A SIMULATION APPROACH FOR SPARE PARTS DEMAND FORECASTING AND INVENTORY MANAGEMENT OPTIMIZATION

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ABSTRACT
Today, the management of the spare parts is a very important problem for the producers companies of industrial mechanical plant.

In this article, we develop and test a simulation approach, to forecast the demand of spare parts components during the lifetime of a complex product, such as an industrial plant.

The model requires a preliminary phase, where the relevant data of the plant should be collected by the manufacturing company. Then, a specific computational process should be carried out.

In the paper, the model is applied to a case example, referring to a hypothetical manufacturer of industrial plants, to demonstrate the model efficacy and its resolution capacity. Indeed, the application shows that the model proposed is able to identify the optimal level of service the company should set to manage the inventory of spare parts, i.e. the service level that minimizes the cost of spare parts inventory management.

The study finally proposes the future developments of the model and its application on the actual industrial reality.

Keywords: spare parts, simulation, demand forecast, stock management

1. INTRODUCTION
Spare parts (also called service parts, repair parts, or replacement parts) are interchangeable parts used for the repair or replacement of failed parts. Spare parts are an important feature of logistics management and supply chain management, and often require dedicated inventory management policies. Indeed, spare parts inventories need to be available at appropriate points within the supply chain, to provide after-sales services and to guarantee the desired service level (Botter and Fortuin, 2000).

Spare parts inventory management differs from managing the traditional manufacturing inventories, in several ways (Kennedy, et al., 2002). First, the functions of spare parts inventory is different from the traditional manufacturing inventory. For spare parts, service requirements are usually higher, since the effects of stock-outs may be particularly critical and financially remarkable (Huiskonen, 2001). However, the prices of individual parts may be very high, so that the cost of inventory can be relevant. Finally, the demand for parts is extremely sporadic and difficult to forecast, and, under some circumstances, could depend upon the maintenance strategy adopted.

At the same time, however, spare parts are essential in a supply chain. Indeed, they are required anytime there are material buffers in production systems, or maintenance operations are carried out, or the material flow is particularly high. Moreover, spare parts are essential to companies manufacturing complex systems, such as plant manufacturers or companies operating in the aviation industry (Fritzsche & Lasch, 2012), or to maintenance organization companies (Driessen et al., 2010).

On the basis of the scenario described above, it is not surprising that spare parts inventory management is a widely debated issue in literature. Researchers, in particular, are seeking for the optimal management of spare parts inventory, i.e. to the definition of an inventory policy leading to improving the quality of spare parts, at the same time reducing inventories and related costs. To this purpose, the problems addressed by spare parts literature focus primarily on those topics (Bacchetti and Saccani, 2012): (1) modeling the demand of spare parts; (2) classifying spare parts and determining criticality; (3)

developing stock-control techniques, integrating spare parts classification and demand forecasting.

Concerning the first topic, there is an extensive body of literature addressing spare-part inventory systems with random demand under different assumptions on the demand probability distributions. Hausman and Scudder (1982), Pyke (1990), Verrijdt et al.(1998), Perlman et al.(2001), Sleptchenko et al. (2002), (2005), Perlman and Kaspi (2007), and Adan et al.(2009) study stochastic multi-echelon inventory systems with several repair modes. Less studies have been carried out concerning spare-part inventories with deterministic demand (e.g., Prager,1956; Gass, 2003; Abdul-Jalbar et al., 2006; Federgruen et al.,2007; Perlman and Levner, 2010).

On the basis of the demand modeling, the corresponding inventory techniques are generally formulated as a cost minimization problem, with a cost function comprising the holding cost, ordering/setup cost, and either an explicit penalty cost or a specified service level constraint. For instance, Al-Rifai and Rossetti (2007) present an analytic inventory model for a two-echelon non-repairable spare parts system, that consists of one warehouse and several identical retailers. The model is grounded on the reorder point policy, and the inventory control problem is formulated to minimize the total annual inventory investment of the system, subject to a defined annual ordering frequency and an expected number of backorder constraints. Simao and Powell (2009) develop a model to determine the optimal inventory levels at each warehouse, for an aircraft manufacturer. The model is solved using approximate dynamic programming, with a proper design, so as to consider the presence of low-frequency observations.

The basic inventory models (such as EOQ or EOI) have been widely applied to the inventory management of spare parts (Liu and Esogbue, 1999). Conversely, there is relatively little evidence of the use of more sophisticated techniques or integrated models (Bacchetti and Saccani, 2012), that start with the inventory classification and ends with the performance assessment of the inventory control policy adopted. Moreover, as regards the inventory management policies, approaches for spare parts management are rarely optimized in terms of overall inventory costs they generate, including not only the holding stock cost, but also stock-out cost and order cost. Therefore, there is no link between the selected policy and the corresponding cost (or performance) of the spare parts management, nor to the evaluation of the practical usefulness of that policy in practical cases.

Starting from those research gaps, in this paper we develop an integrated approach, that, starting from the identification of critical components, provides, as final output, the identification of the optimal inventory management policy for each spare part, i.e. the policy that minimizes the total cost of the inventory management system. Since spare parts are requested on an irregular basis, simulation is exploited to derive an estimate of the components demand, replacing traditional analytic models. To show the practical use of the approach developed, the model is then applied to the case of a food plant manufacturing company.

The remainder of the paper is organized as follows. Section 2 reviews the literature related to spare parts inventory management, with a particular attention to the studies that include an analysis of the cost of the inventory management. In section 3, we present the model developed in this paper. Section 4 provides an application of the model to a numerical example. Finally, section 5 concludes and indicates future research steps.

2. MODELLING

As mentioned above, few studies in literature propose complex models for spare parts management. The aim of this article, therefore, is to develop an analytic method for spare parts management. The starting point of the model is a set of data provided by a real company, manufacturing food industrial plants; as output, the model provides an estimate of the spare parts the company will have to supply during the plant lifetime.

The initial hypotheses of the model developed are the following:

- The industrial plant, and, in general, any kind of complex equipment, can be considered as a group of mechanical components;
- For each mechanical component, some technical serviceability data (e.g., Mean Time to Failure or Mean Time to Repair) are known;
- For each plant, the lifetime data (i.e., the initial time of working and the date of its disposal) are known.
- The unitary inventory management cost (in particular, the cost of holding stock and the stock out cost) is known.

The mathematical model proposed in this paper is developed exploiting a general purpose software, i.e. Microsoft Excel, appropriately programmed with as Visual Basic for Application. This tool has been chosen due to its capacity to perform complex computations in the inventory management context, as demonstrated by Bottani et al., (2012).

To set up the model, the company should provide the amount of industrial plants installed worldwide; such information is used to forecast the demand of internal spare parts.

Typically, the market phases of complex products, such as industrial plants, consists of five phases [Figure 1]:

- Initial phase: the product is new, and therefore unknown to the external market. The company invests much on the marketing of the new technology;
- Development phase: during this phase, the product is well-known and the number of the requested and installed plants increases in time;
- Stabilization phase: in this phase, the number of plants sold during the year remains almost constant in time;

- Decreasing phase: during this phase, competitors can reach and exceed the technology level of the machinery manufactured by the company. Therefore, the number of plants installed decreases gradually;
- Final phase: during this step, the product will be removed from the company's portfolio and therefore that product will no longer be sold to the market..

Up to the decreasing phase, the demand of spare parts the company should fulfill will depend on the plants already installed, as well as on the new installed plants. Conversely, during the final phase, the demand of spare parts will depend only on the plants the company has previously installed. The end-of-life of the product occurs when the last plant stops working.

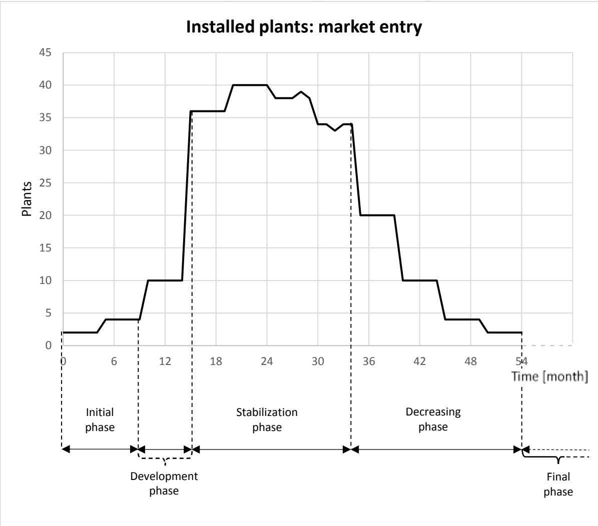

Figure 1 - Different product market phases.

For each plant, it is reasonable that the company knows the number of critical spare parts and its maintenance data. Specifically, for each plant, the model requests these data to be implemented:

- Start operating date: this date is expressed through an absolute temporal system. Conventionally, the first installed plants is sold and begins to work at time $t_0 = 0$;
- End of working time: this date indicates the dismantling of the plant. Since the model is grounded on a simulated approach, the operative life of the machinery could also be hypothesized and varied by means of the simulation. In the numerical case, a particular statistical distribution is used to represent the working life of the plant. Obviously, the model has been developed as a flexible tool, where different statistical distribution can be used to represent the service life of the plant in the specific industrial case.

These two data replicated for each plant analyzed describe the temporal limit of the simulation.

In order to forecast the spare parts demand, the model requires also the maintenance and replace data of those components that can be considered as critical spare parts. In this regard, according to Molenaers et al. (2011), defining the criticality of spare parts is a complex process. In particular, this activity involves several areas of a company, such as logistics, production, business analysis, marketing and more (Braglia et al., 2004).

The relevant criteria for the analysis of critical components depend on the particular industrial application of the method. In general, those criteria can include, among others:

- Logistic characteristics: these factors can be the geometric and dimensional properties. Generally speaking, these factors have a lot of influence on the logistics activities;
- Maintenance and replaceable characteristics: as mentioned above, the higher is the probability of failure, the more critical component is. This point should take into account not only the probability of rupture of the part, but also their corruption, since it can affect the time required for the replenishment of the spare part.

In summary, the proposed model needs several data about the critical component, for which the demand should be estimated. Specifically, to correctly initialize the model, the user must insert the following data about the critical component:

- Mean Time to Failure (MTTF): this is the time elapsing between two subsequent product failures. In the numerical example, this parameter is set to a constant value. Nonetheless, once again, the simulation model has been designed to be flexible, allowing to adopt a different statistical distribution depending on the nature of the component to be examined. Similarly, the MTTF value can change during the lifetime of the component;
- Replenishment Time (RT): the model estimates this data by means of a lognormal distribution. To set up the distribution, the user can insert the average and standard deviation values of the RT in the model. As per the MTTF, a future development of the method can to consider new or other distribution to describe the RT.

Through the data listed above for the critical components, the model is able to compute the rate of the component failure in each plant.

To this extent, the time elapsing from the plant starting date and the first failure is computed according to the classical theory of industrial maintenance, expressed in eq.1:

$$t_I = -\frac{1}{\lambda * \ln(rnd)} + S_t \qquad 1.$$

where:

λ = 1/MTTF

rnd = random number [0;1]

S_t = Start operating time

To estimate the time of the following failures, the models considers the replenishment time as follows:

$$RT \sim logN(\mu, \sigma^2) \qquad 2.$$

$$t_n = -\frac{1}{\lambda * \ln(rnd)} + S_t + RT + t_{n-1} \qquad 3.$$

where:
t_n = time of occurrence the rupture n
S_t = Start Operating Time
RT = Replenishment Time
t_{n-1} = time of occurrence the rupture n-1

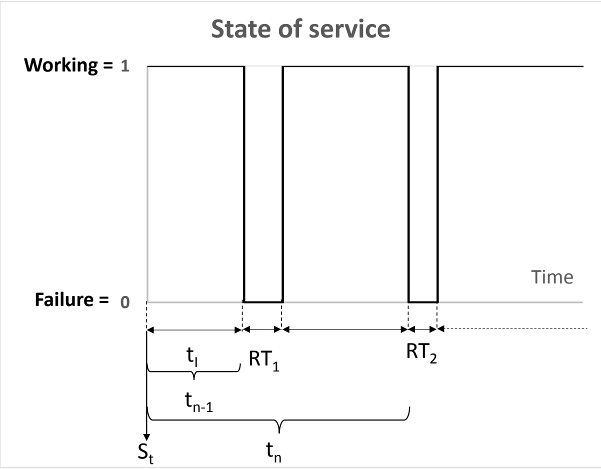

Figure 2 - State of service of a mechanical component.

From this data, the request for components during the lifetime of the plant can be easily computed. This computation should be replicated for each plant sold and installed by the company, to derive the global distribution in time of component failures during the lifetime of the plant.

As a result from the computation of the failure times, the model reproduces the demand of spare parts the company should fulfill, on a selected time unit (e.g., week or month). As an example, the demand of components provided by the model can describe a function as that shown in the figure below:

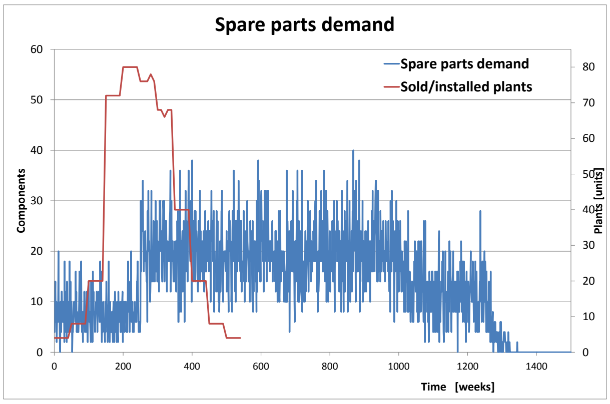

Figure 3 - Spare parts distribution (example).

The model replicates the computation described above, in order to increase the relevance of the statistical analysis related to the lognormal statistical distribution characteristics of the RT and the MTTF. Therefore, for each time step the model does not provide a specific value, but a statistical distribution of the component demand:

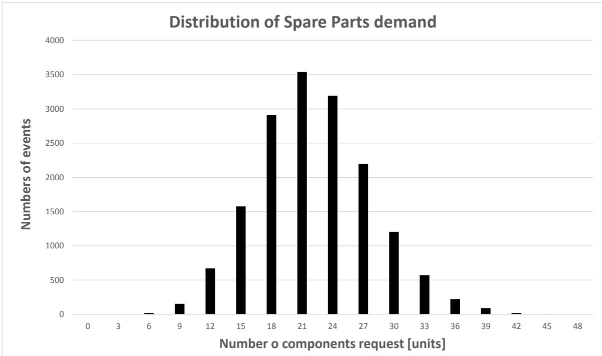

Figure 4 - Distribution of spare parts demand on the model replications for a generic time step.

With these hypotheses, the model tries to identity the optimal level of service through an economic analysis. Specifically, the simulation takes into account the following cost:

- stock-out cost: the company will pay for bad maintenance service. In our model, this costs arises when the required component is not available in the stock;
- Inventory cost: this is the cost that the company pays to maintain the stock of the spare parts.

The simulation system modifies the service level provided by the company, by varying the *k* coefficient, defined by the following equation:

$$k = \frac{number\ of\ service\ events\ soddisfied}{total\ number\ of\ events} \qquad 4.$$

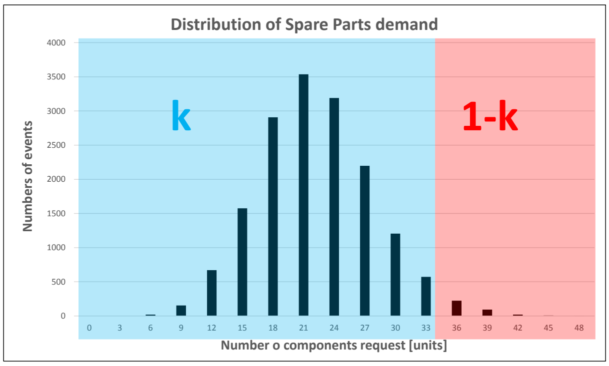

Figure 5 - Service level (k).

The value of *k* varies from 85% to 99.9% with a step of 0.05%; for each value, the model takes into account the distribution of the spare parts demand.

With an integer simulation, the demand value arises with steps of one unit, until the service level reaches the desired value. For each step of each replication, the model computes:

- The expected value of spare parts, as a function of the service level;
- The value of the demand of spare parts.

From these outcomes, for each time step the model will calculate:

- The value of the stock, i.e. the number of components available in the stock. It is assumed that the initial value (at time *t*=1) of the stock accounts for one unit;
- The amount of spare parts to be ordered: by ordering this quantity, the value of the spare parts stock is step by step equal with the expected value.

During the simulation, the model updates the value of the stock and spare parts ordered, as follows:

$$OSP_n = ST_n - EV_{n+1} \qquad 5.$$

$$ST_n = ST_{n-1} - DV_n + OSP_n \qquad 6.$$

where:
OSP_n = spare parts to be ordered at step n;
ST_n = number of component in stock at step n;
EV_n = expected value at step n;
ST_{n-1} = number of component in stock at step n-1;
DV_n = demand value at step n.

The spare parts ordered generates the inventory cost of the time step, as follows:

$$SIC_n = IC * OSP \qquad 7.$$

with:
SIC_n = inventory cost of the temporal step n [€/step];
IC = inventory cost of a unit component [€/unit];
OSP = spare parts to be ordered.

At the same, when the value of the stock is lower than the demand value (ST_n <0), a stock out cost occurs:

$$SCST_n = CST * (-ST_n) \qquad 8.$$

with:
$SCST_n$ = stock out cost at step n [€/step];
CST = stock out cost [€/unit];
ST_n = number of component in stock at step n.

For each service level the total costs of the single replication follow the equations:

$$TIC = \sum_{n=1}^{n} SIC_n \qquad 9.$$

$$TCST = \sum_{n=1}^{n} SCST_n \qquad 10.$$

$$\overline{TIC} = \frac{\sum_{n=1}^{n} SIC_n}{n} \qquad 11.$$

$$\overline{TCST} = \frac{\sum_{n=1}^{n} SCST_n}{n} \qquad 12.$$

TIC = total inventory cost of the replication [€];
TCST = total stock out cost of the replication [€];
$\overline{\text{TIC}}$ = average inventory cost [€/step];
$\overline{\text{TCST}}$ = average stock out cost [€/step].

Finally, the model is able to evaluate the service level cost as the average costs of the replications and the global cost as the sum of $\overline{\text{TIC}}$ and $\overline{\text{TCST}}$. Those cost components could also be combined and compared, to explain the relationship between the cost and the service level. Although the specific cost results may vary depending on the value of IC and CST set into the model, the graph of this relationship is expected to have the following general structure:

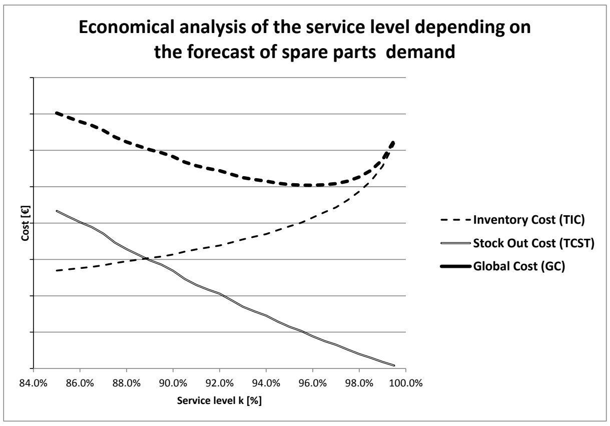

Figure 6 - Final economic analysis (example).

From the economic analysis, the model can calculate the optimal value of k (k_{opt}), i.e. the value that minimize the total costs of inventory.

3. A NUMERICAL EXAMPLE

We then test the model presented in a particular context, reproducing a plant manufacturing company; one of their plants is taken as the example product.

At the beginning, the plants enter in the market with the distribution shown in figure 7.

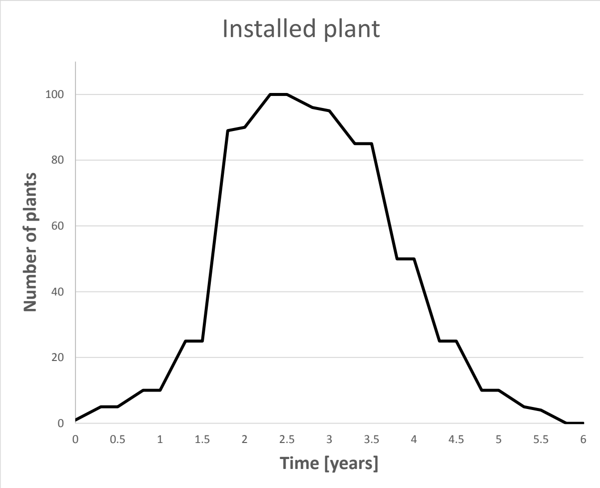

Figure 7 - Trend of installed plants.

According to the graph, the product experiences a rapid increase in its sells between the first and the second year of commercialization; the stabilization phase lasts two years, then the sells decrease. After the sixth years of the commercialization, this product comes out from the catalogue of the company. The graph above describes 1000 plants manufactured by the company and entering the market during the commercialization period.

In this example, the service life (SL) of each plant is modeled as a normal distribution:

- $SL \sim N(\mu, \sigma^2)$
    - μ = 20000 hours;
    - σ = 4000 hours

In this example, we assumed as critical those spare parts that own the following maintenance and serviceability data:

- MTTF = 2000 hours (λ = 0.0005);
- $RT \sim logN(\mu, \sigma^2)$ with:
    - μ = 10 hours;
    - σ = 2 hours.

With these data, the model simulates 16373 replications of the spare part demand, computed using the statistical distribution described above for maintenance and serviceability.

The graph in Figure 8 shows the average of the spare parts demand generated by the characteristic of the plants installed:

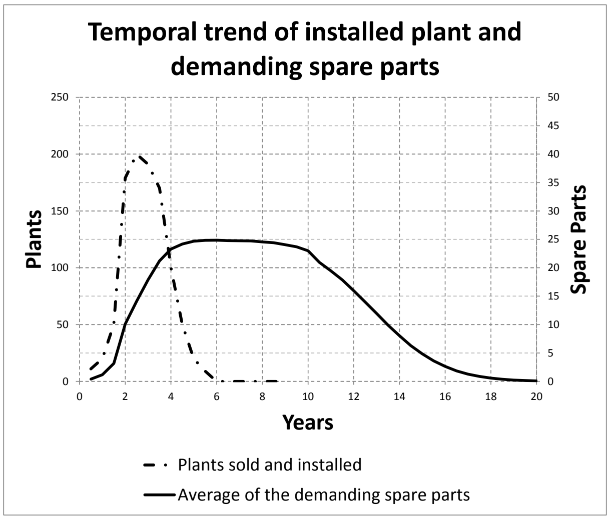

Figure 8 - Trend of the installed plants and relative demand of spare parts.

Then, the model estimates the stock-out distribution, depending on the service level k, whose value varies in the following range:

- minimum service level: 85%;
- maximum service level: 99.9%;
- step of analysis= 0.05%;

In order to identify the optimal value of the k, the costs of stock out and inventory are computed, starting from the following unitary costs:

- Inventory cost (IC) = 75 €/component;
- Cost of stock out (CST) = 3000 €/component.

In our example, the order cost is hypothetically negligible compared to the other cost components, and is, therefore, neglected in the analysis.

With these data, the model can performs an economic analysis, reporting the average weekly costs of stock-out and inventory :

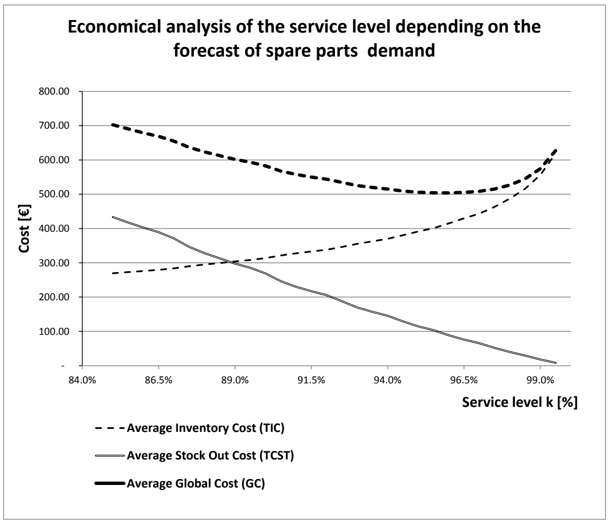

Figure 9 - Economic analysis.

Finally, the model identifies the minimum total cost of the system, in order to find the optimal value of service level. In this example, we found

- $k_{opt} = 96\%$
- $AGC_{min} = 503.79$ *€/week*

4. CONCLUSIONS

This articles has proposed a direct application of a simulative approach to a logistic problem, related to the spare parts inventory management.

In particular, the methodological approach presented in this study allows to define the optimal level of the spare parts stock during the lifetime of a product (i.e., a plant or machinery) containing the component.

The study explains the main steps of the computational process, starting from the distribution in time of the plants manufactured by the company.

The model described represents a preventive and flexible tool for the prediction of spare parts demand. Indeed, a real company can insert the characteristics parameter of its products, in order to adapt the simulative model with its industrial case.

With a numerical example, the articles applies the model on a real case example, based on the theoretical description of the maintenance and the service ability of the mechanical system.

The method involves several activities of the company, basically concerning data regarding the plant, the component and the durability of the product on the global market.

Looking at the results obtained, the natural future develop of this analysis is its application to a real industrial case, with the purpose of testing its applicability in real scenarios. Comparing the proposed approach with other tools in use in a real company could be interesting to test the reliability of the model, as well as to identify potentials for improving its performance and affordability.

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