Resum

El present projecte pretén millorar la previsió de vendes per a productes d'alt consum nous al mercat, posant especial atenció en crear un sistema assequible per a petites i mitjanes empreses i adaptat a qualsevol mida de mercat.

Les solucions desenvolupades fins al moment no aconsegueixen reduir l'alarmant nombre de productes que surten al mercat i fracassen en pocs mesos, degut en part a una mala previsió de les vendes. Actualment els empresaris tenen al seu abast programaris molt potents però no desenvolupats per mercats locals i amb un preu inaccessible; o bé programes que no han estat desenvolupats per productes nous i, per tant, que necessiten molts períodes de dades per produir resultats acurats.

Desprès d'una primera fase d'investigació dels diferents models matemàtics existents i de les fases de desenvolupament dels productes, el projecte tria cinc models de causa-efecte que es basen en, com a mínim, tres períodes de dades per preveure'n les futures.

En la segona fase s'analitza cada detall de cadascun dels models triats i com n'afecta un canvi en cada una de les variables. També s'estudia el tipus de dada que és necessària pel correcte funcionament dels models i el tractament necessari abans de la seva utilització. El fet de disposar de molts pocs períodes de dades dificulta la percepció de l'estacionalitat o possibles anomalies, que en el cas de la previsió de vendes de productes madurs és un procediment senzill i rutinari.

A continuació, es proposa una metodologia a seguir per tal de preveure les vendes. Es posa especial atenció en crear un procediment senzill i fàcil de reproduir, de manera que es pugui dur a terme amb un full de càlcul de Microsoft Excel, que és l'eina més utilitzada per les petites i mitjanes empreses. La part positiva de no crear un software específic és la capacitat de l'usuari de modificar el resultat segons el seu propi criteri expert i alhora d'aprendre a preveure els canvis que ocasionen en el resultat una variació en les dades d'entrada.

La metodologia es prova amb cinc productes reals dels quals es posseeix els tres primers períodes de dades, així com informació sobre publicitat o esdeveniments especials que puguin influir en les vendes. Es comprova que l'efecte de les accions publicitàries en les vendes dels primers mesos és molt important, sent la previsió de vendes d'un producte del qual no es posseeix aquesta informació la menys acurada.

Finalment, es proposa un exemple a seguir per tal de crear un programa informàtic senzill que pugui automatitzar el procés. L'automatització permetria aplicar la metodologia a tots aquells usuaris no experts en l'ús de l'Excel.

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1. Preface

Forecasting is a very wide field that has been explored deeply in the last 70 years of history, applied to several aspects of human life, such as climatology, health or economic activities.

In the last years, firms' research and development departments have become crucial in the sustainability of companies as it is has became a priority to be the first one to launch a better product into the market or to create a revolution by introducing a completely new concept. Larger investments in research, strong advertisement campaigns and years of effort have to be supported by the certain knowledge that costumers are willing to buy the new product; and despite the efforts, each year thousands of products fail few months after the launching and their sales forecasts did not capture that reality.

Inspired by the work of Ching-Chin, Ieong Ka Ieng, Ling-Ling, & Ling-Chieh (2010) and with the advice of a local marketing company, it was decided to investigate a bit more in the forecasting field focusing in frequently purchased new products in order to create a simple but robust methodology that could be use by every local producer without investing huge amounts in sophisticated software.

2. Introduction

2.1. Goals

The main goal of this final thesis is to describe a methodology to forecast sales of frequently consumed new products reaching a value of the Mean Absolute Error (MAPE) under thirty percent. This methodology has to be fully replicable and valid for small and medium companies disregarding their country of origin.

To reach this ultimate goal a list of subtasks have to be accomplished such as an extensive research in the field of forecasting, testing the models with real data sets and establish a different procedure to each one of the possibilities that companies may tackle.

2.2. Scope

Product sales forecasting is a wide field studied for decades; the proof is that some of the most used and still valid methods were developed in the sixties. This final thesis narrows the view to the sales forecast of new frequently purchased products.

Even if only focusing in new frequently purchased products the field is still wide and many different approaches fit under this description. The goal is to gather together different mathematical models already available in order to forecast the sales of those new frequently purchased products having as starting information few periods of historical data sales available and if possible information about the advertisement expenditure or special events.

Any method that uses other starting data than the just described is automatically disregarded, as for instance the forecasting methods using huge databases of older products. These methods might be only commented if any of their characteristics is relevant for the study or for the better understanding of other methodologies or data sets.

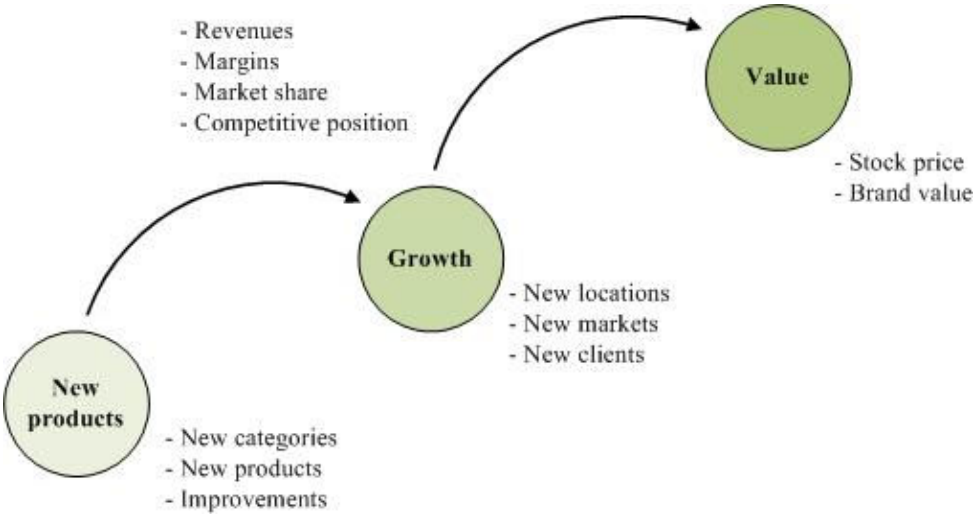
The project aims to develop a methodology combining several of the mathematical models analyzed. The methodology has to be replicable and clear enough to be reproduced by users in different levels of expertise. This methodology could be transformed into software, but in this thesis only the guidelines to automate the methodology are given.

3. Problem analysis and state of the art

3.2. New product

A product is something meant for satisfying some need or necessity of mankind. It can also be defined as the final output of a production process.

Launching a new product is a long and costly procedure, full of uncertainty but at the same time a crucial activity for companies, which need to replace the old products, as every time more and more, the expected life of them is decreasing. According to SAP (1998) the benefits of investing in new products are the following:



Graph 3-1. Adapted from SAP report 1998

An example of the magnificent increase of the number of new product launches, especially regarding frequently purchased products is given in SAP (1998) as well. And using more up-to-date numbers, Kotler & Armstrong (2007), affirmed that 34.000 new products were launched into the market, from whose only 2% can be considered successful.

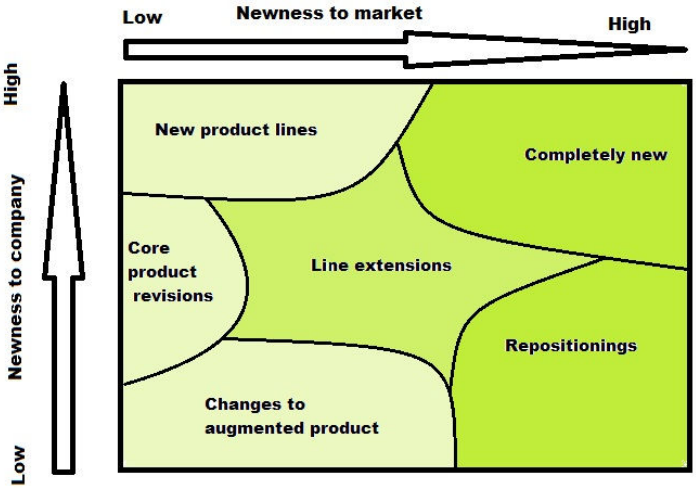
Number of product launches	1980	1998
Cereal	34	192
Ice cream, frozen iogurt	57	556
Spices, extracts, seasonings	61	403
Deodorizers, air fresheners	53	372
Paper towels, napkins	11	126
Milk, yogurt drinks	26	255
Coffee	11	384
Beer, ale	25	187

Table 3-1. Source: SAP report 1998

It is understood for new product any product that has been less than 6 months in the market. Nevertheless there are many kinds of new products; those which are new for the market, those new for the company and those which are new for both of them.

When thinking about a new product, people tends to imagine a completely new concept or a break-through in technology even so a minor modification in an existing product is already a new one.

The following diagram shows the different level of newness in a product: Harjust (2010)



Graph 3-2. Types of new products

Analyzing each item:

1. New product line is introducing a new product inside the company, but not necessary new to the market.
2. Core product revisions are essential changes or improvements to an existing product. These revisions are not just an aesthetic change but a deeper shift in the product functionality or producing method.
3. Changes to augmented product are minor changes on an existing and well-known company product.
4. Line extensions are modifications to the company producing lines in order to add a slightly different product, for instance a new soda flavor or a diet version of an old drink.
5. Completely new products require an innovation effort, investment in new technologies and deep marketing research in order to be introduced in a market that has not seen the product before.
6. Repositioning are products which used to be produced in the past or in outside markets and which are introduced in a new market with actualizations or slight changes.

Regarding the category of the new product a long process has to be done prior to launching; not only regarding the potential costumers' calculus but the development of the product itself.

According to Kotler & Armstrong (2007) the usual product development process follows these steps:

1. Idea generation: brainstorming of new product's idea. The new ideas can be developed by workers (internal source) of the firm or be generated due to costumer request (external source). In average companies create around 3.000 ideas before they find the appropriate one.
2. Idea screening: eliminate unsound concepts and not feasible ideas.
3. Concept development and testing: clarify engineering and marketing details, set the target market, benefits of the product, estimate cost and production process, ask costumers about the product idea.
4. Business analysis: estimate sales volume, selling price and profitability. In this section a marketing strategy is developed as well
5. Beta testing and market testing: create a prototype, test it in usage conditions, produce a first batch of the product and run a test market. Companies are reducing the amount of test markets because of economical reasons, usually if the new product is a line extension or a product copied from another company the test market is skipped.
6. Technical implementation: planning of the whole mass production process including schedule, suppliers, resources, contingencies, etc.
7. Commercialization: launching, advertising and distribution.

During all the process not only technological feasibility has to be taken in account but costumer acceptance and potential number of sales in order to ensure economic profit of the project.

Some steps can be eliminated and some of them can be iterated as many times as needed. Though in the current times money expenditure has become crucial and some companies run several steps at the same time.

Products can be, as well, classified according to the frequency of purchase: durables or frequently purchased products. This project focuses in frequently purchased products; therefore, products which are bought in a weekly or daily base due to its own perishable nature. Clear examples of a frequently purchased product are drinks and food.

Remark that consumer behavior is very different depending on the type of product which needs to buy. For instance, when buying a TV, knowing that it will be a very important economic expense that has to last for years, consumers tend to reflect and take time when choosing the product having lots of influences and informing themselves a priori. On the other hand, if the consumer has to buy yogurts, probably will not take more than 1 minute to decide what flavor to buy; following its emotions and impulses when taking the decision.

3.2. Actual problem

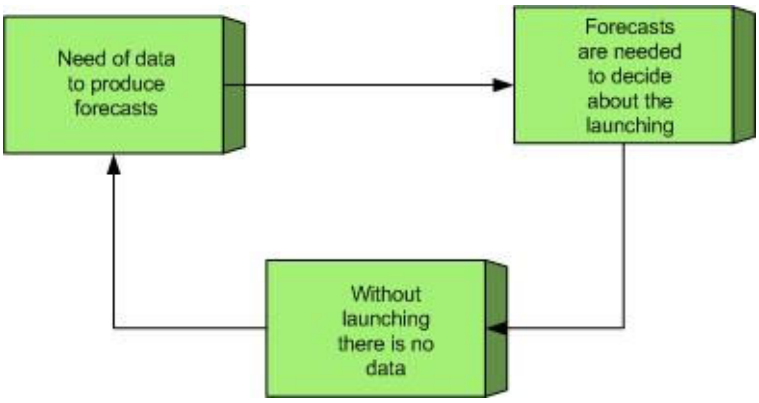
Launching new products into the market is vital for companies in order to survive in such a competitive world. The process of launching a product is long and costly but at the same time full of uncertainty.

Forecasting helps to deal with this uncertainty. According to Lapide (2002) three types of corporate forecasting can be distinguished:

1. Operational forecasting: generated for the next days or weeks in terms of hour-per-hour or day-by day. It is thought to forecast daily operations inside a company such as the inventory changes, warehousing or transportation.
2. Tactical forecasting: generated for several months up to two years in terms of weeks or months. Used to forecast sales but also to create the master production or the labour planning.
3. Strategic forecasting: generated for long periods of time and planned yearly. Used to support vital firm decisions such as new investment or capital planning. (Lapide, 2002) recommends to rely in causal, life cycle and judgmental methods to produce the forecasts arguing that time series might be biased due to the big time span.

Planning the launch of a new product strictly fits into strategic forecasting when talking about the best moment to start the investigation process and the better moment to launch the product for the firm finances. On the other hand, when going through all the stages of new product development (mentioned in paragraph 3.1.) tactical forecasting is needed to approximate the sales of the first periods and evaluate the economic feasibility of the new product.

But the actual problem relies on how to forecast those sales if there is no data available? Obviously it is not possible to use old sets of data sales as the product has not been launched yet and therefore the costumers have not bought it; actually costumers probably have not even seen the product before. So like a dog chasing his tail, sales data are needed to forecast, forecasts are needed to take crucial decisions about the launching but without launching there is no sales data.



Graph 3-3. The actual problem

Forecasting is a deep studied field, counting with many models, software and theories but, surprisingly forecasting sales for new products has not been a target point of study for many researchers. At this moment, firms willing to launch a new product and assess its viability have two different options: rely on its past experience or purchase specialised software such as NEWS or BASES among others.

Despite of these two solutions, countless products reach each year our markets and disappear in few weeks after a total fail in sales; producing high losses for the companies and deteriorating their brand image.

And why do the firms forecasting fail (taking in account the always present uncertainty)? Four possible explanations are the following:

1. Judgmental methods (those relying on the past experience of the company and its experts) fail when the product is very different from the past produced ones or when there is a complete break-through in technology or consumer mentality.
2. Most of the quantitative methods known by managers are unsuitable due to the lack of data.
3. Software packages such as BASES or NEWS are too expensive for small and medium sized companies. Purchasing their services means sometimes an impossible economic effort.
4. Software packages are not very reliable. They are based on enormous data bases of product sales mainly from the United States of America. This fact makes them imprecise when launching products in different and smaller markets such as any country of the European Union.

The problem gets even more struggling when focusing in frequently purchased products. These kinds of products are bought on a regular basis, pretty often weekly or daily such as food, drinks or cleaning products. Due to its frequently bought nature and the extremely high number of options that costumers have when going to the shop, sales get even more unpredictable.

In that situation, durable products which are bought in counted occasions and after a deep thinking from the costumer side are in an advantaged position. The reason is that since Bass (1969) when its sales curve was associated to the pandemics diffusion, several models have been developed matching pretty accurately the sales of new durable products. Remark that those models are not appropriate for recently purchased products, the field of study of this project.

3.3. State of the art

3.3.1. Introduction

In a world constantly evolving, the forecasting of new and extremely new products is a key point for the economy welfare. New product forecasting deals with the major problems of the data lacking and the uncertainty of how break-down technologies and products will be accepted by the consumers. Therefore, not all the existing methods are adequate for this forecasting exercise.

An example of how crucial sales forecasting has become is the appearance of several initiatives to improve its results, such as the M-Competition. This competition ran by a group lead by Prof. Makridakis has already reached its 4th edition, M4-Competition(2010), and aims to investigate on new forecasting models, giving more information about the future sales and improve its accuracy.

All the existing forecasting methods should be analyzed, not only regarding their accuracy but in special attention to the fact that they perform good when few amount of data is available. In the next sections, the most relevant methods for new product forecasting will be analyzed and commented according to several aspects such as the simplicity and good performance.

The vast quantity of methods forces to classify them. Wind (1974) already provided a classification distinguishing between several model factors such as purpose, type of product, variables, required data or analytical procedures. According to it, the paper is analyzing models for frequently purchase products which need two different kinds of data; either historical sales (mathematical models) either pre-market data (commercial software).

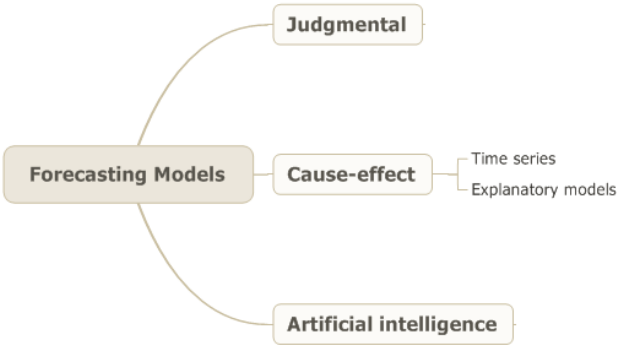
The classification used in this paper merges both Wind (1974) and Makridakis & Wheelwright (1998) classifications, dividing the analytical models for frequently purchased products in judgmental methods, cause-effect models and artificial intelligence methods. Judgmental methods are the ones relying on the forecaster past experience or in opinions given by stakeholders; cause-effect models develop a solution relying on mathematical data relation and finally artificial intelligence methods are methodologies mixing both experience and analytical procedures.

Regarding the grouping of the existing commercial software, it was gathered according the stage of the product creation that applies.

This state of art is organized in two sections. The following section includes the study of the mathematical and judgmental forecasting methods. The commercial software available in the market is commented next.

3.3.2. Forecasting methodologies

Detailed below is the methodology classification followed in the whole paragraph, including the subdivision of cause-effect methods in time series (or chronological series) and explanatory methods.



Graph 3-4. Forecasting models classification

Judgmental methods use the educated opinion of several experts in order to forecast the future sales. Judgmental methods have been usually disregarded due to its strong dependence on user experience, leading to inaccuracy in most of the cases, and the risk involved. However, according to Sanders & Manrodt (2003) and stated in several surveys and analyses, managers still prefer judgmental methods against other more complex quantitative methods.

By judgmental methods we are referring methods such as Delphi, market research, product life-cycle analogy, expert judgment, scenario writing, subject approach or sales force option. Some of these methods involve more risk to produce a biased forecast when the innovation on the product is high; such as expert judgment or scenario writing.

In the launching of a new product, **expert opinion** can be highly valuable. Two situations must be distinguished, if the product is new for the consumer but either the technology is not, or the product is not new for the company, the manager experience can be highly important. On the other side, for break-through products the expert experience can lead to biased conclusions. The recommendation is to use judgmental methods on complement to other quantitative methodologies.

Product life-cycle analogy is a good option when the new product is an extension of an old one or when it is easy comparable with existing ones. Nevertheless for usually purchased product the life-cycle analogy can provide good information as the innovations usually are not such big break-troughs. Gartner & Thomas (1993) stated that an extensive **marketing research** proves to increase the accuracy of the sales prediction when used together with other methods.

Several expert systems' authors decided to mix qualitative methods with judgmental methods in order to increase accuracy and to obtain the top manager approval, for instance Ching-Chin et al. (2010) give the possibility to the manager to adjust the final forecasting results according to its belief and knowledge.

Cause-effect methods include a vast variety of forecasting methods, so another inner classification is necessary. Multiple definitions and classifications were found, being one of the oldest ones done by Wind (1974). The division taken in this text belongs to Makridakis & Wheelwright (1998) dividing the cause-effect methods between chronological series (or time series) and explanatory methods, which includes regression and econometric methods. Makridakis & Wheelwright (1998) defend that in the short term, time series methods provide a higher accuracy in the forecast while explanatory methods give a deep knowledge of the factors affecting the forecast.

A. Time series methods use known past sales and datum to predict future unknown sales before they occur. Included in this group are: random walk (Naïve method), moving average and exponential smoothing.

Random walk or **Naïve I** is the simplest method. Widely used in the stock market value forecasting; random walk gives excellent results instead its simplicity. This method uses the last real value to predict the next period, which is a good forecast if the sales value does not change much between periods.

This method does not give proper results when seasonality is present in the data set. **Naïve II** should be used on those cases. The method consists in removing the seasonality and then applying the same methodology as in Naïve I, therefore it is still a very simple and easy to understand method.

Due to its simplicity and in the current scenario of a new product launch, Naïve I and II can be considered, nevertheless with lot of caution as in the first months sales can be unsettled and the results misleading.

Moving average assumes that the future sales will be an average of the past performances rather than following a linear trend. This method minimizes the impact of randomness as it provides an average of several values. It can be found in different levels of simplicity: simple, cumulative, weighted, exponential and autoregressive.

Simple moving average is the non-weighted average of the previous N periods of data, the largest N becomes the less responsive to the last period the forecast is. This method works well with new product forecasting as long as N is defined properly. This parameter is usually decided by experienced forecasters and it is determinant for an accurate result.

Cumulative moving average is the non-weighted average of the previous data sets, including the current period. In this case, the average is done with all the previous plus the current data and it is divided by the number of periods. In this case we are not dropping older data so the effect of the last data sets is dissolved. In new product sales forecasting, were few data is available and the last set of data has a huge importance, as it can be big sales differences between periods, this method may produce inaccuracy.

Weighted moving average consists on giving a certain weight to each data period divided by the sum of all weights or a triangle number ($n * (n + 1)/2$). This moving

average is widely used for pixelisation and it is not for the interest of new sales forecasting. Same way **exponential moving average**, which involves weighted factors that decrease exponentially, is not adequate for our study as we are seeking to forecast a typically growing sales model.

Autoregressive moving average (ARMA) can be called Box-Jenkins, as the Box-Jenkins methodology usually uses it for estimation. ARIMA or Autoregressive integrated moving average is the generalization of ARMA. ARMA considers that the future sales depend on the past sales and the past errors between prognosis and real sales values. The general equation is the following:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} \qquad \textbf{(eq 3.1)}$$

Where the length and number of components of the equation depends on the values of p and q. The value of these parameters are decided by the forecaster by analyzing the autocorrelation factors of the data and its possible trend and cycle, but usually is comprise between 0 and 3. If the data has no correlation at all the value is closer to 0 or 0, while the more auto-correlated the data are the higher value of the parameters is. Box-Jenkins is an iterative methodology in order to find the best value of p and q and estimate the better forecast. Makridakis & Wheelwright (1998).

What can be understood of this equation analysis is that to extract accurate values of autocorrelation and adjust the ARMA function properly to the data, big amount of data is necessary. In this case of study, where data is very valuable and scarce the probabilities to find the appropriate autocorrelation values are low and therefore the forecast inaccurate.

Exponential smoothing provides a forecast depending on an alpha value $(0 \leq \alpha \leq 1)$ which determines the weight of the last periods of data. So then, the largest alpha is the faster the damping is; thus the response to data variation is very high. On the other side, if alpha is close to zero, the result forecast is much more stable giving more importance to older data. There is several variations of exponential smoothing: simple (Brown), additive trend (Holt), damped additive (Gardner & McKenzie), multiplicative (Pegel) and finally damped multiplicative (Taylor). Moreover each of these methods can be adapted according if any kind of seasonality is found on the data sets.

Description and formulation of each exponential smoothing method, including variations for seasonality can be found in Gardner (2005). For good accuracy a previous analysis of seasonality and trend is necessary.

Time horizon is a problematic as well; Makridakis & Wheelwright (1998) recommend the use of different exponential smoothing techniques according to it. For annual forecasting the more adequate is Holt exponential smoothing, for three-month forecasting is recommended to use any damped exponential smoothing while for monthly forecasting Brown exponential smoothing will perform good enough. Makridakis & Wheelwright (1998)

propose a combination of Brown, Holt and damped as an excellent result due to its complementary properties.

B. Explanatory methods include regression analysis and econometric models. According to Makridakis & Wheelwright (1998) these methods provide more knowledge on the factors influencing the forecast result but less accuracy on it.

Regression analysis is well known to be a very specific and time consuming method. The goal to represent the outcome as a regression of several factors (lineal or not lineal) involves big amount of data and long statistical analysis. This method is automatically excluded as optimal for new product sales forecasting, as its development with 4 or less periods of data provides a result lacking any sense.

Econometric models are a wide field. In this paper the three options used by (Ching-Chin, et al (2010) are commented: sales index, Taylor series and diffusion models.

Sales index consists on estimating the future sales of a new product by relying in the data of the whole class of the product; that is why if no new products have been launched recently in the same product class this method is not applicable. The method consists in the calculus of a sales forecast ratio assuming that the new product follows a trend similar to the same class's product. Consequently, sales index method is suitable for new sales forecasting as long as current data about the same class products is available.

Taylor series were proposed by Mentzer & Moon (2005) to deal with situations where few data was available, either because of a technology breakthrough or the launching of new products. It is based on truncated Taylor series.

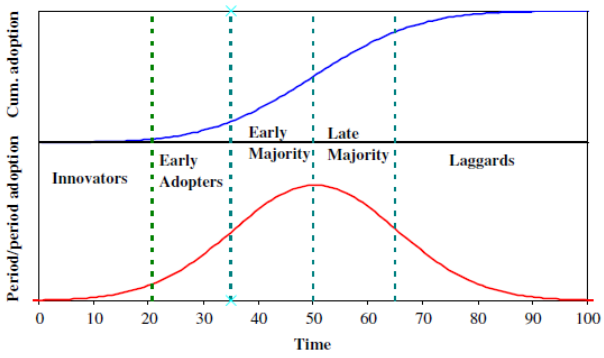
Due to its newness and interesting applications the formula is explained:

$$F_{e,t} = SR_{e,t-1}\left[1+\frac{1}{1!}+\frac{1}{2!}+\cdots+\frac{1}{(N-1)!}\right]-SR_{e,t-2}\left[\frac{1}{1!}+\frac{2}{2!}+\cdots+\frac{N-1}{(N-1)!}\right]+\cdots$$
$$+(-1)^j\left[SR_{e,N-j}\sum\frac{C_j^k}{k!}\right]+\cdots+(-1)^j\frac{SR_{e,1}}{(N-1)!}$$

(eq 3.2)

Where given m periods available $t \leq m+1$ and N is a parameter with value between 1 and m, deciding how many data points are used. At the same time $SR_{e,t}$ are the sales of product "e" at the period "t" after effects are removed.

Diffusion models involve a very large number of forecasting models. All of them are based on the idea that the life-cycle of a product usually follows and S-shape, which different models try to reproduce given certain parameters. At the same time some diffusion models only have in account the first buyers (or innovators), some also include the repetitions (or imitators) and finally some models do not make a distinction between the type of buyers and only count the total aggregated sales. The following graph of Meade & Islam (2006) easily shows the periods of adoption for each kind of buyer:



Graph 3-5.Stylised diffussion curves

Models distinguishing among innovators and imitators (or late adopters) need of special test and pre-test data. As mentioned in Michelfelder & Morrin (2006), to estimate the total sales there is only need of the first data periods after the launch and it is assumed that the launch is successful; the model itself is unable to predict if the product launch will fail.

Regarding the models specifically used for new products and which do not make distinction between first sales and repetitions, according to Morrison (1996), there are mainly two suitable models: logarithmic (or logistic) and Gompertz.

These two models are suitable for three different situations: when the product is completely new and there is no sales history, a relatively new product with short sales history or when the diffusion characteristics of a mature product are needed.

Both models need three parameters: long run saturation level (S), delay factor (A) and inflection point (I). To estimate the sales of a really new product, often these parameters are not known or are hard to estimate; one option is to calculate these parameters from a mature product of the same family or class and estimate the sales with them. Both models also assume that the studied product has a life-cycle following and S-shape, as most of them do.

The **logistics curve model** is characterized by the fact that the inflection point is exactly the 50% of the long run saturation. Therefore the curve is symmetric. The formula used is:

$$F(t) = \frac{S}{1+Be^{At}} \text{ where } B = e^{IA} \qquad \textbf{(eq 3.3)}$$

The **Gompertz model** does not reach the 50% of its saturation long run in the inflection point but only 36,8%, so it reflects a slower penetration into the market as all the other parameters do have the same value. The highest the delay factor is the more similar it will be to a logarithmic curve after its point of inflection. The formula used is the following:

$$F(t) = Se^{-A}e^{-Bt} \text{ where } B = \left| ln\left(\frac{ln\left(\frac{\frac{0.368*S}{S}}{-A}\right)}{I} \right) \right| \qquad \textbf{(eq 3.4)}$$

These two models are suitable for new products as long as the forecaster can estimate "S","A" and "I" or it is possible to calculate them approximately using data from a same product class. It is not necessary to have big data sets of the new product sales to forecast the sales.

Hardie, Fader, & Wisniewsky (1998) studied and collected several trial methods thought to measure the new product's penetration (or cumulative trial) up to some point in time. Some of those models have in account that a group of panelist will never buy the product ("never triers"). The authors collected eight different diffusion models and tested the robustness and accuracy, reaching the already known conclusion that simpler models perform better than more sophisticated. Therefore exponential with never triers, exponential with never triers and stretch factor, exponential gamma and exponential gamma with never triers proved to be more accurate than weibbull gamma with never triers, lognormal-lognormal, double exponential and Bass model. Moreover, **exponential gamma** and **exponential gamma with never triers** stand out for their robustness. For more information about the formulae refer to the above mentioned article.

Bass (1969) model is the most well known diffusion model. **Bass model** describes how products are adopted by new consumers as an interaction of users and potential users (innovators and imitators). The model is based on the assumption that the probability of a new purchase in any time is linearly related to the number of previous buyers and it excludes the counting of repetition purchases, only first purchases are taken in account, so therefore Bass model is not appropriate for frequently purchased consumer products. Bass model was specifically designed for the forecasting of new consumer durables. Being the Bass model:

$$F(t) = p * m + (q - p)Y(t) - \frac{q}{m}(Y(t))^2 \qquad \textbf{(eq 3.5)}$$

Where "m" is the total purchases of the product in the time period, "p" is the coefficient of innovation and "q" coefficient of imitation. The accuracy of the forecasting will depend on the value of these parameters and at least data from 3 time periods are needed to calculate them. (Bass, 1969)

Bass model has been largely studied and used and several modified forms have been developed such as a generalized Bass model including other marketing variables developed by Bass, Trichy, & Dipak (1994) or adapting the Bass model to other growth curves as Meta-Bass or augmented Meta-Bass such as Sood, James, & Tellis (2009).

Artificial intelligence methods are methods with the ability to learn, a midway between commercial software and strictly mathematical algorithms. This section includes neural networks and expert systems.

Expert systems is a wide field, actually all the software products combining several forecasts could be included in this section. The paper introduces another division; whether the forecasting is done using quantitative methods or whether it is based on judgmental knowledge.

Rule-based forecasting is an expert system that develops forecasts using judgmental knowledge reflected in rules. The adequacy of **rule-based forecasting** for new products highly depends on the knowledge used to develop the rules and extrapolations used. The judgmental nuance comes from two sides, firstly forecasting expertise of the developers and experts helping and secondly on the domain knowledge, which includes manager expectations or historical reviews. At the end those rules are used to give different weights to the empirical forecasts given by several methods. Hence, rule-based forecasting uses qualitative knowledge to combine the results of quantitative forecasts. (Adyaa, Armstrong, Collopy, & Kennedy, 2000)

By **quantitative expert systems**, all kind of software applications using the mathematical modeling to forecast are included. There is a huge diversity of applications, thus it is impossible to mention them all. The appropriateness of those applications is only related to the forecasting methods used, which should be suitable for estimating the sales of really new products.

For expert systems in general, the rule of simplicity applies. As mentioned by Fader & Hardie (2005), the simplest the application used is the most acceptance has between the users, as it is possible to reproduce the result and moreover the accuracy is not significantly affected.

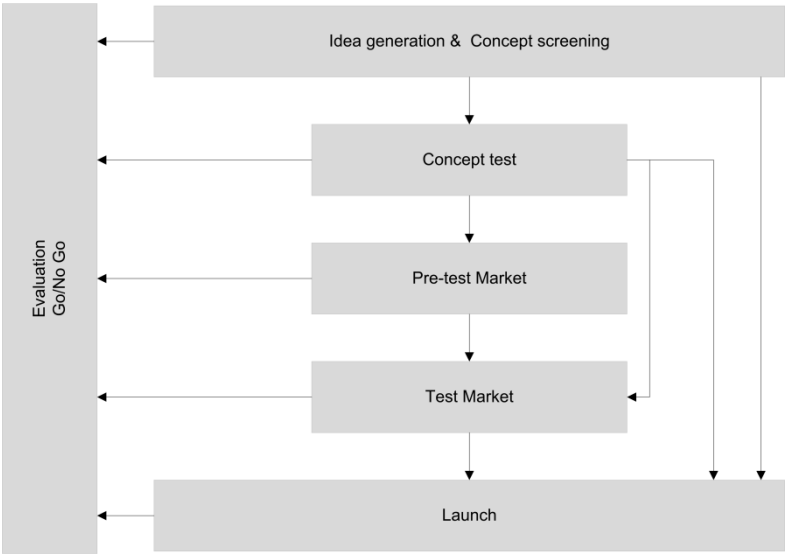
Neural networks are proved to be inadequate for situations with very few periods of data available.

3.3.3. Forecasting software

Up to this point the mentioned were models or combinations of models; the scope of this state of the art also includes a summing up of the most used software application in new product forecasting.

The forecasting process starts further before than the launching of the new product; since the first stages of design the forecasters should have an important role, in order to avoid the failure of the new product in the market. It is widely agreed that the steps of a product development are the following: idea and concept screening, consumer based concept test, pre-test, test market and launching. Different models and software applications can be used regarding the stage of development were the product is.

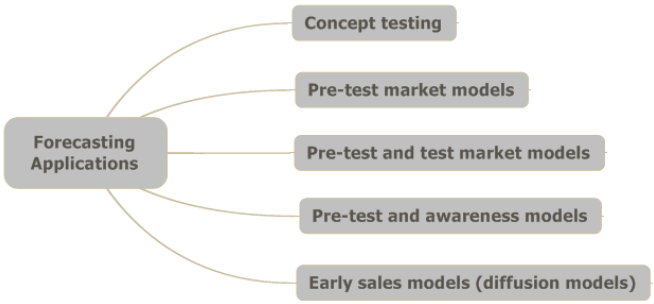
Mahajan & Wind (1988) described the product decision stages as shown in the graph. Firstly, there is the need to develop innovative ideas and to choose the better ones by comparing them against a benchmark. Concept test is the method of evaluating consumer response in front of the new product idea. Fader & Hardie (2001) described pre-test market as a needed step in order to avoid taking a costly decision. Being possible to gather data in two different ways, either exposing consumers to the new product and measuring their intention to buy it, or either replacing the purchase-intention by a simulated shopping task in a mock store. Next step is test market, where the companies launch the product in a controlled environment, usually a small town or a bunch of selected shops, and extrapolate the results to the whole national market. Finally the launching of the product, it can be regional, national or worldwide.



Graph 3-6.Product decision stages

There is uncountable number of software applications for sales forecasting, so a more focused analysis on exclusively new product sales forecast application is done, as well as only considering the most used applications by managers.

The structured considered classifies the software products regarding the stage of product development they focus in. Moreover, not only sales are in the field of study but also awareness of the product.



Graph 3-7.Forecasting applications classification

Mahajan & Wind (1988) reviewed different new product forecasting applications establishing the classification mentioned before. Two main conclusions can be extracted from the article, first of all which are the most used software applications for forecasting sales of new product and the most appropriate type of model depending on the product forecasted.

Concept testing models are appropriate for all kind of products, especially if the product belongs to an established product category, but it lacks accuracy when the product diffusion is highly related to the worth-of-mouth effect, when measurement of depth its essential to obtain market loyalty, when retail promotions affect significantly the sales or

when it is an innovation breakthrough among other situations. Results are short to immediate term.

Pre-test market models are most appropriate for frequently purchased consumer products with some exceptions. For instance, these models are not appropriate if the class product is new; if the market for the product category is growing and the other conditions already mentioned in concept testing models. The sales market estimates are mainly annual forecasting. Some of the most well-known software applications belonging to this pre-test market models are ASSESSOR, BASES II and NEWS/PLANNER.

The managerial decision to run a pre-test market research depends on several criteria. According to Urban & Hauser (1993) the reasons are the following: firstly, sufficient accuracy has to be achieved, the product environment changes in comparison to a full launch, so the results of the pre-test are not perfectly accurate. The timing of the pre-test analysis should be done enough time in advance to stop major investments in case the analysis indicates the product is likely to be a failure. Apart from giving a go/no-go answer, the pre-test should provide a diagnostic about the possible improvements and strong points, either if the product is likely to be a failure (30-50% for packaged goods) or if the product has the go decision. Finally cost of the pre-test market is a key point to decide running it. Pre-test market should not be very expensive in time or money.

Mahajan & Wind (1988) defend that test market models are also appropriate for frequently purchased consumer goods except when the same results can be obtained from pre-test market models, when time, cost and accuracy are critical or when the competitors are likely to influence the results or to mitigate the competitive advantage. Forecasted sales are done in an annual basis

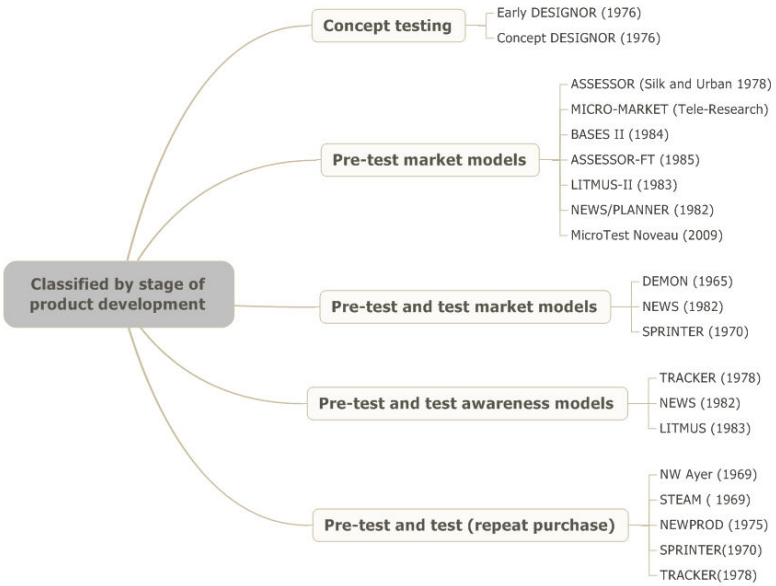
Urban & Hauser (1993) define three different types of test market according to the strategy chosen. First strategy is to replicate national sales. The company tries to replicate the same environment of a national launch but only in one or two middle size cities. The bigger the city is the higher the cost; moreover the city should be representative enough to export the sales results into national sales the most accurate as possible. Second strategy is experimentation on marketing variables, where a controlled store is sometimes used. Promotion, coupons and displays are reduced only to the shop area. Finally behavioral model-based analysis can be used. In this case, there is no specific need of true experimentation and at the same time it corrects the mistakes when extrapolating the results from local to national level by creating a detailed behavioral model of the consumers.

Early sales models, also known as diffusion models, are thought for consumer durables and are not appropriate when the product is seasonal or follows a cycle, when the data cannot be collected differentiating innovators than imitators' sales and repeat sales should not be counted. The results given are long term.

It is complicated to compare the performance of the different software products as some get as results the cumulative sales while others compile the information differentiating

between first sales and repeated. Hence, the most used new product forecasting software applications will be discussed without comparing their performance.

Mahajan & Wind (1988) classified the existing software depending on the stage of production development they belong to. The following graph adapts Mahajan & Wind (1988) classification including new software developed in the past years:



Graph 3-8.Mahajan&Wind adapted graph

Mahajan & Wind (1988) analysis is very extensive and includes non-commercial models. The interest of this state of the art includes only the most used commercial software nowadays mentioned by Mahajan&Wind (BASES, NEWS and ASSESSOR), plus other software extensively used in companies such as MicroTest or DESIGNOR.

NEWS stands for New Product Warning System and was developed by BBDO; it provides the management forecasts about awareness, trial, repeat, usage, sales and others. Also points out the weaknesses and strengths of the marketing plan as well as provides recommendations about the product concept, the product performance, advertising strategy and some strategic decisions for the brand.

NEWS is the evolution of DEMON, which was developed in 1965, after 20 years of forecasting expertise. The models, used to forecast sales or brand awareness, do not follow any of the quantitative models explained before in this state of the art, but are models developed based upon marketing theory, consumer behavior, empirical evidence and intuition.

NEWS is especially suitable for the following situations: when the brand is not seasonal, consumer becomes aware of the brand mainly through advertising, the product/brand is conveniently available for purchase, if the product satisfies the consumer it will continue buying. When the core of repeat becomes stable the product is not new anymore and

NEWS is not suitable. The formulae NEWS uses can be consulted in Pringle, Wilson, & Brody (1982) and appendix C.

BASES is developed by Nielsen and it is the leader on the field with almost 50% of the market as stated by Wherry (2006). As many other similar software BASES consists of different modules according to several necessities; the user has to purchase the more adequate modules to solve its company sales forecasts.

According to the company webpage, Nielsen, the packages specially designed to forecast and improve new products are: pre-BASES, BASES I, BASES II, BASES restager, BASES-suite, ScanTrack, Retail Index and HomeScan.

BASES I and II, are the two main features to develop the forecast of new products. BASES I is a concept only study, which provides detailed information about the multiple possible choices to be made on the commercialization stage. BASES I provides information about the volume sales, consultation in how to improve the odds for consumer adoption, consultation on improving the productivity of the marketing plan and finally comparisons with the peer group as BASES provides a very powerful competitors database.

BASES II complements BASES I as in this case, the prototype is placed with the consumers. Besides the points mentioned in the last paragraph, BASES II also provides assessment about the long-term initiative viability. As for BASES-restager, it gives accurate information about how the new development of products or strategic decisions about the brand's product will affect the brand's impact growth.

According to Wherry (2006) BASES owns a data-base of 60.000 products launched with 1370 validations studies with an accuracy level within 9%. Recently BASES partnered with P&G creating a virtual launch; virtual marketing materials and online shops to better capture the intentions of costumers and investigating about the new marketing environment of nowadays.

ASSESSOR is a pre-test market forecasting software marketed by M/A/R/C Group. The right time for implementation is before the launch but after the design, development and test of the new product. ASSESSOR consists of two models, the preference model and the trial-and-repeat model.

ASSESSOR allows managers to forecast the new product forecast volume and long term market share without the need of a test market which highly increases the costs. Understand the effects of different advertisement methods and quotes on the total sales. Also avoids the development and production of different new products which have few potential or potential failures. ASSESSOR also evaluates different marketing plans and advertising possibilities indicating the most appropriate.

Unlike BASES, ASSESSOR does not rely on historical data and benchmarks but analyses each individual's product competitive set and product trades-off. Therefore, ASSESSOR

developed its own models for forecasting that can be consulted online in Lilien, Rangaswamy, & De Bruyn (2007).

DESIGNOR was first developed in 1976 to forecast consumer goods sales and nowadays is marketed by Ipsos Marketing. The thirty years of experience cover a database of 10.000 new products tested and optimized within 250 categories.

Wherry (2006) explains that DESIGNOR uses a convergent model which integrates behavioral and attitudinal models together with loyalty and fragmentation market models. Like other commercial software, it is divided in several modules seeking to improve different stages of the product development. There is Early DESIGNOR to select the best product concepts, Concept DESIGNOR to improve those concepts and STM DESIGNOR to forecast the sales results after launch.

As key measurements, developers have designed a system based on three evaluation tools: relevance, expensiveness and differentiation as they identified these factors as the key ones to success.

The Japanese Kantar Group recently launched, 2009, a new version of MicroTest: MicroTest Nouveau. The software relies on a database of 40.000 test cases and it is a model of purchase intention like BASES.

The model is characterized by the fact that relies on behaviors of individual costumers, allowing not only to forecast the future sales but to detect potential barriers of entry and improving the marketing plan. It is suitable for new products belonging to new categories.

4. Solution approach

4.1. Analysis of the quantitative methods

From all the different models explained in the state of the art, the most appropriate to deal with forecasting sales of a new frequently purchased product had to be chosen. The election is not trivial not only due to the limitation of possessing very few data but the fact that some models require different kind of it; while some only demand cumulated historical sales others need for more exhaustive data or other similar products information.

In this section the models are described regardless the kind of data needed to run them or the modifications that these data has suffered before being suitable for the model. At the same time, the numerical examples given are done with sales data provided by a company; for confidential issues no other information except that the data belongs to bread product is given.

The selected models are: N-moving average, Brown exponential smoothing, Holt exponential smoothing, Logistic diffusion model and truncated Taylor series.

The models were selected due to several reasons. It was seen that Collopy & Armstrong (1992) used four models in the creation of their rule-based forecasting. From those four models, regression is not suitable for new products; and the random walk is the simplified version of the simple moving average (when N=1). Collopy & Armstrong (1992) choose the random walk because it makes the assumption that there is no trend and Holt and Brown linear smoothing because captures information about the short-range trends.

The reason why the logistic diffusion model and the truncated Taylor series were also selected is due to the research done by Ching-Chin, et al (2010), which proved to be effective methods for new product forecasting.

4.1.1. Data used for the analysis

Assuming that the first three periods are going to be used as historical sales, so known sales at the actual period; and they have already been cleaned from any influence (seasonality, promotions, special events, extra expenditure on advertisement, etc), while the next periods are supposed to be unknown, therefore not manipulated to take away the influences, and used only to calculate the accuracy of the model.

The sales of the product, given in kilograms, are:

t	Period	Corrected Sales (hl)
1	March	211,60
2	April	133,57
3	June	217,77
4	Junly	227,243
5	August	262,593
6	September	237,296
7	October	205,218
8	November	178,029
9	December	179,17
10	January	135,724

Table 4-1. Sales data

4.1.2. Simple moving average

The simple moving average is the non-weighted average of the previous N periods of data. N can take any value from one till the maximum number of periods available, in this case three; but the highest value N takes the less responsive to changes the forecast becomes.

The mathematical expression is the following:

$$F_t = \frac{\sum_1^N A_t}{N} = \frac{A_1+A_2+\cdots+A_N}{N} \qquad \textbf{(eq 4.1)}$$

Where "A" stands for actual values or known values and "F" means forecasted value.

Taking the presented data, the calculus of the future sales are the following:

1. If N=3 then:

$$F_4 = \frac{A_1+A_2+A_3}{3} = \frac{211{,}6+133{,}57+217{,}77}{3} = 187{,}65 \qquad \textbf{(eq 4.2)}$$

2. If N=2 then:

$$F_3 = \frac{A_1+A_2}{2} = \frac{211{,}6+133{,}57}{2} = 172{,}58 \qquad \textbf{(eq 4.3)}$$

$$F_4 = \frac{A_2+A_3}{2} = \frac{133{,}57+217{,}77}{2} = 175{,}67 \qquad \textbf{(eq 4.4)}$$

3. If N=1 is equivalent to run a random walk or Naïve I:

$$F_2 = \frac{A_1}{1} = \frac{211{,}6}{1} = 211{,}6 \qquad \textbf{(eq 4.5)}$$

$$F_3 = 133{,}57 \qquad \textbf{(eq 4.6)}$$

$$F_4 = 217{,}77 \qquad \textbf{(eq 4.7)}$$

Summarizing the three results:

t	Period	Corrected Sales (hl)	N=3	N=2	N=1
1	March	211,60	-	-	-
2	April	133,57	-	-	211,60
3	June	217,77	-	172,58	133,57
4	Junly	227,243	187,65	175,67	217,77

Table 4-2. N-moving average results

If the following periods want to be forecasted, there are three possibilities; first one is to assume the last forecasted value as a real sale and move on with next iteration, second option is to consider the next periods to have the same sales as the last forecasted one as it is not such a further step in the timeline, and last option is to wait till the last period has finished and include the real sales values on the data base in order to forecast the next one. Those three options apply to all the models described in this section.

Other modification of the moving average such as cumulative moving average are not included as the additional sophistication does not translate in any significant improvement when dealing with only three data periods.

4.1.3. Brown exponential smoothing

It is the simplest of the exponential smoothing models. It provides a forecast depending on a factor α (0≤α≤1) which determines the weight of the last periods of data. The largest alpha is, the fastest the damping.

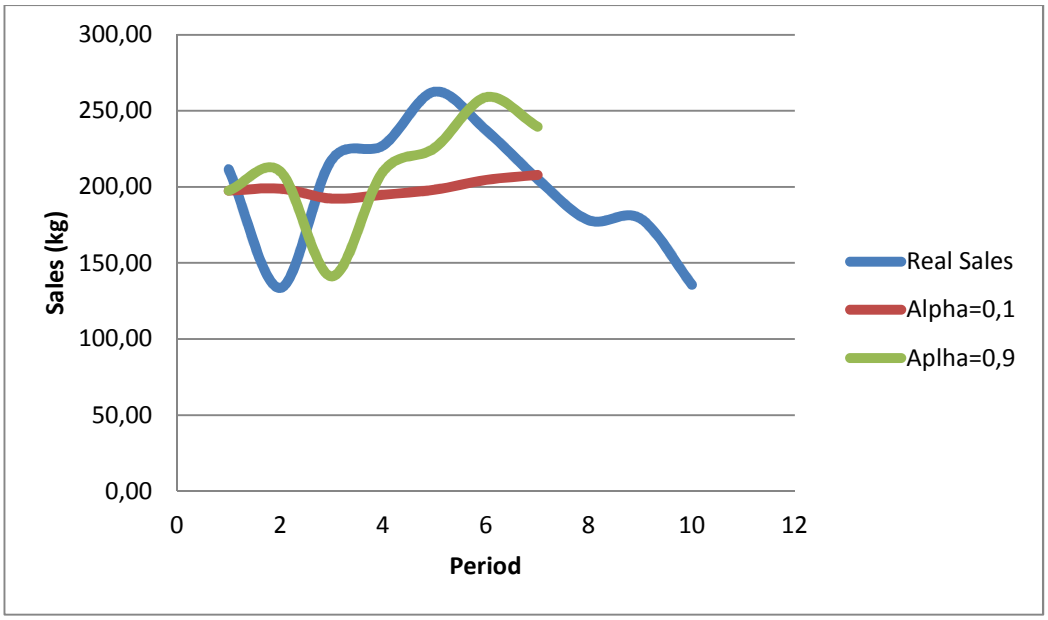
The mathematical formulation is the following:

$$S_t = \alpha A_t + (1-\alpha)S_{t-1}$$

$$F_{t+1} = m * S_t \qquad \textbf{(eq 4.8)}$$

Where (1-α) is known as damping factor, when this factor is close to zero then the response to data variation is really high. Therefore, the closest to α=1 the bigger weight is given to the last real value and the less to the forecasted one. The value of “m” represents the number of forecasting ahead of the actual period.

As explained, in the next graph the forecasting with highest alpha is more affected by the changes on the real sales while the series created with a lower alpha value stays constant and less responsive to variations.



Graph 4-1.Effect of the alpha value

As a consequence the value of alpha has to be chosen very carefully for a good result. In a normal situation, the experienced forecaster or manager having a deep background on the market and the product should be able to choose the better value of alpha or to decide if staying in more conservative values or more daring ones.

A numerical example with the already presented data taking alpha 0,7 (damping factor=0,3):

t	Corrected Sales (hl)	Forecasted
1	211,60	187,65
2	133,57	204,41
3	217,77	154,82
4	227,243	198,88

Table 4-3. Brown exponential smoothing results

Where the first value (period 1) is calculated as an average of the three known periods as an starting point, another possibility for initialization would be just taking $A_1 = F_1$. Then the second value is:

$$F_2 = \alpha * A_1 + (1 - \alpha) * F_1 = (0.7 * 211{,}6) + (0.3 * 187{,}65) = 204{,}41\ kg \quad \textbf{(eq 4.9)}$$

The same applies for the next periods till number 4, the first period with unknown data sales, so therefore a real forecast.

4.1.4. Holt exponential smoothing

Holt exponential smoothing or additive trend exponential smoothing or also called double exponential smoothing depends on two factors: alpha and gamma. Both of them

comprised between zero and one. It usually gives more accurate results when there is a significant trend on the sales.

In this case two parameters are calculated, S_t estimates the level like in Brown exponential smoothing and T_t adds the trend factor to the final forecast by estimating the growth rate. Remark that the values of alpha and gamma do not necessary need to be the same. The mathematical formulation is the following:

$$S_t = \alpha A_t + (1-\alpha)(S_{t-1} + T_{t-1})$$

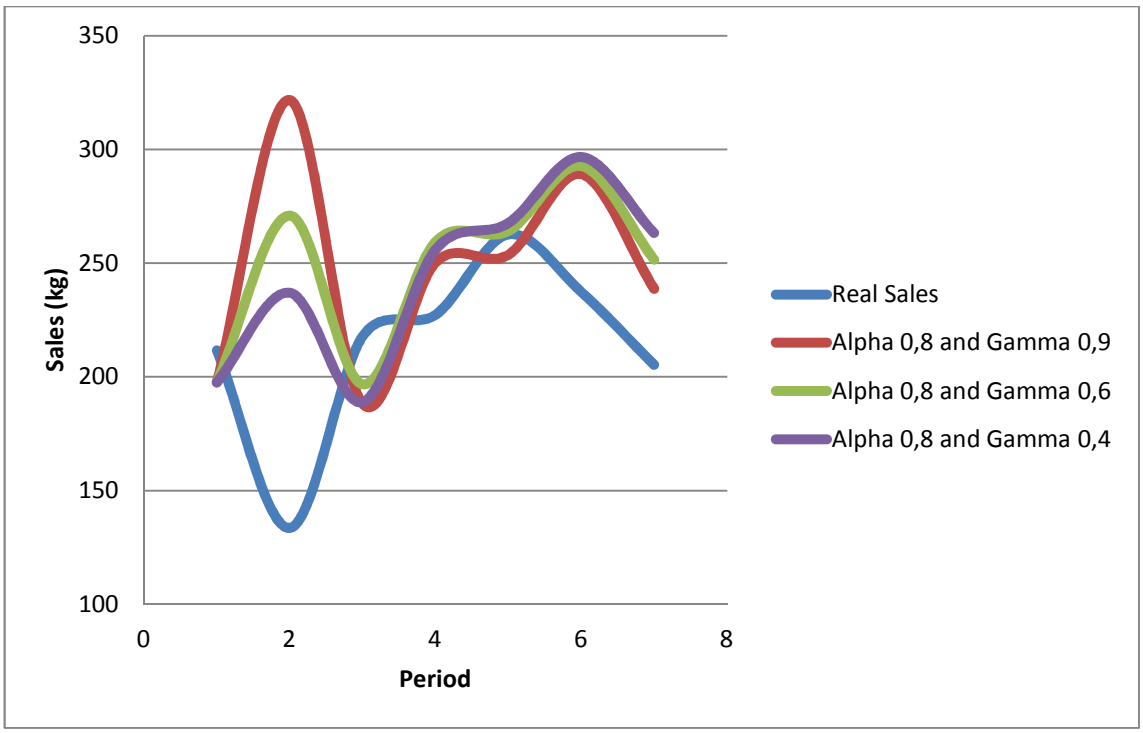
$$T_t = \gamma(S_t - S_{t-1}) + (1-\gamma)T_{t-1}$$

$$F_t = S_t + T_t \qquad \textbf{(eq 4.10)}$$

If there is a need to forecast "m" periods ahead, the calculations for S_t and T_t remain the same but F_t suffers a modification:

$$F_t = S_t + m * T_t \qquad \textbf{(eq 4.11)}$$

As the effect of changing the value of alpha was already stated, in the next graph the change of gamma is represented. Using the same data provided by the company, a forecast maintaining the value of alpha in 0,8 but sweeping the value of gamma from 0,9 to 0,4 was done. The result is the following:



Graph 4-2.Effect of the gamma value

Obviously the forecasted results are not an appropriate estimation as the error is quite big and probably the alpha value should be studied and lowered; nevertheless it is possible to

appreciate a difference between the results depending on gamma. The values with lower gammas are not that sensitive to the data trend. Special attention should be paid at the first 3 periods forecasting.

A numerical example of calculation is the following: the first period S_t and T_t are equal to zero and the forecasting value is the average of the known data periods. From this point, only the equation 4.10 has to be applied.

If α=0.8 and γ= 0.7 then the results are the following:

t	Period	Corrected Sales (hl)	Tt	St	Forecasted
1	March	211,60	0,00	0,00	187,65
2	April	133,57	118,50	169,28	287,78
3	May	217,77	32,14	164,41	196,55
4	June	227,243	44,02	213,52	257,55

Table 4-4. Results from Holt exponential smoothing

Calculated according to the following steps:

1. The forecasted value for the first period is equal to the average sales of all the known periods (March to May).
2. Calculation of period 2:

$$S_2 = \alpha A_1 + (1-\alpha)(S_1 + T_1) = 0{,}8 * 211{,}6 + (1-0{,}8) * (0+0) = 169{,}28$$

$$T_2 = \gamma(S_2 - S_1) + (1-\gamma)T_1 = 0{,}7 * (169{,}28 - 0) + (1-0{,}7) * 0 = 118{,}5$$

$$F_2 = S_2 + T_2 = 169{,}28 + 118{,}5 = 287{,}78 \qquad \textbf{(eq 4.12)}$$

3. Repeat the calculations for the next periods.

Note the important role of the initialization values. In this last example the same initialization as in Brown simple smoothing was taken that means S_t=T_t=0 and$F_1 = \frac{A_1+A_2+A_3}{3}$, but there are other starting points. The different initialization points found in (Engineering Statistics Handbook) are S_1= A_1 and regarding T_1 are:

1. $T_1 = A_2 - A_1$ **(eq 4.13)**
2. $T_1 = \frac{(A_2-A_1)+(A_3-A_2)+(A_4-A_3)}{3}$ **(eq 4.14)**

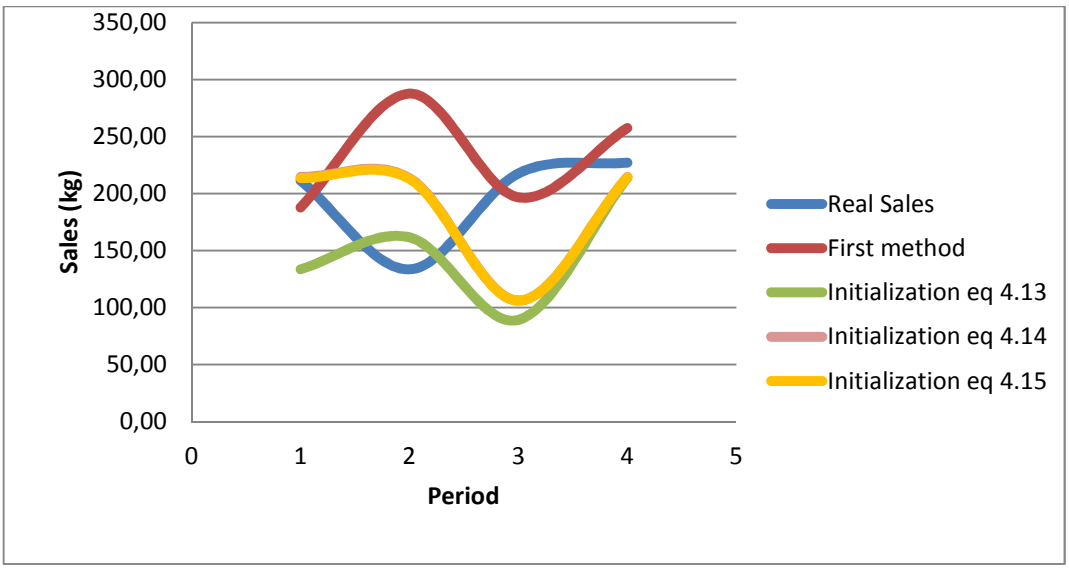
   In case of having four known periods of data, otherwise it has to be adapted.

3. $T_1 = \frac{(A_n-A_1)}{n}$ **(eq 4.15)**

It is as well possible to find the initial values by doing a regression on the data and using the intercept and slope as S_1 and T_1 but again, due to the few amount of data when dealing with new products this possibility is excluded.

The same forecasts were calculated initializing T_1 according to (eq 4.13), (eq 4.14) and (eq 4.15), tables can be found in appendix B.1. The comparison in graph 4.3 shows the last three methods stated by Engineering Statistics Handbook performing against the one used in table 4.4.

So (eq 4.13), (eq 4.14) and (eq 4.15) provide a very similar starting point for initialization, being simpler forms (eq 4.13) and (eq 4.15).



Graph 4-3.Comparison of initialization points

Other variations of the exponential smoothing exist, including seasonality and additive or multiplicative trends; nevertheless talking about new products with much reduced periods of data trends and seasonality are not apparent and the put effort does not pay off the result improvement.

4.1.5. Logistic diffusion model

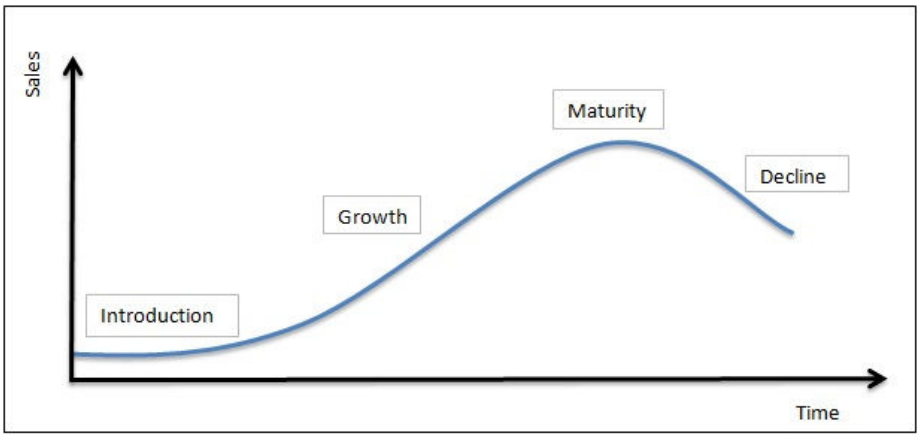
Diffusion models were first inspired in the evolution of epidemics, where starting with a few amounts of infected individuals the illness growths exponentially reaching a very wide percentage of the population. This shape-alike was compared with the sales growth in the initial launching phase of a new product, as long as the new product is successful. In case the product does not reach the expected success and sales decline after some periods after the launching diffusion models are unable to predict it.

So therefore three big problems are encountered when dealing with diffusion models; first one that they only predict accurately if the product becomes a success and the sales follow a growing trend such like an epidemics. Second problem is related with the data needed, most of the diffusion models make a difference between the first buyers (innovative sector of the population) and those who imitate the first buyers (repetitions); this means that a historical sales data base is not enough, but a distinction should be made between the first purchases and the repetitions. Third problem is that most of the

models are only suitable for durable goods and do not adapt to frequently purchased products at all.

For this last reason, models highly validated such as Bass (1969) and its several modifications are not applicable when forecasting frequently purchased products and forecasters have to rely in other simpler models.

The logistic model explained by Morrison (1996) is inspired in the life-cycle of a product, the well known S-shape, which states that products follow a four phase life: introduction, growth, maturity and decline.

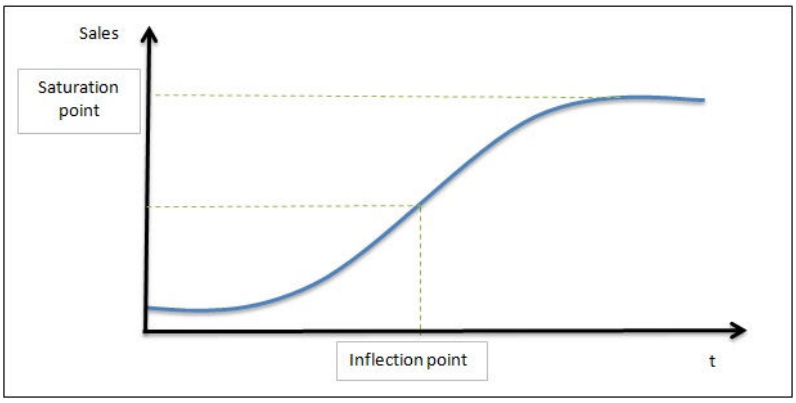


Graph 4-4.Product life cycle. Source: (Kotler & Armstrong, 2007)

To be prepared for this method, Morrisson (1995) asks three questions in advance:

1. What is the maximum level of saturation?
2. What is the inflection point?
3. What is the delay factor?

Because of the logistic method modeling only the first three phases (introduction, growth and maturity) some characterizing parameters of each phase have to be identified. The level of saturation characterizes the maturity phase as it is the maximum cumulated units to be sold in a distant point in time. The inflection point is when the product is sold at its maximum rates, therefore the growth phase, and finally the delay factor is amount of time that the product is expected to remain in the introduction phase.



Graph 4-5.Parameters of diffusion. Source: (Morrison, 1996)

Again when dealing with a new product that has not been launched yet or it has been very little time in the market those parameters are not trivial to estimate. At the end, only two approximations have to be done: saturation level and delay factor.

Saturation level can be obtained from intent to purchase surveys along with primary market research or either to assume that similar products in the market have same saturation points. As for the delay factor, it is a number between 0 and 1. The closest to 0 means the less time the product will stay in the introductory phase as it means there is lot of pent-up demand, and therefore it will reach the saturation point at a slower rate than a product with a higher delay factor. This factor is the most subjective to determine and it can be taken from same family products or by expert assumption.

In the logistics diffusion model the inflection point is defined as the period (month) where 50% of the saturation sales point is expected to be reached.

The mathematical formulation of the logistics diffusion model is the following:

$$F(t) = \frac{S}{1 + B * e^{-A*t}}$$

$$B = e^{I*A} \qquad \textbf{(eq 4.16)}$$

Where “S” is the saturation point, “I” the inflection point, “A” the delay factor and “t” the time index.

According to Morrison (1996) three situations can be encountered: new product with no sales history, relatively new product with short sales history and determining the characteristics of diffusion based on the history of mature products. Last case is used in order to determine the parameters of the first situation (where there is no sales history).

The data used to provide the numerical example in the last sections is not used in this one because a mature product sales are necessary in order to estimate the parameters and obviously a product with only 10 months in the market cannot be taken as so. To provide the example, a data set retrieved from the database of Hyndman and belonging to a cola drink is used. The first periods of data are the following:

Period	Sales (hl)
1	189
2	229
3	249
4	289
5	260
6	431
7	660
8	777

Table 4-5.Cola sales data retrieved from Hyndman

The whole used data set, made of thirty-six periods, can be found in appendix A.1.

In this case the data provided belongs to a more or less mature product so therefore it is possible to extract the parameters S, I and A which can be used later on to forecast the sales of a new product belonging to the same class or family. The method followed is:

1. Transform the data into the log form. Select as saturation point the period with the highest sales and apply the following transformation:

$$Transformed\ sales(t) = LN\left(\frac{Saturation}{Sales(t)-1}\right) \qquad \textbf{(eq 4.17)}$$

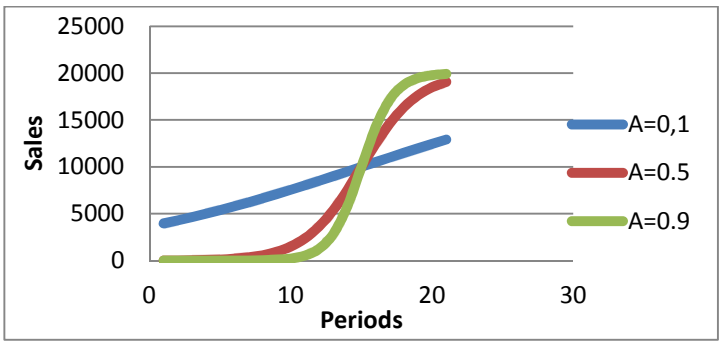
2. Make a regression of the new data points in order to find the slope and the constant. In the case for cola data the slope is -0.0389 and the constant 1.2088.
3. Use these regression estimates to approximate the main characteristics of the data sets. The saturation point was already stated.

$$\mathrm{A} = |\mathrm{slope}| = 0.0389$$

$$I = -LN\left(e^{\frac{ct}{slope}}\right) = 31.07 \qquad \textbf{(eq 4.18)}$$

4. The next period forecasting can be calculated applying (eq 4.16).

As an example of how the delay factor can affect the forecast, the next graph represents three forecasts having the same saturation level (20000 units) and same inflection point (15 periods) but sweeping the delay factor from 0,1 to 0,9.



Graph 4-6.Effect of the delay factor

It can be noticed that the smaller "A" is the latest will reach the saturation point, but at the same time the initial sales are going to be higher and grow more progressively.

4.1.6. Truncated Taylor series

Mentzer & Moon (2005) proposed Taylor series to work in situations where few data was available, later on Ching-Chin, et al (2010) also used this formulation to forecast demand of frequently purchased new products.

The formulation is the following:

$$F_t = A_{t-1}\left[1+\frac{1}{1!}+\frac{1}{2!}+\cdots+\frac{1}{(N-1)!}\right]-A_{t-2}\left[\frac{1}{1!}+\frac{2}{2!}+\cdots+\frac{N-1}{(N-1)!}\right]+\cdots$$
$$+(-1)^j\left[A_{N-j}\sum\frac{C_j^k}{k!}\right]+\cdots+(-1)^j\frac{A_1}{(N-1)!}$$

(eq 4.19)

When "N" is the number of periods used.

This model has not been studied for long and it lacks of easy comprehension. Nevertheless, as new product forecasting relies on very few periods of data, the formula gets strongly simplified.

The numerical examples are again performed with the data set of section 4.1.1. And the results of forecasting using the truncated Taylor series with N=3 and N=2 are the following:

t	Period	Corrected Sales (hl)	N=3	N=2
1	March	211,60	-	-
2	April	133,57	-	-
3	May	217,77	-	55,53
4	June	227,243	383,09	301,97

Table 4-6.Forecasting results with truncated Taylor series

The example for N=3 is explained. N=3 means using three data points for the forecasting, so the forecasted point is F4.

$$F_4 = A_3\left(1+\frac{1}{1!}+\frac{1}{2!}\right)-A_2\left(\frac{1}{1!}+\frac{2}{2!}\right)+\frac{A_1}{2!}=$$
$$=217{,}77*(1+1+0.5)-133{,}57*(1+1)+\frac{211{,}60}{2}=383{,}09$$

(eq 4.20)

Same formulation can be applied for N=2 showing the results on the table.

4.1.7. Market models

There are three approaches to forecast sales for new consumer packaged goods when not even a single period of data is available: pre-test market models, test market models and judgmental-analogy based models.

The difference between pre-test market models and test market models remains on its dimension; while pre-test market measure the intention to buy of selected costumers in mock-stores or just by using surveys, test market launches the product in a small town or controlled environment and measure the consumer reaction in its own environment.

Both are costly and the conclusions given have to be clear and supported by quality data. So when a market test is run most of the times trial/repeat data is collected and the sales forecasts for the first year of the product is done by extrapolating a model followed by the sales.

Test market models

Test markets are costly and long periods of time are needed to run them giving time to competitors to evaluate and develop a similar product. Nevertheless is still difficult to predict the future sales as it is impossible to know how the sales will evolve after the observed period (remain in a stable level, low down but steady or drop to zero). There are two kinds of programs available: those which focus in the depth of repeat using panelist data and those which focus in the hierarchy of effects process using mainly survey data and very little panel data. (Fader & Hardie, 2001)

According to Urban & Hauser (1993) there are three strategies when running a market model:

1. Replicate national. Run a market model in a sample of average medium size cities and extrapolate those results to national level.
2. Experiment. Run the market model in one or several controlled stores.
3. Behavioral models. Analysis based on the behavior of costumer used by software such as NEWS.

In the same article and regarding pre-test and test market models Fader & Hardie (2001) provide some reflections about evaluation and comparison of the existing models. There is very little documental evidence of some software performing better than others, as it is not of public domain neither under which conditions some perform better than others and why. Finally it is not possible to compare the total sales cumulated as some models are better forecasting trial sales and other repeated.

How do the existing test-market software work?

Most of the software packages mentioned in section 3.3.3, the state of the art, rely on massive data bases of new products from different categories, years and countries. Based on those data bases, the developing firms have created formulas adjusted with the available data and which presumably predict the future sales of new products which are not part of the data base yet.

Some of the developing firms have partly made public the formulae used to forecast, such is the case of NEWS and BASES. Though, even if some of the formulae are available to the readership it is impossible to replicate the results without the background data bases and other lacking information.

Some of the formulae used by NEWS and explained by Pringle, Wilson, & Brody (1982) can be found in appendix C, as well as a small part of the formulae of BASES explained by Lin, Pioche, & Standen (1985).

So by analyzing tones of data sets, formulae and parameters where defined in order to fit those data. The bigger amount of data available, the better fitting of those parameters; which is translated in better results for future products forecasted. Therefore, it is virtually impossible to develop a similar method without an unlimited and constantly growing data base.

For this reason, the aim of this project is not to develop a test market model relying on past launching experiences but on quantitative methods. Nevertheless, the option was explored and several documents were created while "playing" with the available data of the soft alcoholic beverage. Another reason for creating these models despite knowing they are not accurate enough is getting to know better the data sets available and therefore understand possible unexpected results in the future.

Creating the models

Given a data set of a soft alcoholic beverage, which similarly to the other data sets more information cannot be provided for confidentially reasons, but this time considering all the data available; not only sales per period but gross rating points (GRPs), market share in within the product category (PDM), acceptance grade of the product (OL, value from 1 to 7), awareness (AW, %) and intention to consume (TTB, %). The full data set can be found in appendix A.2.

As stated before, the model resulting from this analysis is not applicable in any other situation, as in order to create a slightly secure and reliable test market model, lots of products from the same class should be analyzed in order to adjust the parameters.

The goal is to develop an equation with the following recursive structure:

$$Sales_t = Sales_{t-1} + \alpha_1 * GRP_t + \alpha_2 * (PDM_t - PDM_{t-1}) + \alpha_3 * (OL_t - OL_{t-1}) + \alpha_4 * (AW_t - AW_{t-1}) + \alpha_5 * (TTB_t - TTB_{t-1})$$

(eq 4.27)

For this reason the data sales were cleaned weighting by GRPs as explained in section 5.2.1. And the whole statistical analyze was done with Minitab 15.

First of all and in order to find the best regression equation fitting the data, the action "best subsets" was performed, taking as the best option the solution offering the higher R-square adjusted and lowest Cp Mallow (appendix B.2). Following this standards the best regression equation is the one including the five parameters in it, with an R-square

adjusted of 97,4 and Cp Mallow of 6. Therefore, the regression including the five parameters was run separately and studied. The report given by Minitab 15 is the following:

Análisis de regresión: Sales Corrected vs. GRPs; PDM (bimestral, ; ...

La ecuación de regresión es
Sales Corrected (hl) = - 157238 + 12,2 GRPs + 2255 PDM (bimestral, hl)
+ 21823 OL + 938 %awareness - 284 %TTB

Predictor	Coef	Coef. de EE	T	P
Constante	-157238	14230	-11,05	0,000
GRPs	12,169	1,951	6,24	0,003
PDM (bimestral, hl)	2255,1	817,7	2,76	0,051
OL	21823	2925	7,46	0,002
%awareness	937,75	62,32	15,05	0,000
%TTB	-283,59	79,86	-3,55	0,024

S = 548,710 R-cuad. = 98,8% R-cuad.(ajustado) = 97,4%

Análisis de varianza

Fuente	GL	SC	MC	F	P
Regresión	5	102477408	20495482	68,07	0,001
Error residual	4	1204331	301083		
Total	9	103681740			

Fuente	GL	SC sec.
GRPs	1	8569291
PDM (bimestral, hl)	1	1909307
OL	1	3930113
%awareness	1	84271553
%TTB	1	3797145

Graph 4-7.Extract from the Minitab 15 report for the regression analysis with 5 variables

As seen, the p-value for the regression is 0,001 (<0,05) and therefore the equation given is significant, as for the each coefficient parameters only PDM is above the level of 5% and for just one hundredth.

These coefficients were added to (eq 4.27) and pretending that only the first 6 periods are known and therefore period 7 (November) wants to be forecasted the result was the next:

Period	Corrected sales (hl)	Forecasted (hl)
May	9283,336613	-
June	10940,28675	12023,13661
July	12569,13597	20976,28675
August	8788	12569,13597
September	4687,834089	3960,1
October	3892,979754	8628,434089
November	4740	7826,979754

Table 4-7.Forecasting results with the coefficients resulting from regressing with the 5 variables

In this first option the MAPE value reached 54%, and though it is not a catastrophic value for it, it was tried to improve by regressing each one of the variables separately. So then the next regressions were done: Sales-GRPs, Sales-PDM, Sales-OL, Sales-AW and Sales-TTB.

And from this entire regressions only one, the one regarding awareness, gave a p-value under 5%. The extract from the Minitab15 report is the following:

Análisis de regresión: Sales Corrected (hl) vs. %awareness

```
La ecuación de regresión es
Sales Corrected (hl) = - 23497 + 415 %awareness


                    Coef.
Predictor     Coef  de EE      T      P
Constante   -23497   8963  -2,62  0,031
%awareness    414,8  122,9   3,38  0,010


S = 2312,15   R-cuad. = 58,8%   R-cuad.(ajustado) = 53,6%


Análisis de varianza

Fuente          GL         SC         MC      F      P
Regresión        1   60913488   60913488  11,39  0,010
Error residual   8   42768252    5346031
Total            9  103681740
```

Graph 4-8. Minitab regression sales versus awareness

As mentioned the p-value is under 5% (p-value=0,010) and therefore the parameters are significant. If applied to the (eq 4.27), only considering awareness as a variable the result out-performs the last method giving a MAPE of 33%. The results table can be found in appendix B.3.

Following the same process but this time with the bread product data set; the variables available are different: market share in value (%SOM value), market share in volume (%SOM volume), weighted distribution, PVP, PVP465 which is the price compared to the competitors price, GRPs, % penetration and repeat sales. Best subset was run and the regression with higher R-adjusted and smaller Cp Mallows was the one with market share in volume and the weighted distribution. The result of this regression is the following:

Regression Analysis: Sales Correc versus %SOM(volume); Weighted dis

```
The regression equation is
Sales Corrected (Kg) = 200 + 191 %SOM(volume) - 4,68 Weighted distribution


Predictor                Coef  SE Coef      T      P
Constant               199,70    17,56  11,37  0,000
%SOM(volume)           191,44    41,07   4,66  0,002
Weighted distribution  -4,683    1,009  -4,64  0,002


S = 20,9809   R-Sq = 75,9%   R-Sq(adj) = 69,0%


Analysis of Variance

Source          DF       SS      MS      F      P
Regression       2   9705,7  4852,8  11,02  0,007
Residual Error   7   3081,4   440,2
Total            9  12787,1
```

Graph 4-9.Best regression for the bread product

As seen, the p-value is 0,007 (<0,05) and therefore the regression equation is significant. On the other hand, when regressing each variable separately only the variables PVP465 (p-value 0,049) and %penetration (p-value 0,018) are significant though their R-adjusted is under 50% meaning that they fail to explain more than half of the cases.

When forecasting the future periods using the regression equation that performed better in the best subset the results are the following and applying the recursive equation:

Period	Sales corrected (kg)	Forecasted (kg)
1	211,60	-
2	133,57	164,59
3	217,77	190,52
4	180,09	217,77
5	208,11	151,40
6	188,06	223,00
7	162,64	146,37
8	141,09	140,84
9	141,99	140,77
10	107,56	141,89

Table 4-8.Forecasting results with the coefficients of the best subset

In this case, when creating the recursive equation and forecasting for each one of the significant variables each time the better performing result is still the one created with the best subsets.

4.2. Problems associated to data and models' nature

When facing a forecasting exercise there is mainly two different problems that might arise. First one is that the data available for forecasting might have incorporated undesirable effects such as seasonality or effects of a very strong advertising campaign. The second problem relies on the models themselves; not all the models need of the same kind of data or the same number of periods in order to provide a first forecasted sales period.

This section describes all the problems raised while compiling and testing the quantitative methods explained in the previous section.

4.2.1. Problems associated with the data

Seasonality, trend and cycle

Any kind of numerical datum can be described as a pattern and an error. At the same time, it is possible to break it up in trend, cycle and seasonality.

According to Makridakis & Wheelwright (1998), the most common form to represent the data break up is on the multiplicative way:

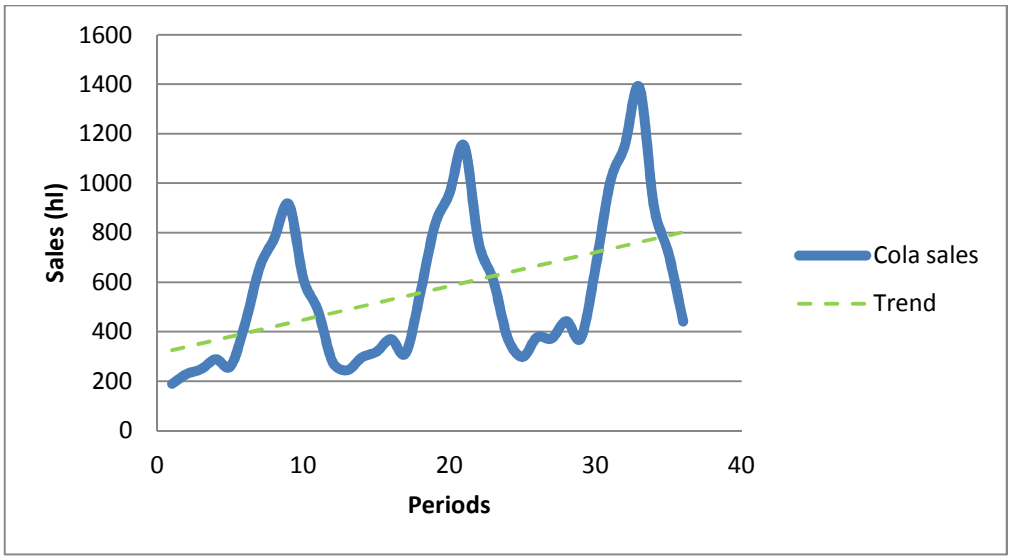
$$A_t = S_t * T_t * C_t * R_t \qquad \textbf{(eq 4.21)}$$

Where A_t is the actual data value, S_t is the seasonality component, $T_t$the trend, C_t represents the cyclic component and R_t is the error. It is interesting when forecasting to identify and remove any kind of influence that can distort the data just before applying the model. Later on the seasonality or trend removed can be applied again giving a more close to reality result.

But how does each of those components affect the data and what do they mean?

1. Seasonality: formed by the intra-annual fluctuations that repeat regularly each year. Mainly due to the economical activities related to climatology, religious festivities (for instance Christmas) and important fixed dates (such as the beginning of the school year).
2. Trend: long term variations caused by demographical, technological or institutional changes.
3. Cycle: oscillatory changes in a much longer time span, usually between two and seven years. Affected by the economical cycles, being the phases of expansion longer than the recession ones.

Seasonality and trend are clearly visible in many time series, especially if the periods available reach more than one year. As an example, the cola sales used in the last section are represented. The green line shows the trend, and the seasonality is clearly visible as the line shape is the same for the three years represented; a moderate grow in the first month of the year, really high rise in the spring-summer months followed by a deep fall of sales in autumn-winter.



Graph 4-10.Illustration of the Cola sales product

The effect of each one of those components affects the forecast differently depending on the time horizon. In the short term forecasting seasonality plays an important role, while in the long term cycle and trend do.

There are several methodologies in order to identify and remove seasonality and trend. The problem relies in the fact that it is impossible to identify any of those factors when very few periods of data are available. The maximum it can be done is to guess when the high periods of sales will be located according to the type of product.

At the same time, the effect of special events highly affects the data when talking about weekly or monthly periods (the most common ones in new product forecasting). Special events can be either conscious action made by the company to influence the sales (promotion, advertising, free samples, etc) or accidents that impact on the sales (wars, climatic disasters, earthquakes, etc). Special effects are impossible to be quantified in a statistical model and can be somehow neutralized by the competence companies and their actions.

Advertising

Another concern involving the effects on the datum is the advertising expenditures and its consequences in the long-run. Does the marketing expenditure have an immediate effect or it persists on time? Dekimpe & Hanssens (1995) analyzed the persistence of marketing effects on the sales, identifying firstly six different channels through a marketing action can affect a brand/product performance:

1. Contemporaneous effects: there is consensus on the fact that advertising does have an immediate effect on sales.
2. Carry-over effects: the effects of advertising in one period can carry-over partially into future periods.
3. Purchase-reinforcement effects: advertisement not only impulses costumers to innovate and buy for the first time but may also reinforce the re-purchase.
4. Feedback effects: Bass (1969) already stated that future sales depend on past and current sales, so therefore the advertisement expenditure should have it in account.
5. Firm specific decision rules: advertisement expenditure is not again independent on past and future sales, and companies should take in account this dependence when taking strategic decisions as it might cause a chain reaction affecting the future sales.
6. Competitive reactions: the activities of competitor firms can affect the effectiveness of the own actions completely.

Finally Dekimpe & Hanssens (1995) conclude that the advertising effects do not dissipate in just one period, but have a persistent effect on the sales within at least one year. At the same time discourages companies to focus their marketing actions in emphasizing sales promotions (offensive marketing) as it is not desirable for the brand's long-run performance.

However, the literature does not reach a consensus on the durability of advertising effects as Landes & Rosenfield (1994) pointed out, being the effectiveness of advertising spent in 90% in less than two months according to some studies, while in others the depreciation rates were very low; around 90% spent in several years.

But sales won't necessarily just increase because of advertising; the effectiveness of advertising depends on several factors summarized by Sexton (1972) like in the amount

of increased expenditures in advertising, so the difference between the previous advertising and the last campaign. Also depends on the effectiveness of each dollar/euro spent per advert and the maximum sales level possible (above the actual level); which actually introduces the possibility of a negative effect of advertising.

Pricing

Pricing strategies also affect the period sales. This importance is reflected on the big amount of pricing models available nowadays and a relatively most effective strategy in changing brand share in frequently purchased products according to Sexton (1970).

Pricing is also mentioned as a strategy with immediate effects when responding to a rival marketing action by Lambin, Naert, & Bultez (1975); much more immediate than advertising campaigns or changing the attributes of the product. However, might not be an interesting campaign to be applied during long time periods.

It should not be surprising that price is an important factor when talking about frequently purchased products, at least for the innovators (first buy) but might not influence that much in the repetitions. This is the reason why, price is a key question done to costumers when running a market research.

Compromise solution

When trying to forecast the sales of a new product with very few amount of data there are mainly two problematic:

1. It is impossible to identify the seasonality and trend, unless the seasonality is guessed due to the market/product knowledge.
2. Advertising campaigns and price promotions are very common when launching a new product and the sales are reinforced by those actions. What will happen when the price promotions come to an end or the advertising campaign expenditures get lower?

In the ideal situation the forecaster should possess the information about especial events (not only firm actions but accidents as well) and the expenditures on advertising. For simplifying and having in mind the lack of consensus between experts it will be considered that advertising expenditures only affect the sales of the period when they were produced.

The data from the soft-alcoholic beverage used in section 5.1 is given, but this time together with their GRPs (Gross Rating Points). GRPs are the percentage of people reached by the campaign multiplied by the number of exposures in a specified time and they are used as a measure of advertisement impact.

t	Period	Monthly sales (hl)	GRPs
1	May	9250	114
2	June	10901	661
3	July	12524	323
4	August	8788	0
5	September	4671	273
6	October	3879	323
7	November	4740	53
8	December	4391	40
9	January	3242	0
10	February	4020	528

Table 4-9.Sales data and its GRPs

For instance, if the first four periods are known data, and have to be cleaned from the advertising effect (measured with GRPs), the procedure is the following:

1. Identify the periods with advertising expenditures and the periods without.
2. Calculate the total GRPs amount for the months that have advertising expenditure, in this case:

$$Total\ GRPs = 114 + 661 + 323 = 1098 \qquad \textbf{(eq 4.22)}$$

3. Calculate the weighted sales for each one of the groups.

$$Av.Sales_{advert} = \frac{S_1 * GRP_1 + S_2 * GRP_2 + S_3 * GRP_3}{Total\ GRPs} = \frac{9250*114+10901*661+12524*323}{1098} = 11207{,}02$$

(eq 4.23)

$$Av.Sales_{NOadvert} = S_4 = 8788 \qquad \textbf{(eq 4.24)}$$

4. Calculate the effect ratio (divide solution of (eq 4.23) by (eq 4.24)):

$$Effect_{advert} = \frac{11207{,}02}{8788} = 1{,}2753 \qquad \textbf{(eq 4.25)}$$

5. Remove the advertising effect from the known sales periods by diving them by the effect, except for the period without advertising expenditure.

t	Period	Monthly sales (hl)	Corrected sales (hl)
1	May	9250	7253,40
2	June	10901	8548,03
3	July	12524	9820,71
4	August	8788	8788

Table 4-10.Data without advertising effect

It is also possible to clean the data from the advertising effects without knowing exactly the GRPs or the expenditure in economical units. In that situation it is only necessary to

know in which periods there was advertisement. Same procedure has to be followed but this time the effect ratio is calculated as the division of the average sales in advertised periods by the average sales of periods without advertisement. The result would be the following including the percentage difference between this method and the used previously:

t	Period	Monthly sales (hl)	Corrected sales	% difference
1	May	9250	7463,41	2,90
2	June	10901	8795,53	2,90
3	July	12524	10105,06	2,90
4	August	8788	8788	0

Table 4-11.Data without advertising effect (no weighting by GRPs)

There is also the possibility that the forecaster knows about a special event in a certain period; for instance a music festival promoted by the brand's product in period 3. Then the data needs to be adjusted just in this period. Makridakis & Wheelwright (1998) proposed to divide the data by a factor "r" between zero and infinity which represents the influence of the special event in the sales. If r=1 the event has no influence.

So for instance, there is the promoted music festival in period 3 and the forecaster team has approximated it's influence on r= 1,09; meaning it increased the sales for about 9%. Then the new sales of that period are:

$$S_{3new} = \frac{Sales_{3no\ advert}}{r} = \frac{9820{,}71}{1{,}09} = 9009{,}83 \qquad \textbf{(eq 4.26)}$$

In case there is the chance to know the high season periods, it is possible to apply this same last method giving the appropriate "r" for each period.

4.2.2. Problems associated with the models

Related to the model's nature, mainly two problems appeared when analyzing them and choosing the most appropriate model for new frequently purchased products. Firstly the amount of data periods needed to produce a stable and accurate forecast; and secondly the type of data needed for it (aggregated versus trial/repeat data).

Critical amount of data periods

The main constraint of forecasting few periods is the few amounts of data periods available, any forecasting model that needs extensive historical data is automatically disregarded. For this reason, well-known methods such as ARIMA or regression are rejected.

After analyzing several models and running test with them it was seen that at least three periods of data are needed it. Accordingly, Ching-Chin, et al. (2010) also request a minimum of three data periods to be able to start forecasting with their expert system.

The biggest worry of managers that have to take go/no go decisions about the launching and starting the production process of products is that most of the times real sales are not

available at that moment. In case real sales are not available, other kind of information can be used as the starting data for the forecasting (those three critical periods to start).

The kind of data that can be used as starting point for the forecasting can be taken from pre-sales data from the pre-market or market test, product classification information or similar product class. Some of this data may need minor modifications as for instance to be generalized if the data was regional, and some may be already good to start the forecast.

Obviously the most periods available the better, and of course the more realistic the data sales are the highest probability of an accurate forecast exists.

Type of data

Running the models is not expensive or difficult itself, collecting the appropriate type of data is where the main difficulty remains. Regardless the GRPs used previously or any other information accompanying the sales datum, this subsection makes difference between two kind of historical sales collections: aggregated sales and trial/repeat sales.

The datum used to exemplify this document belongs to the aggregated kind of historical sales. Where only the total sales of that period is known, without taking in account who or why that sale was done. To collect them is only necessary to sum up all the sales done by the firm or its distributors.

Trial and repeat sales take in account who bought the product and if it was its first time or the costumer already bought the product before. So therefore, there is the distinction between innovator costumers, early adopters, late adopters or laggards or said in another way innovators and imitators.

As described by Urban & Hauser (1993) innovators tend to be consumers with high-incomes, likely to be educated, with high aspirations in life, with a positive attitude towards change and linked to external information media and change agents. These costumers are the first sales bases and their actions will be followed by imitator costumers who are not that keen to changes.

Moreover a proper distinction between trial and repeat sales has to be done. This distinction is impossible to do without a controlled environment such as the ones used in market tests. Market tests are completely unaffordable by small or medium size companies, and each time more and more big size companies, who can afford it, try to cut their expenses and reduce them to the minimum amount.

For the reasons described above no trial/repeat sales is going to be used; only historical aggregated sales are used for the forecasting methodology described in the next chapters, and the models needing trial/repeat datum (diffusion models) were excluded.

4.3. Measures of performance

There is the need to evaluate the performance and usability of the several forecasting methods, not only to choose the most appropriate in each situation but to calibrate them as well. It is of extremely importance to choose the adequate method as upon the results strategic company decisions will be taken.

According to Wind (1974) the criteria for evaluation can be divided in three items (a) predictive accuracy, (b) ability to develop and implement the model and (c) diagnostic power. Following these criteria would not lead to find the best method for forecasting, because such thing does not exist, but the most appropriate in each case.

Under predictive accuracy Wind (1974) states as sub-criteria the ability to identify turning points, the prediction results in short and long term and the economical versus the statistical evaluation. These sub-criteria are mainly numerical evaluations, which are easy to compare from one method to another. On the other side, the ability to develop and implement the model, which includes the technical skills needed to run the model, the management acceptance, time, cost and data required etc, are much more complicated to compare as some of them are highly subjective opinions.

In the following paragraphs, the general performance of different models will be evaluated, followed by the explanation of several numerical performance measures and its advantages and drawbacks.

4.3.1. Assessing different models

There is a fact that concerns the forecasting experts; even if computer science has improved dramatically in the last decades and hundreds of several forecasting methods are available to managers, most of them still rely more on judgmental methods than on quantitative ones. All along literature, there are several authors analyzing the problem such as Fader & Hardie (2005) who propose managers to create their own forecasting methods.

Sanders & Manrodt (2003) evaluated a sample of companies, finding out that companies relying more in judgmental than quantitative methods usually are under conditions of rapid chance (facing a lot of uncertainty), they are usually less structured organizations with a less methodical use of software. These firms tend to use the software on a different way, rather than the expected, which leads them with inappropriate results and dissatisfaction with the purchased software. In the same investigation line Kahn (2002) affirms companies tend to apply the same forecasting model to all the different products they are launching, reaching an overall accuracy of 58%.

Despite the reluctance of certain managers to base their forecasting methodologies on quantitative methods, it has been proved by several authors such as Makridakis & Hibon (1979) or Sanders & Manrodt (2003) that judgmental companies tend to have less accurate results especially in repetitive situations. Nevertheless, Armstrong (1983) found some contradictory results when analyzing the performance of several companies, instead of confirming his hypothesis that objective methods provide more accurate results than

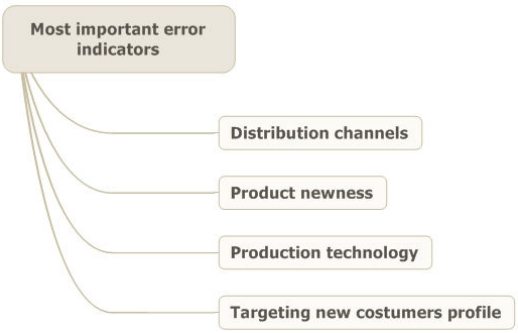
subjective, Armstrong (1983) concluded the opposite after the data analysis. The possible explanation given for this result is the fact that managers have up-to-date data about the situation (new laws, economical changes, sales from the last period) that objective forecasting methods relying on historical sales do not have available.

The contradictory situation just explained, leads to the conclusion that an amalgamated forecasts will perform much accurately than a single forecast method especially if mixing subjective methods with objective ones. This statement is also proven with evidence by Armstrong (1983), Clemen (1989), Gartner & Thomas (1993) and Makridakis & Wheelwright (1998).

However, Clements & Hendry (1998) make a distinction, if the combination of forecasts is mixing together models based on a same pool of information or if the combination unites models of essentially different types or nature. Only the combination is a good idea in the last case, the authors suggest in the case of having the same nature models combined is preferable to derive the best model combining useful features of the other original models, creating a complete forecasting methodology.

4.3.2. Factors affecting accuracy

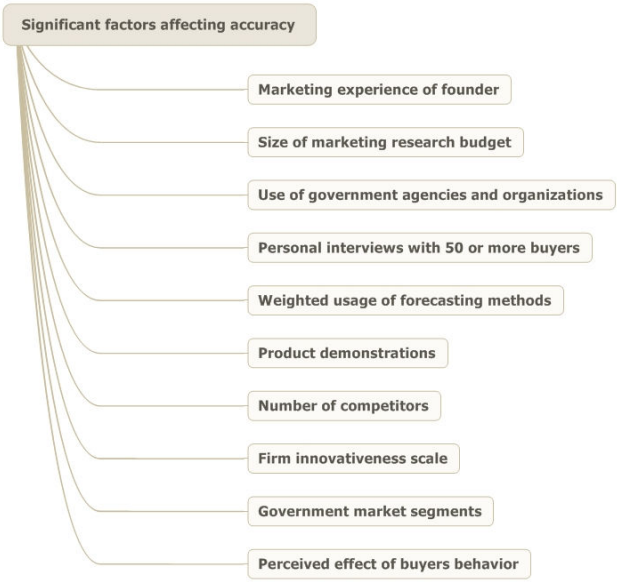
Factors that affect forecast accuracy, independently of the forecasting method used, has been as well a deep field of research. When a new product is launched the uncertainty and risk are so big that not even the best forecasting method can assure a prediction close to the actual sales. Some of the literature specially reviews this problem when facing new product launch and new business as well.



Graph 4-11.Error indicators, Little&Moore (1978)

Little & Moore (1978) analyzed eight different dimensions that might lead to assess the similarity of the new product with older ones, assuming that companies are successful in forecasting products already known by the market and the firm. After their study, Little & Moore (1978) confirmed the hypothesis that the more familiar the situation is the less errors are produced on the forecasting process, being the distribution channels the most sensitive factor when producing errors. Product newness was found as the second most important error indicator, meaning that the newest the product was for the company the greatest the error in forecasting. Other factors following were the production technology and the expected new costumers. It is not given a solution to avoid those errors but the advice to over control the process when any of this factors takes special importance.

In a more recent article Gartner & Thomas (1993) identified different factors affecting forecast accuracy when launching a new product in a new firm: antecedent factors (firm founder factors, data sources and methods) and environmental factors (firm marketing program factors, competitive/industry factors). Finally those factors proven to affect accuracy in forecasting were:



Graph 4-12.Factors for inaccuracy according to Gartner&Thomas (1993)

Those influencing factors belong to different profile of indicators, so the inaccuracy can be explained both with antecessors and environmental factors. In general, the marketing experience of the founder is significant after a minimum level of expertise; the most money allocated in marketing research budget the highest is the accuracy nevertheless Gartner & Thomas (1993) did not discover the nature of this relation (linear or non-linear).

Moreover, the more mature the market is the less risk is involved and better forecasting results are found; this statement lets to the conclusion that it might be impossible to predict sales in certain markets which are experiencing rapid changes.

4.3.3. Performance measures

In this section the different mathematical resources to evaluate the performance of the forecasting methods are explained. While some of this measures are very popular due to its simplicity and ease to be comprehended others are rarely used. Thus, the more used are not always the more precise.

Widely well-known and used by the vast majority there is the Mean Absolute Percentage Error (MAPE). Armstrong (1983) stated that its main advantages are the possibility to be average across years as well as across firms and its easy interpretation. The formulation is:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \qquad \textbf{(eq 4.27)}$$

Where A is the actual value and F forecasted value. One of the main inconveniences of using MAPE is that it is not bounded on the high scale and therefore it penalizes the forecasts that exceed the actual value.

Taking advantage of the simplicity of MAPE and trying to improve its results Makridakis & Hibon (2000) used Symmetric MAPE (sMAPE) in the evaluation of the results of the Third M-Competition. Symmetric MAPE seeks to avoid the penalty given to the values exceeding the actual forecast. The values given by this measuring tool fluctuate between -200% and 200%. The formula is the following:

$$sMAPE = \sum_{t=1}^{n} \frac{|A_t - F_t|}{\frac{A_t + F_t}{2}} * 100 \qquad \textbf{(eq 4.28)}$$

An example to clearly show the penalty produced by MAPE, when the forecast is higher than the actual, and how sMAPE deals with the situation. Given two situations, in the first situation the actual value of sales equals 100 units while the forecasted result is 50 units; then $MAPE = \left|\frac{100-50}{100}\right| = 0{,}5$ and $sMAPE = \frac{|100-50|}{(100+50)/2} = 0{,}66$.

In the second situation, the actual value is 50 units and the forecasted value is 100 units, then the result for each measure is $MAPE = \left|\frac{50-100}{50}\right| = 1$ and $sMAPE = \frac{|50-100|}{(100+50)/2} = 0{,}66$.

The difference between forecasted sales and its actual value is both cases 50 units; nevertheless the value of MAPE is doubled when the forecasted value exceeds the actual. However Symmetric MAPE penalizes the same way both situations either if there is a shortage of units forecasted, either if there is an excess.

The second most used measuring tool is the Mean Squared Error (MSE). According to Makridakis & Hibon (1979) MSE is preferred when more weight has to be given to bigger errors; at the same time this measuring tool does not allow comparison between methods since it is an absolute measure related to a specific series. The following formula has to be followed for calculation:

$$MSE = \frac{1}{N} \sum_{t=1}^{N} (F_t - A_t)^2 \qquad \textbf{(eq 4.29)}$$

Where F is the forecasted value, A the actual value and N is the total number of periods to be evaluated. The units of MSE are squared units, not the same units as the data used for the calculation; therefore it might be interesting in some occasions to calculate the Root Mean Squared Error (RMSE).

$$RMSE = \sqrt{\frac{\sum_{t=1}^{N} (F_t - A_t)^2}{N}} \qquad \textbf{(eq 4.30)}$$

In both cases the values that MSE and RMSE can take are bounded on the minimum by zero (the case where the error is null, forecasted and actual value are the same) till infinity in the maximum value.

Another measuring tool is Mean Absolute Deviation (MAD) or Mean Absolute Error (MAE), being the last one highly used when checking accuracy in forecasting time series. In these cases, the penalty to large errors given in RMSE and MSE is not applied. The formulations are the following:

$$MAD = \frac{1}{N}\sum_{t=1}^{N}|F_t - \bar{x}| \quad \textbf{(eq 4.31)}$$

$$MAE = \frac{1}{N}\sum_{t=1}^{N}|F_t - A_t| \quad \textbf{(eq 4.32)}$$

Other relative methods are found, though not used with the same frequency as the already mentioned. As for instance, the Relative Absolute Error (RAE):

$$RAE = \frac{\sum_{t=1}^{N}|F_t - A_t|}{\sum_{t=1}^{N}|A_t - \bar{A}|} \quad \textbf{(eq 4.33)}$$

Where $\bar{A}$ is the average of all the actual values. To increase the robustness of this measure, several modifications can be done such as calculate the median of RAE or the cumulative RAE. Armstrong & Collopy (1992) used those modifications of RAE in their study of error measures; modifying as well RAE in such a way that the denominator instead of the differences between actual values and their average, contains the error between the actual values and the forecasted values calculated with a simple method such as Random Walk.

Comparing the obtained results with the results obtained with a rival method, usually a simple one, is also a common practice. Thus an important citation to have in mind was made by Granger & Newbold (1986) when talking about rival methods for comparison is "*The evaluation criteria employed should be as demanding as possible since the object ought to be self-criticism rather than self-congratulation*". Meaning an outstanding result might be not that valuable if the method used for comparison (rival method) gives poor results or it is not developed enough to forecast in certain specific situations.

Inside this comparing methods to calculate accuracy it can be found as well the tool called Percentage Better and Average Ranking; used during the Third M-Competition by Makridakis & Hibon (2000).

Percentage Better consists on counting the percentage of times that a given method has the smaller forecasting error than another method for each series. A benchmark or rival method has to be chosen and then recount how many times each forecast out performs or not the benchmarking method.

As for Average Ranking, one of the measuring tool explained till now has to be used, for instance MAPE. All the values of MAPE are calculated and ranked from the smallest till the biggest one. Then the mean rank is calculated for each time horizon over all the series and methods. In this case, it is not a comparison with a rival method but comparing all the potential forecasting models according to their MAPE results.

4.3.4. Choosing the appropriate performance measure

All the measures presented have defects and advantages, but the use of a random sample of them will lead to confusion. There is the need to evaluate the forecasting situation and choose the more appropriate ones for each situation. Armstrong & Collopy (1992) focused on the need to reach a consensus based on the use of multiple measures that might compensate their defects.

Armstrong & Collopy (1992) also run a study to classify a bunch of performance measures according to their reliability, construction of validity, outlier protection, sensitivity and its relationship to decisions. Dividing the importance of these factors depending on the situation; in case of calibration of a method, sensitivity is the most important factor; meanwhile when comparing between models the importance falls on reliability, protection against outliers and the relationship with decision. The authors did not study all the measures mentioned here, but only some of them (RMSE, Percentage Better, MAPE, Median RAE). Their results were the following:

Error Measure	Reliability	Construct validity	Outlier protection	Sensitivity	Relationship to decisions
RMSE	Poor	Fair	Poor	Good	Good
P. Better	Good	Fair	Good	Poor	Poor
MAPE	Fair	Good	Poor	Good	Fair
MdRAE	Fair	Good	Good	Poor	Poor

Table 4-12. Adapted from Armstrong&Collopy (1992)

Therefore, some appropriate measures in order to calibrate the forecasting model would be MAPE and RMSE, as they have higher sensitivity.

Overall and in spite of all the drawbacks, MAPE is still the one better classified. Together with the fact of being a widely used and understood measure, MAPE is going to be the tool to classify the results in this project from now on.

The dilemma of using MAPE or the symmetric version of it (sMAPE) can be solved by analyzing the advantages and drawbacks of each situation. Which of the following situations produces more economical losses: to over produce and retain product in stock or not being able to cover all the product demand on time?

Using Symmetric MAPE (sMAPE) instead of MAPE, the forecasts outperforming the actual value won't be suffer more penalty that those over-performing. Therefore it considers that spending more resources on products that are not being sold is as harmful as not covering the whole demand. Moreover, the sMAPE values are bounded giving protection against outliers and even all this modifications it is still a simple methodology easy understandable by the vast majority.

Having in mind that during the period there is time to react if the demand is visible not covered by actions such as outsourcing production or introducing another work shift and still the costs are lower than spending resources on products which stay on the warehouse; MAPE will be used to measure accuracy even though sMAPE will be calculated in some occasions to be aware of the forecasting trend (is the model over-forecasting or under-producing)

5. Solution development

5.1. Proposed methodology to forecast new products

In this section the proposed methodology to forecast the sales of new frequently purchased products is described step by step. All the calculations can be easily undertaken in a Microsoft Excel file or similar.

Complete replication is vital, not only to expand the methodology between all the interested parts but as mentioned by Fader & Hardie (2005) a simple model is the one that can be reproduced by an student using already available software, and Microsoft Office products are the most used tools in the medium and small size companies. The fact that is easy replicable helps understand the managers and the forecasting team not only the model but the changes in the data and therefore to predict the consequences faster and better.

The structure of the methodology is the following:

1. Collect and process the data
2. Run all the selected models
3. Find the appropriate weights
4. Calculate the final forecast

5.1.1. Collect and process the data

It has been already explained that the lack of historical datum is the first handicap. To run the models at least it is needed to know:

1. Three periods of data sales. These data can come from pre-market test, market test or real sales.
2. Information about special events or promotions. Were there any promotions going on during the periods the sales were recorded?

When information from several sources is available the one more close to reality should be used, or in case there are not enough periods, they can be mixed. For instance, market test is preferred before pre-market test and real sales are preferred among the others. In case none of this information is available, old products sales from the same class can be used together with the experienced manager opinion.

At the same time the more information available about the special events or advertisement expenditures the better; in the ideal situation the GRPs for each period are known, but the minimum necessary to clean the data and avoid the special events mislead the forecasting is to simply know if there is or not any special event in each period.

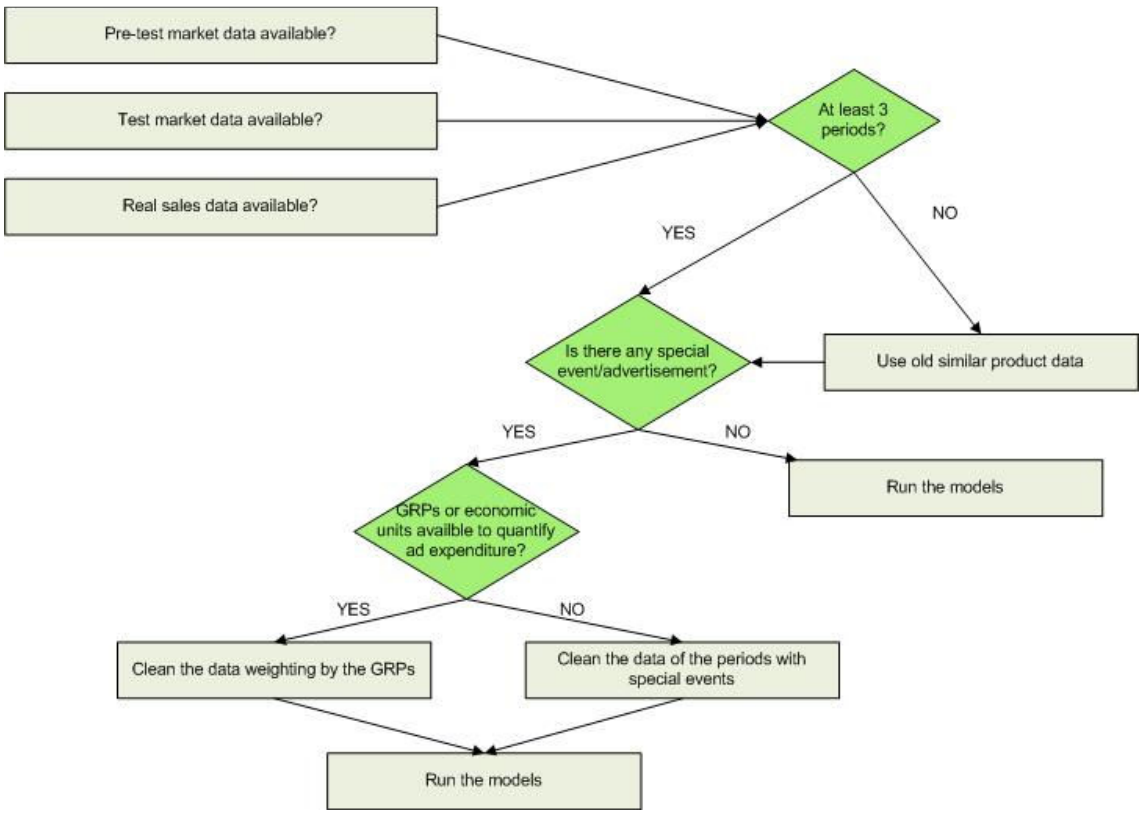
A special case is the diffusion model, only if the parameters “S” (saturation point), “I” (inflection point) and “A” (delay factor) are known is possible to run the diffusion model. Those parameters can be estimated by the management team or taken from similar old

products. If these parameters cannot be estimated the model is directly excluded, but it is still possible to run the other models.

Once the data is collected, it should be "cleaned" from special events and advertising influences using the methodology explained in section "4.2. Problems associated to data and model's nature". There are the two possibilities according to the data available.

The reason why the models are run with the cleaned data is because usually during launching periods companies are doing big efforts in promoting and the future sales predicted can be affected by the influence of those efforts. After forecasting the "cleaning" procedure can be applied in reverse if the management thinks it is appropriate.

The following graph summarizes the steps that have to be followed just before running the models:



Graph 5-1. Collect and process data

First of all the forecaster should have at least 3 periods of data that can provide from different sources (real data, pre-test or test market data). If it is not possible to have three periods of data coming from this sources then old similar products' data can be used, otherwise the forecaster can move to the next step.

If there is no information available about advertisement expenditure or special events the models can be run directly; if the information is available then the forecaster should act differently according to the type of information. If it is GRPs or other economic measure to

quantify the expenditure then is possible to clean the data by weighting. Otherwise, if only special events are known but the GRPs or similar are not available, the methodology explained in the equation 4.22 till 4.25 should be applied. After this process then the data is ready to be applied to the models.

5.1.2. Run the models

Once the data is cleaned from the advertisement or special events effect the different models can be applied to calculate a forecast. All the models mentioned in the section "4.1. Analysis of the quantitative methods" need at least three periods of data except for the logistic diffusion model.

Some of the models depend on certain variables that can take a wide range of values. For this reason the same calculations have to be done taken in account different values of the variables and finally take the one that provides a lower MAPE value. For instance, the simple moving average is calculated for N=3, N=2 and N=1 with the following results and using the data of the bread product (the whole data set can be found in appendix A.3) in order to forecast the sixth "unknown" period:

t	Sales corrected	N=3	Error N=3	N=2	Error N=2	N=1	Error N=1
3	211,60	-	-	-	-	-	-
4	133,57	-	-	-	-	211,60	0,58
5	217,77	-	-	172,58	0,21	133,57	0,39
6	?	187,65		175,67		217,77	
MAPE			?		0,21		0,49
sMAPE			?		0,23		0,47

Table 5-1. Simple moving average results

In this case, the MAPE is clearly better when using the N=2 (as N=3 can't be compared with any value), so this result will be recorded. Then, the rest of models have to be calculated, having in mind that for Brown and Holt exponential smoothing the values of gamma and alpha increase by 0,1 in each iteration.

t	Sales	α=0,1	α=0,2	α=0,3	α=0,4	α=0,5	α=0,6	α=0,7	α=0,8	α=0,9
3	211,60	197,55	197,55	197,55	197,55	197,55	197,55	197,55	197,55	197,55
4	133,57	198,95	200,36	201,76	203,17	204,57	205,98	207,38	208,79	210,20
5	217,77	192,41	187,00	181,30	175,33	169,07	162,53	155,71	148,61	141,23
6	?	194,95	193,15	192,24	192,30	193,42	195,67	199,15	203,94	210,11
MAPE (%)		22	24	25	26	27	29	30	32	33
sMAPE (%)		20	21	22	23	25	26	28	30	31

Table 5-2. Brown exponential smoothing forecast

In this case, simulating a real situation, the sixth period was forecasted based upon the previous three periods. The fact that for Brown exponential smoothing the selected alpha is 0,1 does not necessarily mean that the most optimal alpha for Holt exponential smoothing will the same as the formula used to calculate the forecasting is different.

If the forecaster is experienced enough to guess a starting alpha some calculations can be avoided, otherwise all the possibilities have to be checked. Some literature such as Chatfield & Yar (1988) proposed to take values of alphas starting in 0,4 but the values are very sensitive to change due to the few data available. For the same data set, all the combinations were forecasted giving the following MAPE results:

MAPE	α=0,1	α=0,2	α=0,3	α=0,4	α=0,5	α=0,6	α=0,7	α=0,8	α=0,9	Minimum
γ=0,9	58,53	50,51	43,35	37,06	31,62	32,51	36,20	40,75	46,17	31,62
γ=0,8	59,04	51,44	44,62	38,56	33,29	31,90	35,18	39,23	44,06	31,90
γ=0,7	59,55	52,38	45,90	40,11	35,01	31,37	34,27	37,87	42,15	31,37
γ=0,6	60,07	53,33	47,20	41,69	36,79	32,49	33,49	36,65	40,43	32,49
γ=0,5	60,58	54,29	48,53	43,31	38,63	34,48	32,82	35,59	38,90	32,82
γ=0,4	61,10	55,25	49,88	44,97	40,52	36,55	33,05	34,68	37,57	33,05
γ=0,3	61,62	56,23	51,25	46,66	42,48	38,71	35,34	33,93	36,43	33,93
γ=0,2	62,14	57,22	52,64	48,40	44,50	40,95	37,75	34,88	35,48	34,88
γ=0,1	62,67	58,21	54,05	50,17	46,58	43,28	40,27	37,55	35,12	35,12
Minimum	58,53	50,51	43,35	37,06	31,62	31,37	32,82	33,93	35,12	31,37

Table 5-3. Holt exponential smoothing results

As visible in the table the ones that provide a lower MAPE are alpha 0,6 and gamma 0,7. These values should be kept as well.

In case the parameters for the diffusion model would be known it will be calculated as shown in the section "4.1. Analysis of the quantitative methods", but as they are not available the last method is calculated: truncated Taylor series. And with the only three periods of data available the results are the following:

t	Corrected Sales (hl)	N=3	N=2
3	211,60	-	-
4	133,57	-	-
5	217,77	-	55,53
6	?	383,09	301,97
MAPE (%)		?	74,50
sMAPE (%)		?	118,72

Table 5-4. Truncated Taylor series results

At the point where all the models have been calculated, and the best parameters chosen, there is the need to establish the weight given to each forecasted value.

5.1.3. Find the appropriate weights

It has been stated by several authors that combining different forecasted values gives a better result than just using one forecasting methodology. One of those authors are Clements & Hendry (1998) which point out that the combination has only a sense if the models are significantly different one from the other or the nature of the data is different.

Establishing the weight for each method is indeed an optimization problem. Following the advice of Clements & Hendry (1998), the weights are found by minimizing the MSE (Mean Squared Error) as this measure gives a lot of importance to big errors. Such an optimization problem can be solved using the "Solver" tool of Microsoft Excel. The equation that gives the final forecast is:

$$F_6 = w_1 * F_{moving\ average} + w_2 * F_{Brown} + w_3 * F_{Holt} + w_4 * F_{Taylor} \quad \textbf{(eq 5.1)}$$

Where the constraints that the weights (w_i) have to follow are:

$$0 \leq w_i \leq 1 \quad \textbf{(eq 5.2)}$$

$$\sum_i w = 1 \quad \textbf{(eq 5.3)}$$

And finally the MSE is the cell to minimize (objective function):

$$MSE = \frac{\sum MSE_i}{i} = \frac{(F_3-A_3)^2-(F_4-A_4)^2-(F_5-A_5)^2}{3} \quad \textbf{(eq 5.4)}$$

Where each one of the F_i is calculated equally with the (eq 5.1) and then it is clear that the variables are included inside the objective function. Note that the objective function is not linear and therefore the option "Assume Linear Model" of the Solver tool should not be ticked. The problem being solved is a Quadratic problem as the objective function has quadratic values but the constraints are linear.

t	Sales	N=2	α=0,1	Holt	Taylor	Forecasted	MSE
3	211,60	-	197,55	140,73	-	173,22	1473,28
4	133,57	-	198,95	135,13	-	174,45	1671,38
5	217,77	172,58	192,41	88,28	55,53	189,97	772,72
6	?	175,67	194,95	174,44	301,97	192,57	
Weight		0,12	0,88	0,00	0,00		1305,79

Table 5-5. Solution of the optimization problem

Therefore, as can be read from the table, the moving average result is given a 0,12 in weight and the Brown exponential smoothing a 0,88. For this reason the forecasted result for period 6 is finally 192,57 kg. Having in mind that actually the value of period 6 is known and it equals a value of 227,24 the error done in the forecasting is slightly superior to 15%.

5.1.4. Calculate the final forecast

Even though, once the weights are calculated one could say the final forecast is done there is still one thing to have in mind. The data used to forecast had been previously cleaned of any distortion that advertisement expenditures or special events could have created; that is why the ideal would be to apply the effect removed back into the final result.

So, if it is known that no special event or no advertisement expenditure was accounted during the forecasted period the final result is the one calculated in the section "5.1.3. Find

the appropriate weights". In the opposite, the same ratio that was applied when cleaning the data should be applied here in order to increase (or decrease) the forecasted sales and provide a more accurate forecasting.

For instance in the given example, the real sales were divided by a ratio of 1,2618 calculated according to the GRPs of each period. Therefore the final forecasted sales of bread for period number six should be:

$$F_6 = r * F'_6 = 1{,}2618 * 192{,}57kg = 242{,}98kg \qquad \textbf{(eq 5.5)}$$

Being the final accuracy of:

$$\%Error = \frac{|A_6 - F_6|}{A_6} * 100 = \frac{|227{,}243 - 242{,}98|}{227{,}243} * 100 = 6{,}93\% \qquad \textbf{(eq 5.6)}$$

Therefore, it reached the goal of forecasting the next sales period with an error (MAPE) lower than 30%.

The same procedure just explained with the bread data set, was also applied to the soft alcoholic beverage drink giving as final forecasting for the fourth period a value of 9,345 hl of drink; which means a MAPE value of 6,34%. In this case all the four methods (N moving average, Brown exponential smoothing, Holt exponential smoothing and truncated Taylor series) had a weight in the final result.

Again the same procedure was applied, this time for the cola data set, taking the first 3 periods as known and the fourth to be forecasted. The final forecast after the optimization problem (there was no cleaning procedure of data as the information was not available) is 271,89 hl of cola, which represents a MAPE value of 5,92%. In this case not all the four methods had a non-negative weight, being the only ones contributing to the final forecast Brown exponential smoothing by 0,02 and Holt exponential smoothing by 0,98.

When running the "solver" and instead of the usual message the user gets the following: "Solver cannot improve the current solution. All the constraints are satisfied", then it means that "solver" is cycling. One option is that the system has redundant constraints, another option is that the "Automatic scaling" box has not been checked.

This issue is important as the values of the variables (weights) and the result of the objective function (MSE) differs of various orders of magnitude. This issue was faced when forecasting with a data set taken from Hyndman which represents the sales in thousands of liters of dry wine in Australia.

Unfortunately, in this case the forecasting results were not as good as expected and even surpassing the 30% maximum MAPE value expected. One of the possible reasons is the drastic fall of sales in the fourth period after a steady increasing during the first three periods. Moreover, no data about special effects is available in Hyndman and therefore it is impossible to know if there was a sudden stop in the advertisement expenditure or other marketing reasons to explain why during the third period sales were significantly higher

than in the predecessor periods. The MAPE value of the final forecast is 39,44%, and the result table is the following:

t	Sales	N=1	α=0,9	Holt	Taylor	Forecasted	MSE
1	1954,00	-	1827,50	1827,50	-	1827,50	16001,79
2	2302,00	1954,00	1941,35	2305,48	-	2305,48	12,12
3	3054,00	2302,00	2265,94	2618,71	2650,00	2618,72	189471,23
4	?	3054,00	2975,19	3366,01	3806,00	3366,02	
Weight		0,00	0,00	1,00	0,00		68495,05

Table 5-6. Dry wine forecasting

Nevertheless, as it is expressed in the table, the optimization problem is solved by using only one of the forecasts (Holt exponential smoothing). The reason why the optimization problem is proposed and solved is precisely to not use only one of the forecasts. Solver found this solution as the best because in period 2 and 3, Holt exponential smoothing forecast is much more accurate than the others but by using this result we are not applying the philosophy that the best forecast is that compound of several different forecasts weighted.

In this situation the manager has the power to decide, the solution given by solver can be accepted as a good one or either some modification can be done to it in order to adjust the result with the other methods forecasts.

For instance, a conservative approach could be to give a strong weight to Holt exponential smoothing (as it proved to be best during periods 2 and 3) but release some of the weight to the other methods (the amount given is on the manager opinion and experience). It could be for example weights of 0,2 for n-moving average and Brown exponential smoothing and 0,6 for Holt exponential smoothing, in this case a weight of 0 is given to Taylor method because its forecasts is significantly higher than the rest. With this weights the MAPE lowers till a value of 33,61% as the real sales in period four were of 2414 thousands of liters of dry wine. Emphasize that it is highly probable that marketing decisions are influencing the result but due to the lack of the information is impossible to proceed to clean the data and therefore reach a more accurate result.

From the same Hyndman library, some other data was extracted, for instance the data set including advertisement expenditure called “advert.dat”. The forecasting methodology was applied, this time being able to clean the data by calculating a ratio with their advertisement expenditures and later on multiplying the final forecast by it. Again the result was much more convenient, reaching a MAPE of 13% before applying the ratio and only a MAPE of 1,57% at the end.

Tables with the forecasting for each method and product with its respective weights can be found in appendix D.

5.2. Theoretical description of the software

Even though the procedure can be easily replicated with an excel spreadsheet if the user has a good command of the formula's use, idealistically a software could be created to make the procedure even more easy for the user. Though, on the other side creates a "black box", the user only introduces data and gets a result but does not understand the process which is the current problem with most of the software, as the user does not understand what the software is doing, it is impossible for it to interpret the result and take conclusions out of it.

This chapter won't create the complete software, but only will give some description of how the software should be as a future guideline for implementation.

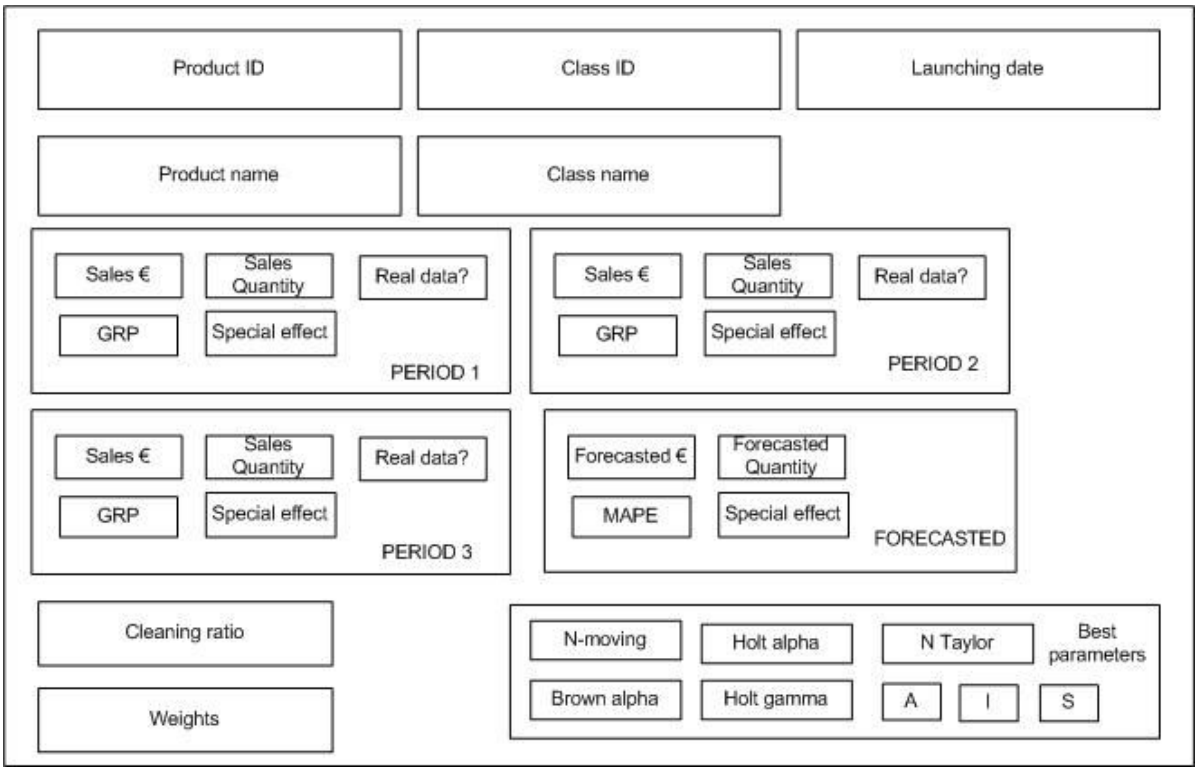
The language chosen to define and describe is C++ as it is the language taught during the studies of "Enginyeria Industrial" in UPC being this thesis under its curricula. Moreover C++ is object oriented design (OOD) which means that creates the programs by defining "object classes" and its relations; this approach is especially useful due to its easily re-usability of the code parts and its easy interpretation.

5.2.1. Data definition

It is a key point to define properly the data which the models have to use. Having in mind the C++ methodology, a product can be seen as a data structure with different fields containing the necessary information.

A data structure is a group of data elements grouped together under one name. The data elements forming the structure do not necessary need to be from the same type neither having the same length. (Cplusplus.com)

What this structure of data has to contain is the main information to recognize the product, its sales data periods and the forecasted result. Some of the fields proposed could be product ID, product name, class ID, class name, launching date, period N, Forecasted, weights, cleaning ratio, best parameters... It was decided to add two different type of sales data (economic and quantity) to prevent the occasion where both types are available and the forecasting can be done parallel regarding no big changes in the product price. A graphical example could be:



Graph 5-2.Data structure

And the type of variable for each one:

NAME	TYPE	NAME	TYPE
Product ID	int	**Cleaning ratio**	float
Product name	varchar (30)	**Weights**	
Class ID	int	w_nmoving	float
Class name	varchar (30)	w_brown	float
Launching date	int	w_holt	float
Period N		w_taylor	float
Sales €	float	w_diffusion	float
Sales Quantity	float	**Best parameters**	
Real data?	bool	N_moving	int
Special effect	bool	Brown alpha	float
GRP	float	Holt alpha	float
Forecasted		Holt gamma	float
Forecasted €	float	N Taylor	int
Forecasted Quantity	float	A	float
Special effect	bool	I	float
MAPE	float	S	float

Table 5-7.Data types

The variables types described above are the fundamental data types in C++, “int” defines the variable as an integer number (size 4 bytes), “float” defines the variable as a fractional number (size 4 bytes) and “bool” defined the variable as a Boolean, which can take the

value 0 or 1 (size 1 byte). The fundamental type “char” in this case is not enough to define the product as it only represents one character alphanumeric in one byte; this is why “Varchar” is used. It is a chain of characters of a defined length: varchar(n), in this case the length is 30 characters as it is thought to be enough to differentiate the given products. The definitions of the fundamental types in c++ programming were taken from Gatius, et al. (2010).

To define the data type there is a need for bigger structures than just the fundamental types. Where first smaller structures have to be define for “Period”, “Weights” and “Best parameters” in order to create the bigger type “Product”.

To create the structure the command “class” could be used. “Class” is an extension of C++ versus C that allows protecting the data structure by being the parameters by default private. Moreover it is possible to create functions that operate only over the members of the class. The word “public” shows that the members of the class can be accessed from outside the class (other options are “private” and “protected”). (Porter, 1993)

A construction function was also created inside the class in order to initialize faster its members. For instance, the command needed to initialize the first period of data of a certain product could be:

```
Period P1; //declaration of a variable class Period

P1.Period(100300, 20500, 1, 1, 550); //initialize the variable
```

Meaning that the period number 1 supposed 100.300€ income, 20.500 kg of product sold, this quantities were real sales and not estimated or taken from a market test and there was a special effect quantified in 550 GRPs.

All the data structures created as an example can be found in appendix E.

5.2.2. Structure of the program

The main idea of this simple software description is being able to have the calculations done without the need to deal with huge excel tables. It is possible to improve the system and create more complicate devices communicating different departments of the company through the internet or blocking certain information to specific users; these are all extra specifications that can be implemented by an experimented programmer in order to make the system more user-friendly but they are not the purpose of this project.

To start running the program the user should introduce the basic amount of data needed: information about the product and the class and the first three periods of data (at least). The other variable values will be created by the system and they are initialized by default to zero.

Certain auxiliary variables will be created and saved during the calculations process of each method in order to save the forecasted values and being able to make comparisons at the end of the process. The result of the comparisons will be saved under the “Bestp”

structure; so this means that "`Parameters.N_moving`" will store the N value that provides a forecast with lower MAPE, the same applies for the other models.

Finally when all the best parameters for each method have been chosen, it is time to run the optimization problem. There is several tools that can be used for it, there is no need in developing the whole program in C++ but already implemented software can be used as for instance Midaco Solver. Once optimized, the formula (eq 5.1) should be calculated and in case there was any special effect the solution should be multiplied by the cleaning ratio. Finally the user can read the information about the final forecast (saved in the variable F, class Forecasted) on the screen.

As mentioned, it is not the goal to develop the code of the whole software, nevertheless a clear structure of how the simplest solution could work is described next. The text that the user will read on the program console is written in *italics*.

1. *Insert Product name (max. 30 characters).*
2. *Insert Insert Product ID (max. 30 characters).*
3. *Insert Class name (Class ID (max. 30 characters).*
4. *Insert the number of data periods available (t).*
5. *Insert the data for period 1 in the following order: sales in €, sales in quantity, real data (1 for yes, 0 for no), special events (1 for yes, 0 for no), GRP (type 0 if the data is not available).*
6. The last step will be repeated as many times as periods of data available (t) introduced by the user.
7. If any of the values of "special_effect" is 1, calculate the cleaning ratio. Else continue to the next step.
    a. If all the GRPs are equal to 0, but "special_effect" adopts different values depending on the period; then the cleaning ratio should be calculated dividing the mean sales during the periods with special effects by the mean sales of the periods without special effects.
    b. If any GRP value is different to 0 then the weighted sales with special effects should be divided by the mean sales without GRP expenditure.
    c. In both cases, real sales should be divided by the cleaning ratio and store in a new internal variable in order to do the calculations.
8. *Insert A, I and S for the diffusion model (in case this data is not available insert 0).*
9. If A=I=S=0, then do not run the diffusion model and assign to the diffusion weight the value 0. If A, I and S have values different to 0, run the diffusion model and save the forecasted value in an internal variable.
10. Run the N-moving average model "t-1" times.
11. Calculate the MAPE for each N.
12. The iteration with a minimum MAPE is the only one whose results should be saved, and the number of iteration assigned to "Bestp.n_moving".
13. Run the Brown exponential smoothing model. Starting value for alpha in 0,9.
14. Calculate the MAPE value for alpha=0,9.
15. Decrease the alpha by 0,1 and calculate the forecast again.

16. Calculate MAPE for alpha=0,8. If the MAPE for alpha 0,9 is lower than the MAPE for alpha 0,8, then save the alpha value in “Bestp.alpha_brown” and save the forecasting results in an internal variable. Else, continue decreasing by 0,1 the alpha value till the MAPE value of the bigger alpha is lower than the lower alpha.
17. Run the Holt exponential smoothing model. Starting value for alpha 0,9 and gamma 0,1.
18. Calculate the MAPE for the current alpha and gamma values.
19. Increase by 0,1 the gamma value and keep stable the alpha value. Calculate the forecast with these values.
20. Calculate the MAPE for alpha 0,9 and gamma 0,2. If MAPE (γ=0,1) < MAPE(γ=0,2). Then save the values of the variables and the forecasted values and move to alpha 0,8 and gamma 0,1. But if, MAPE (γ=0,1) > MAPE(γ=0,2), then increase gamma by 0, 1 and repeat this step.
21. At the end, there should be nine pairs of variables saved (one for each alpha value) and a search looking for the smallest MAPE value should be done. The value corresponding to the smallest MAPE should be saved in “Bestp.Holt_alpha” and “Bestp.Holt_gamma”.
22. Taylor model should be run with 1<N<t-1.
23. Calculate the MAPE for each N value.
24. Save the value of N with smallest MAPE in “Bestp.n_taylor” and register the forecasted values in auxiliary variables.
25. Run the optimization program (Midaco or similar) in order to find the weights for each method and save the results in the corresponding variable.
26. If the cleaning ratio is different from 0, then multiply the forecasted value resulting from the optimization problem by it and save the result in “Forecasted.forecasted_e” or “Forecasted.forecasted_q”. If the cleaning ratio is 0, go to next step.
27. Show the final forecast in the screen for the user to read.

6. Project's budget

In order to determine the budget for the project the activities and expenses are divided according to the phases followed to create the forecasting methodology: preparation, investigation and final phase. Next, find the explanations of the expenditure for each phase and at the end the summarizing table with the total values.

According to the study plan of "Enginyeria Industrial" the final thesis has a 24 credit value, which translated to hours according with the formula provided in the final thesis guidelines corresponds to a minimum of 540 hours invested in the development of this project. In this case, the project was done between middle February till September 2012.

6.1. Preparation phase

This phase includes all the study time and materials previous to the project; as the author was not very familiar with the problematic it was the longest phase.

Meaning three seminars with two professors from the "Departament d'Organització d'Empreses" and one from "Departament d'Enginyeria de Sistemes, Automàtica i Informàtica Industrial" from Escola Tècnica Superior d'Enginyeria Industrial de Barcelona from "Universitat Politècnica de Catalunya" (UPC). Having a total duration of ten hours, as the seminars where held in the university facilities there was no need to rent any meeting room or similar and therefore the logistics costs of these seminars is inexistent. The price per hour considered for all the budget is 30€/h.

The main task during this period was collecting information from reliable sources. Most of the articles used can be accessed freely thanks to the free access to "Web of Knowledge" provided by the university library to all the UPC students, some others were found through "Google Scholar" and only a very few amount had to be purchased (10€).

Due to the huge amount of information that needed to be processed the most relevant articles were printed. In total, an amount of 200 impressions were done in the university copy store.

The total amount of hours employed in this phase was 190, divided in reading articles and analyzing the problem.

6.2. Investigation phase

In this phase again the fungible materials did not represent the biggest expense. A symbolic amount of 10€ is counted for office materials, such as pens and plastic folders. Moreover, 100 impressions more used to proof-read parts of the chapters that had already been started to write during this phase, such as the state of the art.

The time spent on the project is divided in three different tasks: data testing, checking the test for bugs and mistakes and creation of the model. The time spent in each one of these tasks is respectively 50, 20 and 70 hours.

6.3. Final phase

In this phase, conclusions had to be taken from the test results, but the most important part is to write clearly all the procedures that had been done and write the report and appendixes. The time spent on each one of these tasks is 40 and 180 hours.

The table representing the total amount of hours distributed and the expenses of the project are the following:

Concept	Units		Unitary cost (€)	Total (€)
1. Preparation phase				
1.1. Three seminars with professors+ company	10	h	120	1200
1.2. Purchasing articles	2	articles	10	20
1.3. Reading articles	100	h	30	3000
1.4. Printed materials	200	copies	0,05	10
1.5. Problem analysis	80	h	30	2400
2. Investigation phase				
2.1. Printed materials	100	copies	0,05	5
2.2. Data tests	50	h	30	1500
2.3. Check for bugs and mistakes in the testing	20	h	30	600
2.4. Model creation	70	h	30	2100
2.5. Office material	-		10	10
3. Final phase				
3.1. Analyse the results of the forecasting	40	h	30	1200
3.2. Writing the report and appendixes	180	h	30	5400
TOTAL				**17445**

Table 6-1.Project budget

7. Environmental impact

In every project is necessary to study the impact and consequences in the environment (soil, air, water, flora and fauna, landscape and used resources) and the society. Each project affects the environment in a different way so an exhaustive study should be developed before implementing it. The study should analyze every step of the project from the pre-project stage, the construction stage to the dismantling stage.

It is possible to classify this project as a software project. This kind of projects do not have a remarkable direct effect on the environmental as there is no soil or water resources directly used to the development of it, the biggest impact of software projects is often social. Nevertheless the economic impact on the manufacturers industries of applying the tools developed in this project has to be taken in account.

For the development of the project itself, mainly computer devices were used, being electricity the most important used resource. There was not a need to effectuate large calculation which could involve having the computer open for hours and for this reason the computer devices were only switch on when it was necessary and disconnected during periods of inactivity.

At the same time, “F.lux” software was used. This software regulates the brightness of the screen according to the time, season and working conditions, avoiding the use of extra energy to light the computer screen if there is enough light outside and, at the same time, a better lighting of the screen does not blind the users eyes despite being night or late.

The other possible source of impact in the environment is the materials printed in order to develop the project. This means mainly two resources, paper and tonner. The printings where done in the copy store belonging to the university and therefore the used tonners are treated according to the university regulation and it is out of the author’s control; being this part probably the one with more environmental impact. Approximately 300 pages were printed between investigation articles and draft versions of the project, the pages that were not useful anymore were if possible reused or recycled.

The possible impact of using the methodology proposed in this project in a real company is very wide. A better sales forecast implies a better production planning, optimizing the company resources and labor. If each period sales is forecasted more accurately, the stock is less numerous and the possibility to predict a product failure higher; therefore resources that in the past where used and were warehoused for long periods are not spent, meaning a saving in raw materials, unnecessary transportation and energy as well as labor.

Moreover, products that are predicted to be unsuccessful are directly disregarded and never mass manufactured; saving not only the already mentioned but testing, economic resources, and labor time in the development stages. This way firms can use their resources in developing other new products that might be successful.

8. Conclusions

The project strives to give a methodology to forecast sales of frequently purchased new products, especially for aliments and beverages. Several situations are presented depending on the amount of data available (number of periods) and the background data or economic information about advertisement expenditures.

A special concern was the capacity to replicate the results. The methodology developed does not follow the “black box” structure, where the user introduces inputs and get outputs without knowing the process in between. All the methodology can be replicated by using a Microsoft Excel spreadsheet and some add-ins such as Solver, giving the user the possibility to modify the final result according to its own experience and at the same time learn about the sensitivity of the forecasting.

After an extensive analysis on the existing mathematical models to forecast sales, the more appropriate for new products and the most suitable for the kind of data available were chosen. Finally five models are considered in the methodology: N-moving average, Brown exponential smoothing, Holt exponential smoothing, a logistic diffusion model and Truncated Taylor series.

In order to test the methodology five products sales were forecasted. Having only three periods of data for each product, four of them reached the goal to forecast the fourth period sales with a MAPE value lower than 30%, actually all four of them with a MAPE value under 10%. The product that did not succeed to perform under thirty percent had a difference on the data available as the information about advertisement expenditure was not known and it has been proved to be critical in the first periods.

Therefore it can be concluded that the methodology works under the desired conditions if there is at list three periods of data available and any kind of information regarding special events or advertisement expenditure. The sales from the first three periods can also be deduced from pre-market or market tests. The methodology can also be used using hypothetical data in order to forecasts sales in different scenarios.

Some recommendations for the future are implementing user-friendly software in order to automate the procedure. Though it will create a black-box structure, at the same time it helps to expand the procedure among other users that do not have the ability to use Microsoft Excel in a high level of command. In this project only some indications and a possible simple structure were given, but the range of possibilities is high.

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