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ARTICLE

Study on Customer Demand Forecasting Models, Stock Management, Classification and Policies for Automobile Parts Manufacturing Company N.A.C.C. (An Advance on Classical Models)

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ABSTRACT

The primary intent of the current research is to provide insights regarding the management of spare parts within the supply chain, in conjunction with offering some methods for enhancing forecasting and inventory management. In particular, to use classical forecasting methods, the use of weak and unstable demand is not recommended. Furthermore, statistical performance measures are not involved in this particular context. Furthermore, it is expected that maintenance contracts will be aligned with different levels. In addition to the examination of some literature reviews, some tools will guide us through this process. The article proposes new performance analysis methods that will help integrate inventory management and statistical performance while considering decision maker priorities through the use of different methodologies and parts age segmentation. The study will also identify critical level policies by comparing different types of spenders according to the inventory management model, also with separate and common inventory policies. Each process of the study is combined with a comparative analysis of different forecasting methods and inventory management models based on N.A.C.C. parts supply chain data, allowing us to identify a set of methodologies and parameter recommendations based on parts segmentation and supply chain prioritization.

1. Introduction

With acute competition between economies, the necessity of organization, optimization of industrial processes, and management is essential to guarantee the evolution of companies due to the evolution of the triptych cost, quality, and service.

To be able to guarantee the optimization of one of the key functions in the logistics chain through industrial processes This word, logistics, whose Greek etymology is synonymous with logical reasoning, or mathematical cal-

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culation, was first used in military vocabulary to designate the coordination of transport, supply and communication activities in a war camp. Nowadays, there exist numerous ways to define supply chain management. It could be a process that involves activities to enhance a product or service from one state to another from the first supplier to a final customer. For better working order of products, the maintenance service is in charge of the designation of the activities. These operations often require the replacement of defective parts, hence the need for a stock of spare parts and therefore an inventory management process.

Traditionally, the management of these stocks is done by the maintenance technicians. However, this configuration does not allow a sharing of stocks and coordination of logistic activities, so it is now replaced by centralized management of the spare parts logistic chain which allows not only rationing of stocks, but also supervision and a mutualization of flows.

Spare parts management is within logistics and maintenance, with that being said it also permits to differentiate and compare to the classic case, which justifies the interest of its treatment by independent literature. Among these characteristics, we can distinguish the weak and erratic aspects of the demand. The highly significant and unpredictable demand forecast and inventory management have significantly impacted the general performance indicators in the supply chain: inventory levels and service. Moreover, the priorities between these indicators differ according to the segmentation of the parts and the customers of the chain, hence the need to take this differentiation into consideration when sizing the stocks. Thus, this article will analyze two issues such as forecasting and inventory management processes, before proposing improvements to their steps, to enable the establishment and integration and to permit the selection of newer prediction methods. At last, to bring up the unfamiliarity's of spare parts inventory management. In each phase of this article, the proposed processes will be analyzed using a design of experiments of real N.A.C.C. (North automobile components company) data and the results will be compared according to the segmentation of demand profile and the segmentation of parts maturity level.

This paper aims to ameliorate the responsiveness to the distribution of N.A.C.C. to great geographical demand by improving the internal inventory, in the case of a very large portfolio of references and a weakly controlled behavior of maintenance technicians, which requires the use of an approach based on the history of the demand rather than a reliability approach.

Thus, this research will analyze two forecasting and inventory management processes before proposing improvements to their steps, to establish a connection between the alternative processes and other methods, and to provide forecasting methods with a better understanding of the processes, it will be necessary to develop new approaches to forecasting. Ultimately, this will allow for a new approach to customer differentiation. In each part of the paper, we will go through data and experiments, finally, the maturity degree of parts will be compared based on their design and demand model.

2. Literature Review

In the following discussion, we will outline the definition of customer demand forecasting and highlight the current state of the art in research and build on it to expand on existing accomplishments.

2.1 Customer Demand Forecast

Forecasting is defined as the observation of a set of data that allows one to envisage a future situation and to undertake actions to deal with it concretely. Forecasting is the practice of estimating possible events or developments through the use of the past and the present as tools to estimate the future.

The task of forecasting is not merely to estimate potential future occurrences. "It also represents a principal input for decision support models, especially when it is a question of a very uncertain environment." A forecast is often required each time a decision is taken. "Forecasts are not meant to be used for their own sake, but to inform decisions." It is also used for the construction of anticipation strategies by companies.

Demand forecasting is a specific form of forecasting: "Demand can be described as the quantity of a good or service that people are wanting and willing to buy during a specific time frame"; "Demand forecasting is the science of anticipating the level of demand that may be expected to occur at a given time in the near or distant future". Demand forecasting can use methods, processes, and practices related to other types of forecasting (meteorological, econometric...), as well as using methods common to these types, known by their statistical efficiency such as smoothing methods.

To meet the specific requirements of the spare parts request described hereinafter, independent spare parts demand forecasting literature was developed and was dissociated from classical demand forecasting (such as product sales/purchase forecasting).

2.2 State of Art of the Research

An improvement of the Croston's estimator was done "*by simply adding a smoothing parameter for forecast-*

ing" Syntetos and Boylan (2007) [1].

After several tests some good results have been achieved when "*the bootstrapping method was applied to forecast component demand"* Willemain et al. [2].

"Grey systems theory has been employed to forecast material equipment in the Taiwan Navy" proving its effectiveness Chiou et al. [3].

Propositions of models based on "*support vector machines have been employed in several domains of forecasting"* such as (computing, motors, car parts etc…) which has also proven handy Hua Zhang [4],

Implementation of "*Neural networks have proven their effectiveness in forecasting auto parts, airplaine parts etc*…" it dealt with large scale data more effectively than most of the methods to forecast parts demand Gutierrez et al. [5].

The "*Kano model principle examined personalized demands, built a hierarchical model of personalized demands for products, and established the priority order of importance of personalized demand"* based on the hierarchical model and the ranking of importance, the customizable attributes of the product and their priorities for customization were determined (Tang Zhong-jun and Long Yu-ling 2012) [6].

"Large-scale spectral clustering with landmark-based representation selected K-means clustering of large customers" based on the dimensions of electricity, electricity prices, and capacity to classify customers into five categories. Second, customer requirements were identified based on large customer service orders, customer surveys, etc., and the requirements were hierarchically classified according to business types and customer perceptions. Finally, based on the findings of the customer cluster analysis, the specific electricity demands of customers in each category were identified, and demand stratification and resource allocation were proposed (Chen Xinsheng, Cai, D. 2011) [7].

"*System optimization method for customer demand prediction based on support vector regression analysis in the process.*" They proposed three-step algorithm including mathematical model formulas of nonlinear programming (NLP) and linear programming (LP) to obtain the regression function, and the last step used a recursive method to predict customer demand effectively (Levi et al. 2005) [8].

"Demonstrations of the ability of self-organizing maps (SOMs) were used to classify customers and their responsiveness potential using merchants, trade, and customer flow demand databases, and helped load response modeling as supporting tools." "*Customer suitability searches are limited to daily and real-time products, and interest in such products is growing in developing countries. Therefore, customer demand and responsiveness (demand response and distributed generation strategies) were tested and compared to the price curve*."

The results significantly demonstrated the ability of the method to improve data management, and it is easy to find a systematic strategy to achieve clear demand ratios in different price scenarios (Valero et al. 2015) [9].

Studies have been done on the optimal inventory management of some companies. "*The price of products sold by the companies were driven by an exogenous stochastic pricing process"* that impacts the customer acquisition rate between ordering cycles, the author also analyzed the backlog and turnover of optimal ordering decisions. The research results show that the price-based inventory strategy is optimal under certain conditions (Canyakmaz et al. 2019) [10].

Based on the results of real Amazon datasets, forecasting the demand for remanufactured products is a complex nonlinear problem. "*With the help of advanced machine learning techniques, we can achieve highly accurate predictions of product demand"* (Truong Van Nguyen, Li Zhou et al. 2020) [11]. Another proposition to model customer demand using evaluation data has been made to firstly, address the concern that the number of issues in the clustering analysis is not easy to determine, a product performance Dictionary was provided to ascertain the clustering issues. The TF-IDF method was improved for the dictionary creation and based on product performance the dictionary completed customer demand mining. Secondly, in view of the lack of a demand analysis process in existing product review studies, a "*Kano analysis method based on product review data was proposed"*. On this basis, the matter-element representation was introduced to quantify the customer demand model (Wenxu Zhang; Renbin Xiao; Wenguang Lin 2019) [12].

Most of these works used statistical models for demand prediction. "M*achine learning approaches have achieved promising results in time series forecasting over the past decade*." This trend is not recognizable for automotive spare parts demand forecasting, which is a related field. Despite the advantages, the overall picture of customer demand forecasting methods influenced by improved classical methods still remains unclear according to Borempi et al. (2017) [13].

This motivates the identification of automotive component time series characteristics to conduct a literature review to determine possible approaches applicable to the spare parts demand forecasting problem. To bridge this knowledge gap, this survey aims to explore ways to improve classical forecasting and inventory management models in terms of improving customer forecasting.

3. Research Method

As such, a well-functioning spare parts supply chain is mandatory to maintain the accessibility of spare parts to help technicians by providing alternative transportation and storage facilities while optimizing and streamlining inventory.

The planning team is responsible for centralized inventory management. Its tool provides plans based on forecasts to the procurement staff. One of the first things that stand out of our analysis is the need to standardize practices which today are too often based on individual initiatives that do not offer the control of the spare parts management and distribution process desired by the company. This standardization of practices, to be adopted and effective, should not be positioned in total rupture of practices, especially since the experience of the suppliers remains preponderant. Thus, from our point of view, the standardization of these practices will have to be based on a rationalization of current practices in terms of spare parts inventory management.

An additional point that we can emphasize here is that, although the amount of data that supply houses have to deal with, the volume of data dedicated to the handling of a reference is very limited and their volatility is significant. The accuracy of the forecast estimates of each reference is then significantly affected. Such as in the below (Figure 1).

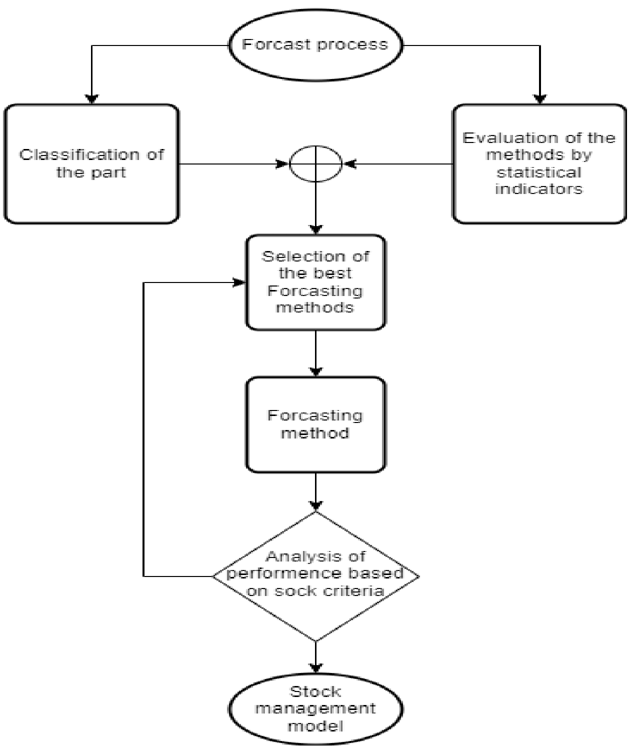

Figure 1. A classical approach to assessing the performance of forecasting methods

Demand forecasting is among the most challenging aspects of inventory management, particularly for spare parts. In fact, in this context, it is essential to precisely estimate the appearance of demand: an under-estimate causes almost immediate stock-outs (and consequently a significant outage time of the process), Over-estimation entails high capital costs and risks of obsolescence due to very weak demand. In addition, the demand for spare parts is related to product failure or a certain preventive maintenance strategy. In our case, linking the process of characterizing the demand for spare parts to reliability analysis of the products does not seem to be realistic, because of the internal practices of all the actors in the supply chain, as well as the usage behaviors of the customers, are poorly controlled. Therefore, we propose to focus our literature review on demand forecasting models using an approach based on historical demand, in order to improve inventory management. In regard to measuring the outcome of the forecasting model in the case of spare parts, a commonly proposed process is comprised of three phases.

The focus of this subsection below is to address the latter three by highlighting the limitations of existing approaches for each approach. Then, we will derive from this analysis a proposal for improving this process, in particular by taking into consideration the level of maturity of the parts, the suggestion of a hybrid forecasting method, and the development of indicators allowing a choice of forecasting methods in function of the risks involved in the management of the stocks.

This part will conclude with a comparison of the selection of forecasting methods by different performance indicators and by different classifications of N.A.C.C. spare parts data.

3.1 Improvement of the Classical Spare Parts Forecasting Methods Process

In the following, we outline the advancements, that we do at all stages of the forecasting process.

- The "pre-processing" stage, allows us to sort the requests based on the frequency and the degree of this demand.

- "Processing", which defines the forecasting methods to be used.

- The "post-processing" is the same as the evaluation of the efficiency of the adopted model.

- This stage involves the elaboration of the data in order to develop the appropriate forecasting algorithms.

3.1.1 Pre-processing Stage: Consideration of Criteria Extension

However, this is often limited to a classification of the type of demand and parts, while neglecting other essential aspects such as the definition of the type of history to be used as well as its size. To broaden this pre-processing step we consider these features in Figure 2.

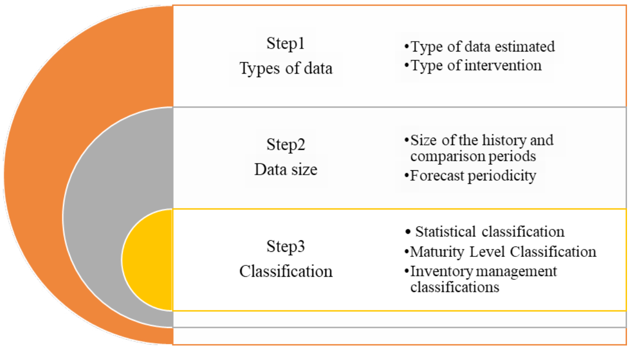

Figure 2. Novel pre-processing chart

The pre-processing step is accordingly split sequentially into three sub-steps:

Sub-step 1:

So, in the following section, we discuss the various types of forecasts that can encompass the inventories of a spare parts supply chain.

Sub-step 2:

We choose the size of the input data: this includes the size of the history to be used, the size of the comparison between the models, and the periodicity of the forecast.

Sub-step 3:

We list the set of spare parts criteria that can have an influence on the forecast and we define an adequate classification for our problem. When forecasting a spare part reference (processing), this classification will not only allow us to select the forecasting methods to be tested for this reference.

When forecasting a spare part reference (processing), this classification will not only allow to select of the forecasting methods to be tested for this reference but also to use the data of similar references (of the same class), to define the selection procedure of the best forecasting method and to designate the appropriate measures for this reference.

Sub-step 1: Data type

In this section, we detail the data types that can be used for pre-processing. These are focused on the types of demand generated and the response required.

Type of demand that has been generated, there exists four major types of demand generation:

1) The actual demand, which accounts for the actual overall needs of the maintenance technicians.

2) Productivity: Estimates of spare parts productivity flows refer to the creation of added value in parts without the need to purchase new parts from suppliers. This can include warehouse repair capabilities of parts, reclamation of refurbished parts from old systems, exchange of defective parts under warranty, etc.

Substep 1: Type of intervention

The traditional method of forecasting is to utilize a unique forecast independent of the operation type; an alternative approach involves separating the inputs by operation type into this estimate. so we can distinguish:

Installation intervention is related to the replacement of parts during the installation of systems. Often, this is not a failure to use the system, but a malfunction due to handling or installation problems.

Corrective maintenance intervention is related to the replacement of parts following breakdowns.

Intervention for systematic preventive maintenance, which is the replacement of parts on the basis of time conditions.

These different types of interventions have different degrees of difficulty in estimation. For this reason, the assessment of the frequency of the demand is much easier in the context of predictive maintenance than corrective maintenance. Moreover, this can lead to different requirements regarding the availability of parts.

Substep 2: Data size

After defining the types of data to be used in the forecasting process, the next step is to define the amount of data to be utilized in forecasting models and intercomparisons:

- The size M of the history to be used in the forecasting algorithms.

- The size N of the forecasting behavior simulation.

- The size N of the simulated demand forecasting behavior for performance measurement.

- The periodicity P of the forecast: Monthly, Quarterly, Yearly.

Substep 3: Classification of a spare part

Several classifications can be used in the case of spare parts. Indeed, a classification can be used as long as it is relevant for instance whether it impacts the database pattern, the prediction outcomes, the choice of prediction models.

Contrary to the literature which often limits itself to a statistical classification to select a set of forecasting methods, we list here other types of classification which can strongly influence this selection such as the level of maturity of the part in its life cycle or criteria related to inventory management (such as the cost of the part for example).

Statistical classifications

Several types of statistical classifications can be distinguished. They are obtained by a statistical analysis of the history of the demand. We identify the various criteria as follows:- Significance of the demand: High demand/Medium demand/Low demand.

- Correlation of demand: High correlation/Low correlation/Positive correlation/Negative correlation. This is calculated by the correlation coefficient.

- Demand Interval: Large non-zero demand interval / Small non-zero demand interval (measured by A automatic D demand I interval).

- Demand variability: Variable demand/stable demand. (Measured by CV).

Classification by part maturity level

The pattern of demand can vary significantly based on the maturation level. Therefore, a classification taking into account these aspects may be necessary. We mainly find the three following maturity phases: Introduction phase, Maturity, End of life.

Installed base

The size of the installed base (number of products sold for a given system) has a significant influence on the frequency and size of the demand for spare parts for this system. In another way, the system's life span may also have a significant impact on the demand profile created. Additionally, the degree of innovativeness of a newly installed base can affect the requirement for spare parts. It is possible to therefore introduce the following three classifications: Installed base categories: Large base, Medium base, Small base.

A. Product life phase categories: Launch, Saturation, Decline.

B. Level of innovation of the installed base: High, Medium, No innovation.

C. Inventory management characteristics. These characteristics are normally used to define the parameters of inventory management models. Usually, they only come into play from the inventory management process. However, considering our objective of building an inventory management-oriented selection approach, it seems logical to make them intervene in the forecasting process. Thus, they will have an impact according to the priorities they translate into stocks or service levels, which will better reflect the objectives we have set in terms of stock management performance. Among these classifications we can distinguish for example:

- Classification of the part price: Cost classification A/ B/ C.

- Classification of the part criticality to the system: Vital v/Essential e/Desirable d (v.e.d).

Further detail on these inventory management classifications will be included in Chapter 5, which presents the inventory management process, specifically the inventory management classification step. See the classifications in the below (Table 1):

The boundaries between the categories of the identified classifications are established based either on suggested boundaries in the literature or on the findings of experiments.

Table 1. Overview of categories for spare parts forecasting

Classifications	Category 1	Category 2	Category 3	Category 4
Significance of the demand	Low	Average	Important	
Coefficient of correlation	Low negative	Low positive	Strong negative	Strong positive
Statistics (retained ADI/CV)	Stable	Intermittent	Lumpy	Erratic
Level of maturity	Introduction	Mature	End of life	
Technical classification 1 (cost)	A	B	C	
Technical classification 2 (criticality)	Vital	Essential	Desirable	
Installed base	Low	Average	Important	
Life cycle of the installed base	Launch	Saturation	Decline	
Level of innovation	No innovation	Slight	High	

3.1.2 Illustration of Hybrid Methods

Why a hybrid forecasting method?

A hybrid forecasting method allows a combination of the characteristics of the forecasting methods used in this approach. For example, it can combine the results of the smoothing principle of one method with those of the averaging principle of another. Moreover, in most cases, there is no method that completely outperforms the others. Thus, this combination may allow the best method to be reinforced by the performance of the others.

3.1.3 Implementation of Hybrid Method for Improvement

The processing step: Hybrid methods

Why a hybrid forecasting method?

A hybrid forecasting method combines the properties of the forecasting approaches in this study. For example, it can combine the results of the smoothing principle of one method with those of the averaging principle of another. Moreover, in most cases, there is no method that completely outperforms the others. Thus, this combination may allow the best method to be reinforced by the performance of the others.

3.2 The Two Hybridization Approaches Proposed

In this section, we propose two methods for hybridizing N forecasting methods.

In the following we will use the notations given in Table 2:

3.2.1 Hybridization Method 1

The idea behind the method is to provide a non-zero weight to the methods according to their performance in each historic period. The use of these weights will make it possible to combine all the methods which were dominant over at least one period. We will use the following additional notations in the following (Table 3):

The following pseudo code describes how to evaluate the weight of each prediction method:

Algorithm 1

```
For i from to 1 to N

End For
For t ranging from 1 to H
    For i ranging from 1 to N

    End For
    For i ranging from 1 to N
            Best=true
            For j ranging from 1 to N
                  IF ( then
                            Best=false
                  End if
            End for
            If better then

            End If
     End For
End For
```

The forecast obtained by the hybrid method 1 (Hy 1) at period H for period $H + t$ is:

3.2.2 Hybridization Method 2

For this method, we introduce a memory effect by defining transition probabilities from one method to another. That is, unlike the previous method, we take into account for each period the performance history of each method in that period but also in the previous period and we count the number of times there is a transition from one method to another in terms of dominance. The following additional notations are used (Table 4).

Table 2. standard notations for both hybridization approaches

Notation	Signification
N	: Number of forecasting methods to hybridize
H	: Size (in number of periods) of the history used
D_t	: Demand at period t
$F_i^j(t)$	: Forecast made at date j for period t by the method of forecast i, $(i,t) \in [\![1,N]\!] * [\![1,H+1]\!] (i,t) \in [\![1,N]\!] * [\![1,H+1]\!]$
$SE_i(t)$	: Error calculated at period t by the forecasting method i,

Table 3. Notation for hybridization approach 1

Notation	Signification
P_i	: Weight given to the forecasting method i

Table 4. Notation for hybridization approach 2

Notation	Signification
P_{ij}	**:** Transition probability of forecasting methods ***i to j, (i, j)*** : Transition counter for forecasting methods ***i to j, (i, j)***

The following pseudo code describes how to evaluate the different transition probabilities:

Algorithm 2

```
For i from to 1 to N
    For t ranging from 1 to N

End For
End For
For t ranging from 1 to H
    For i ranging from 1 to N

    End For
    For i ranging from 1 to N
            For j ranging from 1 to N
                  IF [(
                  Then

                  IF not
                   IF [(Then
            If better then

            IF not
                   If [(
                  Then

                  If not
                         If [(
                         Then

                          If not

                          End if
                   End if
            End if
       End if
     End if
End if
For i from to 1 to N
   For i from to 1 to N

     End For
  End For
```

To obtain the forecast by the hybrid method 2 at period H + t, based on the method j that has been best evaluated over period H (the lowest (H)) we will calculate:

Impact of the two approaches:

In what follows, we present two simple estimates to explain the impact of the two approaches.

Example 1: We take the case of part A on a 6 months history (January to June). We also know the forecasts that have been made on the history and we study the behavior of the hybridization method 1. Table 5 summarizes the input data considered.

Table 5. Input data for illustration 1

	Jan	Feb	Mar	Apr	May	Jun
Demand	4	5	4	6	4	5
Forecast Method 1	3	4	4	4	3	3
Forecast Method 2	6	5	5	5	7	6

If we evaluate the two forecasts by a classical statistical indicator (mean square error), we obtain mse1 = 1.83 and mse2 = 2.66, which indicates dominance of method 1. However, we note that forecast 1 tends to underestimate demand, unlike forecast 2. Let us now use the hybrid method 1 whose results are given in Table 6.

Table 6. Results obtained by hybridization approach 1

	Jan	Feb	Mar	Apr	May	Jun
P_1	1	1	0.5	0.67	0.5	0.6
P_2	0	0	0.5	0.33	0.5	0.4
Forecasts Hybrid Method 1	3	4	4	4	5	4

When we proceed, we obtained statistical indicators, such as m.s.e hyb1= 1.33. It can be seen that we have been able to considerably improve the prediction quality and if we analyze the outcomes, we observe a diminution of the tendency to underestimation or overestimation. Example 2: We take the case of part B over a 5-month history (January to June). In this history, we notice a strong increase in demand over the last two periods. We also know the forecasts that have been made on the history, we study the behavior of the hybridization method 2. Table 7 summarizes the input data considered.

Table 7. Input data for illustration 2

	Jan	Feb	Mar	Apr	May	Jun
Demand	3	2	3	4	8	10
Forecast Method 1	2	2	1	3	5	6
Forecast Method 2	7	5	5	5	7	8

If we evaluate the two forecasts by a classical statistical indicator (mean square error) we obtain m.s.e1 = 5.66 and mse2 = 6.66, which indicates dominance of method 1. This method should therefore naturally be preferred. However, we note that forecast 1 tends to underestimate demand, unlike forecast 2, but that the latter reacted better to the sudden increase in demand. Let us now use the hybrid method 2 whose results are given in Table 8.

Table 8. results obtained by the hybridization method 2

	Jan	Feb	Mar	Apr	May	Jun
N_{11}	0	1	2	3	3	3
N_{12}	0	0	0	0	1	1
N_{21}	0	0	0	0	0	0
N_{22}	0	0	0	0	0	1
P_{11}	1	1	1	1	0.75	0.75
P_{12}	0	0	0	0	0.25	0.25
P_{21}	0	0	0	0	0	0
P_{22}	0	0	0	0	0	1
Forecasts Hybrid Method 2	2	2	1	3	6	8

Calculating the statistical indicators obtained, we have msehyb2=2.33. We can observe that also the accuracy of the forecast has improved significantly and when we consider the results, we have a diminution of the underestimation or overestimation tendency. Additionally, we observe how the hybrid method has adjusted to high fluctuations in demand.

4. Classification for Classical Methods of Spare Parts Demand Forecasting

We use the following classifications:

- the statistical classification of demand;

- the classification of the maturity of the part;

- inventory management classifications to give stock/service priorities.

The innovativeness of the chosen classifications is in contrast to the classical experiments in our literature. We are also using the part maturity classification in our case; we shall test the selection of the method depending on the degree of maturity. Moreover, we also use the classifications in inventory management of the part such as its criticality or its price, this will allow judging the weight to be given by the decision.

-makers to the selection measures;

-the thresholds of the classifications;

-the statistical classification of demand.

For this classification, we retain the thresholds suggested by the literature. For the demand interval threshold: automatic demand interval=1.33 it separates between high and low-frequency demands. For the demand variability threshold: cv2=0.49 it separates between low and high variability demands.

Part maturity classification: the classic way to have a part maturity classification is based on: design and life cycle studies within the conception process of a part. Reliability data of the part and the type of the part (mechanical/electrical...) by sampling on parts already in use. To accomplish this, we are basing the simulation on a great number of references from the N. A. C. C. Databases. Using a wide range of resources will allow us to assess the structure of the demand depending on the degree of maturity of the part. The following (Figure 3) is the graphic evolution of the demand based on the maturity of the part.

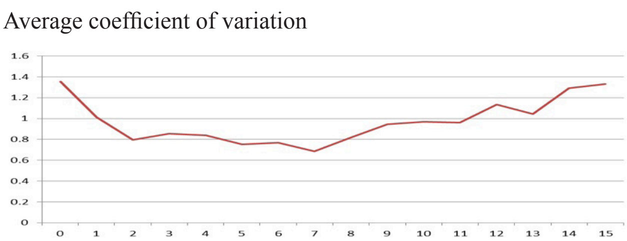

Figure 3. Development of the evolution of the demand as a result of the degree of maturity of the parts.

The below (Figure 4) is the graphic evolution of A.D.I based on the maturity of the part.

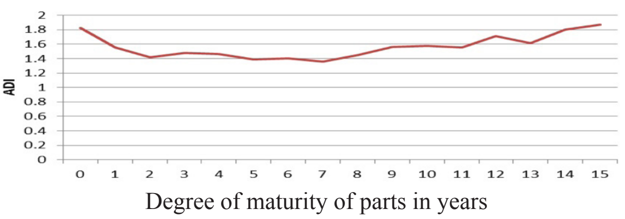

Figure 4. Evolution of the average demand interval according to the maturity level

The distinctions in the maturity levels of these two charts between two successive points are as follows Table 9:

Table 9. Degree of maturity Variation Divergence in automatic demand interval

Maturity degree	Variation divergence	Divergence in Automatic demand interval
0 → 1	–0.34	–0.28
1 → 2	–0.22	–0.13
2 → 3	0.06	0.06
3 → 4	–0.01	–0.01
4 → 5	–0.09	–0.08
5 → 6	0.01	0.02
6 → 7	–0.08	–0.04
7 → 8	0.13	0.09
8 → 9	0.13	0.11
9 → 10	0.02	0.01
10 → 11	–0.01	–0.03
11 → 12	0.17	0.16
12 → 13	–0.09	–0.09
13 → 14	0.25	0.18
14 → 15	0.04	0.07

Both charts indicate that the pattern is in a curve in respect of both the demand variability standard and the average interval between requirements standards. However, this correspondence with the bathtub curve is clearer by the demand variability criterion. The numerical comparison of the transition gaps (Table 9) between the various maturity levels in years approves this graphical analysis and helps to identify the inflection points of these curves. The progression from 2 years to 3 years: indicates the completion of a declining trend in variability and automatic demand interval of demand that originated at a very high degree in the initial year. Thus, the shift to a more stable period. The transition from 7 to 8 years: identifies the end of a stable evolution of the level of variability and the automatic demand interval, towards an upward trend in these two statistical measures. We can therefore find the three classic maturity levels of spare parts, by identifying them by thresholds. Thus, we will retain the following thresholds:

- introduction: between 0 and 2 years.

- maturity: between 3 years and 7 years.

- end of life: more than 8 years. Processing stage in the interest of conciseness, we restrict the analysis to the use of 4 forecasting methods:

- the moving average (ma) method as representative of methods with an averaging principle.

- the simple smoothing method (ses) as representative of the methods with a smoothing principle.

- the Croston (cr) and it's variant (sba) methods as representative of the methods with a double quantity and interval prediction principle.

We will evaluate in a dedicated part the contribution of the hybrid methods proposed (hy1) and (hy2). Post-processing step we contrast the resulting separations by the following measures: - the mse measure is typical of those statistical selection measures. The mse measure is representative of statistical selection measures.

- the LTFE measure takes into account the supply time, with 4 scenarios: lt= {1,3,5,8} months.

- ioe measure takes into consideration the tendency to overestimate or underestimate demand and the risk of overstock and shortage of stock, with 2 scenarios: one = 0. To prioritize stock at the service level. This can correspond to a classification of low-cost parts and high criticality. Conversely = 0. 3 a stock priority can correspond to a classification of high-cost parts and high-criticality parts with the high cost and low criticality.

4.1 Results of the Comparison of the Selection by Classifications with the (LTFE, MA, SES, CR, SBA) Methods

We run a test of the above experimental design on data obtained from the N.A.C.C.

This database consists of requests for 1500 spare part references.

We represent the results in a percentage of selection of each method against the demand profile classification and then against the spare parts maturity level classification. In addition, we display the findings in a way that allows us to measure the impact of the change in the lead time, as well as inventory or service prioritization.

Selection Results by Demand Profile Segmentation Impact of Supply Time

The following (Tables 10, 11, 12, 13) will classify the results of different demand profiles below.

Stable parts

Table 10. Sampling according to the supply time for stable parts

LTFE	LT = 1	LT = 3	LT = 5	LT = 8
MA	68.2	65.6	62	59.4
SES	5.4	6.4	6.8	7.4
CR	8.2	10	10.2	12
SBA	18.2	18	21	21.2
Total	100%	100%	100%	100%

Sporadic Parts

Table 11. Sampling according to supply time for sporadic parts

LTFE	LT = 1	LT = 3	LT = 5	LT = 8
MA	6.4	33	19	18.4
SES	3.8	9.6	25.4	30.2
CR	26.6	18.8	17.8	15.8
SBA	63.2	38.6	37.8	35.6
Total	100%	100%	100%	100%

Erratic Parts

Table 12. Sampling according to the supply time for erratic parts

LTFE	LT = 1	LT = 3	LT = 5	LT = 8
MA	23.6	24	30.6	42
SES	28.6	42.6	51	39.2
CR	23.2	25.8	7.8	8.4
SBA	24.6	7.6	10.6	10.4
Total	100%	100%	100%	100%

Summary of method performance

Table 13. Sampling of the selection according to the supply time by demand category

Supply time / Demand category	Supply time Short	Supply time Long
Stable	1. MA	1. MA
	2. SBA	2. SBA
Sporadic	1. SBA	1. SBA
	2. CR	2. SES
Erratic	1. SES	1. MA
	2. SBA	2. SES

The results first confirm the results of the literature, concerning the adaptability of the Croston variants for sporadic parts, the moving average variants for stable parts, and the smoothing method variants for parts with high variability.

However, the main added value of this analysis by the long-term forecasting error measure is that while for stable parts the sensitivity to the length of supply time is low, it is significant for sporadic and erratic parts. Indeed, the distribution of the selection changes significantly for these last two categories when the supply time increases.

Hence, the usage of the spare part supply time data will be suggested in the choice of the forecasting methods for sporadic or erratic parts. For stable parts, the use of this piece of data is not essential.

In this chapter, we have provided input into the spare part demand forecasting process with the goal of matching the points that have been identified in the spare part analysis.

The goal of this chapter is to match the points identified in the analysis of the spare parts forecasting and inventory management issue in Chapter 3.

Indeed, these contributions extend the classification of spare parts in this setting, particularly by considering the maturity degree of the parts. They are based on the historic demand forecasting models. They consider the weak and erratic aspects of demand in the selection approach and propose new selection measures that allow the first consideration of inventory management priorities. The results of an experimental design based on these proposals demonstrate the relevance of segmentation by maturity degree of spare parts in the choice of forecasting methods. This analysis also justified the need for the proposed measures that often select different methods based on the length of the supply time and on stock or service priorities.

Finally, an analysis of the performance of the hybrid forecasting methods proposed by our work showed a good quality of its second configuration and that its performance can vary depending on the class of the part.

Yet, given that the optimal goal of a full inventory management process based on forecasting is the improved management of inventory, service level, and inventory level indicators, it is essential that the forecasting process be implemented in a way that is efficient and effective, this implies a need for integration with inventory management policies in order to evaluate the forecasting methods by the final indicators of inventory management.

4.2 Improvement of Inventory Management Methods

In this section below we will identify the types of inventory management methods and consider improvements as well.

4.2.1 Types of Inventory Management Methods Types of Reviews

(1) Periodic review (R, Q)

With T periodicity $T \in N$, if the present period is $N \times T$ with $N \in N$ the stock level is being measured, if it is less than R an economic quantity order is placed to attain the Q level.

This gives a good synchronization of orders and tracking, but its major disadvantage is the inability to react and the lack of full traceability during the given period.

(2) Continuous review (s, S)

The logic of this policy is to monitor the state of the stock in a continuous way. Once the stock level decreases below s, an order is issued to attain level S.

This policy allows more reactivity to the variability of the demand and the reduction of the time of shortage of stocks.

4.2.2 Types of Order Quantities

Inventory management policies use two types of order quantities.

Fixed quantities

In this case, the model always places an order of the same quantity, this may be due to constraints imposed by the supplier or in the case of very stable demand.

Variable quantities

In this situation, the model issues an order that may fluctuate from period to period, thus requiring a certain amount of flexibility from the supplier. This approach is often advisable in the instance of variable demand.

Thus, four types of inventory management policies can be identified according to the two types of stock review and order quantity (Table 14).

Table 14. Varieties of Inventory Management approaches

When / How much	Periodical review	Continuous review
Fixed quantity	Calendar method	Control point method
Variable quantity	Replenishment method	Replenishment to order

In terms of spare parts, the ongoing service and variable volume "make-to-order" policy is the most suitable due to its responsiveness to varying demand and the critical aspect of the breakdown which requires more reactivity of supply.

4.2.3 Order Management Mode

Lost Sales: LS order management mode

In such a case, if an order is not satisfied by the stock, then it will be canceled. This pattern occurs in the situation where there is a stock of finished products or no existing contract, or where there is a risk of a stock-out.

Backorder: BO

In this case, if a request is not satisfied from the stock, then the request remains on hold, it is said to be in "backorder".

The Backorders scheme is most commonly encountered in the case of managing spare parts for equipment, because of the difficulty of finding a replacement from the competitor and because often a contract is established with the customer.

4.3 Application of the Improved Inventory Management Models Based on Forecasts

A majority of the model literature is focused on a demand hypothesis or on probabilistic demand flow scenarios.

Simultaneously, specific literature suggests forecast-based inventory management strategies and highlights their contrast with demand-based inventory policies. Indeed, these models use an estimation of the inventory projection by forecasting calculations in the supply logic, integrating the forecast error in the calculation of the supply thresholds which are often dynamic according to the variability of the forecasts over the next periods.

Since our work is focused on a forecasting approach for spare parts, and our goal is the connection of the invento-

Table 15. Ratings

Notation:	Meaning.
L	: supply time
$F_{i+k}^{(i)}$	: Forecast made at period i for period i + k
$f^{-1}(\propto)$	: the theoretical risk of inventory shortage ∝ on L, with the theoretical service level SL=1-∝
	: The calculated forecast error on the start of period i
M	: The average demand
	: the standard deviation of the demand
T	: The stock review period, with T=1 if the review is continuous
H	: The desired duration of coverage by the stock
OC	: the cost of placing an order
UC	: the unit cost of the spare part
HR	: the inventory holding rate

ry management process with forecasting in the upcoming chapter., we will therefore use models based on forecasts.

How much Periodical review?

Continuous review; Fixed quantity calendar method; Control point method; Variable quantity replenishment; Method replenishment to order.

So, taking the ratings in Table 15 as a starting point, we provide the threshold calculations for these models in the following table, while emphasizing they differ from the demand-based ones.

Thus, inventory management policies are constructed by combinations between the thresholds in this table, for example:

The policy (SI) represents the continuous review and variable quantity policy, at each point in time in the period I if the stock level is below the level if an order is placed to reach Si.

4.3.1 Indicators for Evaluating Inventory Management Models (Service Level Assessment)

The inventory management service level is linked to the stock availability degree, meaning its failure to satisfy a customer's demand by the supply, in the present case it is a failure to satisfy a demand of the maintenance technician.

This level of service can be in quantities or in periods. We consider the case of inventory management with backorders.

We present performance evaluation measures over N periods using the notations in Table 17:

Quantity measures:

The quantity of service level is:

$$QSL=\frac{\sum_{i=1}^{N} Di-\sum_{i=1}^{N} BOi}{\sum_{i=1}^{N} Di}$$

Measurements in periods:

A further measure related to the level of service can be the amount of time that back orders occurred.

If BO $L_i > 0$ then, Pi=1; If not Pi=0.

The level of service in periods is:

$$\text{PSL}=\frac{N-\sum_{i=1}^{N} pi}{N}$$

4.3.2 Evaluation of the Stock Level

The evaluation of the stock level is done by measuring it in quantity, by measuring the inventory value during the inventory is measured in quantity, or by measuring the inventory value during the comparison period.

Inventory Level:

$$IL=\frac{\sum_{i=1}^{N} OH_i}{N}$$

Inventory Value:

An alternative measure often applied in this context is the measurement of inventory to demand (or inventory turnover), which provides a reference of this level and thus allows for the comparison of inventory levels among

Table 16. Comparison of forecast and demand inventory management policies

Model thresholds \ Approach	Model On request	Model On forecast
Safety stock ss	$ss=f^{-1}(\propto)*\sqrt{L}*\sigma$	$ssi=f^{-1}(\propto)*\sqrt{L}*\sqrt{MSEi}$
Control points	s=ss+M*L	$si=ssi+\sum_{k=0}^{L-1} F_{i+k}^{(i)}$
Periodicity of review P	N*T	N*T
Completion level S (or R depending on the notation)	S=ss+M*(L+T)	$Si=ssi+\sum_{k=0}^{L+1} F_{i+k}^{(i)}$
Economic quantity Q (according to Wilson)	$Q=\sqrt{\frac{2*oc*M*H}{HR*UC}}$	$Qi=\sqrt{\frac{2*oc*\sum_{K=0}^{H-1} F_{i+k}^{(i)}}{HR*UC}}$

Table 17. Ratings for the performance evaluation of the inventory management model

Notation	Meaning.
O	: The inventory at beginning of a period i
D_i	: The demand at period i
BOi	: The amount of backorders that result from the simulated inventory during period i

parts of different types or volumes of demand.

Relative Inventory Level:

$$RIL = \frac{\sum_{i=1}^{N} OH_i}{\sum_{i=1}^{N} Di}$$

Synthesis and improvement

Thus, we summarize what has been presented above by a three-step process of inventory management on forecasts (Figure 5):

The initial purpose of the first step in the above process is to establish the service level to be applied in the inventory management model. Very often a service level matrix is defined, based on the objectives of the decision-makers in service and the budget.

Example: the case of classification in criticality and cost (Table 18).

Table 18. Sample of a service level matrix by inventory management classification

Criticality	Vital (V)	Essential (E)	Desirable (D)
High(A)	95%	94%	93%
Medium (B)	97%	96%	95%
Low (C)	99%	98%	97%

However, if we want to reach for example a 95% service level for the category (Vital (V), High (A), this can be equivalent to using a 99% service level for sporadic parts and 95% for stable parts. Indeed, as the demand for spare parts is highly unpredictable, the assessed service level can be entirely unrelated to the predefined theoretical service level.

In this sense, although they have an impact on the quality of the forecasts and consequently on the measured service level, the classifications of spare parts in the spare parts demand profile and the maturity degree of the parts have not been employed for the determination of this service level of the forecast-based inventory management model and its associated use was limited to the forecasting process (forecast method selection).

We employed an experimental design based on these two classifications: first, to measure the impact of these classifications on the inventory management indicators, especially on the difference between the theoretical and measured service level. Subsequently, this analysis will enable us to suggest improvements to the classic inventory management procedure in order to establish a better definition of the service degree to be applied in the inventory management model in the case of spare parts based on the above rankings.

4.4 Application and Impact of Part Classifications on Inventory Management Performance

We use the same database used in Chapter 4, which consists of 36 months of demand history for 1500 spare part references. We use the profile classification of demand into three categories: stable, sporadic, and erratic, and that of the maturity level of parts into three categories: introduction, maturity, and end of life. We use a single inventory management policy based on continuous review and variable quantity forecasts (Si), we recall that this policy being continuous review and variable quantity is the most suitable for the case of spare parts inventory management. Also, we consider an order management mode with Backorders. See Figure 6.

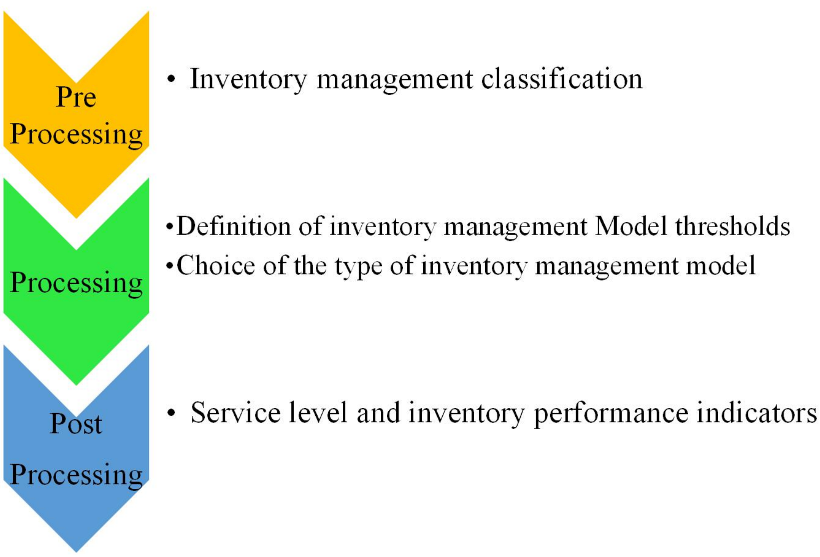

Figure 5. Overall stock Management Flow chart

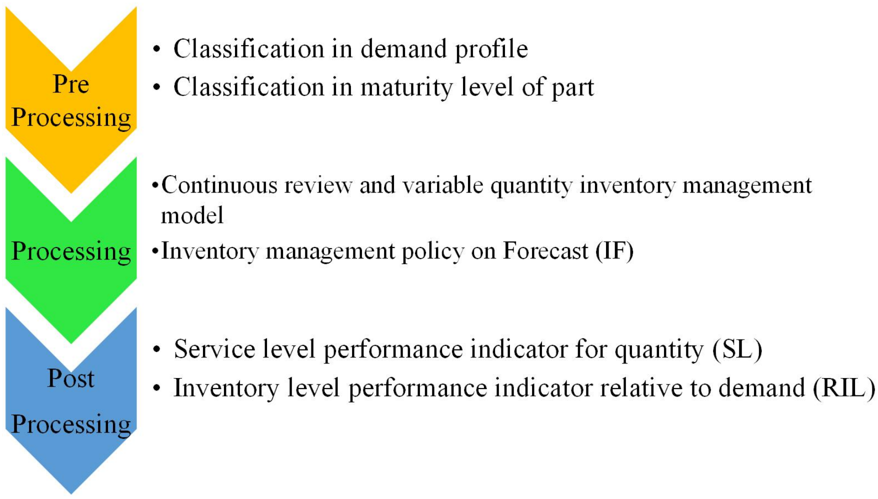

Figure 6. The experimented procedure of inventory management on forecasts

5. Data Analysis and Discussions

Here we represent the Data analysis and results of the experimental design described above by demand profile classification and then by part maturity level classification.

Results in-demand profile classification. See Figures 7-9.

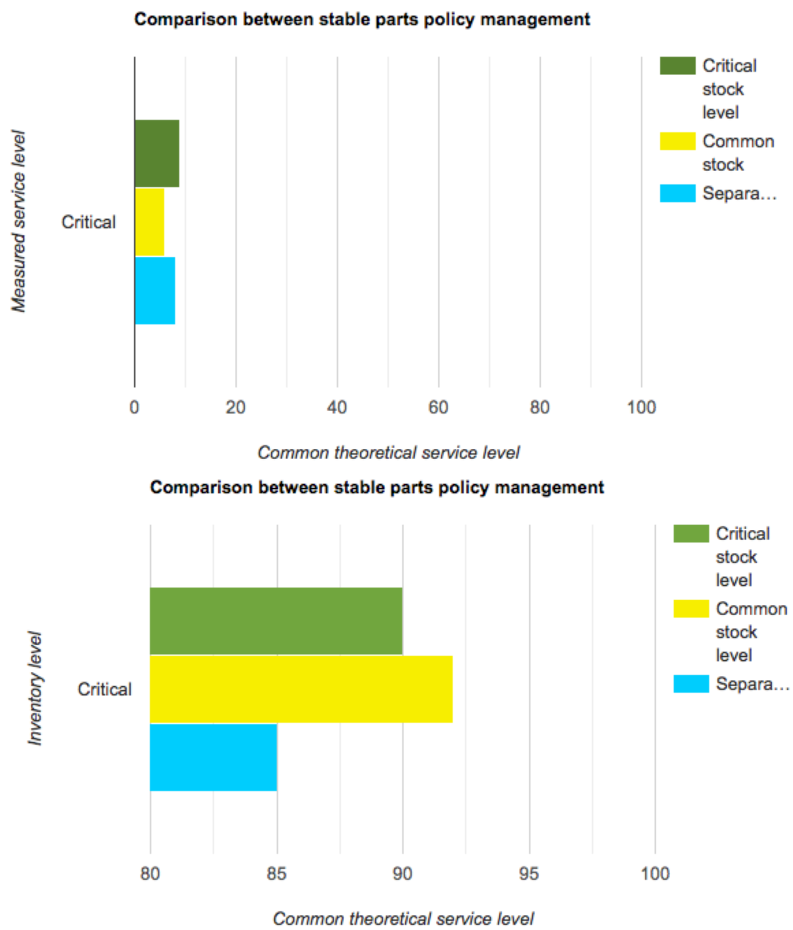

Figure 7. Comparison between policy management for stable parts

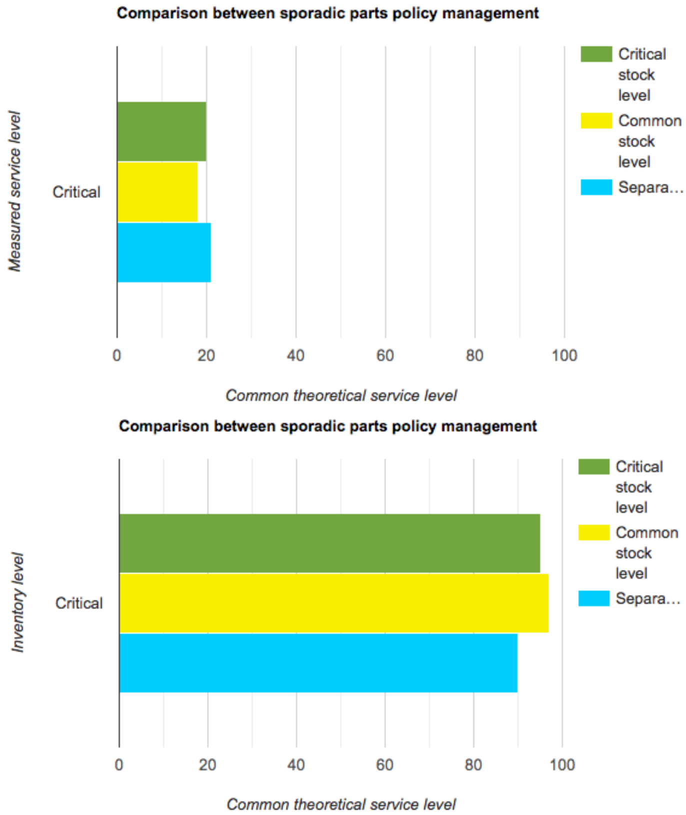

Figure 8. Comparison between policy management for sporadic parts

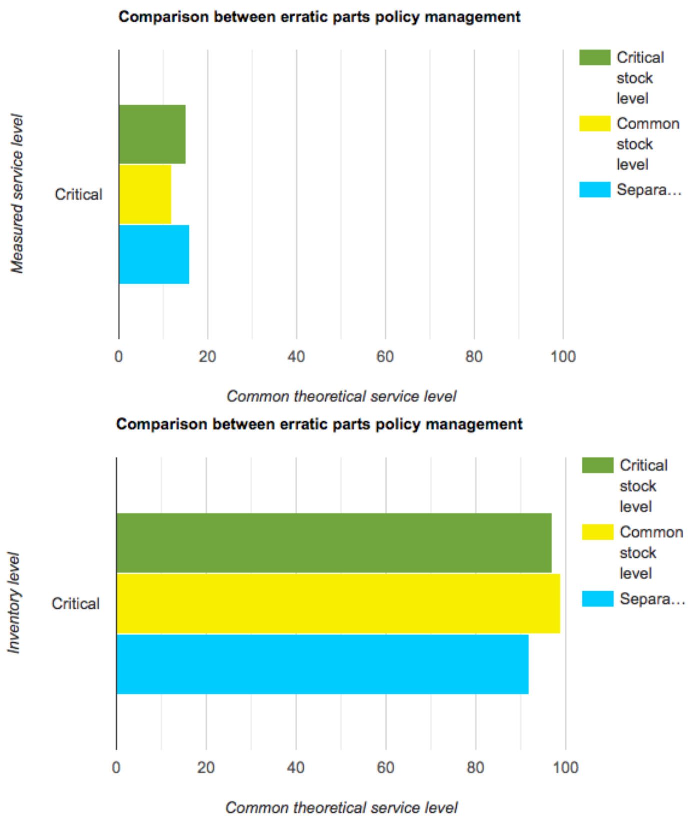

Figure 9. Comparison between policy management for erratic part

Discussion

This chapter confirmed the performance of the critical stock policy compared to the common stock policy and the separate stock policy from the point of view of the stock level regardless of the category of the part but highlights its limitation compared to other service level policies when dealing with sporadic demand.

Until there is a policy that outperforms the others for all classes of parts in terms of service and inventory performance, it is appropriate for decision-makers to first define their service or inventory priority for each class of parts, for instance by segmenting by unit cost, criticality, etc., and then choose, based on the demand ratio of each customer class and its required service level, demand profile, and degree of maturity, which policy to use for deciding on each class of spare parts.

In this work, we have addressed the problem of segmentation of forecasting and inventory management in the supply chain of spare parts at different service levels. The goal we set was to contribute to this issue in order to meet its objectives: improving service levels and optimizing inventories while considering certain specific characteristics of spare parts.

The management of the spare parts supply chain is both complicated and essential.

Complex, given the many flows in the chain, the demand profile, the risk of low turnover, inventory according to obsolescence, and the need to meet different service levels based on the priority of the maintenance contract and the prioritized parts.

It is essential because it enables the company to meet its commitments in terms of rapid maintenance interventions by improving the availability of parts and reducing transport and inventory costs by synchronizing flows and sharing stocks between maintenance technicians.

Forecasting and inventory management are key functions in this chain. Indeed, their production quality assures the best combination of service and inventory degrees. In this article, the reader is given a comprehensive overview of the instruments available in the literature in these processes, as well as a critical analysis of this work which raised the following main points:

- Segmentation: The absence of a consistent application of segmentation to both processes and the lack of use of segmentation into part life phases in model selection and performance evaluation.

- Performance assessment: The lack of a combination of forecasting method and inventory management model in performance assessment. In the absence of a combination of forecasting methods and inventory management models in the performance assessment, the selection of forecasting methods is restricted to statistical data.

- Customer Distinction: The absence of forecast-based inventory management models in the case of customer differentiation and a comparison with conventional policies based on spare parts segmentation.

6. Conclusions

Hybrid forecasting: hybrid methods have provided the opportunity to explore a combination of the characteristics of each method. Measures for evaluating the selection of forecasting methods were presented, enabling the use of information on lead time and the risk of over-or underestimating demand.

Inventory Management: Demand profile and part maturity level segmentations were included in this process to align with the forecasting process and to better determine the service level to be used in inventory management models.

In addition, approaches for evaluating forecasting methods based on inventory management criteria have been proposed to replace the classical statistical approach: by integrating the inventory management model in this selection, by considering service/inventory priorities based on part segmentation, and by using a multi-criteria decision support method.

Forecasting process and inventory management in the case of customer differentiation: The inventory rationing policy was adapted to the case of a forecast-based inventory management model and then compared to the separate stock and common stock policies based on demand profile segmentation and part maturity level.

This work was developed in parallel with an industrial application to the case of N.A.C.C. (North automobile components company). This company manages the supply and deployment of a very large number of spare parts references worldwide, for a large installed base of products and with a very high level of inventory, via a global and highly efficient supply chain. Therefore, the expertise of its inventory forecasting and procurement functions is essential to achieve its objectives. This work led to a complete revision of its industrial logic of inventory management by the implementation of a new segmentation of the parts considering the aspects of variability and intermittency of the demand, the construction of a decision-making logic of parameterization of the models used according to this new segmentation, the enrichment of the base of the methods used by the scientific methods of forecasting and the development of the approach of forecasting and inventory management presented in this article. This has resulted in significant improvements in service and inventory levels and, more significantly, in bringing the industrial process in line with a scientific methodology that provides a basis for a set of future improvements.

Conflict of Interest

There is no conflict of interest.

References

[1] Boylan, J.E., Syntetos, A.A., 2007. The accuracy of a modified Croston procedure. International Journal of Production Economics. 107, 511-517.

[2] Teunter, R.H., Duncan, L., 2009. Forecasting intermittent demand: a comparative study. Journal of Operational Research Society. 60, 321-329. DOI: https://doi.org/10.1057/Palgrave.Jors.2602569

[3] Chiou, H.K., Tzeng, G.H., Cheng, C.K., et al., 2004. Grey prediction model for forecasting the planning material of equipment auto parts in the navy of Taiwan. Proceedings World Automation Congress. 17, 315-320.

[4] Zhang, H., 2019. Improved transudative support vector machine for a small labelled set-in motor imagery-based brain-computer interface. pp. 2-3.

[5] Gutierrez, R.S., Solis, A.O., Mukhopadhyay, S., 2008. Lumpy demand forecasting using neural networks. International Journal of Production Economics. 111(2), 409-420.

[6] Tang, Zh.J., Long, Y.L., 2012. Research on method of acquiring individual demand based on kano model. pp. 127-131.

[7] Chen, X., Cai, D., 2015. Large scale spectral clustering with landmark-based representation. IEEE Trans Cybern. pp. 313-318.

[8] Levi, et al., 2005. https: //www. ResearchGate. Net/publication/260162679 approximation algorithms for the stochastic lot-sizing problem with order lead times. pp. 14-24.

[9] Valero, M., Averkin, R.G., Fernandez-Lamo, I., et al., 2017. Mechanisms for selective single-cell reactivation during offline sharp-wave ripples and their distortion by fast ripples. Neuron. pp. 1234-1247.

[10] Canyakmaz, et al., 2019. https: //www. ResearchGate. Net/publication/330894006_an_inventory_model_where_customer_demand_is_dependent_on_astochastic_price_process. pp. 27-38.

[11] van Nguyen, T., Zhou, L., Chong, A.Y., et al., 2020. Predicting customer demand for remanufactured products: a data-mining approach. European Journal of Operational Research. 281(3), 543-558.

[12] Zhang, W.X, Xiao, R.B., Lin, W.G., 2020. Review data-driven customer need model research based on product performance lexicon. pp. 34-43.

[13] Bontempi, G., Borgne, Y.A.L., Destefani, J., 2017. Factor-based framework for multivariate and multi-step-ahead forecasting of large-scale time series. pp. 14-27.