SERVICE LEVEL DEFINITION FROM FORECAST ERROR COST EVALUATION

Sosa A.[(a)], Wellens A.[(b)]

[(a),(b)]Facultad de Ingeniería, UNAM-MÉXICO

[(a)]armandososas@yahoo.com.mx, [(b)]wann@unam.mx

ABSTRACT
Although forecast errors can imply important losses, frequently its financial impact in business is neglected; some researchers have studied this issue but it is not being used as a common tool for evaluation of the forecasting process. The present paper describes the assessment of the forecast error cost in order to define the most appropriate service level for an inventory control system, considering a product classification that is able to focus on those articles that need more management attention. A key point is the cost function, which allows to quantify the over forecasting cost represented by excess inventory and the under forecasting cost represented by lost sales.

Keywords: forecasting, service level costs, inventory optimization

1. INTRODUCTION
Forecasting for business is a very important process in any industry; finding a formal method to assess the result is particularly of interest. In order to improve the forecasting process, many metrics have been developed, as for example MAPE, Bias, MAD, tracking signal among others; for a complete overview please see Makridakis (1997).
In the last decade, different authors have implemented approaches where the cost associated to forecast errors was introduced as a metric. Some of these methods are very general, as for example the determination of an associated index in balanced scorecards. Others are more specific; for example, Kahn (2003) takes into account monetary costs for lost sales, operational inefficiency and transport costs for urgent stock replenishments, quantifying the effect of a 1% over or under deviation of the prediction during one year. Götz and Köhler (2006) define a metric to quantify the cost of error based on lost sales and the cost of residual inventory; however, they do not consider safety stock so they find many lost sales as a consequence. Catt (2007) proposes a cost function where holding cost and lost sales are the main components of the cost of forecast error estimation (CFE). Singh (2013) shows a forecast accuracy impact in both financial and operational KPI´s, and establishes the relationship between forecast accuracy, customer service and shipping cost and finally simulates the cost of forecast error.
In this paper, the CFE metric proposed by Catt (2007) is preferred as it considers both relevant costs and poor service, and even when some assumptions are subjective (for example, the percentage of lost sales), it is a very practical approach that has been well received by experts in the field.
A correct forecast is difficult to achieve, as many variables impact the final result and randomness is present at different levels. In an intend to find a realistic approach to assess the financial impact of forecast error that can be used to define the optimal service level, this paper presents a practical guide to get more accurate results in the forecasting process and measure its effect in the company profits.

1.1. Product Classification
A product classification is crucial for making appropriate planning decisions, as the products in a catalogue not necessarily pertain to the same category, and the inventory should be constructed accordingly (Broeckelmann, 1998). The ABC classification is very extended and well known; it is frequently used as service level tag, due to a strong desire to have better service levels for the items at the top of the scale, and leaving lower service levels for C parts. However, it can lack information, as some items with high demands but low costs can be ranked low, while a high cost article with low volume can be ranked at the top. A fixed service level specification by product category does not consider the accuracy of the forecast and therefore can cause unnecessary costs, for example, considering a low service level for a highly predictable B or C part or a high service level for an A or B part that is very difficult to forecast. In this way, the information obtained by the forecast technique can be inconsistent with the service level specification suggested by the ABC classification. To overcome this inconvenient, this paper proposes a wider classification in order to strengthen the link within the information for every item, by adding a third factor, volatility, and combining all three factors. In this way, articles become more relevant if one of these elements is important, whichever the cause is: cost, volume or volatility.

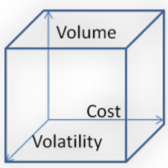

Figure 1: Tridimensional VCV Classification

1.2. Product Life Cycle

In a context of shorter and shorter product life cycles, it is relevant to point out that the proposed methodology is applied to articles in a maturity stage, or at the end of the growth phase, which is when its growth rate is decreasing significantly.

1.3. Volume, Cost and Volatility

Having three factors for the classification of any product in high, medium or low-level items defines 27 different classification options. The *volume* corresponds to the number of parts sold during a given period of time, usually one year. In general, the range in *cost* for different items in a catalogue can be huge; consider for example the difference in cost for a machine and a spare part. The concept of *volatility* is given by a statistical measure, and corresponds to the variation coefficient, which is the standard deviation of the past sales divided by the corresponding mean:

$$CV = \frac{\sigma}{\mu} \tag{1}$$

This measure shows how scattered the data are with respect to the mean, so a high volatility or a high scattering means a potentially less accurate forecast; on the opposite, a low volatility allows a higher accuracy and therefore less forecast error and a lower forecast error cost. Previous studies indicate that a high correlation exists between the volatility and the forecast error, so considering this measure in the final classification can give a clue about the articles that need special attention in order to increase the forecast accuracy.

1.4. VCV Matrix

To be able to use the volume-cost-volatility matrix (VCV matrix – Figure 1) as a standard for comparison, it is necessary to define for each product its level for these three components; normally *low*, *medium* and *high* are used, but depending on the type of facility a different range can be proposed. In this paper, the mean and standard deviation of each set of data for volume and cost will be used to define the ranges corresponding to low (first 2 σ), medium ($\mu \pm \sigma$) or high (last 2 σ) levels. Limits for volume and cost are defined in terms of business data, while the category range for volatility is dimensionless and is valid in any case. Different authors consider different ranges where volatility can be considered high; in this study a range of 0.2 – 0.6 is considered for medium volatility. Table 1 shows the proposed definition of the ranges for volume, cost and volatility.

Table 1: Ranges for the Definition of the VCV Matrix

	Volume / Cost	Volatility
Low	$x < (\mu - \sigma)$	$x < 0.2$
Medium	$(\mu - \sigma) < x < (\mu + \sigma)$	$0.2 < x < 0.6$
High	$x > (\mu + \sigma)$	$x > 0.6$

2. FORECAST MODELS

Choosing the right forecasting technique is vital for the prediction process. The next step is to compare different models in order to select the best fit for every item. Common models with reliable results are single exponential smoothing or SES, double exponential smoothing or DES and the Winters method which considers all components in demand patterns, being the level component, trend and seasonality. Generally, a naïve method is recommended as a starting point as it can be used without extra costs in readily available spreadsheet software as for example Excel. Its results can be compared with the results of the other methods; any additional forecast effort has to add value to the process (Gilliland, 2010).

An additional step is to optimize the smoothing parameters for every component in the model; for SES the parameter corresponds to alpha, for DES they are alpha and beta, and for the Winters method parameters are alpha, beta and gamma. All of them are optimized by a nonlinear method in order to get the minimum error and therefore the best fit. The objective function is represented by a forecast performance metric like the mean absolute deviation (MAD), which is minimized. In addition, restrictions for non negativity and values below 1 have to be set.

3. METRICS

Different metrics in forecast evaluation are available; calculating more than one allows a better understanding of the forecasting process. Some of the most useful and less biased metrics are presented here, although from a practical viewpoint only one is needed when assessing the forecast; in this case, either MAD or the standard deviation are proposed.

The most used metrics are the forecast accuracy, the bias, the mean absolute deviation and the tracking signal.

3.1. Forecast Accuracy

A measure of forecasting performance that has the useful characteristic of always being scaled between 0% and 100% is the *forecast accuracy*, *FA*. It uses the maximum within the actual or forecast as the denominator (Hawitt 2010). Kolassa and Martin (2011) show that there exists less bias when using the maximum of the actual and forecast instead of using the forecast or actual in the denominator, as the mean absolute percentage error (MAPE) does.

$$FA = \left(1 - \frac{\sum|F - A|}{\sum max(F, A)}\right) * 100 \tag{2}$$

3.2. Bias

The *bias* is a measure of forecasting performance that indicates whether the forecast is chronically too high (positive bias) or too low (negative bias).

$$Bias = 100 * \left[\left(\frac{\sum F}{\sum A}\right) - 1\right] \tag{3}$$

If the loss function of overestimating or underestimating is asymmetric, a bias in a given direction would be preferable.

3.3. Mean Absolute Deviation

The *mean absolute deviation*, *MAD*, is the average of the absolute forecasting errors through time, given as follows:

$$MAD = \frac{1}{n}\sum_{t=1}^{n}|F_t - A_t| \quad (4)$$

It is the most common metric to evaluate forecasts and its relationship with the corresponding standard deviation has been proved to be a factor of approximately 1.25.

3.4. Tracking Signal

The *tracking signal* for a given period *t*, TS_t, is the ratio of bias and MAD in this time period and shows when a forecast is out of control. In that case a change in forecast model is recommended.

$$TS_t = \frac{Bias_t}{MAD_t} \quad (5)$$

4. INVENTORY MODELS

Depending on the inventory model definition, different costs are considered relevant; any model can be addressed, but generally EPQ models are used for production environments, while EOQ models with backorder and lost sales are the most appropriate ones for commercial services. It is important to evaluate in which case a customer would be willing to wait for a product which is out of stock and in which cases the customer just cannot wait. For retail companies, costs of inadequate stock can be huge. Corsten and Gruen (2004) report results of a survey of 71,000 retail consumers worldwide. They found that if the desired item is out of stock, 31% of the customers will leave the store to buy it elsewhere, while another 9% will choose not to make the purchase at all; this consideration depends on the brand and type of product, as a commodity can be replaced very easily, but a specialized item cannot. In general, three different situations can occur for any out of stock product demanded by a customer: the customer can wait which means a backorder, the customer cannot wait which means a lost sale and finally the brand or store can substitute the necessity of the customer with a similar product. In this case, the company does not lose a customer but sales records will be biased and thus will not reflect the real needs of the customer.

It is necessary to express the occurrence probability for each of these situations and to distinguish between different classes of items; in this paper, item categories include commodities, specialized articles and intermediate products for which more than one competitor offers an available solution. A possible probability distribution is shown in Table 2.

Table 2: Probability Distributions of Stock Out Customer Reactions

Item category	Backorder	Lost sales	Substitute
Commodity	0	0.8	0.2
Medium	0.2	0.5	0.3
Speciality	0.8	0.1	0.1

Depending on the type of item (for example, rice vs. iPhone) and the strength of the brand in the market, these probabilities can vary, and an appropriately conducted research at the point of sales will be needed to show how willing clients are to substitute their preferred product.

5. INVENTORY COSTS

The inventory cost can be divided in three different types, being the holding cost, the setup cost and the shortage cost. On the other hand, also a cost due to forecast error can be defined.

5.1. Holding Cost

The holding cost is the cost due to having the item available in stock; it is an opportunity cost for capital tied up in inventory and in this sense it is important not to include in the inventory expensive slow movers whose holding cost could provide a higher return when using an alternative investment. The dominating part of the holding cost usually corresponds to the capital cost. Other costs included are material handling, storage, damage and obsolescence, insurance, and taxes. All costs that vary with inventory level should be included (Axsäter 2006).

5.2. Ordering or Setup Cost

There are usually fixed costs associated with replenishment (independent of the batch size). In production, common reasons are setup and learning costs. Also administrative costs and fixed costs associated with transportation and material handling have to be included and can decrease if order size increases. The setup cost may be especially high if an expensive capacity constrained machine has to stop during the setup. In some situations, though, most of the setup can take place outside the machine, which reduces the costs. When ordering from an outside supplier there are also various fixed costs for an order, like costs for order forms, authorization, receiving, inspection, and handling of invoices from the supplier (Axsäter 2006).

5.3. Shortage Cost

If an item is demanded and cannot be delivered due to a shortage, various costs can occur. There are situations where a customer agrees to wait while his order is backlogged, but also situations when the customer chooses some other supplier. If the customer order is backlogged, there are often extra costs for administration, price discounts for late deliveries,

material handling, and transportation. If the sale is lost, the contribution of the sale is also lost. In any case, this usually means a loss of goodwill that may affect sales in the long run. Most of these costs are difficult to estimate. Shortage costs in production are, in general, even more difficult to estimate. For example, a missing component can cause a chain of negative consequences like delays, rescheduling, etc.
There are also situations when shortage costs are easy to evaluate. Assume, for example, that a missing component can be bought at a higher price in a store next door. The additional cost can then be considered as the shortage cost. Because shortage costs are so difficult to estimate, it is very common to replace them by a suitable service constraint. Of course it is also difficult to determine a suitable service level, but yet it is regarded to be somewhat simpler in most practical situations. Still, the motivation for a service constraint is nearly always some underlying shortage cost (Axsäter 2006).

5.4. Cost of Forecast Error

The cost of forecast error (CFE) was introduced by Catt (2007), in addition to the common metrics that measure the forecast error. This metric measures the impact in cost and indicates if it is more convenient to under- or overestimate the inventory needed to satisfy the customers' requirements, so it can be used to plan the inventory in a more efficient way. The cost of forecast error (CFE) is represented by:

$$CFE = \left(SS * v * r + \frac{B_s * m_p * \sigma\sqrt{L+R} * G_u(k)}{R} \right) * P \tag{6}$$

CFE = annual cost of forecast error, \$
SS = safety stock, units
v = unit cost, \$/unit
r = inventory carrying charge, \$/month
B_s = lost sales margin per unit short
m_p = product margin, \$
$\sigma\sqrt{L+R}$ = standard deviation of forecast error, units over the replenishment cycle
$G_u(k)$ = loss function used to calculate shortages per replenishment cycle
R = review period
P = period multiplier to convert from months to year

It is common to refer to the total inventory as total stock (TS). The total stock is partitioned into two components: cycle stock (CS) and safety stock (SS). The cycle stock is needed to fill the forecast of demands from the customers, and the safety stock is needed in case the demand exceeds the forecast or supply fluctuations.
Assuming a normal distribution for the demand, the security factor can be found as the z-value corresponding to the service level or probability not to stock out. The loss function is than the probability to be out of stock (Table 3).

Table 3: Security Factor and Loss Function as a Function of the Service Level

Service Level	Security Factor (k)	Normal Loss Function
90%	1,28	0,0475
91%	1,34	0,0417
92%	1,41	0,0358
93%	1,48	0,0306
94%	1,55	0,0261
95%	1,64	0,0211
96%	1,75	0,0161
97%	1,88	0,0116
98%	2,05	0,0074
99%	2,33	0,0033

The safety stock is the product of the service factor given a desired service level and the standard deviation of forecast error and lead time:

$$SS = k\sigma\sqrt{L} \tag{7}$$

$$\sigma \approx 1.25MAD \tag{8}$$

6. SIMULATION

Sometimes it can be difficult to choose suitable inventory control methods; for example, if the service level is suddenly changed, it can take weeks before the consequences are observed. If the change turns out to increment unsustainably the inventory levels or provokes lost sales due to missing items, the change in service level can highly impact financial results.
One way to evaluate different control methods without taking them to practice is to use simulation. In simulation, the real system is replaced with a mathematical model. Simulation experiments can be carried out very quickly and can be used for analyzing the system. Using simulation, it is possible to evaluate the system's long time behaviour in a few seconds; in this case, it is easy to make various test runs with different inventory control techniques. A simulation model has, however, the same type of limits as other mathematical models and can never give a complete illustration of the real system.

7. STUDY CASE

The proposed VCV classification and posterior simulation was applied in a specific department of a retail store in Mexico City, where data for the 300 items of the product portfolio of a specific department were available, including two years of historical sales for most of the items. Currently, and according to top management guidelines, the service level is set to 95%. At present, the moving average forecast model is used, which is a very simple model. The retail store is interested in comparing the forecast error cost for their actual policy and wants to establish if a new service level policy is necessary after balancing the cost of overestimating against the cost of underestimating.

At present, the service level policy is the same for each item, although an optimal service level for different types of products may lower overall costs. As a part of the methodology and to focus on some specific items, a classification is proposed based on cost, volume and volatility where H stands for *high*, M for *medium* and L for *low*. The first letter corresponds to *volume*, the second one to *cost* and the last one to *volatility*, so HML stands for example for a product with high volume, medium cost and low volatility. The VCV classification for the items in the study case is presented in Table 4.

Table 4: VCV Classification for the Study Case

VCV Classification	items	MAD/ mean ratio	CFE Share	Management attention
MHM	12	28%	24%	**special**
MHH	8	40%	20%	**special**
MMM	29	21%	12%	**special**
HHM	2	20%	7%	**special**
LHM	16	27%	6%	**special**
MML	25	16%	5%	regular
HML	8	16%	5%	regular
LMM	37	25%	4%	regular
LMH	16	35%	3%	regular
MLM	33	20%	2%	regular
HMM	2	19%	2%	regular
HLL	14	15%	2%	regular
MMH	3	35%	2%	regular
HHL	1	16%	2%	regular
MLH	14	31%	1%	regular
MLL	35	15%	1%	regular
LHH	6	45%	1%	regular
HLM	6	18%	1%	regular
MHL	1	23%	0%	regular
LML	10	17%	0%	regular
LLH	6	36%	0%	regular
LLM	11	20%	0%	regular
LHL	1	19%	0%	regular
LLL	4	19%	0%	regular
HHH	0	NA	NA	NA
HMH	0	NA	NA	NA
HLH	0	NA	NA	NA
All items	300	20%	100%	

Table 4 includes the number of items in each VCV classification and the corresponding level of management attention required; it also includes the MAD/mean ratio in order to recognize those categories with highest forecast error, and finally the cost share per classification. Medium and low volatilities are observed for more than 80% of the products, making its forecasting less complicated. It can be observed from table 4 that items with high volatility present high MAD/mean ratios (37% on average), being low volume, high cost and high volatility the worst combination for accurate forecasting. However, forecast accuracy is not always the best criterion to determine priorities, as items with low forecast accuracy not necessarily have the biggest influence on the cost of forecasting. To define the items that require special attention, the CFE share is proposed in addition to the MAD/mean ratio, finding 5 categories (MHM, MHH, MMM, HHM and LHM) that include 22% of the total number of items and represents 68% of the total cost of forecast error; items with these characteristics will require more attention and effort to improve the forecast process.

7.1. Forecast Model Results

The presently used moving average model was compared to an alternative method, being *single exponential smoothing* (SES) the best fit. SES is an appropriate forecast model for the study case data, as a regular pattern for demand without trend and with low volatility can be observed and SES fits well. Moreover, the purpose of this investigation, in addition to the assessment of the results of the forecast technique, is to measure the financial impact of a forecast deviation, so a more complex model like ARIMA can be evaluated in future research.

As a next step, the smoothing factor α for the level component of the historical sales was optimized through a non linear process using solver, minimizing the MAD subject to a non negativity restriction and ensuring it to take values between 0 and 1. In general, the common method of moving averages works well due to the fact that the data shows a constant pattern and a low or medium volatility for most items. The average reduction of MAD using the SES method with regard to the moving average method is of about 12%, which is a considerable improvement. Based on informal comparisons with real demands in the past, the forecast model presently used by the store's administration seems to forecast with acceptable results; however, as no formal comparison or evaluation was ever carried out, the improvement obtained with the proposed method cannot be quantified.

Figure 2 shows the last two years of sales at an aggregated level, showing a steady behaviour, calculating a coefficient of variation of 0.12, being considered low.

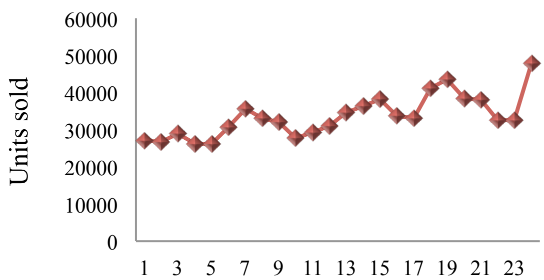

Figure 2: Aggregated Sales, 2013 – 2015.

The final step of the forecasting process is its evaluation. As mentioned before, although different metrics can be used, MAD is preferred for two reasons. In the first place because the current planning system determines MAD as a default output and according to equation (8) there is a proportional relationship between the amount of safety stock required and MAD, so no additional calculation step is needed.

7.2. Inventory Model Results

As the study case corresponds to a retail store where the products come from several suppliers, the model that best fits is the classical economic order quantity (EOQ), assuming a constant demand and an immediate supplier response. Furthermore, the portfolio does not include any special product, neither a commodity; instead, for most of the products moderate competence exist, so all products can be considered in the second category defined in Table 2 which corresponds to a 50% probability of lost sales if a stock out takes place.

7.3. Costs

Once the forecast has been optimized, the next step is to determine the costs inherent to forecast error. As discussed before, many factors can be involved but two of them are the most important, being the inventory holding cost and the cost of lost sales.

7.3.1. Inventory Holding Cost

The most important factor is the opportunity cost, as the average gross utility margin in the retail store in study is about 50%. A higher rate could result if an investment in a different product category is considered, although alternative investments always involve a risk. Another component of interest is the storage cost, as the store is located in an area of expensive rental rates. Although it is difficult to apportion the holding cost among individual products, generally a good estimation is 35% of the capital cost per year per unit.

7.3.2. Cost of lost sales

As reported by Corsten and Gruen (2004), the loss of utility margins in retail can be up to 40%; additionally, a penalty of 10% for loss of future margins as a result of customer dissatisfaction will be considered, so 50% of loss margin can be reasonable for a product provided by more than one competitor (Table 2). Of course, this can differ depending on the brand, the product, accessibility to other stores and customer loyalty.

7.3.3. Cost of forecast error

The purpose of this study is to measure the financial impact of forecast deviation in order to provide an optimal service level, and many variables are involved. The safety stock results from the desired service factor and the standard deviation or MAD of the forecast errors through time. The higher the MAD and the service factor, the higher will be the amount of stock needed; on the other hand, the loss function of normal distribution will be smaller, as well as the cost of lost sales.

The unit cost, the stock out penalty and the margin can vary with every product in a given portfolio, and therefore also the holding cost, which makes the computation more complex. The cost function is the key step in order to balance the overestimating and underestimating costs and thus optimize the total cost using the proper service level.

The cost function involves two components: one of them represents the forecast overestimation which increases the inventory holding cost, while the second part represents the underestimation of real sales and therefore lost sales. A key point is to understand to which kind of deviation the cost is more sensible in order to assure that if a forecast bias exist, it is always in the less expensive way.

7.3.4. Simulation

Given the difficulty to optimize the service level, the MAD and loss function for 300 items each month, a practical and cheaper method to find a solution is to simulate the impact of service level variations and possible MAD reduction, estimating the cost reduction through an improvement in the forecasting process.

Changes in the following variables will lead to different scenarios:

- Service levels from 90% to 99% with 1% gradual increments.
- Hypothetical MAD reductions from 1% to 50% with variable increments (considering that more accurate forecast methods may lower the MAD still more than the 12% obtained for SES forecasting).

7.4. Some Scenarios and Results

Once the components of the costs function are defined, the estimated cost can be simulated varying the service level and therefore the service and loss function factors. Two different methods were defined.

1. One service level common to all items, which facilitates the master data administration.
2. Choose the service level with minimum cost per item.

After running the first method, the service level with minimum cost of forecast error was found to be 98%, which means 6.9% in savings compared to the current service level of 95% (Figure 3). Additionally, the improvement of 12.6 % in MAD leads to a 397,802 MNX or 18.4% in savings, which cannot be disregarded (Figure 4). As said before, different MAD reductions may be achieved with different forecast techniques.

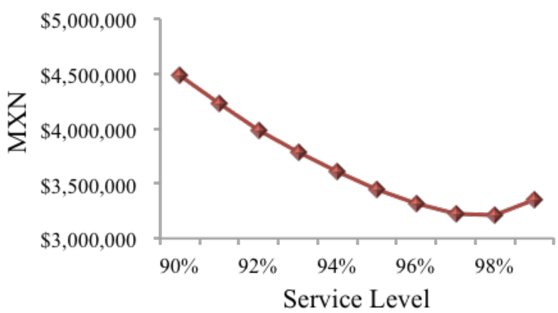

Figure 3: Optimal Unique Service Level using CFE

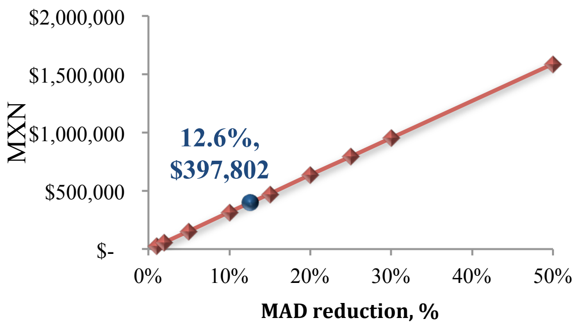

Figure 4: Savings as Function of Hypothetical MAD Reduction

For the second method, choosing an individual service level that leads to the minimum cost for each item, yielded results are presented in Table 5. For 189 items or 63% of the items, the optimal service level of 98% corresponds to the unique service level if chosen the same one for all products.

Table 5: Optimal Service Level, Individual Products

Service level	Items
96%	14
97%	93
98%	189
99%	4

The difference of the total cost determined when using individual service levels as compared to a generalized service level is less than 0.1%, so due to easy handling the first method is preferred. However, the present service level of 95% does not result to be the most efficient; a unique service level of 98% is proposed to reduce overall costs.

According to Figure 3, the cost function is more sensible to underestimating the sales, as the cost increases rapidly towards the left of the service level scale, while the cost increases more slowly if the inventory on hand is enough for a higher service level, so overestimating the real sales is preferred to underestimating them.

8. CONCLUSIONS

A VCV product classification is proposed as an alternative to the classical ABC classification, to have more information in a single tag and focus in those articles with high volume, cost or volatility, in order to link the forecasting process and service level definition.

It is possible to determine the service level policy from the assessment of forecast error cost, even though to get an optimal result it is necessary to estimate the cost function properly, particularly the holding cost and cost of lost sales, otherwise the result can be biased.

This proposal shows an alternative way to design the service level policy through analysis of the financial impact of forecast error beyond the strategic definition that most of the time is subjective.

The reduction in forecast error can be quantified in real savings; it can be used for managers as an argument for investments to improve the process, such as training, information systems and planning processes like S&OP. Using the VCV classification along with the CFE metric leads to focus on relevant categories.

According to the presented study case a low service level can be more expensive than having a high inventory, in which case overestimating is better than underestimate the demand.

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AUTHORS BIOGRAPHY

Armando Sosa obtained his bachelor degree in Industrial Engineering at the Instituto Politécnico Nacional in México and is studying at present a Master course on Systems Engineering.

Ann Wellens is a chemical engineer with postgraduate studies in Industrial Administration (KUL, Belgium) and a master degree in Environmental Engineering (UNAM, Mexico). At the moment she is a full-time lecturer in the Systems Department of the Industrial and Mechanical Engineering Division of the National University of Mexico (UNAM). She has been working in air pollution issues for the last 15 years, dictating courses, collaborating in research projects and participating in conferences related with mathematical modelling of air pollution dispersion and statistics.