Dynamic Model to Design and Control Maintenance Spare Parts Stock

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Abstract: The extremely competitive environment in the markets create an increased pressure for now a day's companies, therefore in order to face the difficulties there is an urge to create and improve all the tools to reduce costs and increase operations productivity and efficiency. Amongst several created or improved tools are the fields of Maintenance and Stock Management. The following paper goes into the Stock Management topic, with the goal of improving companies' response to the market fluctuations. To do so, a Dynamic Model was created that helps companies to ensure stock availability while reducing costs related to warehousing and Supply Chain. The model developed starts with a decision algorithm that distinguishes which parts should be in stock, simultaneously, the model splits the parts in different categories per demand pattern and predicts the demand using forecasting methods, adjusting stock levels accordingly to the expect demand. Finally, the Dynamic Model was tested in a case study, using historical data supplied by Mercedes Benz Comercial – Sintra during the year of 2014. Using this data, is an important step, as automotive spare parts have high demands and high costs when compared with other industries. The obligation of immobilizing clients' vehicles in most cases that replacement spare parts are needed is also of extremely importance for client satisfaction.

Keywords: Maintenance, Stock Management, Stock, Decision Algorithm, Forecasting Methods, Spare Parts, Automotive.

1 Introduction

During globalization, companies that were once local producers and distributers begun to face competitors from other corners of the world, and felt the need to relocate facilities and restructure strategies to become the number one in their markets.

During these changes, areas that once were secondary started to be in the central core of the business. Maintenance and Stock Management are included in these areas, and are, nowadays highly developed and extremely important.

According to Brown, et al., "maintenance describes the management, control, execution and quality of those activities which will reasonably ensure that design levels of availability and performance of assets are achieved in order to meet business objectives" [1]

Maintenance can be divided in four main categories, improvement maintenance, predictive maintenance, preventive maintenance and corrective maintenance.

Improvement maintenance can be described as the process of improving equipment performance [2]. And is used in continuous improvement processes such as KAIZEN, Toyota Production System and 3M.

Predictive maintenance is described according to the standard SS-EN 13306 (2001) as a "Condition based maintenance carried out following a forecast derived from repeated analysis of known characteristics and evaluation of the significant parameters of the degradation of the item"

Preventive maintenance is defined according to the standard SS-EN 13306 (2001) as "Maintenance carried out at predetermined intervals or according to prescribed criteria and intended to reduce the probability of failure or the degradation of the functioning of an item"

And Corrective maintenance can be defined by the standard SS-EN 13306 (2001) as "maintenance carried out after fault recognition and intended to put an item into a state which can performed a requires function".

Stock Management have become a fundamental tool in most companies, having an important role in operational management, easing the balance between supply and demand, which can be adjusted by the clients' needs and suppliers necessities [3].

Several models have been created to improve stock management and stock availability, focusing on the quantity needed to order and the time to order. These models are known amongst several as "continuous revision model" (Q Model), "economic order quantity" (EOQ) and "periodic revision model" (P Model).

There are also other methods to help and improve stock management, such methods are able with levels of accuracy to forecast the demand of a certain item, and therefore help the supply chain to respond to clients' needs.

2 Dynamic Model

The model is divided in four parts, the first one, which is completely independent from the others and is called "Decision Method" has the objective to decide which components should be in stock during the analysis period.

The second, third and fourth parts of the dynamic model, are processed in chain, and have the responsibility to classify the components based on the demand, forecast the expected demand for each component and adjust the stock levels. Being the second part called "Classification Method", the third "Forecasting Methods" and the fourth "Stock Adjustment"

In the end of each period, the model uses the information from the Decision Method and the Stock Adjustment to make the necessary orders or returns.

The Dynamic Model was also based in several assumptions, on which should always be applied. These assumptions were created to understand the Model's behavior and results, and are the following:

- When a component is categorized by the decision algorithm as "not necessary in stock", the stock available for the forecasted period is 0. This assumption is based on a bi-directional supply chain, which when delivers the necessary components, also returns the not needed ones. With this the amount of components needed not only on site, but also trough the supply chain can be decreased.
- The model assumes two types of orders, emergency orders and regular orders. The emergency orders are done once a day with the exact number of components that were not sold because they were out of stock, to guaranty those buyers have the components they need. Regular orders are made once per week, usually in the end of the week, using the entire structure of the model developed.
- The model uses as minimum amount to order, 1 unit and has no limit regarding the maximum.
- The model assumes order are made in unitary quantities.

2.1 Decision Method

During the research phase for the model, it became clear that finding the right components to be in stock was one of the most important steps. But unfortunately, not many articles which analyze and develop solutions to the topic were found. Nevertheless, in a case study made in Brazil which observed some methods used by the automotive industry, Rego (2006) found a particular one used by Volkswagen, that computes a weighted frequency to decide if a specific component should be in stock.

This frequency follows the equation:

$$FP = 0.9\,FP_{i-1} + 1.2\,x \qquad (1)$$

Where FP stands for the weighted frequency, FP_{i-1} stands for the computed weighted frequency in the period immediately before the one being analyzed and x can have two values, 1 or 0. The value of x is 1 when the component has demand in the period immediate before the one being analyzed and 0 when that referenced demand did not occur [4].

The final decision of having, or not, the studied component depends if the result of the computed weighted frequency id higher than 1.6, in which case the component should be available in stock, however if the result lies under 1.6 the component should not be in stock.

This method before chosen to be incorporated in the dynamic model, was tested and showed good results.

The decision method follows the algorithm shown in Figure 1.

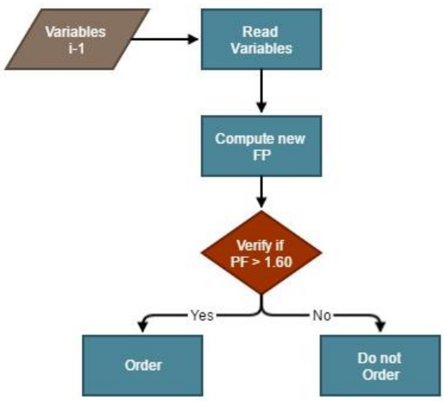


Figure 1 – Decision Method Algorithm

2.2 Classification Method

Every component has a unique demand, and, therefore should be treated as a single case. To do that, components must be classified and divided into groups. In this dynamic model, the know SBC Classification was used.

This classification was created by Syntetos & Boylan [5], which computes for each component two variables, demand size variability and average demand inter-interval. Then using cut-off values for these two variables divides the components in four groups according to the following nomenclature:

- Smooth
- Erratic
- Lumpy
- Slow

Components classified as Smooth, are highly demanded, however in small quantities, Erratic components are also highly demanded, but in high quantities, components with Lumpy behavior are rarely demanded however, when they are, usually is in high quantities, finally components categorized as Slow are also rarely demanded and when they are it is usually in small quantities.

The SBC Classification is shown in Figure 2

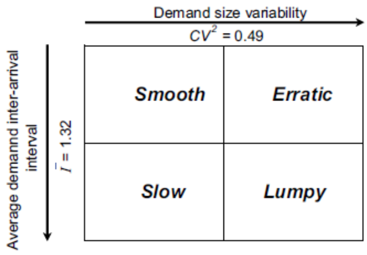


Figure 2 - SBC Classification

And the algorithm used in the Classification Methods are shown in Figure 3.

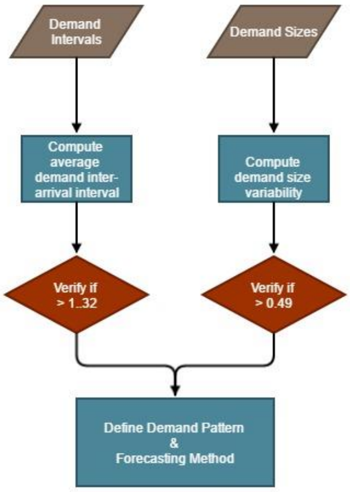


Figure 3 - Classification Methods Algorithm

2.3 Forecasting Methods

The SBC Classification also suggests forecasting methods for each type of demand, according to Figure 4.

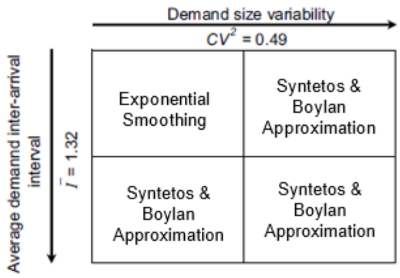


Figure 4 - SBC Classification Forecasting Methods

However, in 2011, Teunter, Syntetos & Babai developed a new method which, according to the authors should be applied to components with lumpy behavior and therefore, to develop the dynamic model, such method was used for the specified behavior pattern, having in result a modification of the known SBC Classification, shown in Figure 5.

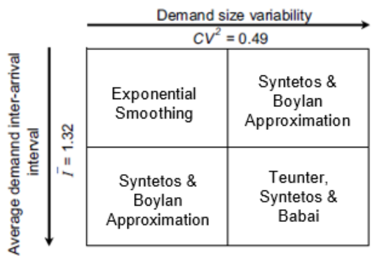


Figure 5 - SBC Classification Modification

After the classification is defined, the model proceeds to forecast the demand of a component for the next period according to the algorithm defined in Figure 6.

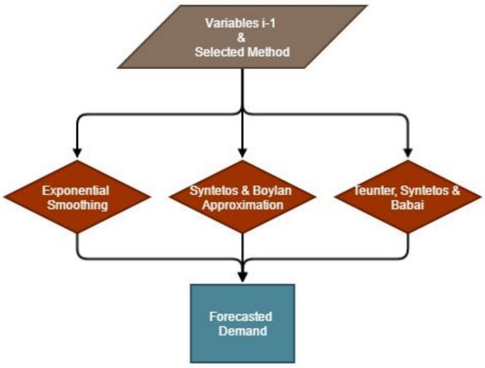


Figure 6 - Forecasting Methods Algorithm

2.3.1 Exponential Smoothing

Exponential smoothing is one of the most commonly used methods of all forecasting techniques. The high acceptance rate of this method is based in his simplicity and overall good results for components without zero demand periods [6]

This method only requires three variables, the forecasted demand of the previous period, the actual demand for the previous period and a smoothing constant, and is applied according to the following equation:

$$F_i = \alpha \cdot D_{i-1} + (1-\alpha) \cdot F_{i-1} \quad (2)$$

Where F_i represents the forecasted demand, α the smoothing constant, D_{i-1} the observed demand for the previous period and F_{i-1} the computed demand for the previous period.

2.3.2 Croston Method

When it comes to forecast the demand of components with periods of zero demand, the exponential smoothing method is not the most reliable, and Croston (1972) developed a new method to surpass this problem.

The method uses the following formulation:

$$F_i = \frac{Z_i}{P_i} \quad (3)$$

With,

$$Z_i = Z_{i-1} + \alpha\,(D_{i-1} - Z_{i-1}) \quad (4)$$

$$P_i = P_{i-1} + \alpha\,(q - P_{i-1})$$

Where F_i stands for the forecasted demand, Z_i is the demand dimension for the forecasted period, P_i the average interval between demands, α is a smoothing constant, D_{i-1} the observed demand for the previous period to the analysis and q is the number of consecutive intervals with observed demand [7].

2.3.3 Syntetos & Boylan Approximation

In 2001, Syntetos & Boylan [8] through a case study proved that Croston's method was positively biased and proposed a modification which would decreased its biased tendency, by adding correction factor to the formulation, as follow:

$$F_i = (1 - \frac{\alpha}{2}) \cdot \frac{Z_i}{P_i} \quad (6)$$

2.3.4 Teunter, Syntetos & Babai

Finally, in 2011, Teunter, Syntetos & Babai [9] using the exponential smoothing method of demand and dimension probability estimates, developed a new method which, according to the authors, would completely resolve the bias tendency observed in both methods, Croston's and Syntetos & Boylan Approximation.

The formulation is the following:

$$F_i = p'_i \cdot z'_i \quad (7)$$

With,

$$p'_i = \begin{cases} p'_{i-1} + \beta(0 - p'_{i-1}), & y_{i-1} = 0 \\ p'_{i-1} + \beta(1 - p'_{i-1}), & y_{i-1} = 1 \end{cases} \quad (8)$$

$$z'_i = \begin{cases} z'_{i-1}, & y_{i-1} = 0 \\ z'_{i-1} + \alpha(z'_i - z'_{i-1}), & y_{i-1} = 1 \end{cases} \quad (9)$$

Where F_i stands for the forecasted demand, p'_i the estimate probability of demand, z'_i the estimate demand dimension, α, β are smoothing constants and y_{i-1} is demand indicator for the period previous to the analysis. This indicator has the values of 0 or 1, depending on the observed demand of the component, being 1 if the component had demand in the previous period to the analysis and 0 if no demand was observed in the same period.

2.4 Stock Adjustment

The stock adjustment segment is where the model defines que number of components it should order with the following formulation:

$$E_i = F_i - S_{i-1} \quad , E_i \geq 0$$

Where E_i represents the number of items that should be ordered for a specific component, F_i is the forecasted demand and S_{i-1} the stock observed in the end of the previous period.

To order the correct number of components, the result obtained from the Decision Method is needed, and therefore has the algorithm shown in Figure 7:

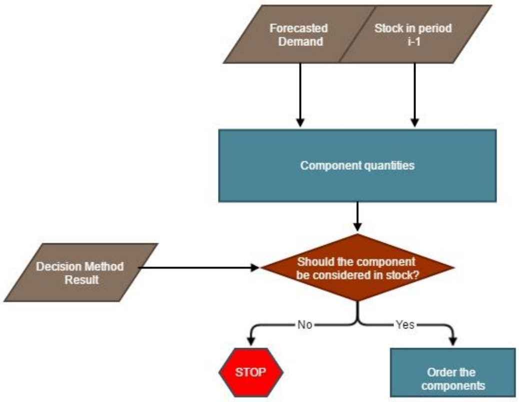


Figure 7 - Stock Adjustment Algorithm

3 Case Study

To evaluate the performance of the developed model, a case study was created using the demand history from Mercedes Benz Comercial – Sintra, only with components for the Smart vehicle. These historical data was collected between the 1st of January and 31st of December 2014 with 1,485 different components.

Due to the high number of components present in the data file, a decision to study the behavior of the model in a selected few was made. To differentiate which components should be studied, Almeida (2015) started by using the known ABC Categorization.

This categorization splits the components in three groups, and suggests that 20% of the products sold represent 80% of the revenue [10]

These three groups are usually called group "A", group "B" and groups "C", on which the group "A" has the maximum importance with 20% of the components and 80% of the revenue, followed by group "B" with 30% of the components and 15% of revenue and finally group "C" with 50% of components and 5% of revenue.

Using the annual demand figures for all the 1,485 components, Almeida obtained the results shown in Figure 8.

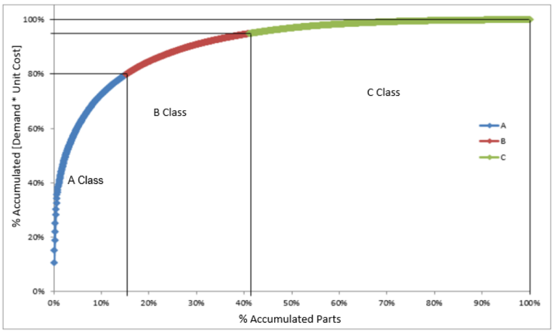


Figure 8 - ABC Classification (Almeida, 2015)

Then Almeida decided that there were still too many components and applied a second criteria, using the median demand value of 2 units and the median unit cost of 17.84€. Through this criterion, the components were divided in four categories, the first groups with the components with high unit cost and high demand, the second with high demand and low unit cost, the third with high unit cost but low demand, and the fourth with low demand and unit cost.

The components were then reduced to 250, within these, the first 30 components were selected to be studied, with a total of 1,197 sales.

After the component selection, and in order to assess the effect of time periods in the dynamic model, three models were defined. These models only differ from each other on the period of time they use to collect the data.

The first model, which will be called "52 Weeks", starts by using the first 8 weeks of data to initialize the model and adjust all the variables. This model will then add one week at a time, increasing the overall weeks to study.

The second model developed, which will be called "8 Weeks", also uses the first 8 weeks of data to initialize and adjust all the variables, however every week that is passed, the model updates the data necessary to only account for the 8 weeks before the one being forecasted.

Finally, the third model, called "Static", uses at the beginning the entire years in weekly periods to initialize and adjust all the variables, and therefore the classification, and forecasting method will not suffer any change during the analysis.

4 Results

Forecasting methods are usually analyzed according to the errors produced, such as “Mean Square Error”, “Mean Error”, “Percentage of Absolut Mean Error”. However, since the model should be treated as a whole and the analysis of the model do not lie only on the forecasted methods, five other indicators to assess the performance had to be used.

One of the chosen indicators was the stock out observed per component during the entire year. This indicator has an increased importance, not only because it means that a customer was not satisfied when he needed, but also because it represents a vehicle stopped in the shop and a service vehicle that could be requested by the customer. This indicator should have the lowest value as possible. The results are shown in Figure 9

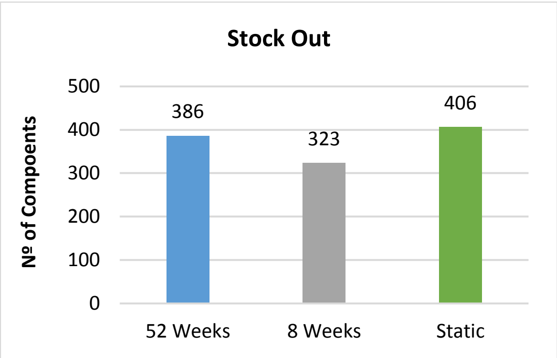


Figure 9 - Stock Out results

As it is shown the model “8 Weeks” is the one that responds better in this indicator with 323 units in stock out, followed by the “52 Weeks” model with 386 and finally the “Static” model with 406. This result is obtained because since the model “8 Weeks” only analyses the 8 previous weeks, whenever it is updates, it responds faster to the changes when compared to the other models, and therefore increases the number of clients served.

The second indicator is the weekly average stock levels. This indicator is used because it represents financial resources spent in components that are stored and eventually are not sold but also represents physical space that needs to be attributed to those components and cannot be used for something else. This number also should be reduced as much as possible.

The results obtained by this indicator when applied to the dynamic model were best for the “Static” model, with an average of 9.5 units per week, followed by the “52 Weeks” model with 10.8 units per week and by the “8 Weeks” model with 18.6. As can be seen, the “Static” and “52 Week” model, once again had relatively similar results, due to the tendency for the “52 Week” model to evolve to “Static” during the time. The “8 Week” model, had the highest average weekly stock, which is the negative side of being able to fulfill the demand of more clients, due to the faster response of market changes.

For the third indicator, a well-known KPI was used, called Inventory Turnover. This indicator represents the average number of stock rotation occurred during the year of study in time periods, in this case is weeks. In this case, the results should be as high as possible.

To obtain this indicator the following formulation was used [11]:

$$Inventory\ Turnover = \frac{n^{\underline{o}}\ of\ outgoing\ items}{Average\ n^{\underline{o}}\ itemns\ in\ stock}$$

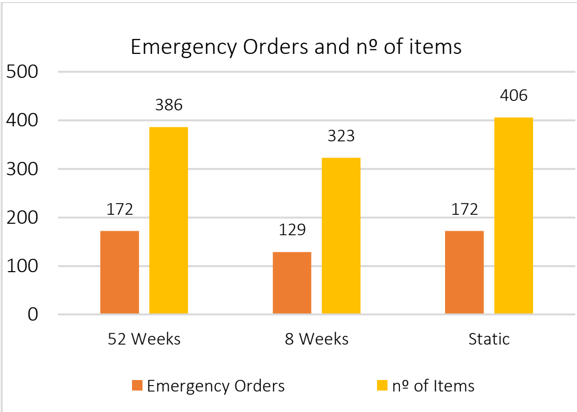
As a result, the “52 Weeks” and “Static” models a similar result, with 5.9 and 6.0 inventory rotations per week respectively and the “8 Weeks” model obtained 4 inventory rotations per week. In this indicator, the model “8 Weeks” was the one with the lowest results, however in the industry values over 3 rotations per week are considered good.

The fourth indicator chosen was the number or regular orders and the average items per order. In this case, both indicators are treated as one, since they are closely related. It is assumed that the lower the number of order and the average number of items ordered the better.

As results, all three models order in the 44 weeks analyzed, however the average components order differ from model to model. The “8 Weeks” model had the better results, with an average of 5.7 components per order, and the other two models, “52 Weeks” and “Static” has 6.4 and 6.5 components per week respectively. This behavior is somewhat expected since the model with highest average stock should need less components when adjusting.

For the final indicator, the number of emergency orders was considered, also considering the lowest number of orders as possible.

The results are shown in Figure 10



As shown, the model with less orders was “8 Weeks” with 219 orders and an 2.5 average components per order, the “52 Weeks” and “Static” models had an average of 2.25 and 2.32 components per order. The model “8 Weeks” was able to reduce the emergency order by 25% and the number of components ordered by 16%

In short, the model that gives the highest satisfaction amongst the clients is the “8 Weeks” model, because it offers a better response to the market needs, increasing the number of sales when the demand was observed and reducing the number of

Table 1 - Results Resume

Indicator	**Model “52 Weeks”**	**Model “8 Weeks”**	**Model “Static”**
Stock Out	306	323	406
Average Weekly Stock (nº of maximum items in stock)	10.8 (28)	18.6 (44)	9.5 (24)
Inventory Turnover	5.9	4	6.0
Regular Orders (Average nº of ordered items)	44 (5.2)	44 (5.7)	44 (6.4)
Emergency Orders (Average nº of ordered items)	172 (2.25)	129 (2.50)	172 (2.32)

emergency orders, however as consequence, this model obtains the highest values of weekly average stock and lowest numbers of inventory turnover, which should imply highest costs managing the stock.

A simpler version of the results can be seen in Table 1.

5 Conclusions

During the initial phase of the model it was quickly understood that there weren’t forecasting models suitable for all components and therefore they had to be divided in different categories to be, and in each category, a specific forecasting technique was used. Several scientific articles acted as guidance to that end, and this division showed to be essential for the model development, which the forecasting techniques used proving to be the best ones from all the studied ones.

It was also clear that it would be unrealistic to consider that the warehouse would be able to store all the components available for the Smart vehicle, and, once again, the decision of which components to store proved itself to be also fundamental. Although it was more complicated to find solutions for this problem than expected, with very few scientific articles approaching the subject, one of the solutions found in a case study gave good results and was decided to be incorporated to the dynamic model.

After the analysis of the dynamic model results, came the realization that some of the components studied were sold in liters or meters, with the possibility of going to decimal cases, this was not anticipated and became a problem with the components in this situation being the ones that gave the worst results and decreased the performance of the three models, however they were still considered for the results and helped understand that the models cannot be applied to all kinds of components, being one more restriction to add in a previous work.

Finally, a perfect solution was not found, but came the conclusion that depending on the goal of the company, different solutions should be applied.

In this particular case, the model “8 Weeks” is the best candidate to have better client satisfaction and therefore the period of 8 weeks should be considered when client satisfaction is the main goal.

The model “52 Weeks” and “Static” can also be used, in cases when the company’s main goal is to reduce costs with storing the components, but always keeping in mind less customers would be served when they need.

Overall the design and implementation of the Dynamic Model was well achieved, with capable solutions for stock management. The difficulties found during the design and implementation of the model were surpassed, achieving a reliable model which combines components’ demand forecasting and the difficult decision of stocking them.

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