Development of Inventory Management Policies

The Case Study of Portuguese Railway

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Abstract

REFER, as a corporate public entity, has faced challenges inherent to the requirements from the restrictive fiscal policies in Portugal. In this context, its operation has evolved to become as efficient as possible, intending to adopt better management practices, which involve planning maintenance materials. The company has an ongoing project which aims to assess the accurate stock policies for maintenance materials.
In this sense, the purpose of this study is the identification of the methods that can be used in the development process of a stock policy for REFER's maintenance materials. The literature's review allows the definition of a course of action as well as supporting the methodology for the resolution. Initially, the data are gathered and analysed, followed by the classification of the materials according to demand pattern. The third phase consists in demand forecasting. And for that, three methods are applied: Simple Exponential Smoothing, Croston's method and Syntetos and Boylan approximation. Finally, Naddor's heuristics, a periodic review policy (T, s, S), was applied as possible stock policy,
The outcome of this study shows that is impossible to adjust the historical data to a normal distribution. It is also perceived the specificity of the problem under investigation that makes it difficult to establish the parameters which constitute the inputs to the stock policies. However, the application of Naddor's heuristic showed satisfactory results and falls under the company's current situation.

Keywords: maintenance materials, classification by demand pattern, demand forecasting, inventory management policies.

1. Introduction

The transportation systems play a major role in the regional and economic development, enhancing the society's quality of life, although with an environmental impact. For that, the governments spend a large amount of resources in developing and monitoring more effective transportation services (Murray et al., 1998). In recent years there has been an attempt to adjust the macroeconomic imbalances and structural issues identified in Portugal. As a result, a continuous reduction of expenditure and investment in Public Administration is observed.
REFER is a state company responsible for managing the national railway infrastructure. This company is responsible for the

infrastructure management of National Railway Net (RFN). Its purpose is to ensure regular and continuous transportation of passengers and goods, providing a competitive transportation infrastructure, safe and respectful towards the environment. Since 2011, its budget is a part of the state budget. There are now significant restrictions on financing and investment, which creates complex challenges, but also leads to an optimization of capacity and rationalization of the systems and processes necessary for their activity.

The management and maintenance of railway infrastructure proves to be costly and complex, not just when it comes to the creation of new infrastructure, but also in the maintenance of existing ones. This is due to the strict quality and safety standards, the high specificity of materials, the shortage of suppliers, the long acquisition times, among other events.

The main goal of this paper is to identify the methods that can be used in the development process of a *stock* policy for maintenance materials thus making possible to coordinate the maintenance activities with the planning of the maintenance materials that are needed.

So, the paper is structured as follows: In section 2 the most relevant literature is reviewed. Section 3 presents the case study. In sections 4 a summarized description of the methodology proposed is presented. In section 5 the main results are presented. Finally in section 6 the main conclusions are drawn.

2. Research Background

The maintenance activities are crucial to the correct and safe performance of systems and its components. As such, maintenance activities not only allow to control and optimize costs but also have a positive input in the overall work of the organizations (Waeyenbergh & Pintelon, 2002).

The maintenance stocks and spare parts are different from other kinds of stock, whereby the management policies of the former must be adjusted to these materials specificity (Kennedy et al., 2002).

The literature concerning spare parts is extensive, both related to maintenance activities as to classification methods and forecast. A few examples are: Ghobbar & Friend (2003) conducted a study on the aviation sector on the evaluation of forecasting methods for spare parts; Hua & Zhang (2006) lead a study of forecasting spare parts from a petrochemical enterprise; Mikalsen (2008) suggested a structured method to manage the demand for spare parts and applied in a large global production company; Lanza et al. (2009) calculated the optimal time for preventive maintenance and spare part provision; among others.

A spare part is a subcomponent of a system. The railway infrastructures are a group of systems, each one with different components and characteristics, from its function to its dimension. On account of the above mentioned, throughout this study the term maintenance material/spare part is used in its wider definition.

According to Mohammaditabar et al. (2012) and effective inventory control system involves two problems: classification of inventory items in groups and finding appropriate strategies to manage each one of the groups identified. These aspects are going to be developed in the next sections.

2.1. Spare Parts

Spare part is a subcomponent of a system formed by others components, allowing the system to function. Kennedy et al., (2002) in their review of recent literature on spare parts inventory highlighted the importance of a trade-off between the unavailability of required spare parts and their overstock, both leading to unnecessary costs.

Intermittent demand is a random demand. When it occurs, it is not necessarily for a single unit or a constant demand size (Syntetos & Boylan, 2006). The proportion of the stock that is devoted to intermittent demand items is often substantial. Therefore, small improvements in a company's system, regarding those items, may be translated to significant cost saving (Eaves & Kingsman, 2004).

However, the intermittent demand forecast is, without a doubt, a very difficult business task, on account of both the demand incidence and the demand size variabilities (Syntetos & Boylan, 2006).

2.2. Demand Classification

The categorization of alternative demand patterns is an essential element for *stock* management. The common practice is to arbitrarily categorize demand patterns and then select an estimation procedure and *stock* control method in order to forecast future requirements and manage *stock* efficiently (Syntetos et al., 2005).

A first proposal of a method of categorization of demand patterns was made by Williams (1984) based on an idea that was called variance partition, which split the variance of the demand during lead time into its constituent parts. This categorization aimed to identify the best forecasting and inventory control methods for the resulting categories.

Years later, Eaves (2004) was able to determine that the conceptual classification scheme from Williams was not suitable to describe the observed demand structure. Therefore, Eaves proposed an improved classification scheme where the demand was categorized based on three elements: variability of the transaction' rate, demand size variability and lead time variability.

The uniqueness of both categorization schemes was the inclusion of alternative demand patterns and as a result to distinguish between them, intending to select the most appropriate forecasting procedure. Nevertheless, the cut-off values - the values that separate the different quadrants - had been arbitrarily selected, creating doubts concerning the applicability of the categorization schemes to any different context (Heinecke et al., 2013). For this reason, Syntetos et al. (2005) proposed the matrix in Figure 1, in which the cut-off values were mathematically determined through the comparison of the Mean Square Error (MSE) from different forecast methods.

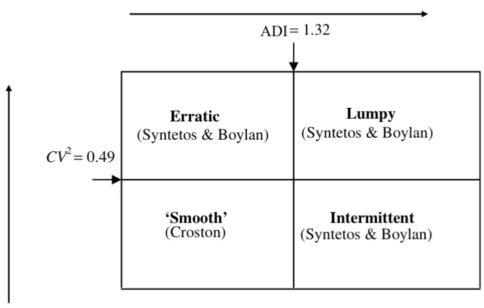

Figure 1 – Demand Pattern Classification Matrix (Syntetos, et al. 2005)

The matrix of Figure 1 was divided in four quadrants determined by both the demand quantity variability, obtained by the squared covariance (CV^2), and the average demand interval (ADI). The cut-off values obtained by Syntetos et al. (2005) were 0.49 and 1.32, respectively.

The demand of maintenance materials was commonly characterized as intermittent or lumpy. On one hand, the demand is intermittent when the intervals between demands are long (ADI>1.32), leading to a sporadic demand (Kourentzes, 2014; Prestwich et al., 2014). On the other hand, the demand is lumpy when the demand quantity variabilities (CV^2>0.49) are added to the intermittence.

2.3. Demand Forecasting

A study made by Ghobbar & Friend (2003) identified the unrealistic forecast of spare parts as the main problem of the forecasting methods, due to the unpredictability of the activities that require such materials.

In the last few decades, the spare parts stock management has been investigated. The Croston method and its continuous modifications have been widely applied in the demand forecast of such materials (Bachetti & Saccani, 2012).

A specific forecast method for the intermittent demand was proposed by Croston (1972). The original Croston method is a deterministic model, in which the time series are divided and forecasted in its constituent elements. This means that in this method the demand sizes, which are the non-zero demands, and the time between consecutive demands, are predicted separately through simple exponential smoothing (Willemain, et al., 2004).

Willemain et al. (1994) made a comparison between Croston's method and the simple exponential smoothing and have concluded that the former was more robust, although the real data in some case studies were proved similar in both methods.

Syntetos & Boylan (2001) have showed that the original Croston's method was biased and later proposed a modified version, the Syntetos-Boylan Approximations (SBA) (Syntetos & Boylan, 2005).

2.4. Stock Control Policy

Spare parts stocks have unique management characteristics and therefore stock polices have to be adapted in order to respond to its specificity.

The (T, s, S) period stock control system has been widely discussed. Under this stock control, the inventory position is reviewed at the end of a fixed period T and if it is found to be less than or equal to the re-order level s, enough is ordered to bring it up to the replenishment level S (Babai et al., 2010).

In order to overcome the impossibility to determine the optimal values of s and S, the heuristics that have attracted the most attention are: (I) the power approximation (Ehrhardt, 1979); (ii) Naddor's heuristic (Naddor, 1975) and (iii) the normal approximation (Wagner, 1975).

A study conducted by Babai et al. (2010) lead to the conclusion that Naddor's heuristic is the one best able to minimize the total costs associated with stock policies.

Naddor's heuristic combines a continuous review policy (s, S) with a periodic review policy (T, S) (Babai et al., 2010).

Having analysed the relevant literature within the inventory management of spare parts, the following section will describe the case study that is going to be addressed along this paper.

3. Case Study

As mentioned previously, the main goal of this paper was to propose methodologies that would be able to contribute to the making and possible implementation of stock policies. These stock policies should be suitable to the limitations of a state company and to the specificities of both the acquisition process and the railway materials used in REFER's maintenance processes.

The company has absence of both a stock classification system based on its management characteristics, which could be beneficial to choose the best management approaches to the different materials and a stock policy system for maintenance materials. Additionally, the company does not have standard procedures to demand forecast, hence the empirical and subjective manner in place to forecast. Besides, the long lead times cause unpredictability in the availability of the materials and difficulties in the planning.

The methodology (Section 4) is consisted by its different phases, explaining how each phase relates to the problem under study, as well as the theoretical base to its resolution.

3.1. Characterization of Data Sample

The materials under analysis are maintenance materials with the purpose of a systematic use. They are materials used for the most part in non-planned maintenances and, as so, its needs are difficult to forecast. For that reason, REFER wants to have at all times a stock of such materials.

The sample under study has 55 materials. Although they represent only 1% of the total materials of REFER, there value constitutes 40% of the total value in stock.

This study was carried out with the data from SAP demand of materials – reserves. This data was the one take under consideration because after analyses where considered the more accurate. The data of each month amongst the years 2010 to 2014 were analysed. The registered demands for each maintenance centre were aggregated to serve as ground to decisions involving stocks policies considered.

4. Development and Implementation of the Proposed Methodology

The aim of this methodology is to follow a series of essential phases to a stock policies' system implementation, taking under consideration the limitations mentioned above. This section's organization (Figure 2) reflects the methodologies' different phases.

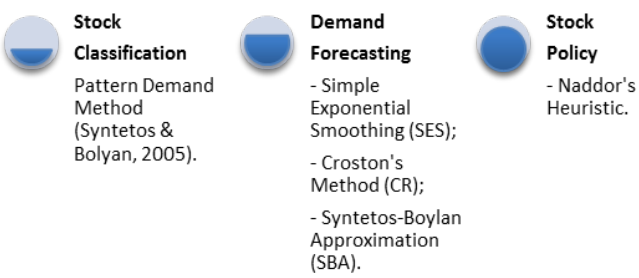

Figure 2 – Phases of the Proposed Methodology

After the selection of the materials that would be focused on this study, a data processing begun. This data is the input to the following phases. The first phase is the stock classification, followed by the demand forecast. The stock policies are the third and last methodology phase, gathering all the results for the previous phases.

4.1. Stock Classification

The classification of the maintenance materials analysed in this paper was developed according to Syntetos et al. (2005) methodology. The authors propose a classification scheme of stock items (Figure 3) according to the demand pattern (Section 2.2, Figure 1).

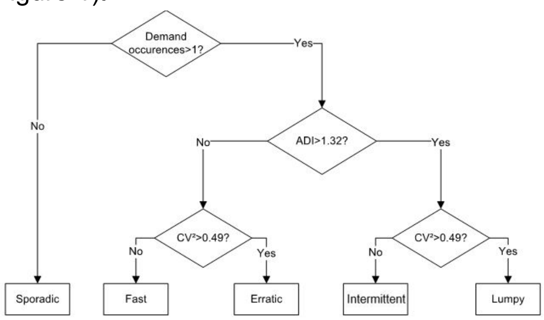

Figure 3 – Classification Scheme According with Demand Pattern (Velagic, 2012)

The underlying idea is, after having identified the four patterns - smooth, erratic, intermittent and lumpy - identify the forecasting method that leads to better results of demand forecast for each one of the patterns, through the measurement of the lowest absolute error.

4.2. Demand Forecasting

In this phase of the methodology, the point was to find the forecasting methods and its parameters that give the forecasts with the lowest absolute error for each of the patterns.

The studied methods were: Simple Exponential Smoothing (SES) – according to Teunter et al. (2011) SES responds rapidly to demand decrease situations; Croston Method – developed for time series with intermittent demand and the time series are divided and forecasted in its constituent elements (non-zero demands (S_{t+1}) and time between demands (k_{t+1})); Syntetos-Boylan Approximation (SBA) – adds a correction to the previous method.

Simple Exponential Smoothing (SES)

$$F_{t+1} = \alpha X_t + (1-\alpha)F_t \qquad (1)$$

Considering the following notation:

α Smoothing constant$(0 \leq \alpha \leq 1)$;
X_t demand for an item in period t;
F_t demand forecast for an item in period t.

Croston Method

$$s_{t+1} = \begin{cases} s_t, & se\ d_t = 0 \\ (1-\alpha)s_t + \alpha d_t, & se\ d_t > 0 \end{cases} \qquad (2)$$

$$k_{t+1} = \begin{cases} k_t, & se\ d_t = 0 \\ (1-\alpha)k_t + \alpha d_t, & se\ d_t > 0 \end{cases} \qquad (3)$$

$$x_{t+1} = \frac{s_{t+1}}{k_{t+1}} \qquad (4)$$

Syntetos-Boylan Approximation (SBA)

$$x_{t+1} = \left(1 - \frac{\alpha}{2}\right)\frac{s_{t+1}}{k_{t+1}} \qquad (5)$$

Considering the following notation:

s_t forecast of demand in month t, provided this demand is positive;
k_t number of months since the last positive demand at the beginning of month t;
α smoothing constant$(0 \leq \alpha \leq 1)$;
d_t demand for an item in period t;

4.2.1. Initialization

To initiate the forecast, Babai et al. (2010) and Chase (2009) divide the historical demand data in two sets. The first dataset is used estimate parameters such as the smoothing constant and to initialize the forecasting methods (Babai et al., 2010). A second dataset is used as proof, meaning it is used to forecast and then compare the results with the real demand. Chase (2009) advocates making the initialization from $^2/_3$ of the oldest historical demand data and the proof from $^1/_3$ of the most recent historical demand data.

In this study, the historical demand data analysed are from a period of 60 months, from 2010 to 2014 inclusive. Following Chase (2009), and in order to not separate historical data from the same year, it was chosen to use 36 months for the initialization ($\approx ^2/_3$) and 24 months for the proof ($\approx ^1/_3$).

The mathematical formulation for the AES forecasting method initialization is given by $\hat{x}_{36}$, where d_t is the demand in month *t* (Velagic, 2012):

$$\hat{x}_{36} = \frac{1}{36}\sum_{t=1}^{36} d_t \quad (6)$$

The Croston's method and SBA shared the same mathematical formulation for the initialization. The initialization for these methods is divided in its elements: the non-zero demand sizes ($\hat{s}_{36}$) and time between consecutive demands ($\hat{k}_{36}$). According to Velagic (2012), being T the number of months in which the demand was positive and d_t the demand in month *t*, it was obtained:

$$\hat{s}_{36} = \frac{1}{36}\sum_{t \in T} d_t \quad (7)$$

$$\hat{k}_{36} = \frac{36}{T} \quad (8)$$

4.2.2. Smoothing Constants

In the intermittent demand, the literature advices low smoothing constants values. Values between 0.05 and 0.2 are seen as realistic for authors like Croston (1972), Willemain et al. (1994) and Johnston and Boylan (1996). In addition, Syntetos et al. (2005) suggests the values 0.05; 0.10; 0.15 and 0.20, as more useful and commonly used. For this reason, these were the α values chosen for the case study resolution.

4.2.3. Selection of the Forecasting Methods

Afterward the forecasting methods and the smoothing constants were analysed to assess the one with the lowest error for each one of the groups. Then, the demands for 2015 and 2016 were forecasted for all the materials.

For each one of the smoothing constants values, the mean error (ME) is calculated for all the time series. An arithmetic average is applied to summarize the results of all the series and to determine both α and method (AES, Croston or SBA) that had the best results, in other words, the lowest error.

The mathematical formulation of performance measurement is:

$$ME = x_t - d_t \quad (9)$$

Considering the following notation:

x_t forecast at the beginning of month *t* of demand in month *t* ;

d_t demand in month *t*.

4.3. Stock Policies

Babai et al. (2010) studied the performance of the three heuristics (T, s, S) coordinated with the demand forecast. The authors concluded that Naddor's heuristic is the one with highest capacity to reduce the total costs associated to stocks policies. Naddor's heuristic consists in a combination between a continuous review system (s, S) and a period review system (T, S). Thus, it consists in a stock policy system (T, s, S) in which the stock level is reviewed at the end of a fixe period T. If it is found to be less than or equal to the re-order point (s_0), enough is ordered to bring it up to the replenishment level (S_0) (Babai et al., 2010).

$$T_0 = \sqrt{\frac{2\,k}{\mu_t\,h\,\lambda}} \quad (10)$$

$$Q_0 = \sqrt{\frac{2\,k\,\mu_t}{h\,\lambda}} \quad (11)$$

Where,

$$\lambda = \frac{b}{b+h} \quad (12)$$

$$\mu(T_0) = \mu_t\left(LT + \frac{T_0}{2}\right) \quad (13)$$

$$\sigma(T_0) = \sqrt{\sigma_t^2 + \left(LT + \frac{T_0}{3}\right) + \frac{(T_0\,\mu_t)^2}{12} + \frac{u^2(1-P_0)}{6}} \quad (14)$$

$$\mu(Q_0) = \mu_t\left(LT + \frac{w}{2}\right) + \frac{Q_0 - u}{2} \quad (15)$$

$$\sigma(Q_0) = \sqrt{\sigma_t^2 + \left(LT + \frac{w}{3}\right) + \frac{(w\,\mu_t)^2}{12} + \frac{u^2(1-P_0)}{6} + \frac{Q_0^2 - u^2}{12}} \quad (16)$$

Finally,

$$s_0 = \mu(Q_0) + \mathrm{F}\,\sigma(Q_0) - Q_0 \quad (17)$$

$$S_0 = \mu(T_0) + \mathrm{F}\,\sigma(T_0) \quad (18)$$

Considering the following notation:

λ service level;

b *backorder costs;*

h	holding costs;
k	order costs;
μ_t	estimate of the mean demand per time period;
σ_t	estimate of the standard deviation of demand per time period
LT	lead time;
u	unit of demand;
w	time unit;
$\mathrm{P}(0)$	probability of no demand per unit time (computed based on the Gamma distribution);
F	inverse cumulative standardized normal distribution given by $\mathrm{F} = \varphi^{-1}(\lambda)$

The values for T_0; Q_0; s_0; S_0 are rounded to the nearest integer as they are computed.

5. Results

5.1. Stock Classification

In the demand historical data of the 60 months under study, and high intermittence of demand occurrence was verified, with a value of zero in several months, which translates into positive demands no higher than 38. Regarding the materials' classification method considering the demand pattern, all the materials REFER selected fit within the lumpy pattern hence the ADI is always higher than 1.32 and the CV^2 is always higher than 0.49.

In Table 1 a summary of the results' intervals for the cut-off values are shown, that establish the demand classification method.

Table 1 – Summary of result's intervals of Demand Pattern Methodology

ADI	CV^2	Pattern
1,58 - 30,00	1,87 – 35,06	lumpy

Following Syntetos et al. (2005) methodology, in the group of materials already classified as lumpy, the materials were aggregated in subgroups, in order to identify the forecasting method with the lowest absolute mean error for each of the subgroups.

An ABC analysis was made towards finding these subgroups with the criteria of hierarchy according to N, the number of non-zero demands. From this ABC analysis three classes of materials with lumpy demand were obtained each with materials with closer non-zero demand (N).

5.2. Demand Forecast

The demand quantities for each of the 60 months were aggregated for all the materials in each one of the three classes – A, B and C. In order to select the most proper forecasting method for each class, the mean error (ME) was calculated for all the data in the time series of the last 24 months (proof) e for the four α values considered. In the end, ME's arithmetic average was calculated. The method and α value that lead to the lowest absolute value of ME's arithmetic average, in other words the lowest biased for each class forecast, was selected.

Class A – Forecast by SBA method, with α of 0.05;
Class B – Forecast by SBA method, with α of 0.2;
Class C – Forecast by AES method, with α of 0.2.

In the end, a forecast for the needs of 2015 and 2016 was made for each one of the materials through the method identified as the most suitable for each class they belong to. The demand forecast was made monthly and the results were aggregated, achieving an annual forecast. The results are presented in Table 2, for a material from Class A, this material will be used as example throughout of this paper. This approach allowed to acknowledge the possibility that not all the months were able to lead to good forecasts, but other months could bring the forecasts closer to reality and, in this way, the aggregated could correct the demand intermittence. It was also calculated the monthly average.

5.3. Stock Policy

The stock policies were simulated using the procedure presented in Figure 4.

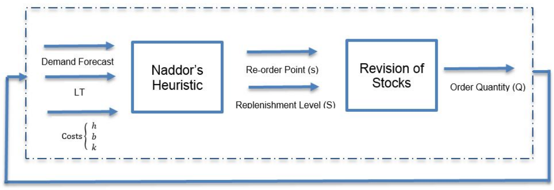

Figure 3 – Scheme of the Proposed Stock Policy

Four scenarios were established in which a percentage is given to the h/b ratio, meaning the ratio between the holding costs (h) and the backorder costs (b). This percentage looks to assess the current situation of the company.

Table 2 – Results of Demand Forecasting for one material of Class A

Month/ Year	1	2	3	4	5	6	7	8	9	10	11	12	Total per Year	Monthly Average
2015	829	888	913	894	946	927	955	960	1 021	996	996	996	11 321	943
2016	1 006	1 019	1 032	1 043	1 056	1 066	1 077	1 087	1 099	1 109	1 118	1 127	12 838	1 070

Each one of the scenarios translates in four distinct service levels: 99% for h/b=1%; 95% for h/b=5%; 91% for h/b=10% and 83% for h/b=20%.

For the heuristic it was necessary to calculate also the demand per period average ($\boldsymbol{\mu_t}$) and the demand per period standard deviation ($\boldsymbol{\sigma_t}$) of the years under analysis. All of this because the time unit (w) considered was year. Note that the majority of the materials have a lead time higher than or equal to one year. That being said, the review time T was established to be one year. It is also important to mention that the demand unit (u) took the value of one, once the management was made by the unit and not by the box.

The monthly forecast of 2015 and 2016 (Table 2) were aggregated and formed the Naddor's heuristic inputs. Through the methodology point of view, the forecasts were the most important inputs, hence it was from them that the ordering point (s0) and the replenishment level were calculated.

In order to analyse the results from the application of the methodologies, Naddor's heuristic results for 2014, having as inputs the real demands of 2014, were compared to the real data of 2014. On the other hand, Naddor's heuristic results for 2015, with the previous obtained demands as inputs, were compared with the real demands from January to September 2015. At last, Naddor's heuristic results for 2016 were simulated as in 2015 and were compared with the forecast demand made by the company (Table 3).

The stock policy simulation started by analysing the stock quantities at the end of each year. If they were less than or equal to the ordering point (s0), an order is placed with Q quantity equal to (S0 – s0) or (S0 – Stock level at the end of the previously year), respectively, where S0 is the replenishment level. The end of the year stock forecast is equal to (S0-demand forecasts), assuming that demand forecasts will be translated into consumptions.

The demands considered for the 2014 simulation were the real 14 870 UN. For 2015 and 2016, the demands considered were obtained through the demand forecast method for this material (Table 2) and were 11 321 UN and 12 838 UN, respectively.

6. Conclusions

The fact that the stock classification result, accordingly to the demand pattern, was of only one pattern – lumpy – was an unique situation, undescribed in previous literature. Nevertheless, a solution was found in aggregating the materials for a second time according to the non-zero occurrences (N), enabling the identification of which forecasting method was the most suitable to the subgroup of materials found within the lumpy group.

The results explained the difficulty found by REFER in stock management, regarding the assessment of the demand quantities and the moment when the orders should be placed. In fact the lumpy pattern is, by Syntetos et al. (2005), the most complex for managing a company's stock.

At the moment what happens in REFER is that the logistics department receives the forecasts from the maintenance department, analyses each material's quantity in stock and for the ones that the quantity are insufficient to satisfy the demand forecasted, an order is placed and the acquisition process begins. Nonetheless, it is important to mention that the demands forecasted by the maintenance department include some safety that is predicted through the experience of the workers.

The main differences between the simulated stock policy and the policy that is in force in REFER, is that the quantity to order is not a demand forecast, but in fact the quantity that is seen as necessary considering the replenishment level (S0), that is obtained in the Naddor's heuristic. The Naddor's heuristic assures the existence of a stock level that

Table 3- Results of the Proposed Stock Policy for one material of Class A

	2014				2015				2016			
Service Level	s_0	S_0	Q	Final Stock	s_0	S_0	Q	Final Stock	s_0	S_0	Q	Final Stock
99%	14 484	24 805	14 933	9 935	13 961	23 913	13 978	12 592	13 355	23 092	10 500	10 254
95%	12 594	21 617	11 745	6 747	12 140	20 840	14 093	9 519	11 652	20 160	10 641	7 322
91%	11 642	20 012	10 140	5 142	11 222	19 293	14 151	7 972	10 795	18 684	10 712	5 846
83%	10 591	18 240	8 368	3 370	10 210	17 585	14 215	6 264	9 849	17 054	10 791	4 216

faces the demand's intermittence, considers the material's lead time and implements correction factors to the optimal ordering time (T0) and to the optimal ordering quantity (Q0).As predictable, the bigger the service level, the more protective stock policy becomes, meaning that the ordering point, replenishment level and final stock (or safety stock) assume higher values than the ones for a lower service level. This issue will be translated into higher holding costs, in case of the demands not being higher than the forecasted. However, if there ought to be any extra demands, there should be enough quantity in stock to fulfil the demand.

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