Forecast for products with a short life cycle and their relationship with the supply chain

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Resumen: El propósito de este trabajo es formular y describir un método de pronóstico para productos con ciclo de vida corto. La ecuación logística y la curva-S son el punto de partida para modelar el comportamiento de la demanda de un producto con esta propiedad, por ejemplo videojuegos o teléfonos móviles y en general tecnologías de base electrónica. El mercado actual favorece con creces la variedad, la novedad y el *status quo* que brinda los artefactos electrónicos, en consecuencia la gestión de la cadena de abastecimiento debe responder con flexibilidad y prontitud, modificando las condiciones de planeación del aprovisionamiento, el sistema de producción y la logística de distribución, siempre y cuando el método de pronóstico reduzca sustancialmente la incertidumbre, estimando la duración posible del ciclo de vida y el máximo volumen de ventas que podrá ser descrito por un modelo de difusión.

Palabras clave: Logística, pronóstico, cadena de abastecimiento, ciclo de vida.

Abstract: The purpose of this paper is to formulate and describe a forecasting method for products with a short life cycle. The logistic equation and the S-curve are the starting point for modeling the demand behavior of a product with this property, for example videogames or mobile phones and in general technologies based on electronics. The current market is more conducive to the variety, novelty and *status quo* of electronic devices, so supply chain management must respond flexibly and promptly, by modifying the conditions of supply planning, the production system and distribution logistics, provided that the forecasting method substantially reduces uncertainty, estimating the possible life-cycle duration and the maximum sales volume that can be described by a diffusion model.

Key words: Logistics, forecasting, supply chain, life cycle.

1. Introduction

Companies need to have control over their operations, increase their planning capacity and convert data into knowledge, to minimize costs and increase profits; for this reason it becomes extremely important to achieve accurate forecasts. These are instruments of planning of the productive organization and even allow estimating the magnitude of the profitability. In addition, they provide information that serves to decide the level of risk that the organization takes based on the management of resources, in the achievement of the established goals. Forecasts is the input information for any ERP (Enterprise Resource Planning), which triggers all activities to be carried out within the business and in the supply chain. Not all products have the same life cycle, some have it longer and in others it is ephemeral, they can also be in the introductory or declining stage. The life cycle analogy has been a popular forecasting method despite its qualitative nature, which has been the starting point for formulating quantitative methods that contribute to the design of supply chain management and respond to the urgency of predict the behavior of the demand in particular of new products or Short Life Cycle (SLC).

The objective of this work is to build a forecast model for products with a short life cycle and to look at their role in the management of the supply chain. Chung (2012) states that the electronic games industry even generalizes that any entertainment media product has a reduced life cycle. The logistic function, the diffusion models and the S curve, respond to equations that describe an exponential growth phenomenon, which will then reach a maximum level and stop. Similar to the life cycle of a product; Initially the market is launched with increased sales up to a maximum limit, for example a new mobile phone model or a Tablet, it is sold generously at the beginning, however if an innovation or new Tablet arrives, whether it is from the competition or its own, it will affect the sales in such a way that there is a rapid decline reaching obsolescence and death of the product in question.

Many of the current products exhibit a Short Life Cycle (SLC), of months or very few years, perhaps maximum three. Televisions and telephones of the 1950s easily had a life cycle of 20 years or more, today it is necessary to update the device to two or three years but less. Concepts such as "programmed obsolescence", technological innovation and consumer capitalism, are intimately related, in all cases they wipe out the environment, depredating natural resources and turning them into polluting waste, just for the sake of making money and low the pretext of increasing the quality of life of the client. The virtue of saving, the concern for reparation and "conscious consumption" have been replaced by exhibitionism, narcissism and fashion "Selfie". This background and business competitiveness have shortened the life cycle of products, particularly electronic and entertainment products; digital cameras, consoles or video games, cell phones and computers, among many others, are products that are marketed in the market for 12 to 24 months, but are then replaced, improved or surpassed by new products, making them obsolete either by use or by perception.

Making an effective forecast is not easy, each organization according to its type of business must find the best way to do it. You must understand what are the factors that influence the behavior of the demand, as well as the processes that facilitate the availability of the product or service for the final customer. When the company proposes its strategic direction, in which it formulates the mission and vision, scaling them up into objectives, then into goals, then into specific, measurable, achievable, realistic and determined indicators over a period of time (Darío, 2012). It includes the degree of uncertainty implicit in the operating results and, of course, in the indicators, which are essential for making the production plan and foreseeing the disposition of resources (Orozco, 2012). Reducing uncertainty along the entire supply chain is the key aspect (Chopra & Meindl, 2013), the selection of the prediction method is crucial in this task, as well as the understanding of the characteristics of demand behavior.

Demand prediction methods are as varied as the nature of the products or the consumer's consumption habits, ranging from classic qualitative methods such as the Delphi or the life cycle analogy (Chase, Aquilino, & Jacobs, 2009), quantitative techniques based on time series, such as exponential smoothing (Nahmias, 2007), Brown's method, Winter's method, simple and multiple linear regression (Krajewski, Ritzman & Malhotra, 2010) or hybrid methods such as prospective (Godet, 2000), scenario planning (Chermack, Lynham & Ruona, 2001), even more sophisticated based on metaheuristics; genetic algorithms or neural networks, but what method to use when you have little data and you know exactly that the product will die in a short time? That is, knowing in advance that the life cycle of the product is ephemeral. Consequently, what characteristics should the management of the supply chain have when the products are from SLC?

2. Forecasts and supply chain management

Among the many considerations in the formulation of a project, the expansion of a business or the sizing of operations, the estimation of demand requires a special effort, above all, due to the speed of the changes, the quality required and the diversity of the competition. There are so many factors that influence the future behavior of demand that it is necessary to complement any prediction of demand with other types of studies such as prospective, strategic analysis and scenarios, including sectorial characterization studies, technological intelligence or regional logistics. Even then no company will be totally sure that the forecast will be fulfilled.

Therefore, it is very important to characterize the economic structure of the market, identify the market of inputs and materials, technical and human talent, which are part of the business, because these factors determine the future and the magnitude of operations. What to produce? How much to produce? And where to produce? Should be answered clearly and accurately. In this way, the work to make a forecast will have fruits in context and will help validate the quantitative techniques that are used.

The forecast is a quantitative estimate about the possibility and credibility of future events that is elaborated based on past and current information (Pindyck & Rubinfeld, 2001). Demand forecasts are defined as the prediction of what can happen with a variable (demand in the market) in the future to determine the planning of an entire production line or purchase orders (García, 2003). From another perspective, forecasts are considered as a critical element in decision systems in the areas of production or administration of operations in which the logistics management processes are also related, such as purchases, inventories, among others (Buffa, 1976).

The forecast is a prediction of future events, its purpose is to reduce the risk in decision making. The forecasts are usually in error, the magnitude of this depends on the method used and the characteristics of the demand (Velásquez, 2003). A forecast that is much deviated from the actual data indicates that the model or method must be adjusted, revised or changed. To perform the evaluation of the model, the error is calculated using the appropriate statistical tests. The best forecast is considered to be the one that produces the smallest average difference and with minimum variance, between the real and predicted data.

Supply chain management has become the mantra of many companies looking for a way to meet the competitive challenges of today's business environment. Supply chain management is a broader perspective of the business environment, compared to more traditional approaches. Instead of managing a business as a virtually separate group of functions, supply chain management sees these functions as tightly connected links in a chain. The chain extends beyond the boundaries of the organization to include suppliers and customers. The supply chain management involves the entire flow of a product from the purchase of raw materials from the supplier, to the purchase made by the final consumer. The concept of supply chain management is based on several key principles. The key principle is that the entire strategy, decisions and measurements are made taking into account their effect on the entire supply chain, not just separate functions or organizations. This broader approach is based on partnerships and the exchange of information between the links in the chain. The objective of the management of the supply chain is to satisfy the needs of the final consumer by supplying the right product in the right place, time and price. The supply chain management approach allows companies to meet this objective, while gaining competitive advantages (Helms, Ettkin and Chapman, 2000).

As companies implement supply chain management, they should look for ways to bring the concept to each of the functional areas of their organization. This requires making the cultural and process changes that support the concept of Supply Chain Management (SCM), which will ultimately lead to the levels of savings, efficiency and customer service they seek. The function of forecasting must be an area with priority, in the functional redesign and in the change of logistic processes. The demand of the final customer is the driving force behind the activities in the supply chain. Each of the links in the chain operates in reaction to the actual or anticipated demand of the consumer. The level of precision and efficiency with which this demand is communicated up and down the chain is directly related to the levels of inventory and customer service. Forecasting and demand planning are therefore a key factor in the successful implementation of a supply chain management strategy (Helms et al., 2000). The whip effect evidenced and exemplified in the "beer game" (Senge, 1999), describes how the supply chain of a local beer is affected by the variation in consumer demand, increasing the error of the forecasts and increased the inventories of the retailer, the wholesaler and the manufacturer, thus generating over costs and cancellation of orders (Velásquez et al., 2008).

The complexity and uncertainty that exist in the supply chain make the concept of accurate and effective prediction a difficult goal to achieve. Many companies, however, are making significant improvements by using an approach that supports and facilitates the concept of supply chain management. Collaborative prediction is a way in which the entire supply chain participates in the decisions about the demand that will boost its activity. Collaborative prediction reaches internally and externally to collect information that allows the best and most timely predictions of demand. The latest technological advances are used to collect and gather information, as well as to transmit forecasts to chain members (Helms et al., 2000).

The forecast is often highly criticized in any company regardless of whether it is the responsibility of finance, marketing, sales or logistics. Most companies know that their forecasts are inaccurate, but they do not know what to do about it and therefore ignore the problem. The idea that forecasts are always inaccurate and that there is nothing that can be done forces companies to find ways to compensate for uncertainty. The most used method is to increase inventories or reserves of security. Thus each link in the chain creates its own buffers for the uncertainty of the forecast. However, in articles with SLC, it is very expensive to have shock absorbers since they become easily obsolete and therefore in loss of money. It is necessary to establish accurately the inventories in the distribution channel or the capacity of the same and that once the product reaches its phase of decline only very attractive promotions would save those inventories from obsolescence.

The flexibility in managing the supply chain for products with a short life cycle requires reducing vulnerability and the occurrence of unpredictable events. Flexibility is the strategy with which it seeks to respond quickly to demand when it occurs, not from inventories, but from production processes or suppliers, avoiding long delivery periods or excessive inventories. Products with a short life cycle have a rapid obsolescence, which generates inventory lags due to uncertain demand, probable causes of whip effect, which makes it difficult to make decisions about the size of the production lot and a low level of customer service. Therefore, an adequate design of a supply chain for this type of product is required (Alarcón, Peña & Rivera, 2016).

The market has inexplicable variations, it grows quickly and capriciously. The demand of the product is very uncertain and unpredictable in its launch, this generates absence of sales history and makes difficult the use of classic models for calculating forecasts. The decrease in the quality of the sales forecast leads to an immediate increase in the level of security stocks, whose function is to compensate for unpredictable variations in demand. Moreover, the expected demand shows growth and decline in a shorter time; this makes the use of an accurate forecast for these items more demanding. Likewise, the company must be more flexible in terms of changes in its production capacity in accordance with the market demand. As for the inventories, they have high turnover and their possibility of accumulating for the final period is greater. The importance of considering phantom demand is that it can alter the perception of real demand; for products with a short life cycle, their recognition time in the system plays a key role, since it facilitates the accurate decision making. (Alarcón et al., 2016).

3. Forecast methods

Demand forecasts are defined as the prediction of what can happen with a variable (demand in the market) in the future to determine the planning of an entire production line or purchase orders (Garcia, 2003). From another perspective, forecasts are considered as a critical element in decision systems in the areas of production, management of operations in which they relate to logistics management processes such as purchases, inventories, among others (Buffa, 1976). Likewise, they affect the design of production systems since they affect the use of production capacity, processes, personnel hiring and distribution planning (Garcia, 2003).

Demand forecasting techniques can be grouped as follows (Navales, 2012):

- Explanatory or causal methods: They use historical data and their objective is to determine the behavior of the demand according to the causes that produce the variations (Garcia, 2009). Some examples are multiple regression or econometric models.
- Simulation models: Determine by means of a model in the form of an algorithm to establish the parameters that best suit the demand.
- Models of historical projection: Linear regression, moving averages, exponential smoothing, Brown, Holt, Winter and ARIMA are found.
- Metaheristic models: They consist of algorithms that find feasible solutions that although often do not reach the optimum, they are reasonably close, they are applied in very complex problems. They are applied when there is no exact method, when a necessarily optimal solution is not required, as an intermediate step for another application. Some cases are:

    - Neuro-diffuse models: hybrid neuro-diffuse model based on the dynamic update of the adaptation and calibration of the diffuse heuristic learning rules.
    - Vector support machines: model of vector support machines that uses a hybrid method of selection of relevant inputs in order to improve the model's forecast, the F-Score method is applied to filter the inputs and the F-SSFS method for select the optimal characteristics of the input data.
    - Neural networks: two models are presented for the forecast of the direction of market index changes: a model based on multilayer perceptron neural networks and an adaptive model of exponential smoothing in which the parameters of the model are updated throughout of the prediction; hybrid model of artificial neural networks that uses rules defined by experts used for the training of the neural network.

- Association rules: model based on data mining techniques to find association rules for the prediction of the direction of market index changes, time series of other indices are used to predict the target index.

The forecasting methods are varied and there are multiple alternatives to make the projections. Now we will review alternative methods for the projection of sales of products with short life cycle (SLC).

4. Forecast model for short life cycle products

The demand for a product with SLC, can be described with an S-curve and the logistic equation, then the mathematical model is explained in detail and the technique that allows to minimize the error, make the adjustment and find the parameters of the logistic function, is presented an example solved using real sales data for a TV (LG 42 LED Full HD Smart TV-Silver)

What does it mean that a product exhibits a short life cycle (SLC)? The concept is very relative, however, planning horizons of one to two years, are recognized as short term, keeping proportions it is possible to identify this category. So, how to establish a forecast for this type of products? The products with SLC, will die soon, this destination requires therefore to establish a border or perhaps a maximum expected sale (diffusion of Bass), estimated the horizon and define the goals, it only remains to describe the behavior of sales. The same uncertainty will be high, an example of unsuccessful products that are not sold or that are launched on the market but that are never welcomed or worse are immediately replaced by other innovations.

A. Product Life Cycle

The life cycle of the product is a metaphor and analogy of existence, originated by neo-Darwinian biology (birth, growth, reproduction and death) applied to consumer goods. The dynamics of the market evolves significantly, the consumerism, the perception of the client and the constant creation of innovations, causes that the life cycle of the product today is very short, of months in the case of electronic and digital products; telephones, computers, televisions and printers. The life cycle of the product is defined as the period of time since a good or service goes through the phases of design, introduction, growth, maturity, decline and discarding (Krishnamoorthi, 2012).

Figure 1 shows the stages of the product life cycle and the sales levels (D) for each period (t). During the introduction phase the product is put on the market and acceptance is low. In growth the product starts to have better sales due to the efforts put in place during the launch. At maturity, sales grow continuously and consolidate reaching the highest point of the cycle. During the decline and discard the sales begin to decrease absolutely while the product is replaced by new products.

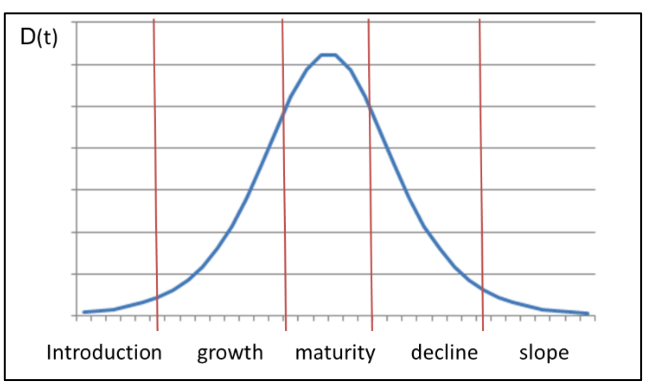

Figure 1. Product life cycle (Kucharavy y De Guio, 2007).

The first requirement to design a forecasting method for products with a short life cycle is to initiate sales (introduction stage), keep the records day by day or week by week, the records could be between 20% - 25% of the time of the expected life cycle, perhaps 52 to 80 weeks or according to SLC's product sales experience.

The product life cycle (PLC) can be represented by an S curve, provided that the performance function (sales or demand) is plotted historical data accumulated. Figure 2 shows the number of accumulated units that are placed on the market during the product life cycle (ΣD (t), cumulative sales).

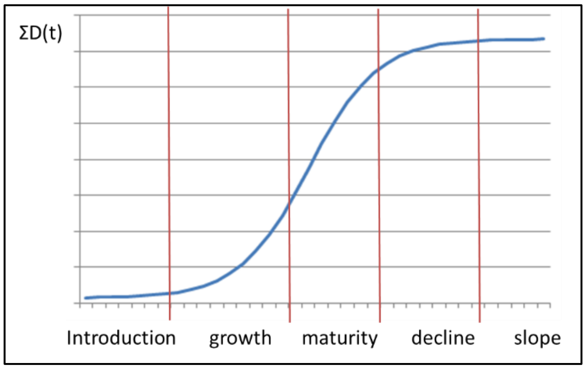

Figure 2. Curve S of the product life cycle (Buccini et al., 2011)

So far are traditional concepts and necessary to understand the behavior of the sales of a product, its significance is in its application to products with SLC, based on mathematical modeling.

B. The Product Life Cycle as a prediction method.

A strategic investment and marketing plan can be made based on the life cycle of the products, using a logistic model. The CVP analysis starts from graphing a performance parameter accumulated over time, presenting a curve type behavior in S. The inflection point indicates the moment in which the performance of the product decreases. The most widely used model to predict this behavior is that of Verhulst (Belgian mathematician, 1804-1849), called logistic model (Aguilar, Avalos, Giraldo, Quintero, Zartha & Cortes, 2012).

The logistic equation was introduced to describe the self-limiting growth of a population, equation (1). Today this model is often used to describe the dynamics of systems. For example, a population of bacteria grows in a closed container. The rate of chemicals in the bacteria transformation broth is proportional to the number of bacteria present and the transformable concentration of chemicals. Solution to this problem of calculation and evolution of the population is a logistic function (Kucharavy and De Guio, 2007):

$$N(t) = \frac{m}{1+e^{-(ct+d)}} \qquad (1)$$

m = function asymptote
c = Growth parameter
d = Point of inflection

A product lifecycle can be divided into several stages characterized by revenue generated.

There are different situations that make the demand forecast complex for SLC products. On the one hand, the time series of demand for these non-stationary products is not linear and is transitory.

These are disadvantages despite the existence of forecasting methods for linear and non-linear time series, since they generally require large amounts of data to obtain accurate forecasts (Basallo, 2012).

By using the life cycle, companies can anticipate sales behavior and their evolution, and can develop strategies to influence sales. This paper demonstrates how the logistic function and the Bass method can be used to predict the life cycle of a new product.

C. The Bass model

Estimating the future demand for an existing product in the market is a complex task. But there is no doubt that the task of predicting the potential demand of a new product, unknown until now in the market, is even more complex. At the end of the decade of the 60s, Frank Bass developed a mathematical model known as the "Bass Broadcast Model", which has been the cornerstone of the different techniques for estimating the demand for new products over the years, last 40 years. Its use has had an immense influence on marketing and administration, particularly in the last 10 years given the remarkable shortening of the life cycle of products as a result of the incessant and growing flow of technological innovation (Weissmann, 2008).

According to the Bass model, which allows estimating the number of consumers who will adopt (start buying) a new product over time, innovators or avant-garde dare or risk acquiring the new product regardless of what the consumer does, rest of society. Meanwhile, the rest of the consumers, the so-called imitators, only begin to consume the new product once they have observed that others already consume it and as a result of the interaction and influence of the innovators on the imitators. The model assumes that an individual consumes a product only once, which is why it was initially used for durable consumer products such as televisions, dry-clothes, dishwashers and refrigerators. The basic parameters of the model are:

m: maximum number of consumers that can acquire the product, number of adopters or potential market.
p: coefficient of innovation. It is the probability or rate at which an innovator buys the product in period t.
q: imitation coefficient. It is the probability that an imitator adopts the new product. It is also called contagious effect.

$$S(t) = [p+(q/m)*N(t-1)]\ [m-N(t-1)] \qquad (2)$$

Where:

- $N(t)$ = number of consumers who adopted the product at time t.
- $S(t)$ = number of new consumers who adopted the product in period t.

So:

$$S(t) = N(t) - N(t-1) \qquad (3)$$

From equation (2) it can be interpreted that $S(t)$ is equal to the product between the probability that a new consumer acquires the product at time t (first bracket) and the number of consumers who have not yet adopted the product (second bracket). Given the parameters *m*, *p* and *q* (both greater than zero) it is possible to plot the curve of adoption of a new product with S curves, that is, the curve of accumulated sales $N(t)$;

$$N_t = m \left(\frac{1- e^{-(p+q)t}}{1-\frac{q}{p}e^{-(p+q)t}} \right) \qquad (4)$$

The moment of maximum sales

$$t^* = \frac{\ln q - \ln p}{p+q} \qquad (5)$$

Next, the logistic equation is presented as an alternative method.

D. The Verhulst model (logistic equation)

Supply chain management does not work exactly the same for consumer products as for products such as DVDs or books, which have a short life cycle. Affecting the forecast of the demand, the inventories and the management of the production. In this case, it is necessary to estimate the demand per period, the accumulated sales observed and the total possible sales, using the logistic model. For an example with CD see Berbain (2011).

For each t an N_t will be calculated, it is assumed that the demand has a sigmoid behavior:

$$N_t = a + \frac{b}{1+e^{-c(t-p)}} \qquad (6)$$

Notation:

N_t: Value of the function in period t
a: Initial value
$a + b$: Asymptote of the function
c: Growth parameter
p: Inflection point

Where N_t is the cumulative sales function, which describes the life cycle of the product.

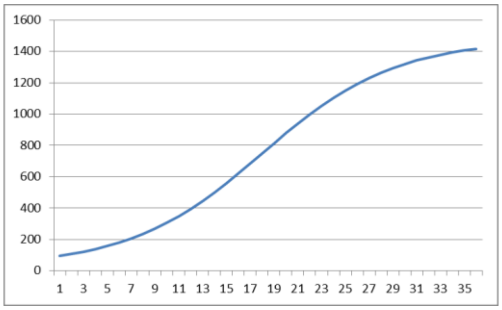

Figure 3. S curve, cumulative sales.

a and b is the upper limit or maximum estimated sale, c growth parameter, t the time or analysis period and p the point in time where sales begin to decrease.

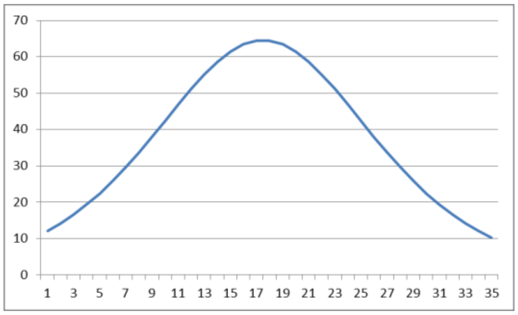

Figure 4. Product life cycle sales by period

Based on these two models; the Bass and the logistic equation was an application case to evaluate the predictive capacity of demand for a SLC product.

5. Application case

The methodology that will be presented in the development of this article was applied in data provided by a commercial company of varied products on the Internet, this company had the need to increase the accuracy of the forecasts and redefine its replenishment model to increase the level of customer service and reduce inventory costs mainly represented by obsolescence. The situation is described below:

- The methods of traditional forecasts or for products with a long life cycle generate over stock, costs due to obsolescence, so it had excess inventory of codes of low demand and missing codes of high demand.
- The forecast of the demand, quantities and frequency of purchase were calculated with a model based on the average weekly sales. The control of the inventories was carried out by means of a systematized transcript based on the Regional Repurchasing Model (own application).
- According to a survey conducted by the company, 17 percent of the customers were completely dissatisfied with the service provided by the company. Basically for the shortage in the best-selling products or newly introduced in the market.

A. Problem excesses of stock and missing

Leftovers and shortages are basically caused by the calculation of the forecast, which is traditionally based on averages and safety inventories. For example, for a TV (LG 42 LED Full HD Smart TV-Silver) the maximum expected demand is D (13.020), it was calculated based on the average of the most deviation, the average of sales up to the current period, 250 units (22 weeks) multiplied by 52 weeks (maximum life cycle size).

$$D_m = {}^{\sigma}/_{r} + \overline{D} * m \quad ; \quad D_{52} = {}^{417}/_{22} + 250 * 52 \qquad (7)$$

The stock or missing is calculated based on the stock in storage, estimated, for the TV is 53 units, the costs of asking and storing are calculated, they add up to $ 4,194,447, costs are added for missing or left over, which corresponds to 50% of the costs of the unit for the number of units, for the Television, $ 26,561,503, for a total of $ 800,161,720, only for the first 10 items, for 22 weeks of operation. The proposed model substantially reduces these costs.

B. Application of the Bass model

Based on historical sales data of a TV (LG 42 LED Full HD Smart TV-Silver), a population of adopters m = 10,000, p = 0.348 and q = 110.2 were estimated minimizing the mean square error (MSE), with Excel solver, non-linear regression model. In addition, the average life is 52 weeks (maximum duration).

Minimization of MSE (718.248):

$$Min\ MSE = \frac{1}{22}\sum_{i=1}^{22}(Ventas_t - N_t)^2 \qquad (8)$$

Results for p = 0.348 and q = 110.2

Table I. Non-linear adjustment

t	Sales(t)	N(t)	MSE(t)
1	1.323	1.381	3.414
2	1.014	931	6.915
3	1.303	669	402.541
4	587	515	5.226
5	326	417	8.266
6	163	350	34.980
7	82	302	48.209
8	150	265	13.196
9	41	236	38.080
10	41	213	29.594
11	66	194	16.394
12	33	178	21.071
13	41	165	15.296
14	13	153	19.627
15	124	143	362
16	100	134	1.171
17	31	126	9.105
18	45	119	5.547
19	21	113	8.513
20	-	108	11.591
21	1	103	10.320
22	4	98	8.830
∑Total	5.509	6.913	718.248
Average	250	314	

$$N(t) = 10.000\left(\frac{1-e^{-(0.348+110.2)t}}{1-\frac{110.2}{0.348}e^{-(0.348+110.2)t}}\right) \quad (9)$$

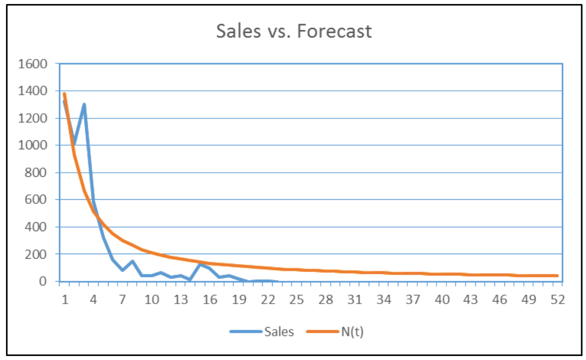

Figure 6. Forecast with the Bass model

The Bass model as observed, overestimates the future demand, for the period 23 a demand of 94 up to a demand for the 52 period of 42 units, although it is much lower than the forecasts that the company previously made, still presents an excess of inventory.

Results of accumulated sales:

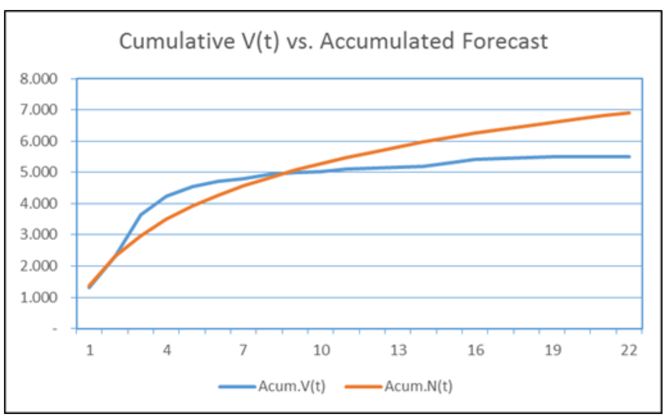

Figure 7. Forecast with the Bass model

C. Application of the Verhulst model

To estimate the parameters of the following logistic function:

$$N_t = a + \frac{b}{1+e^{-c(t-p)}} \qquad (10)$$

The mean squared error (MSE) was calculated, then by means of Excel Solver, it is minimized by varying the parameters, until reaching the optimal values.

$$Min\ MSE = \frac{1}{n}\sum_{i=1}^{n}(Acum.V_t - N_t)^2 \qquad (11)$$

Table II. S-curve estimation

t	V(t)	F(t)	Accum.V(t)	N(t)	MSE(t)
1	1.323	1816	1.323	1.816	243.306
2	1.014	576	2.337	2.392	3.073
3	1.303	868	3.640	3.261	143.707
4	587	877	4.227	4.138	7.929
5	326	591	4.553	4.729	31.125
6	163	299	4.716	5.028	97.408
7	82	129	4.798	5.157	128.938
8	150	52	4.948	5.209	68.110
9	41	20	4.989	5.229	57.727
10	41	8	5.030	5.237	42.892
11	66	3	5.096	5.240	20.771
12	33	1	5.129	5.241	12.606
13	41	0	5.170	5.242	5.144
14	13	0	5.183	5.242	3.468
15	124	0	5.307	5.242	4.230
16	100	0	5.407	5.242	27.230
17	31	0	5.438	5.242	38.418
18	45	0	5.483	5.242	58.082
19	21	0	5.504	5.242	68.644
20	0	0	5.504	5.242	68.644
21	1	0	5.505	5.242	69.169
22	4	0	5.509	5.242	71.289
∑Total	5.509	5.242			1.271.912
Average	250	238			

Minimization of MSE (1.271.912):

$$Min\ MSE = \frac{1}{22}\sum_{i=1}^{22}(Acum.V_t - N_t)^2 \qquad (12)$$

Results for a = 1.323 b = 3.919, c = 0.958 y p = 3.023

$$N_t = 1.323 + \frac{3.919}{1+e^{-0.958(t-3.023)}} \qquad (13)$$

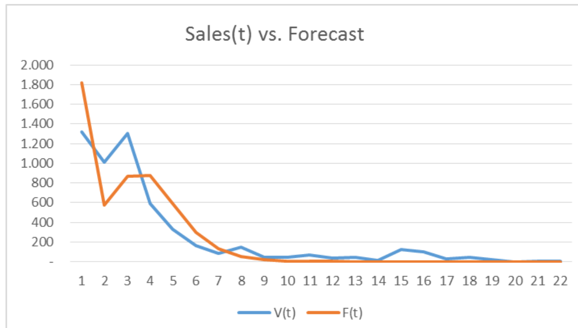

Figure 8. Accumulated sales and forecast

It is observed that the curve N_t, from period 13 is blind to the residual sales, that is, that predicts the sale of zero units, which insurance will not generate on inventory, but perhaps surely some missing, at least for 10 weeks, which is a serious situation.

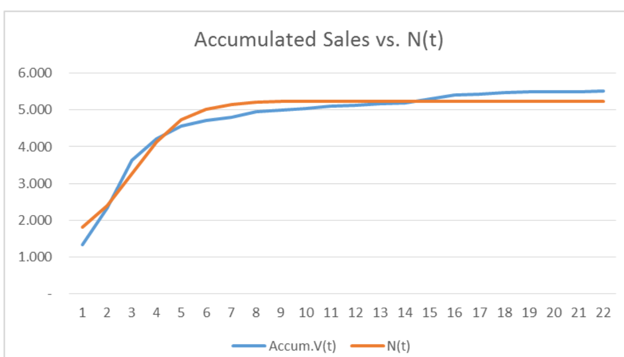

Figure 9. Product life cycle Vs. Logistic function

As noted, the adjustment is acceptable. In Figure 9, it is evident that demand D_t, decreases as the life cycle of the product (TV) is exhausted.

6. Discussion of results

Both the Bass model and the Verhulst model (logistic function), although they reduce the problem, they do not solve it, the first one because of excess and the second one because of defect. Here it is proposed to make an adjustment to the logistic method, calculating a maximum demand for period 52 and estimating the parameters c and p. Without taking into account the initial value of sales, take the value of b and add the deviation to the current period, r = 22.

$$D_m = b + \sigma_r \quad ; \quad D_{52} = 3.919 + 417 = 4.336 \qquad (14)$$

Table III. Second adjustment

t	V(t)	F(t)	Accum.V(t)	N(t)
1	1.323	2268	1.323	2.268
2	1.014	407	2.337	2.675
3	1.303	487	3.640	3.163
4	587	524	4.227	3.686
5	326	502	4.553	4.188
6	163	430	4.716	4.618
7	82	335	4.798	4.954
8	150	242	4.948	5.196
9	41	166	4.989	5.362
10	41	109	5.030	5.472
11	66	70	5.096	5.542
12	33	44	5.129	5.586
13	41	28	5.170	5.614
14	13	17	5.183	5.631
15	124	11	5.307	5.642
16	100	7	5.407	5.648
17	31	4	5.438	5.652
18	45	3	5.483	5.655
19	21	2	5.504	5.657
20	0	1	5.504	5.657
21	1	1	5.505	5.658
22	4	0	5.509	5.658
∑Total	5.509	5.658		
Average	250	257		

The new parameters are obtained and with the new logistic function the forecast is performed, c = 0.486 and p = 3.628.

$$N_t = 1.323 + \frac{4.336}{1+e^{-0,486(t-3,628)}} \qquad (15)$$

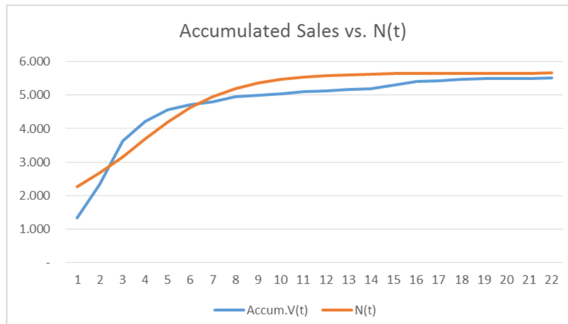

Figure 10. Cumulative sales Vs. Logistic function

It is observed that the new logistic function is above the historical data, it is a sign of a better approximation.

This exploratory trial has shown that it is possible to establish a method adjusted to the historical sales data of a product with SLC, effectively reducing the current problem of excess inventories and therefore high costs of maintaining inventory, especially those caused by obsolescence and the need to make onerous promotions to leave the inventory close to death.

In the next phase, any model proposal must be validated statistically with tests such as Durbin-Watson or Kolmogórov-Smirnov. Which were omitted but with the adjustment over the minimum of the non-linear MSE is the best approximation.

The main result is to reduce the costs of maintaining inventory for the TV of \$ 26,561,503, the current existence is 154, according to the last sale of 4 units the serious scope for 39 weeks, that is to say that you have inventory until the week 61, which implies a constant behavior of sales, it is evident that there is an over stock since the prediction according to the applied models is zero, if the second adjusted forecast model had been applied, the company would not have the 154 units in inventory, but it would have a maximum of 4. Thus the savings would be around 20 million.

Conclusion

As technology becomes faster and smarter, the availability of supply chains to share information increases, so the forecasting function can be radically different, for example the replacement of inventory by information is a reality in the management of the supply chain. That is, the company should not release purchase orders until a credible estimate of the possible sale is guaranteed. So, for SLC products, monitoring must be real in time to activate supply chain management and make it effective, minimizing the costs of maintaining inventory and the risks of obsolescence.

The models explored in this essay need to be complemented with methodologies such as; Collaborative forecasting, CFAR and CPFR technology, coordinating the planning and forecasting efforts among the external partners of the supply chain, reducing uncertainty. It is likely that the forecast function evolves to intelligent and deterministic certainty levels, pulling the operations eliminating the need to push. The role of the forecaster will be to coordinate and manage the information in the supply chain in such a way that "zero forecast" is achieved.

Managing information, cooperation and relationships along the entire supply chain require changes in traditional behaviors and ways of thinking about the forecasting process, and also requires a spirit of partnership between customers, suppliers and manufacturers, leading to a credible, timely and accurate exchange of information.

It is possible to design a model tailored to the needs of a company to solve particular problems. Today products have a very short life cycle, which is not contemplated by most of the planning, forecasting or inventory models, but it is increasingly common to find sales structures for SLC products.

The techniques proposed here reduce uncertainty, reduce excess merchandise and therefore minimize the risk of obsolescence and inventory costs, as was demonstrated in this article.

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