Service Parts Forecasting in the Automotive Sector

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Abstract
The present paper reports the creation of a Decision Support System developed for a Mexican automotive company; it was created to facilitate the generation of forecasts for over thousand service parts, considering intermittent patterns. The system applies different forecasting methods, compares the results of them, and selects the best method.

Keywords: Service Parts, Intermittent Demand, Decision Support System

Introduction
Many companies around the globe have started focusing an important part of their strategic efforts, into the aftermarket business. One of the main components of this economical sector is the one consisting on Service Parts; those components are used as replacements for preventive or corrective maintenance of equipments. Contrary to common products, Service Parts tend to present special demand patterns. Because of the fact that the nature of those patterns is not always clear, the forecasting process tends to be very difficult for demand planners. One of the reasons is the fact that intermittent demand patterns are commonly associated with Service Parts; that is, demand is infrequent in the sense that the average time between consecutive transactions is considerably larger than the forecasting's review period. Many authors have proposed different techniques to deal with this special issue. However many of them assure that there is still the need to use those methods in empirical data. Another issue with this is that companies tend to manage from hundreds to thousands of different codes for Service Parts, making the forecasting process a very resource consuming activity.

The present paper presents the creation of a Decision Support System, developed specifically for an automotive company in Mexico, in order to facilitate the generation of forecasts for service parts. The main objective of the Decision Support System (DSS) consisted on facilitating data analysis, and providing better forecasts than the ones currently used by the company. It considers the usage of different forecasting methods, the process of comparing the methods developed for each article, the process of deciding whether the method is being adjusted correctly or not, and finally the selection of a specific method to provide the forecasts. With the analysis of results, it was also possible provide some insight in the creation of forecasts for a series of over a thousand different articles. The paper is divided as follows: 1) Review of commonly used techniques to forecast Service Parts, 2) Review of commonly used methods to select forecasting techniques, 3)Review of measurements used to validate the usage of the models, 4) Optimization of smoothing variables for forecasting methods, 5) The Decision support system algorithm employed to obtain the forecasts and 6) The analysis of the results obtained with the implementation of the model.

Forecasting techniques for Service Parts

Service parts are those employed as a replacement for those parts of productive systems that need to be replaced, as part of corrective of preventive maintenance (Muckstadt, 2005). One of the most important characteristics of service parts is it's demand behavior. It is described as erratic and intermittent. Erratic in the sense, that the article has primarily small demand transactions with occasional large ones. The term intermittent applies to those articles in which demand appears sporadically with some time periods with no demand at all. (Boylan and Syntetos 2008). Based on the nature of the data, that is there were only the records of sales and forecasts available, the review of forecasting techniques was conducted assuming a time series approach.

Usually the method employed to forecast intermittent demand was Single Exponential Smoothing (SES), however the usage of this method tends to lead to inadequate stock levels (Croston 1972, Syntetos and Boylan 2005). Another methods employed are: Double Exponential Smoothing (DES), (Lindsay and Pavour 2008); and the Additive (AW) and Multiplicative (MW) Winters methods (Sani and Kingsman 1997). Since those methods are commonly employed in most common cases, the focus on this section is centered on those methods developed specifically to deal with Service Parts demand patterns.

The excellence method for forecasting this specific kind of articles is known as the Croston Method (Croston 1972, Rao 1973, Syntetos and Boylan 2005). This method proposes that the occurrence of a demand on a determined interval is generated based on a Bernoulli process, with a constant probability *1/p* of occurrence. The average interval between arrivals would be of p review periods, following a geometric distribution. The size of demands when they occurs in an independent manner based on a normal distribution $N(\mu,\sigma^2)$.

It considers the usage of two independent and unbiased estimators; the first one employed to estimate the demand size, and the second one to make an approach to the interval between demands different form zero. Both estimators are updated whenever a different from zero demand occurs. The method considers the following formula (Croston 1972):

$$y_t = x_t(\bar{z}_{n-1} + e_n) \quad (1)$$

Where:

$$x_t = \begin{cases} 1, prob\ (1/p) \\ 0, prob(1-1/p) \end{cases} \quad (2)$$

t: refers to the review time

n: periods where demand is different from zero
y_t: represents demand on time t
e_n: forecast error that follows a normal distribution $N(\mu,\sigma^2)$, it is measured as:

$$e_n = y_t - \hat{y}_t \tag{3}$$

Where $\hat{y}_t$ is the forecasted demand for period t

z_n: represents the demand different form zero, which is considered as an exponential smoothing estimator:

$$\bar{z}_n = z_{n-1}(\lambda) + e_n$$

The method also includes the variable q_t in order to measure the amount of periods that occurred since the last demand different form zero, which is used to estimate the interval between two consecutive demands. The algorithm is the one that follows:

if $y_t = 0$,

$$\bar{z}_n = \bar{z}_{n-1}$$

$$\bar{p}_n = \bar{p}_{n-1}$$

$$q_t = q_{t-1} + 1$$

if $y_t \neq 0$,

$$\bar{z}_n = \bar{z}_{n-1} + \alpha(y_t - \bar{z}_{n-1}) \tag{4}$$

$$\bar{p}_n = \bar{p}_{n-1} + \alpha(q_{t-1} - \bar{p}_{n-1}) \tag{5}$$
$$q_t = 1$$

Where:
α: represents the smoothing constant, that takes values in the interval between (0,1)

Finally the method considers the usage of both estimators as follows:

$$\bar{y}_t = \bar{z}_n / \bar{p}_n \tag{6}$$

The method presented previously was conceived as one of the first alternatives to make more accurate forecast on items that have an intermittent behavior on their demands; due to this fact, there have been several reviews around the original method, in the ones many authors have tried to enhance the results obtained with it. In some reviews it is considered that even when this method has a theoretical superiority to its predecessors; it has been less reliable that what it was predicted (Boylan and Syntetos, 2008).

One of the most accepted reviews to the original Croston Method (Croston 1972) is the one known as the Approximation Method (Eaves 2002, Syntetos and Boylan 2001).

This method proposes the usage of an exponential smoothed estimator of demand $x_1 = z_t'$ and assumed that $E(x_1)=\mu$ being the exponentially smoothed estimator of demand in the interval as $x_2 = p_t'$. The authors applied the Taylor's theorem to the function $g(x_1 x_2)= x_1/x_2$ and assuming that there's independence between the estimators obtained:

$$E[g(x_1 x_2)] = \frac{\mu}{p} + \frac{1}{2}\frac{d^2 g(u,p)}{dx_2^2} Var(x_2) + \cdots = \frac{\mu}{p} + \frac{\mu}{p^3} Var(x_2) + \cdots$$

Due to the fact that x_2 is an exponentially smoothed estimator to represent the interval between demands, geometrically distributed with variance $p(p-1)$:

$$E\left(\frac{z_t'}{p_t'}\right) \approx \frac{\mu}{p} + \frac{\alpha}{2-\alpha}\mu\frac{p-1}{p^2} \; from \; it \; is \; propossed: \; E\left(\left(1-\frac{\alpha}{2}\right)\frac{z_t'}{p_t'}\right) \approx \frac{\mu}{p} \tag{7}$$

That proves that the estimator is not biased, and that improves as the value of p, increases. From the last it is proposed as a new estimator of demand the following (Syntetos and Boylan 2001):

$$y_t' = \left(1-\frac{\alpha}{2}\right)\frac{z_t'}{p_t'} \tag{8}$$

For the derivation of this new estimator the same seasonality, equality and independent assumptions followed by the Croston Method were used (Syntetos and Boylan 2001).

Method used to select forecasting methods

One of the most common techniques employed to evaluate forecasting methods, consists on comparing the accuracy of measures calculated on the basis of errors in the past (Ghiani et al 2004).

As one of the first measurement indexes the Mean Absolute Deviation (MAD) is employed to calculate the deviation of the forecast over forecasted values in the past, the main advantage of this measurement is that it captures the degree of the error no matter the sign of it.

$$MAD_t = \frac{\sum_{k=2}^{t}[e_k]}{t-1} \tag{9}$$

Due to the fact that it is not affected by the compensation between and negative values, the Mean Squared Error (MSE) is one of the most commonly used measurements employed to select the forecasting method for a determinate time series, another benefit of this measurement is that due to the fact that it is calculated on quadratic units, it can be directly compared with demand variance:

$$MSE_t = \frac{\sum_{k=2}^{t} e_k^2}{t-1} \tag{10}$$

A second widely utilized index is the one called Mean Absolute Percentage Error, it evaluates in a percentage basis, how well the past data values were adapted to the real demand values, it is measured as follows:

$$MAPE_t = 100 * \frac{\sum_{k=2}^{t}[e_k]/y_k}{t-1} \quad (11)$$

For each one of the cases it is expected that the selected method will be the one that presents the lowest value on this index (Ghiani et al 2004). This measurement is also useful when defining the adequate levels for each of the smoothing constants.

Methods used to guarantee forecasting control

Another important aspect on forecasting methods consists on maintaining Forecasting control, a well known technique to accomplish with this important aspect consists on the use of the Tracking Signal (TS), which is defined as the ratio between the cumulative MAD (Ghiani et al 2004):

$$TS_t = \frac{E_t}{MAD_t} \quad (12)$$

Several authors recommend different values for estimating the limits to suppose control employing the TS, those limits vary from ±3 to up to ±8 (Ghiani et al 2004, Pyke et al 1998). By the calculation of TS for each one of the periods forecasted, the following aspects can be evaluated:

1. If the errors have an expected value different form 0, it can be implied that the forecast is biased.
2. If there's a negative or positive trend in the model, the accuracy of the forecasting method can be considered to be progressively diminishing.
3. If there's a periodic error pattern, it possibly means that a seasonal effect has not been considered (Ghiani et al 2004).

Optimization of smoothing variables for forecasting methods

As the reader might realize, each one of the methods proposed to forecast Service Parts use at least one smoothing parameter. Usually those smoothing are considered in the interval from 0 to 1. However it doesn't guarantee that the model is representing in an adequate way the demand behavior, that's why the following table presents the intervals considered for each forecasting method presented.

Table 1 – Smoothing constants intervals considered

Method	*Smoothing constant and ranges*
SES	$0.05 \leq \alpha \leq 0.5$ (Silver et al 1998, Eaves 2002)
DES	$0.05 \leq \alpha \leq 0.5$; $0.05 \leq \gamma \leq 0.5$ (Silver et al 1998, Eaves 2002)
AW	$0.02 \leq \alpha \leq 0.52$; $0.005 \leq \gamma \leq 0.176$; $0.05 \leq \delta \leq 0.5$ (Silver et al 1998, Bowerman and O'Connell 2005)

MW	$0.02 \leq \alpha \leq 0.5$; $0.005 \leq \gamma \leq 0.176$; $0.05 \leq \delta \leq 0.5$ (Silver et al 1998, Bowerman and O'Connell 2005)
Croston and Approximation Methods	$0.05 \leq \alpha \leq 0.5$ (Croston 1972, Syntetos and Boylan 2005)

In order to obtain the adequate smoothing values, it is proposed as the usage of a non linear programming model (NLPM), developed to minimize the error measurement index. The following is a representation of the model employed for SES in order to minimize the MSE:

Scalars

n Length of the historical time series

Con Number of periods considered to start the forecasting method

Parameters

D(i) Registered demand for period *i*

Decision variables

α Smoothing constant employed for the forecast

F(i) Forecast estimated for period *i*

Optimization Model

$$Min\ z = \frac{\sum_{i=Con+1}^{n}(D(i)-P(i))^2}{n-Con} \tag{13}$$

Subject to

$$P(Con) = \frac{\sum_{i=1}^{Con} D(i)}{Con} \tag{14}$$

$$P(i) = \alpha D(i-1) + (1-\alpha) * P(i-1)\ \ i > Con \tag{15}$$

$$0.05 \leq \alpha \leq 0.5 \tag{16}$$

Equation 12 represent the objective function of the model, as it is seen it represents the MSE for the model over the time, equation 13 assigns the value for the first forecast to be considered in the model, equation 14assigns the forecast model formula to each one of the periods to be reviewed and finally equation 15 indicates de range of values that the smoothing constant can consider.

Decision Support System Design

As it was mentioned at the beginning of the paper, the application of the current research consisted on the design of a DSS for a Mexican Company that currently distributes

Service Parts to several countries around the Globe. Some of the aspects to be considered are:

1. The universe of Service Parts: nowadays the company is managing over 15000 different stock keeping units (SKU's) solely on the Service Parts department.
2. The forecasting process update: currently the company updates the forecast once a month.
3. The current forecasting methods: nowadays the company is not using any forecasting method oriented to the intermittent nature of Service Parts; it is reflected on forecasts that rarely match demand.
4. The available time to update forecasts: due to the fact that the main business of the company is located on the production sector, the amount of headcount available for the Service Parts division is limited, that is why one of the main aspects of the DSS consists on giving the best possible forecasts without human being intervention.

Due to data availability, the DSS was developed employing the historical time series of demand for 2200 SKU's over the last three years. It was also possible to consider with the forecast for the first eight months, after the three years historical data. The process considered by the DSS is the one that follows:

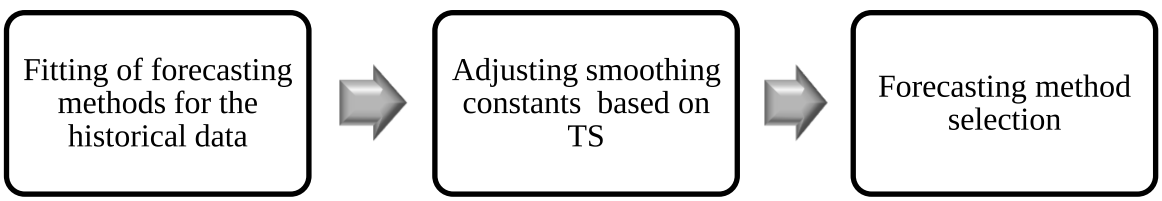

Figure 1 – General process developed for the DSS

1. Fitting of Forecasting methods: the forecasting models selected to perform the forecasts calculations where: SES, DES, AW, MA the Croston Method and the Approximation Method. For each method the procedure to start the forecasts consisted on:

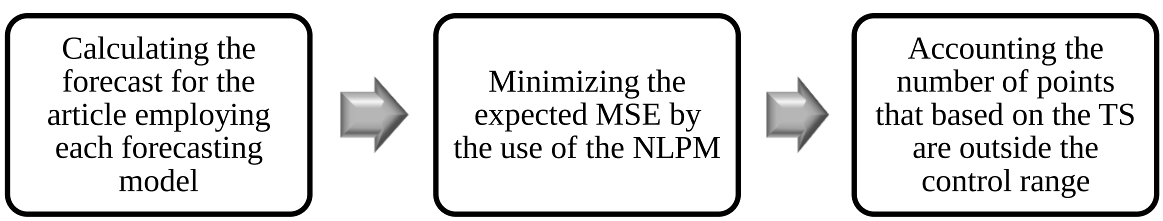

Figure 2 – Fitting of the forecasting models

For the estimation of the starting forecasting parameters, the model considers the values considered on Table 2. Once the forecasts for the article have been obtained the second step of the process consists on using the NLPM to obtain the minimum MSE for each one of the articles. Finally, the DSS estimates the TS for the article and accounts the number of points that fell out of the control range.

Table 2 –Values considered to start calculating the forecasts

Method	*Smoothing constant and ranges*
SES	Average value for the first 12 months
DES	Level and tendency estimators based on linear regression for the first 12 months
AW and MW	Level and tendency estimators based on linear regression for the first 12 months. The seasonal component was estimated by subtracting the regression estimate for the first 12 months and calculating the average for each month.
Croston and Approximation Methods	The average quantity of demand for the first 12 months divided by the average number of periods between nonzero demands for the first 12 months.

2. Adjusting smoothing constants based on the TS: once the forecasting models were adjusted for the article. The updating for the first eight months after the three years of historical data performed. It also updated the value of the TS, whenever the TS fell off the control range; the DSS uses the NLPM for the corresponding method in order to try to control the forecast. At the end of the eight months the model counts every optimization performed.
3.

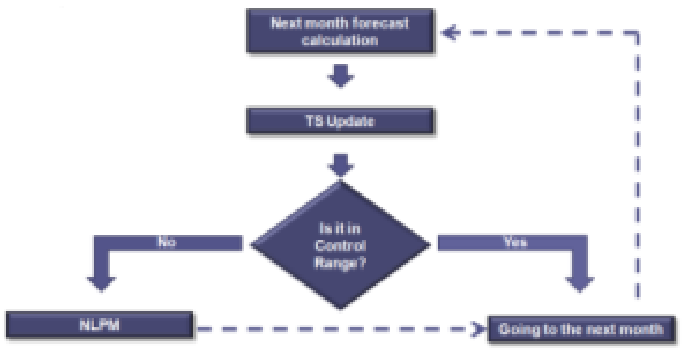

Figure 3 – Process employed to adjust the smoothing constants

4. Selection of the forecasting method: In order to choose the adequate forecasting method for each article the process evaluates:
   a. Comparison between the historical MSE using each model against the variance of demand for the historical data. If the calculated MSE was greater than the variance then the method could not be selected.
   b. Comparison between the MSE obtained with the usage of the method during the last eight months. If the MSE was greater than the historical variance the method was less eligible than other one in the case there were more than one methods that could cover points a, c and d.
   c. Number of Points out of the control range for the historical data. If for the historical data, the model applied has more than 3 points out of the TS ±6 range, the model could not be selected.
   d. Number of optimizations performed during for each article during the last eight months. If the optimizations or number of points out of the TS ±6

range were over 2 for the last eight months, the model could not be selected.

It is important to mention that due the fact that there were only the forecasts for the last eight months, the criteria to consider the current forecast of the company adequate for the article consisted only on comparing criteria *b* and as a representative of *d*, the number of TS points out of the TS ±6 range.

Obtained results

The DSS was run all over the 2200 SKU's, the first analysis consisted on reviewing what was the capability of the current method and the one of the DSS. That is, how many articles could from the list meet at least the three basic requirements defined on the previous section, and how many of them meet at least one of the two defined for the current forecasts of the company. The results are shown bellow.

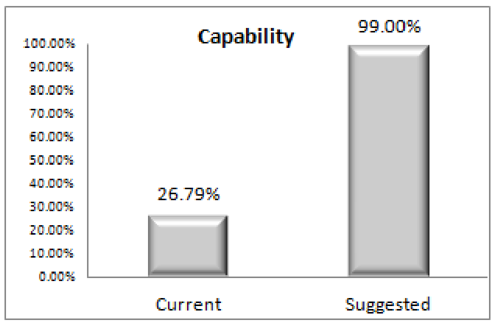

Figure 4 – Process employed to adjust the smoothing constants

As it is seen on figure 4 in 99% of the cases it was possible for at least one of the methods to cover the four criteria defined. As a contrast, only in 27% of the cases the current forecast of the company was meeting at least one of the two criteria defined.

From the total list of articles, there was a comparison between the current method and the ones suggested, considering only the MSE for the last 8 months and the number of points out of the TS control range. The results are shown bellow.

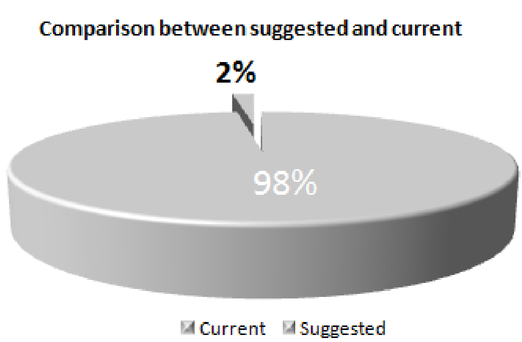

Figure 5 – Comparison between the current and the suggested methods

As the reader might see on figure 5 on 99% of the cases the suggested methods outperform the current ones used in the company. However, since this comparison was used considering absolute values, a second comparison allowing a 10% difference between the methods was allowed, the results are shown bellow.

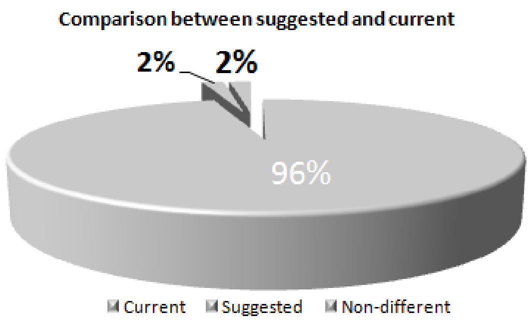

Figure 6 – Comparison between the current and the suggested methods allowing a 10% difference.

As it is seen in figure 6 even when there’s the allowance of a difference of 10% between the current and the suggested methods in 96% of the cases there’s still the suggested ones outperform the current one and in 2% of the cases they can be considered as equal.

Conclusions

With the usage of different forecasting methods, and implementing NLPM it is possible to improve the quality of forecasts in an industry, for those cases. For those cases in which big volumes of data need to be processed, it is important to consider the fact that DSS can be designed to facilitate the amount of time needed to significantly improve forecasting quality. However it is still important to keep on reviewing which were the most used methods and the characteristics that could define the behavior of the articles to relate them to the best model adjusted.

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