand in each tertile calculated by actual sales in the tertile divided by the number of weeks).

Beyond the already mentioned articles 2, 3 and 4, which in fact sold out during the periods, we should be award that articles 8 and 9 appear to be in a particularly fragile situation that can quickly fall into a default situation at the end of the second tertile.

It must be noted that it was already expected that the average stock in the second tertile would be smaller than in the first one, due to the fact that SS is made as a provision for a 2 period lead time. Therefore, the consumption is theoretically made gradually along the 2 periods.

The display of every product evolution in terms of stock, replenishments, s, SS, and demand values along the first two tertile of 2012 is showed in ANEXO A.

Table 11- Management Products Stock Left

	Product	Service Level	Stock Left (Weeks) 1ºTertile	Stock Left (Weeks) 2ºTertile
A Stable	1	100%	8.0	23.3
	2	92%	0.0	0.0
	3	87%	0.0	0.0
A Unstable	4	62%	0.0	0.0
	5	100%	32.2	15.1
	6	100%	20.9	23.0
B Stable	7	100%	8.6	9.0
	8	100%	8.0	2.3
	9	100%	6.7	0.8
B Unstable	10	100%	12.9	2.9
	11	100%	12.2	16.6
	12	100%	5.5	8.5
C Parasite	13	100%	103.0	14.4
	14	100%	59.7	42.4
	15	100%	67.3	15.7
C Slow	16	100%	26.4	18.4
	17	100%	77.8	32.6
	18	100%	14.1	26.8
Average		97%	25.7	14.0

6 Conclusions and future work perspectives

This study corroborates empirical studies conclusions, providing opportunities of improvement by the use of exponential smoothing forecasting methods and inventory management policies.

The first test points out the need of continuously reviewing the time series and suggests a future discussion to conclude about the extension of data to use in the analysis in order to reduce the SS level. It is important to understand the consequences of the life cycle of the product and the effect that it can produce in the method. It is believed that a 3-year database is wide enough to avoid this effect and to still have a trustful method.

All the calculations were conservative, according to a 95% service level, whether for A, B or C products. The stock level could decrease even more, if a service level of 95% for A, 85% for B and 75% for C products was considered (by standards).

Despite the robustness of the procedure the human factor was found to be important to prevent cases such as article 4, therefore correcting information's that the system cannot handle.

On the same basis, the implementation of a "expected sales" data is recommended, to complement "actual sales" database and ticking the point in the period where the sales started to be restricted due to low stock. This will perform a more reliable and accurate forecasting.

For each supplier, the method follows fixed points of review. In particular, the system considers the ordering in 3 production seasons. A more conservative approach should be considered in future works, projecting different review points with the same interval and avoiding peaks in the factories.

Comparisons were made using different suppliers, but never regarding all the products. It is reasonable to accept the fact that big suppliers demand can require more than one container in each order. Therefore, a future analysis should consider planning rules where the total order should be divided in two or more sub orders along the period, according with the total volume and MOQ constraints.

A significant improvement can be attained in the average stock by this approach, while giving the opportunity to correct under or over forecasting.

The collection and storage of lead-time data for each supplier is also a suggestion for a more reliable safety stock level.

Finally, it would be interesting, in products with clear and deep seasonality, to explore the possibility of 2 or 3 different safety stock levels along the year.

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ANNEX A:

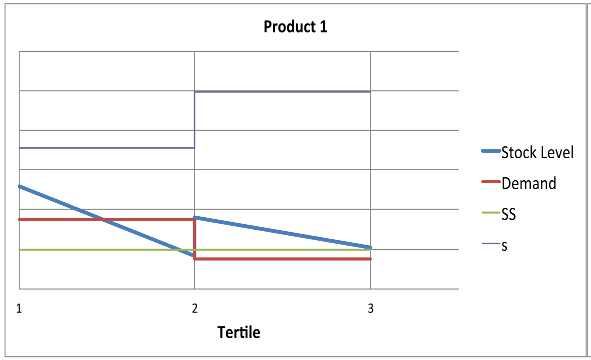
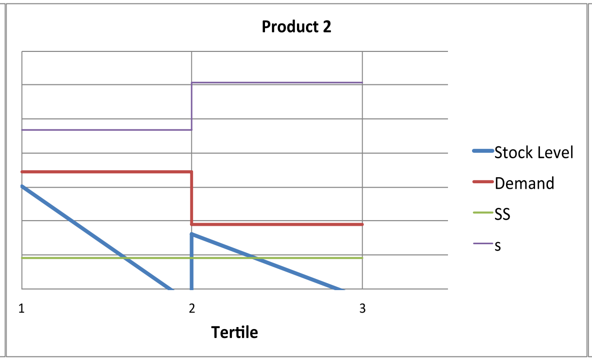


Figure A 1



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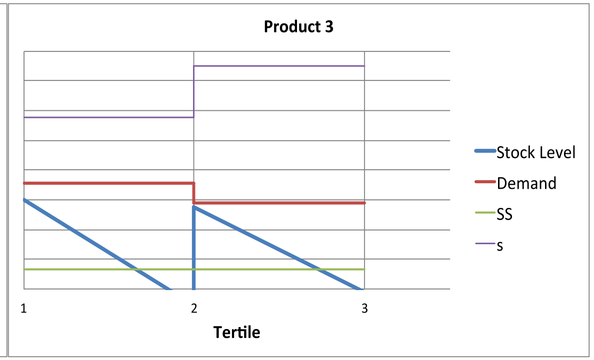

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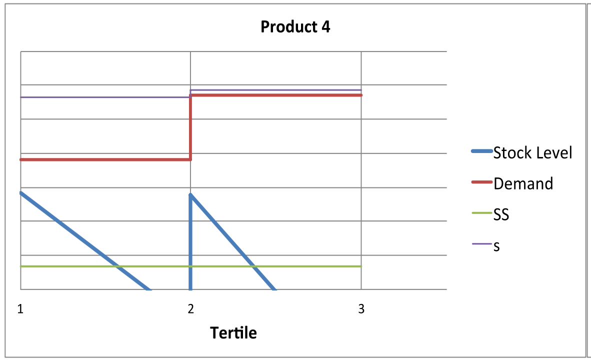

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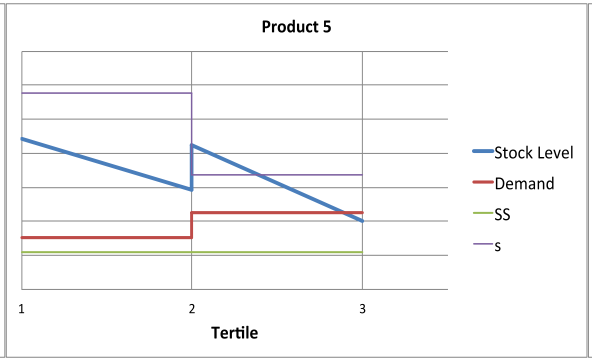

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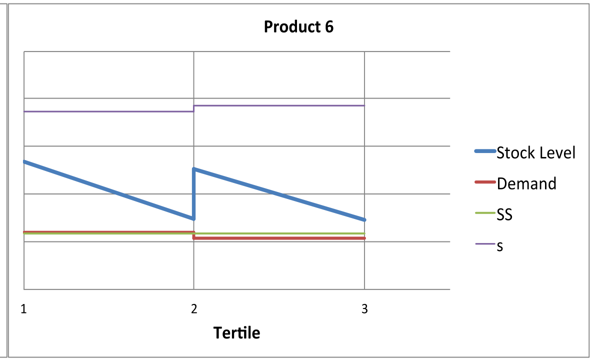

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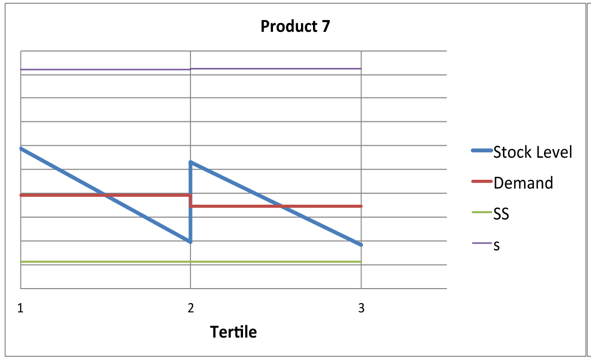

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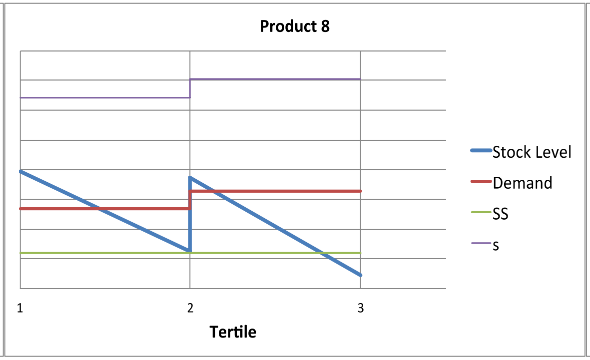

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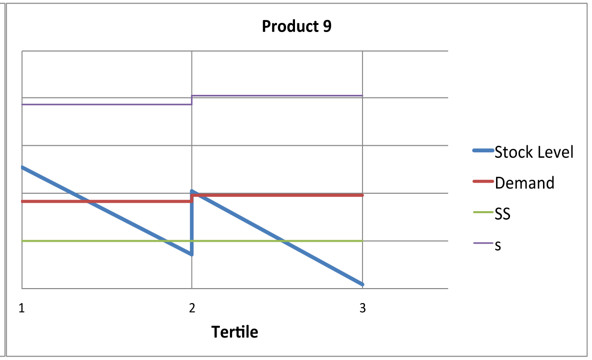

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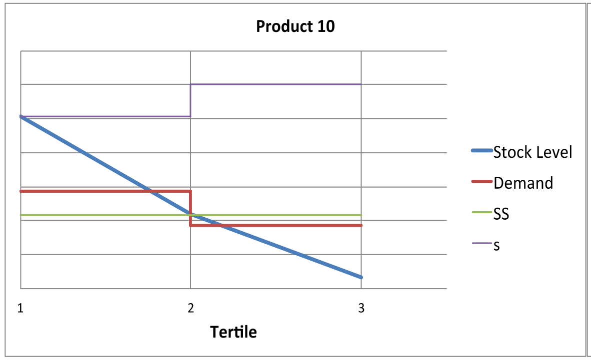

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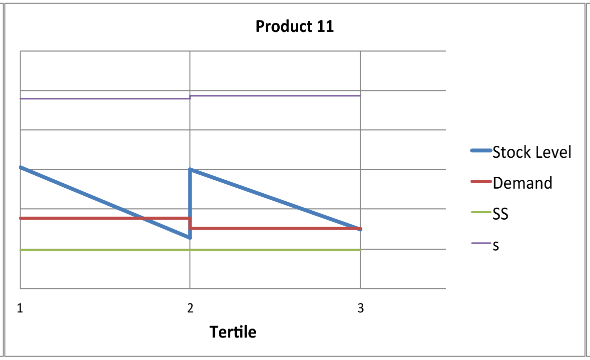

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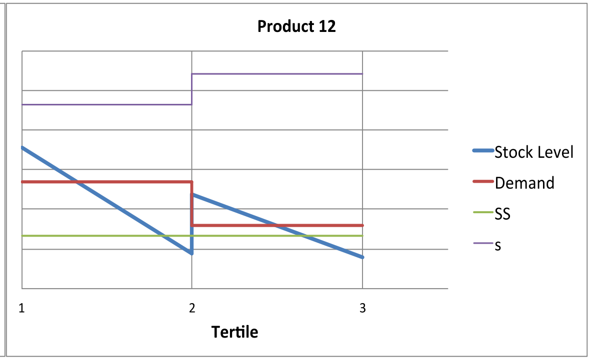

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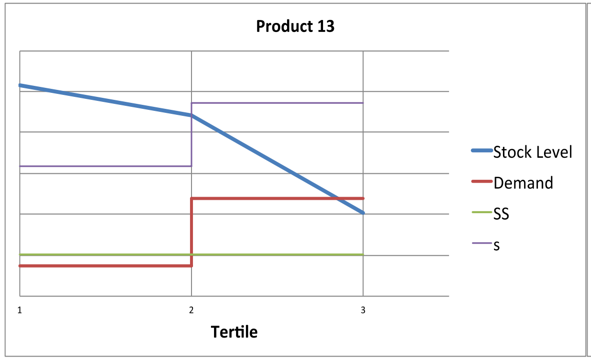

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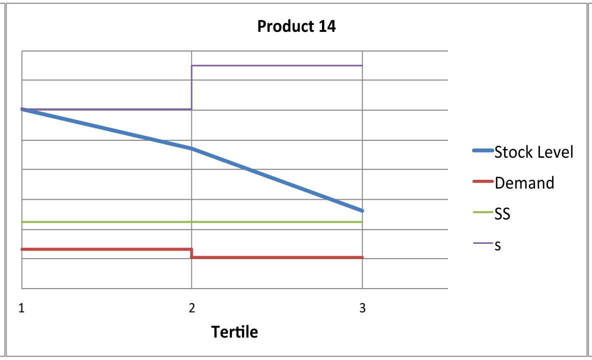

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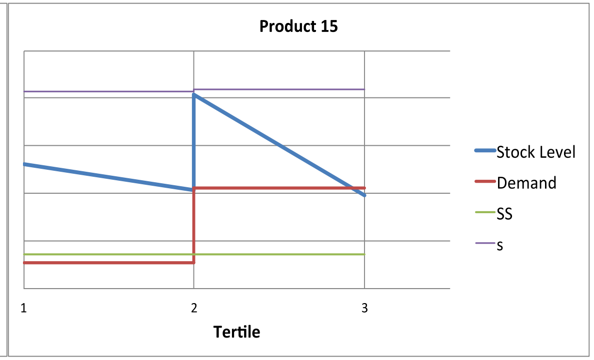

Figure A 15

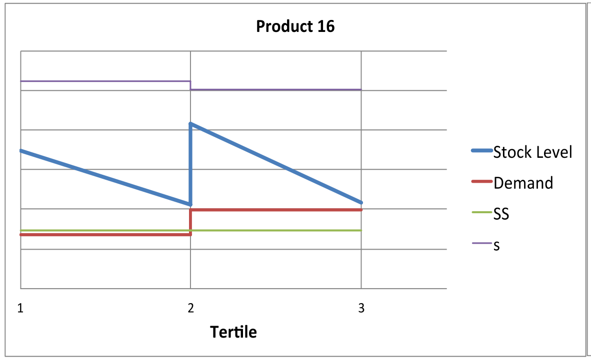

Figure A 16

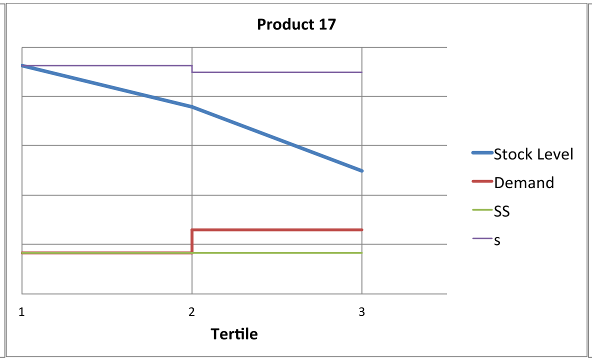

Figure A 17

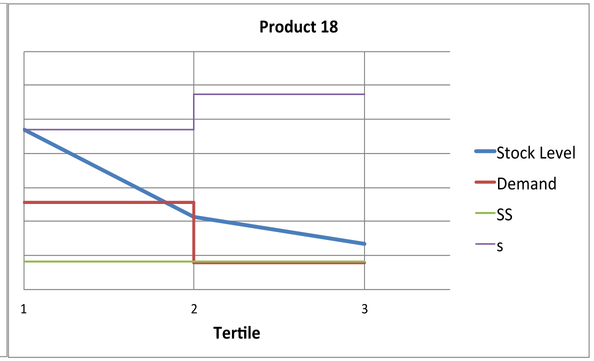

Figure A 18