Spare Parts Management: an Optimized Service Level-based Model for Inventory Control

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Abstract: Spare parts optimization can significantly reduce inventory costs while avoiding compromising equipment availability. However, the distinctive trend of spare parts demand makes it difficult to establish the optimal stock level. Many literature studies address and classify the different criticalities of spare parts, but there is a lack of workable and structured tools related to the effective management of these items. For this reason, this paper proposes a practical approach to compute the stock quantities by setting a target service level, which is pre-defined by considering some critical factors, ad-hoc tuned to the company's needs. The presented approach is composed of three sequential steps: the first aims at classifying the demand time series behavior as intermittent, lumpy, erratic, or smooth; then, forecasting methods are applied to predict consumption events, and the forecasting accuracy metrics are compared to identify the optimal one, per each item; lastly, reorder strategies are selected according to the results of the previous steps and reorder events are triggered by the probability of achieving the target service level for the next time bucket. This model has been validated in a pharmaceutical manufacturing facility, leading to excellent results in reducing stockholding costs.

Keywords: Spare parts management, Inventory, Target service level

I. INTRODUCTION

Spare parts are common inventory stock items needed to maintain equipment. [1] They play an essential role in preventing and reducing equipment downtime. Such downtimes can heavily impact system availability and thus generate a financial loss, especially for those industries with sophisticated technologies that operate in continuous production. Therefore, spare parts management aims at achieving the desired equipment availability at the minimum cost without compromising service continuity. Management complexity increases due to the particular behaviour of demand trends over time. Spare parts have four main distinctive features that distinguish them from the rest of warehouse items and determine a special consideration for the general inventory management rules. Firstly, they are characterized by sequences of zero demand observations interspersed by non-zero demands. This leads to high difficulties in forecast computations. Then, the number of spare parts is very high across the entire organization, even for moderate-sized companies. The high variety carries out problems in choosing the best stock control strategy for each of them. Thirdly, they are affected by the risk of obsolescence, so the stock kept in the warehouse should be as minimum as possible. Because of that, the order quantity could be a constraint that may result in extra stock order costs or equipment downtime costs. Lastly, the consumption of spare parts is closely related to maintenance; hence, unexpected failures or the uneven distribution of maintenance tasks over time cause intermittency in spare parts demand that severely complicates inventory control. [2] For all these reasons, managing spare parts is very complex and requires special attention from the Operations departments. Moreover, its unusual behaviour has attracted and led many researchers to throw themselves into this challenging research field.

This paper aims to design a model for estimating the optimal quantities of spare parts to be kept in stock according to the target service level (TSL) to be guaranteed. The latter is preliminary set by considering one or more critical factors that trigger business decisions in the specific company case. Indeed, through this approach, managers can directly assess the spare parts stock with the corporate business priorities. Therefore, before applying the model, it is necessary to brainstorm with the top management about the main aspects that drive the company's target service level.

The rest of the paper is structured as follows: section II presents the literature review about spare parts management. Section III describes in-depth the overall approach presented in this paper along with the application in the operative scenario, i.e., pharmaceutical industry, in section IV. Lastly, section V discusses the main results and concludes by highlighting both the current research's strengths and limitations.

II. Previous research

This section presents a brief review of the literature related to spare parts. Spare parts inventory management has received noticeable research interest in the last few decades. With a general overview of the state of the art, [3] reviews spare parts inventory management with more than 140 papers published between 2010 and 2020 and it groups them in two clusters. The first includes the characteristics of spare parts, products, inventory systems, and supply chains, while the second group focuses on the characteristics of research methodologies and topics in the reviewed studies. In [1] the authors present a framework for Operational Research (OR) in spare parts management based on the product lifecycle process, including the objectives, main tasks, and OR disciplines. According to this framework, a systematic literature review of OR in spare parts management has been developed. A considerable portion of the existing literature is about forecasting methods. In particular, a 50-year review on forecasting for inventory control is presented by tracing the main scientific contributions related to statistical forecasting for slow and intermittent demand items. [4] Moreover, [5] concentrates on spare parts management by offering a new framework for spare parts forecasting, encompassing forecast support systems. Many works on intermittent demand forecasting are based on Croston's method [4], but several further improvements and bias correction of that method have been developed, as shown in [6], [7]. In the former, four forecasting methods, Simple Moving Average, Single Exponential Smoothing, Croston's method, and a novel method (based on Croston's approach), are compared. As a result, the proposed method is the most accurate estimator for intermittent demand data. Moreover, [7] proposes a new forecasting method that is always up-to-date and can deal with obsolescence and other inventory decisions. It is based on Croston's method as well, but instead of updating the demand interval, it updates the demand probability. Other important research questions addressed to spare parts concern the spare parts classification. For example, [8] asserts that item classification drives the choice of the most appropriate forecasting techniques. Furthermore, [9] brings together the issues of distributional assumptions and items classification by using compound distributions to model demand during lead time, while [10] uses the Kolmogorov Smirnov goodness-of-fit test to find the best fitting distributions to their data and compare the results to those in the literature. Despite the considerable works, spare parts classification is not necessarily related to demand trends, but there are other criteria based on: the definition of classes of SKUs (e.g., ABC), the priority associated (VED, vital-essential-desirable), methods and frameworks (e.g., Analytical Hierarchy Process (AHP) and, recently, unsupervised machine learning techniques. Other works, instead, connect spare parts inventory management with maintenance planning [12], [2]. Lastly, optimizing spare parts management has shifted the focus to additive manufacturing (AM) in recent years. In [13], the authors illustrate under which conditions a transition from conventional manufacturing (CM) to AM is economically profitable for spare parts supply. Likewise, [14] responds to the research question of whether print or stock spare parts. Although many papers have appeared on spare parts inventory management, and despite their increasingly relevant role in the industries, the research and business communities devote little attention to the implementation. As a result, a gap between theory and practice has emerged. [15] To fill this gap, the novelty of this work lies in the proposal of a practical model that correlates quantities stocked with the TSL to be guaranteed for the line. In this way, the strategic decisions that drive the service level definition are transferred to the assets and, as consequence, to the individual items, creating a TSL-driven line-machine-spare parts tree structure.

III. Methodology

The proposed methodology is a 3-steps procedure that receives as input the historical demand series, procurement lead times, stock quantity in the warehouse, target service level, and returns the reorder quantity for each spare part in each time bucket. Therefore, the methodology can be summarized as reported in Fig. 1.

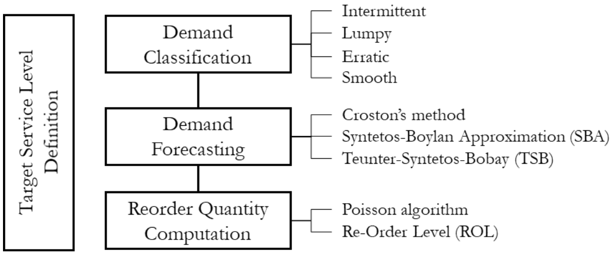

Fig. 1: Block scheme of the proposed model

Before entering the technical detail of the model implementation, the first step is the target service level definition. Service level is the probability that no shortages occur within the time interval in which the new order has been launched and the moment it arrives at the facility, i.e., it is the probability of avoiding stock-out conditions. Setting the target service level is a strategic decision, and if it is not defined a priori, it requires sensitive attention from the top management. The proposed model outlines a practical and effective approach for target service level estimates of spare parts: each item needs to be associated with the production lines that may require it. Then, through the application of many qualitative and quantitative techniques such as brainstorming or AHP methods, the importance of each line is weighed according to one or more critical factors ($i = 1 \dots N$, in Eq. (1)) set by the company. Finally, the following formula needs to be applied to obtain the target service level (TSL) per each production line:

$$TSL = SL_{min} + \sum_{i=1}^{N} \alpha_i \cdot x_i \tag{1}$$

The previous considers a minimum service level (SL_{min}), and the critical factors (x_i) emerged from the preliminary analysis. They are binary variables that enhance the importance of the production line by assuming 1 if they affect the considered lines or 0 otherwise. The last value α is a coefficient between 0 and 1 that can be arbitrarily set according to the impact given to the x_i variables. In any case, the upper bound of the TSL value cannot exceed 100%, so α_i coefficients need to be computed accordingly.

A. Demand Classification

As previously discussed, spare parts demands are characterized by long zero demands periods. Hence, in the first step, it is necessary to take into account this peculiarity and sort the demands for each item as intermittent, erratic, smooth, and lumpy according to the classification suggested in [16] that consider two metrics:

- Squared Coefficient of Variation (CV^2). This is a statistical parameter that computes the ratio between the standard deviation of the demand (σ) and the average demand for non-zero demand periods (μ):

$$CV^2 = \frac{\sigma}{\mu} \tag{2}$$

- Average Demand Interval (ADI). It is the average interval in time periods between two non-zero demands:

$$ADI = \frac{\sum_{t=1}^{N} t_i}{N} \tag{3}$$

  where, t_i is the time between two consecutive demand periods, and N represents the number of all the occurrences with non-zero demand.

Each item is classified according to the resulting CV^2 and ADI as reported in Fig. 2.

Intermittent	Lumpy
Smooth	Erratic

ADI = 1.32

$CV^2 = 0.49$

Fig. 2: Historical demand series classification proposed by Syntetos and Boylan in [15]

B. Demand Forecasting

After a thorough literature review, the model applies three different methods: Croston, Syntetos-Boylan Approximation (SBA), and Teunter-Syntetos-Bobay (TSB), and then compares the evidence by choosing the one that best approximates the historical demand series. Croston's method is widely used, and it is based on exponential smoothing. It divides exponential smoothing computations demand between events with positive demand ($Y_t > 0$) and those with zero demand ($Y_t = 0$). Thus, the first category computes the size of the demand, while the second evaluates its intermittency. Future periods forecasts are obtained by the ratio between the estimated quantity and the estimate of the average interval between two consecutive demands. Given these parameters:

- Y'_t is the estimated average demand at period t for period $t+1$;
- z_t is the demand size in period t, when it occurs, with mean μ and variance σ^2;
- z'_t is the average demand size estimated at period t;
- p_t indicates whether demand occurs in period t:

  $$p_t = \begin{cases} 1, & \textit{if demand occurs at period } t \\ 0, & \textit{otherwise} \end{cases}$$

- p'_t is the estimated demand probability at period t;
- T_t is the interval between consecutive non-zero demands at period t;
- T'_t is the estimate of the average interval between demands at period t;
- α and β exponential smoothing parameters between 0 and 1;

the algorithm updates the prediction as follows [16]:

- if $Y_t = 0$

$$T'_t = T'_{t-1} \tag{4}$$

$$z'_t = z'_{t-1} \tag{5}$$

$$Y'_t = Y'_{t-1} \tag{6}$$

- if $Y_t > 0$

$$T'_t = T'_{t-1} + \beta(T_t - T'_{t-1}) \tag{7}$$

$$z'_t = z'_{t-1} + \alpha(Y_t - z'_{t-1}) \tag{8}$$

$$Y'_t = \frac{z'_t}{T'_t} \tag{9}$$

The second method, known as modified Croston or SBA, was introduced because the previous leads to a distorted estimate of average demand per time bucket, as it compresses periods of zero demand and updates forecasts only when positive demand occurs. Indeed, when a decumulation event does not occur, Croston forecasts remain unchanged. Differently, a long period without any demand events should be an incentive to reduce the forecasted quantity to keep in stock. To overcome this limitation, SBA proposes to generate more uniform estimates by introducing a correction factor β that multiplies the demand estimate. Thus, the last formula of the previous method (9) becomes:

$$Y'_t = (1 - \frac{\beta}{2})\frac{z'_t}{T'_t} \tag{10}$$

where $(1 - \frac{\beta}{2})$ is the bias correction coefficient [18].

Finally, the TSB method differs from the previous ones because it updates the probability of a demand event in each period, while the estimate of demand size is updated only at the end of the periods with positive demand. For instance, if the demand for a specific item remains zero for a long time, it is worth considering the probability that the item has become obsolete. This risk is not counted in Croston's method. TSB predicts an exponential decay when the demand ceases. Demand size is updated as in the original Croston's method, but instead of using the time interval between two positive demand events, it estimates the probability that a decumulation event may occur. [19]

- if $Y_t = 0$

$$p'_t = p'_{t-1} + \beta(0 - p'_{t-1}) \tag{11}$$

$$z'_t = z'_{t-1} \tag{12}$$

$$Y'_t = p'_t \cdot z'_t \tag{13}$$

- if $Y_t > 0$

$$p'_t = p'_{t-1} + \beta(1 - p'_{t-1}) \tag{14}$$

$$z'_t = z'_{t-1} + \alpha(z_t - z'_{t-1}) \tag{15}$$

$$Y'_t = p'_t \cdot z'_t \tag{16}$$

The accuracy of the implemented forecasting methods is evaluated by computing the Root Mean Square Error (RMSE) as a key measure. It can be computed as:

$$RMSE = \sqrt{\sum_{t=1}^{n} \frac{(F_t - D_t)^2}{n}} \tag{17}$$

where t represents the considered time interval, F_t the forecast, D_t the actual value and n the number of all the periods. RMSE is always a non-negative value, but 0 would indicate a perfect fit for the data. In general, the lower the RMSE, the more accurate the prediction of the actual observation.

The methods returning the lower RMSE value per item are chosen as forecasting methods for that specific part.

C. *Reorder Quantity Computation*

After successfully calculating the forecasts according to the most appropriate method for each item, the model proceeds with applying the reordering strategies. In particular, the Poisson algorithm has been chosen to deal with items characterized by extremely sporadic decumulation events. However, before applying the algorithm itself, it is worth verifying that the empirical distribution can be assimilated, with good approximation, to Poisson distribution through hypothesis testing. If the test conducts to the acceptance of H_0 it is possible to proceed with the application of the homonym algorithm; otherwise, to obviate the problem, the model suggests applying the Re-Order Level (ROL) as reorder strategy. As known in the probability theory, Poisson distribution is used to simulate the probability of historical series occurrences whose frequency, sporadic and irregular, is characterized by many zero demand values. At each iteration, the algorithm computes the probability of having a positive demand (F_0) in the next time bucket Eqs. (18, 19) and, consequently, the probability of incurring a stock-out condition Eq. (20) by considering the complement to 1 of the sums of the probabilities of non-null demand. Finally, if the probability of stock-out falls within the range defined by the target service level, then no reorder is made for that specific item. On the other hand, if the probability of stock out exceeds the threshold accepted in the definition of the target service level, then a reorder is launched. The reorder quantity must be as minimum as possible to reach the target service level.

$$p_i = prob(F_0) = \frac{e^{\mu_D} \cdot (\mu_D)^{F_0}}{F_0!} \tag{18}$$

$$p_{i+1} = prob(F_0 + 1) = \frac{prob(F_0) \cdot \mu_D}{F_0 + 1} \tag{19}$$

$$P_{stock\ out} = 1 - \sum_{i=0}^{k} p_i \tag{20}$$

In the previous formulas, μ_D is the average demand within the referred time interval. In parallel, for those items for which the hypotheses tests discard the Poisson approximation, the model proposes to apply the ROL as reorder strategy. Therefore, a new purchase order happens every time the quantity in stock is under the established threshold defined as the Reorder Level (RL). Batch reorder size is set as the Economic Order Quantity (EOQ). It is worth highlighting that the target service level, set in the very first step of the model, is used to trigger the reorder event.

IV. Application

The proposed approach has been validated in a pharmaceutical company, a multinational leader specialized in the production, development, and delivery of drugs and biological products for third parties. The company has two warehouses, the first one where they allocate raw materials and finished products and the second one dedicated to spare parts stocks. The value of the last has grown considerably in recent years, and it currently has about 17 thousand items, more than half of which are slow movers. The problems to face are mainly related to reducing the overall stockholding costs and the items number to be kept due to space constraints. So far, the company has not carried out any spare parts classification through the methods analysed in the model, neither a structured reorder logic based on forecasting the demand overtime aiming to reduce inventory amount. The necessity to promptly satisfy customers requests and therefore final patients has been the main driver for spare parts reorders to prevent slowdowns and reduce as minimum as possible the downtime period of the production lines. To further increase warehouse management complexity, the company has many assets from different suppliers that cause a close dependence to purchase materials. For all these reasons, the proposed model for spare parts management pertinently fits with the company warehouse configuration. Several brainstorming sessions were convened to identify the critical factors enhancing the service level. In the end, the company concluded that revenue impact (x_1) and medical needs production (x_2) are the primary drivers affecting service level increases. Then, Eq. (1) has been computed for each line by considering $SL_{min} = 90\%$ and $\alpha_i = 5\%$ both for x_1 and x_2, since their relevance has been considered equal from the managers. With these parameters, Eq. (1) becomes:

$$TSL = 90\% + (5\% \cdot x_1 + 5\% \cdot x_2) \tag{21}$$

For this research work and without loss of generality, the model application has been conducted on a sample composed of 18 Stock Keeping Units (SKUs). The historical series covering 10 years' time horizon of the demands, monthly reported, have been classified according to Eq. (2) and Eq. (3). In particular, the mean and standard deviation of the sample demands and their classification are reported in Fig. 3 and Fig. 4, respectively.

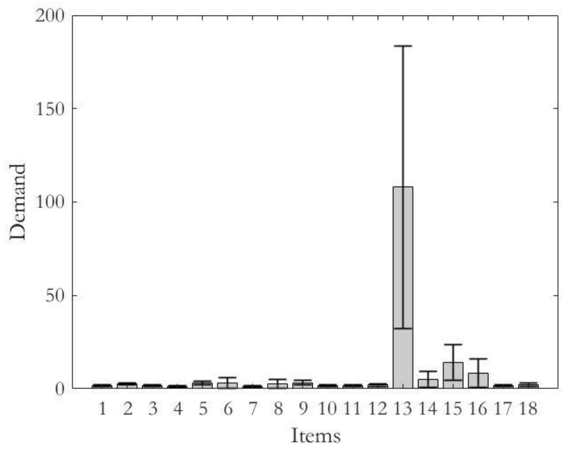

Fig. 3: Mean and Standard Deviation of demands

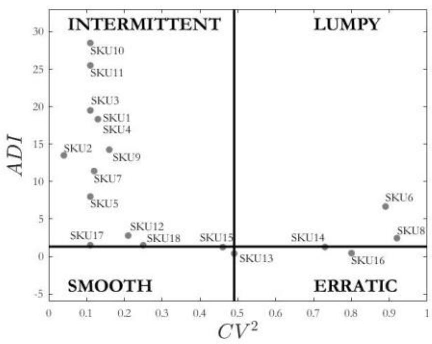

Fig. 4: SKUs classification

As introduced in Section III, the three forecasting methods have been applied, and their accuracy is computed according to the RMSE metric. For the sake of brevity, the iterative applications of Eqs. (4), (5), (6), (7), (8), (9), (10), (11), (12), (13), (14), (15), (16) for the 18 items have been omitted, but they are implemented on three worksheets, one for each method, obtaining the vectors of the future demand forecasts. These last are compared though RMSE indicator and the method with lower RMSE values has been chosen. Fig. 5 summarizes RMSE performance computed for the three methods.

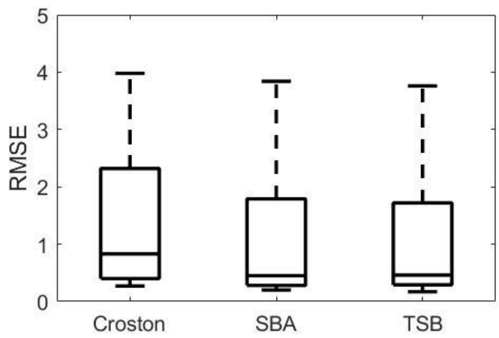

Fig. 5: RMSE box plot analysis

As evident, the performance of the three methods is comparable, i.e., none of the three drastically outperforms the other two. Anyhow, Fig. 6 shows the suggested methods according to the demand pattern and, in bold, it highlights the chosen one in the application.

ADI = 1.32		
	Intermittent **SBA**/TSB	Lumpy **SBA**/TSB
	Smooth Croston/**TSB**	Erratic Croston/**TSB**
	$CV^2 = 0.49$	

Fig. 6: Forecasting method and demand pattern association

Given the demand series of the analysed SKUs, the hypothesis tests are applied to evaluate their approximation with the Poisson distribution. As a result, all the intermittent and lumpy demands report a p-value higher than 0.05. For this reason, along with the consideration of having a quite large dataset (10-year historical series), the null hypothesis has been accepted, so Poisson distribution correctly approximates the demand series of the considered items. On the contrary, the erratic and smooth demand types lead to rejection of the null hypothesis, and the ROL strategy has been applied for those items. The following table shows the result of the hypothesis tests:

TABLE 1:
HYPOTHESIS TESTS EVIDENCE

SKU	Trend	P-value
1	intermittent	1
2	intermittent	0.997
3	intermittent	1
4	intermittent	1
5	intermittent	0.998
6	lumpy	0.85
7	intermittent	1
8	lumpy	0.357
9	intermittent	0.252
10	intermittent	1
11	intermittent	1
12	intermittent	0.263
13	erratic	0.000001
14	erratic	0.000001
15	smooth	0.000001
16	erratic	0.000001
17	intermittent	1
18	intermittent	0.987

Hence, SKUs 13, 14, 15, and 16 follow the look-back strategy based on the RL. Such items have been considered high-rotating items coherently also with the category product they belong to, since they are consumables. Instead, Poisson algorithm iterations have been applied to the remaining articles by computing the stock-out probability in each time bucket and reordering the necessary quantity to satisfy the target service level. Table 2 presents the quantities to reorder for the next 7 months.

TABLE 2:
REORDER QUANTITY FOR EACH TIME BUCKET

SKU	Strategy	1	2	3	4	5	6	7	8
1	Poisson	0	0	0	0	0	0	0	1
2	Poisson	0	0	0	0	0	0	0	0
3	Poisson	0	0	0	0	0	0	0	1
4	Poisson	0	0	0	0	0	0	0	0
5	Poisson	0	0	0	1	1	1	1	1
6	Poisson	0	0	0	0	0	0	0	0
7	Poisson	0	0	0	0	0	0	0	0
8	Poisson	0	0	0	0	0	0	1	1
9	Poisson	0	0	0	0	0	0	0	0
10	Poisson	0	0	0	0	0	0	0	0
11	Poisson	1	0	0	0	0	0	1	0
12	Poisson	0	0	0	0	0	0	0	0
13	ROL	67	0	67	0	0	0	0	0
14	ROL	6	0	0	0	0	6	6	6
15	ROL	11	0	11	11	0	11	0	0
16	ROL	16	0	0	16	0	0	16	16
17	Poisson	0	0	0	1	0	0	0	0
18	Poisson	1	0	0	0	0	0	0	0

The benefits of the model application in this case study are quantified in terms of quantities kept in stock and costs and reported in Table 3.

TABLE 3:
SAVINGS ASSESSMENT AFTER MODEL APPLICATION

SKU	C_u (€)	Q_{stock}	C_s (€)	Q_{TSL}	C (€)
1	15.2	7	106.4	5	76,0
2	35.7	6	214.4	1	35.7
3	182.6	2	365.2	1	182.6
4	3705.0	1	3705.0	1	3705.0
5	7.2	4	28.6	2	14.3
6	5.2	24	124.8	5	26.0
7	150.2	2	300.3	2	300.3
8	19.0	6	114.0	2	38.0
9	9.2	4	36.8	3	27.6
10	1121.2	1	1121.2	1	1121.2
11	36.0	2	72.0	3	108.0
12	1.8	30	54.3	7	12.7
13	1.2	397	464.5	275	321.8
14	3.7	27	99.9	21	77.7
15	0.3	32	8.6	28	7.6
16	3.5	24	85.0	75	265.5
17	2580.0	2	5160.0	1	2580.0
18	46.0	3	138.0	1	46.0
Total			12199.2		8946.1

Where:

- C_u (€) is the unit cost for each item;
- Q_{stock} is the actual stock quantity;
- C_s (€) is the overall stockholding cost per item;
- Q_{TSL} is the minimum quantity to reach the TSL;
- C (€) is the overall stockholding cost after applying the model.

It is worth observing that, in the previous computation, due to the lack of available information, only purchase costs have been considered rather than all the costs tied to the operating management. It is not possible to estimate the savings for the entire population by evaluating only this sample. To globally quantify the savings induced by the model use, the normalized percentage of reduction is computed as:

$$S_{\%} = \frac{C_S - C}{C_s} \cdot 100 \tag{22}$$

Except for items 11 and 16 that caused a stock and cost increase, the remaining SKUs exhibit a stockholdings costs reduction of 11.62%, $72.91 \pm 8.83\%$, $39.10 \pm 30.62\%$, and $26.47 \pm 6.00\%$, respectively for the smooth, lumpy, intermittent, and erratic patterns. However, it can be easily noticed that the model proposed in this paper leads to a mean percentage of reduction of about $40.03 \pm 29.25\%$.

V. Conclusions

This paper presented the design of a model to estimate the optimal quantities of spare parts to be kept in stock. This research provides a dynamic and effective model for spare parts management based on the target service level. It links the TSL and the quantity to keep in stock in order to carry out the company's operating choices based on strategic considerations. A sample of 18 SKUs is considered in the case study, and a mean saving percentage of about $40.03 \pm 29.25\%$ is obtained through the model use. The main limitations of the research relate to the small sample used in the application and the systems involved in the analysis (limited data management capabilities, such as spreadsheet and charged systems, not available to all). Finally, the definition of the drivers to set the TSL requires a strong management commitment. Future work will be devoted to the application of the model on large scale and to its impact assessment on the performance indicators, such as space reduction, spare parts, and machine availability.

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