# Diplomarbeit

## Development of a Global Inventory Management Tool for Spare Parts in the Machinery Engineering Industry.

### Application in the Wafer Production Sector.

ausgeführt zum Zwecke der Erlangung des akademischen Grades eines

## Diplom-Ingenieurs

unter der Leitung von

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von


**Melchior de Varax**

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Wien, im November 2017

Melchior de Varax

Ich habe zur Kenntnis genommen, dass ich zur Drucklegung meiner Arbeit unter der Bezeichnung

# Diplomarbeit

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Wien, im November 2017

Melchior de Varax

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# Abstract

The purpose of this work is to develop a practical approach for spare parts inventory management. In the industrial context of capital goods production, the necessity to build efficient after sales services is twofold: maximizing the revenues through costs minimization and judicious management, and ensuring customer satisfaction. Within this vast field of activities, the management of spare parts is often neglected due to the lack of practical guidelines. In this prospect, the objective of the present thesis is to provide an assistance to choose and apply relevant techniques through the study of a real case study. It appears that possibilities are numerous, but not always applicable, as spare parts management mostly rely on data collection and treatment. The process is, however, always the same: multi-criteria classification, strategy mapping, demand forecasting, and inventory control. For each of these steps, methods are compared and analysed with a very pragmatic vision, the final objective being to implement an operative tool for the company related to this thesis. The practical application of the concept reveals that every choice includes a part of subjectivity, given the unpredictable aspect of spare parts demand. Nonetheless, the approach towards smart spare parts management is worked through given the specificities of the case study. An emphasis is given the introduction of accurate forecasting methods, whose impact on final benefits is most significant. The results provided by the tool highlight the inappropriateness of current practices as for spare parts inventory management. But the main outcome is the demonstration of potential benefits for the organisation in terms of sales and service level.

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# 1 Introduction

## 1.1 Relevance of the Topic

The recent global economic downturn particularly affected the manufacturing industry who still struggles to recover and to reach their previous level of performance. In this context where companies have to face relentless global competition, rising commodity prices and weak demand, profit margins are highly threatened to be shrunk. In addition to cuts in capital expenditures, manufacturing players are looking for sustainable alternative sources of revenues to ensure their profits. A new emerging and promising field of focus is the after-sale service. Studies show that aftermarket sales and services activities are 75% more profitable than core business activities.[1] In this prospect it is legitimate for manufacturing companies to put the emphasis on their service and sales department, in order to generate new sources of revenues.

The particular case of the machinery and plant engineering industry present characteristics which are perfectly suitable for the implementation of a Service Lifecycle Management. Indeed, the economic context pushed asset owners to slow down their expansion plans, and to conduct a more economical strategy regarding their capital investments.[2] Instead of renewing regularly the machines, assets should last longer and therefore need a proper maintenance. It appears then that for both assets manufacturers and assets owners, the need for a Service Lifecycle Management is more than ever a priority.

Beyond the economic aspect of after-sales services, customer support presents tremendous benefits for manufacturers:[3]

- Achieves customer satisfaction and loyalty and ensures good long-term relationships
- Can provide a competitive advantage within the targeted market
- Enhances the success rate of new products

[1] Natarajan and Tarannum, 2012
[2] Barkai, 2014
[3] Goffin and New, 2001

Looking closer to the concept of *customer support*, Maintenance and Repair is identified as one of its seven key elements, among installation, user training, documentation or warranty.[1] Ensuring a high level of service to customers is obviously depending on the investments given to maintenance activities. The machinery industry is particularly related to this concept as customers request a full reliability on their machines, in order to keep the production of goods going. In this way, no compromise is generally given to down-time because the "costs run typically at anywhere from 100 to 10,000 times the price of spare parts or service."[2] In both cases of preventive or reactive maintenance, spare parts availability consequently plays a key role in the customer support activities. A well-managed spare parts sales service is therefore essential for any machine manufacturer, all the more so it is very profitable (see figure below).

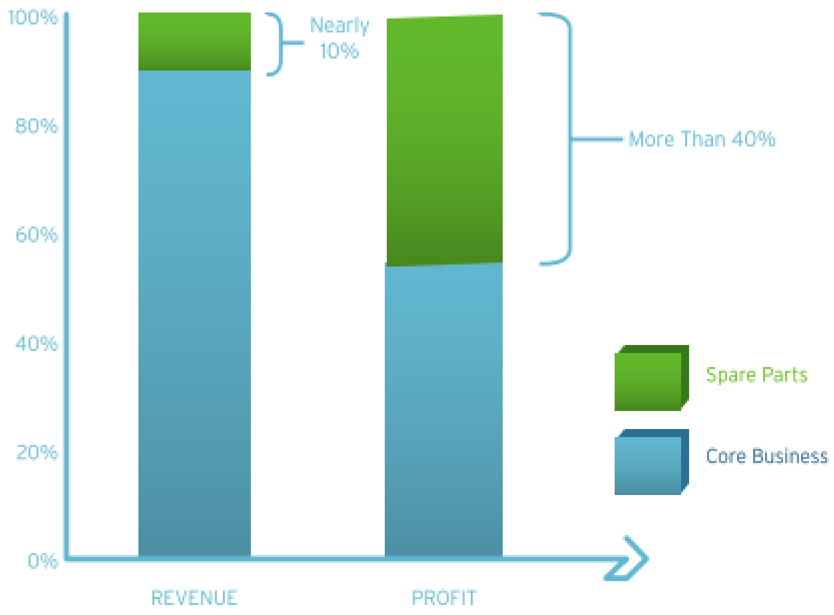


**Figure 1: Spare parts revenue and profit for industrial companies[3]**

Spare parts warehousing in the machinery industry is thereby a very topical issue in regard to the economic context and to its potential benefits. However, this topic is still developing and practical guidelines for companies are deeply lacking in order to implement concrete decisions regarding their spare parts inventory management. The

[1] Goffin, 1999
[2] Knecht and Leszinski., 1993, p. 2
[3] Natarajan and Tarannum., 2012, p. 2

framework of this thesis is thus part of an innovative and applied approach towards a decision-making process into an industrial context.

## 1.2 Problem Statement and Research Question

As previously mentioned, spare parts warehousing is still a developing science and is far from reaching maturity from a practical point of view. Cavalieri et al. (2008) underline the lack of pragmatic guidelines for companies, despite a huge amount of theoretical research on spare parts management.[1] There are two main reasons behind: the benefits of implementing such policies are still underestimated, and it is not an exact science due to the unpredictability on the spare parts demand, and to the lack of data. The result is that decisions regarding spare parts inventory are mostly based on “gut feeling”, or on rough analysis.[2] The problem tackled by this thesis is precisely to provide a support in the decision-making process for spare parts management, applied into the machinery industry. Although it is difficult to provide exact directives regarding life cycle management, it is possible to estimate the right direction to choose and thus to observe significant benefits.

This master thesis was conducted within the company FHW Franz Haas Waffelmaschinen GmbH (hereafter referred to as “FHW”), in the Sales and Service department. FHW designs and produces baking lines for the wafer industry to confectionery companies based all around the world. These machines are long-term capital investments for FHW’s customers who therefore need an after-sale service to ensure the good maintenance of their assets, and so during their whole life cycle, up to a couple of decades. Due to the complexity of the machines, the custom-made design, and the high diversity of components, the company has to face huge challenges in terms of spare parts warehousing: approximately 42,000 parts are referred as spare parts. Besides, the worldwide distribution and the organization of the company make the logistics activities even more complex. However, no proper spare parts management is currently implemented, and decisions are only based on the experience gathered over the years. Additionally, it has been observed that sales on spare parts were very weak in comparison to the real demand: only 50% of the offers

[1] Cavalieri, Garetti, Macchi and Pinto, 2008
[2] Bååthe, Hell, Tengö, Viberg and Ab, N.d.

emitted by FHW are converted into a sale. It is assumed that this deficiency is mostly due to the unavailability of the parts, more than their price.

In the prospect to enhance the success rates on spare parts sales and to develop its after-sale service activities, it is relevant for FHW to implement a dedicated tool which both analyses and steers its inventory. In this context, the objective of this thesis is to fulfil these expectations through the conduct of a theoretical research, and especially trough the development of an operational deliverable.

**The thesis will address the following research questions:**

1) What kind of spare parts classification can be built up, and under which prerequisites?

2) How to forecast the intermittent demand on spare parts?

3) What are the logistics strategies associated to each group of spare parts?

4) Outlook: how to optimize the stocks of spare parts in a multi-echelon system?

## 1.3 Research Goal

As previously mentioned, the objective of this thesis is to provide a pragmatic approach to introduce smart spare parts inventory techniques into a practical context. The expectations stemming from the research questions are the following.

- Find the most appropriate criteria to establish a spare part classifications, in regard to the available data.
- For each criteria, set the proper parameters.
- Implement a forecasting method
- Identify logistics strategies corresponding to each group of parts
- Give quantitative directives on stock management

In addition, the relevance of the work has to be validated through a comparative approach, in order to estimate whether its implementation within the company would be beneficial or not.

## 1.4 Methodology and Structure of the Thesis

Although the final result of the thesis is expected to be really practical and useful, the approach of the thesis is based on theoretical fundamentals. It is indeed essential in a first time to integrate properly the basic concepts and definitions that will be used all along the paper. Besides, it is important to have a global overview on what techniques are existing in order to choose the most appropriate ones. In this way, the first chapter of the thesis is dedicated to a literature review on spare parts management. After general literature researches and the first meetings at FHW with spare parts specialists, three main lines identified: classification, forecasting methods, and logistics strategies. These three concepts will constitute the sub-sections of the theoretical background of the thesis.

The second chapter is then focusing on the case study, meaning the practical application of the theoretical concepts. The first analysis have revealed the importance of the data used to build up the tool: it is indeed essential to know which data are available and to assess their quality. The next subsections focus on the reasoning and the implementation on each stage of the tool programming. A strong emphasis is put on the demand variability and the selection of the corresponding forecasting methods, as it is one key factor in spare parts inventory management.

Finally, the results of the work are discussed and validated in the last chapter through a comparative approach with the current situation. The goal is to estimate and underline the benefits of the research as well as its implementation within the company activities. An outlook on further developments is moreover proposed.

The research map below recaps the approach and structure of the Thesis.

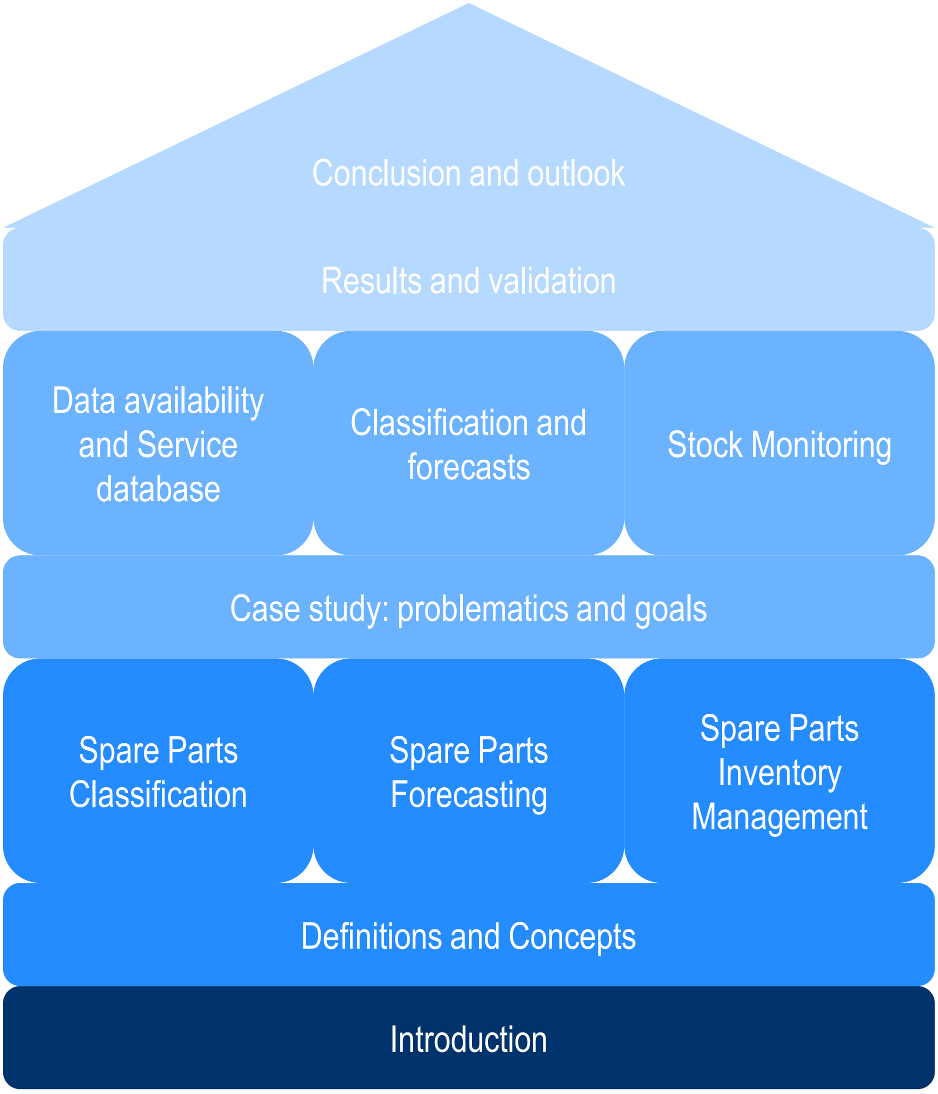


Figure 2: Structure of the Thesis

It is important to make the following remarks on the **limitations** of the work:

- This topic has been developed in a practical context, meaning that its vision is very pragmatic. A major concern of this thesis is therefore to present theoretical notions that have great effect into real business activities.

- In the same connection, this field of techniques has proven not to be an exact science, yet. In addition to the lack of practical applications, arbitrary decisions are a permanent feature along the development of the work, reflecting one possible and subjective reasoning.

- The concept of *logistics* being very vast, this works only focuses *stocking logistics*. Also, most emphasis is given on stock analysis, strategies and forecasts. Operative practices (stock levels, replenishment) are here mostly given as suggestions.

# 2 Fundamentals and Approach

In this chapter, the fundamentals and the methods used to conduct the thesis are presented. The necessity for spare parts management as well as its general process are firstly determined. For each step of the approach towards spare part management, a literature review of the existing methods is exhibited.

## 2.1 General Aspects on Spare Parts Management

### 2.1.1 The Role of Spare Parts in the Maintenance Process

Capital goods such as machinery or tools are tangible assets that an organization uses to produce consumer goods and goods for other businesses.[1] In addition to their vital role in the production process, they are characterized by long life cycles as they are usually long-term investments for the organization that makes use of them. To ensure a maximal use duration at the best performance level, capital goods therefore need **maintenance**. It is defined as “the combination of all technical and associated administrative actions intended to retain an item in, or to restore it to, a state in which it can perform its required function.”[2] During its life cycle, a capital good is indeed bound to undergo several types of maintenance activities in order to maintain its level of use. The reasons and the triggers for such activities are diverse and will be discussed later in this section. The maintenance treatments on capital goods are from four different types:[3]

- Servicing (cleaning, lubricating, inspecting...)
- Repair
- Replacement
- Design improvement (upgrading, modifying)

Among these four treatments, the **replacement** of a part or an assembly within a capital good necessarily implies the setting up of a new part or assembly. A **spare part**

[1] Cf. http://www.investopedia.com/terms/c/capitalgoods.asp (read on 03.07.2017)
[2] Cf. http://www.referenceforbusiness.com/management/Log-Mar/Maintenance.html (read on 03.07.2017)
[3] Takata, Kimura, van Houten, Westkämper, Shpitalni, Ceglarek and Lee, 2004

is therefore a part or an assembly that is dedicated to replace a damaged, worn or defective part or assembly.[1]

Spare parts have in this way an essential role within the life cycle of a capital good as they are one of the key factors for a successful maintenance. The reliability on spare parts availability is especially important within the machinery industry where life cycle of products stretches until several decades.

***Maintenance strategies***

As mentioned before in the section, several types of maintenance can be implemented according to the policy of an organization regarding its assets. The choice of a maintenance strategy has great influence on the management of spare parts as it implies different level of criticality and investments. Three main maintenance policies have been identified and are depicted below:[1,2]

- The **corrective maintenance**, also known as "run to failure" maintenance, is the simplest approach. It consists in repairing an asset as soon as it breaks or fails. The exact moment of the maintenance is therefore unpredictable, and so is the need for spare parts. The need for their immediate availability depends on the criticality of the asset within the production and on the downtime costs (see next section).
- A **preventive maintenance** is implemented to avoid the consequences of failure of equipment. The aim is indeed to prevent a failure of an equipment by maintaining its reliability over its time of usage. Maintenance activities are triggered when a failure is likely to happen. Planned Maintenance (PM) and Condition Based Maintenance (CBM) are two types of preventive strategies. The first consists in running maintenance activities at preplanned specific times while the second performs maintenance tasks only when an objective need arises, after regular inspections. CBM involves thus investments in measurement methods and corresponding analysis. Leading a preventive policy consequently decreases the criticality on spare part availability for the capital good manufacturer.

[1] Biedermann, 2008
[2] Barkai, 2014

- The **predictive maintenance** is an evolution of the preventive maintenance as it aims to determine theoretically and precisely the right time to launch a maintenance activity. The objective is to avoid unnecessary maintenance tasks that could happen with a preventive policy by being more accurate in the prediction. It is however very difficult to implement and requires high investments, especially for data acquisition, and for analysis (complex statistical models).

The table below compares the three maintenance strategies.

| | **Corrective maintenance** | **Preventive maintenance** | **Predictive maintenance** |
|---|---|---|---|
| *Trigger* | Failure/break | Regular inspection (CBM) Or planned maintenance | Analytical decision |
| *Planning investment* | None | High | High |
| *Costs to implement* | Low | Moderate | High |
| *Downtime Costs* | High | Moderate | Low |
| *Spare Part need* | Unpredictable | Easily predictable | Easily predictable |
| *Spare Part availability* | Critical | Non critical | Non critical |

**Table 1: Maintenance Strategies Comparison (own research)**

The preventive and predictive maintenance entails on non-criticality concerning the availability of spare parts because the need is predictable and therefore easy to plan from a logistics point of view.

It is clear now that a predictive maintenance leads to high benefits over a corrective maintenance in terms of downtime costs reduction. However, implementing a predictive maintenance is costly and has to be a priority for the concerned organization. Implementing a viable and reliable predictive maintenance is a long and difficult way that only few "elite" companies can afford.[1] It is indeed observed in the practice that corrective and preventive strategies are the most used. This point of view is adopted in the remainder of the thesis and it will be assumed that corrective maintenance is the default strategies used by capital goods owners.

### 2.1.2 The Incentives for Spare Part Management

A maintenance activity such as the replacement of a part within an equipment necessarily implies a downtime. The consequences of equipment failure are huge for producers as they represent tremendous losses of income when the equipment is vital in the production process. The failure of a single equipment can jeopardize the productivity of a whole plant[2], and on a long term influence the image of the organization. Considering a corrective maintenance strategy, the total downtime of the damaged equipment is actually the addition of diverse activities. The figure hereafter displays an example of these activities during a downtime.

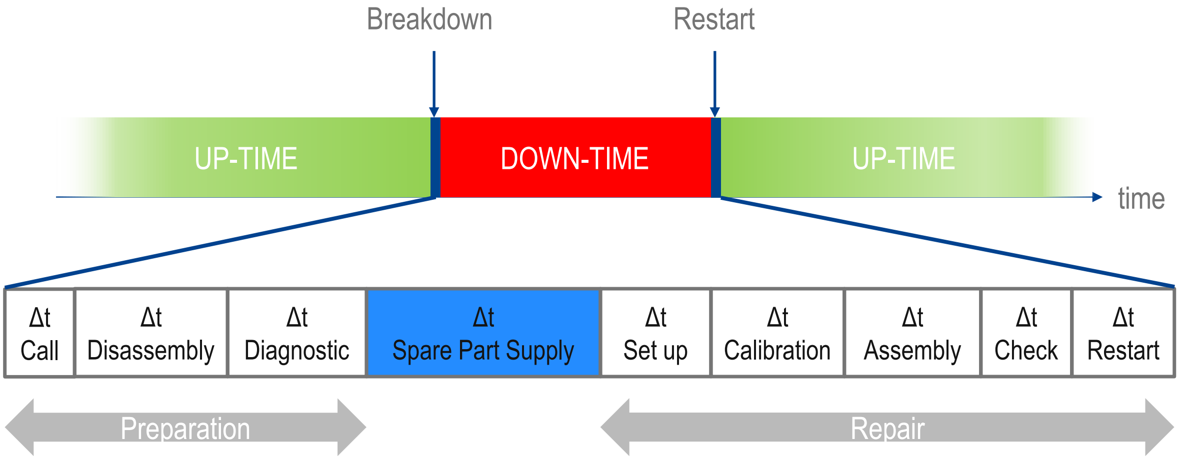


**Figure 3: Activities during breakdown intervention[3]**

[1] Barkai, 2014
[2] Cavalieri, Garetti, Macchi and Pinto, 2008
[3] Adapted from Cavalieri, Garetti, Macchi and Pinto, 2008, p. 380

Although the supply of the spare part appears as one activity among a lot of others, it is nonetheless the longest one if the part is not directly kept in stock at the installed base location. The only delivery of the spare part from the supplier to the production site lasts inevitably a few days. Also, it is mentioned that contacting and negotiating times with the supplier that potentially increases significantly the supply time of the spare part.[1] But the supply delay is firstly dependent on the **availability** of the spare part: an *available* part will be shipped directly by the supplier whereas an *unavailable* part has to be ordered, inducing an additional delay. As the main factor influencing on down-time and on the related productivity and profit losses, it is now clear that capital good owners have to minimize the delay on spare parts supply.

Moving on to the side of spare parts suppliers, they have the role to achieve spare part availability to ensure the performance of asset owners. This role is usually assumed by the after-sale service of the equipment manufacturer who provide maximum value for their product.[2] As mentioned in the introduction of the thesis, customer support has many advantages for both parties:

- The equipment manufacturer benefits from a source of revenue as well as the insurance of customer satisfaction and loyalty. It may provide a competitive advantage as well.[3]
- The asset owner, in turn, takes advantage of the support for its own productivity through reliable and confident services.

An after-sale service agreement is usually set-up between the two sides in order to guarantee the achievement of pre-specified service targets, also referred to as **service level:**[4] the equipment manufacturer commits itself to ensure the agreed service level, and so through spare parts availability.

**Spare parts management**, as one side of after-sale services for equipment manufacturer, is therefore defined as the activity of controlling service parts inventory with the objective to ensure the best service level to customers at the lowest costs.[5]

[1] Cavalieri, Garetti, Macchi and Pinto, 2008
[2] Goffin, 1999
[3] Goffin and New, 2001
[4] Botter and Fortuin, 2000
[5] Lewandowski and Oelker, 2014

It is important to notice that spare part management is a vast topic that includes several aspects at different levels within an organization. This covers for example:

- *Strategic decisions*: warehouses network design, suppliers network design
- *Tactical decisions*: inventory management, pricing
- *Operational decisions*: transport logistics, resource allocation

Within those activities, **spare parts inventory management** is actually the one that requires the most attention as the decisions to take are numerous and can vary a lot. Also, decisions on spare parts inventory are making the biggest difference – in the right or the wrong way – within the whole spare parts management activity.[1]

The concept of spare part inventory management is consequently mixed up with the term of Spare Part Management in the remainder of the paper and constitutes the topic of the research.

### 2.1.3 Spare Parts Inventory Management

**Inventory management** refers to the "activities employed in maintaining the optimum number or amount of each inventory item. The objective of inventory management is to provide uninterrupted production, sales and/or customer-service levels at the minimum cost."[2] This definition exhibits firstly the universal aspect of inventory management across the different functions of an organization, but underlines also its diversity. Production, sales and customer-service differ in many ways that make their related inventory management considerably variable. The production deals for example with raw material and parts whereas the sales department focuses on end-products. In addition to the type of item to manage, the differences come also from the characteristics of the demand on the items. In this way, the main challenges that spare part management faces are the following:[3]

[1] Van Houtum and Kranenburg, 2015
[2] Cf. http://www.businessdictionary.com/definition/ inventory-management.html (read on 08.07.2017)
[3] Bacchetti, Plebani, Saccani, and Syntetos, 2010

- The number of parts to manage is tremendous, as the after-sale service is to be ensured during the whole life-cycle of the products, which are more and more complex.[1]
- The demand is very variable and intermittent patterns are observed, that makes it very unpredictable and difficult to forecast.[2]
- Due to the widespread corrective maintenance strategy among asset owners, high availability and responsiveness is required to minimize downtime costs.[3]
- A risk of stock obsolescence due to the inexistent demand or substitutes appears.[4]

In regard to these specific features, spare part management appears to be part of a very complex environment submitted to high *unpredictability* and *criticality*. However, despite a huge amount of literature on specific spare part inventory methods in the last decades, guidelines to practical application are lacking.[5] Managers are consequently reluctant to adopt new methods whose efficiency has still not be proven from a practical point of view. The result is that inventory techniques dedicated to spare parts are often not differentiated from traditional ones, used for end-products and in production.[6] The use of such methods lead inevitably to unappropriated decisions concerning inventory management: some parts are stocked in too big quantities, some other in too low quantities, and also some parts are stocked for no reason, whereas some should be. The direct consequence of a poor spare part management is the creation of unnecessary costs due to overstocks, and missed revenues because of unavailability and competition. On a long term, repercussions on customer satisfaction and the image of the organization are observable.

Spare parts management ultimately aims to find the optimal compromise between inventory holding costs and unavailability costs, as presented on Figure 4.

[1] Cohen, Agrawal and Agrawal, 2006
[2] Syntetos and Boylan, 2005
[3] Murthy, Solem and Roren, 2004
[4] Cohen, Agrawal and Agrawal, 2006
[5] Bacchetti and Saccani, 2012
[6] Boylan and Syntetos, 2007

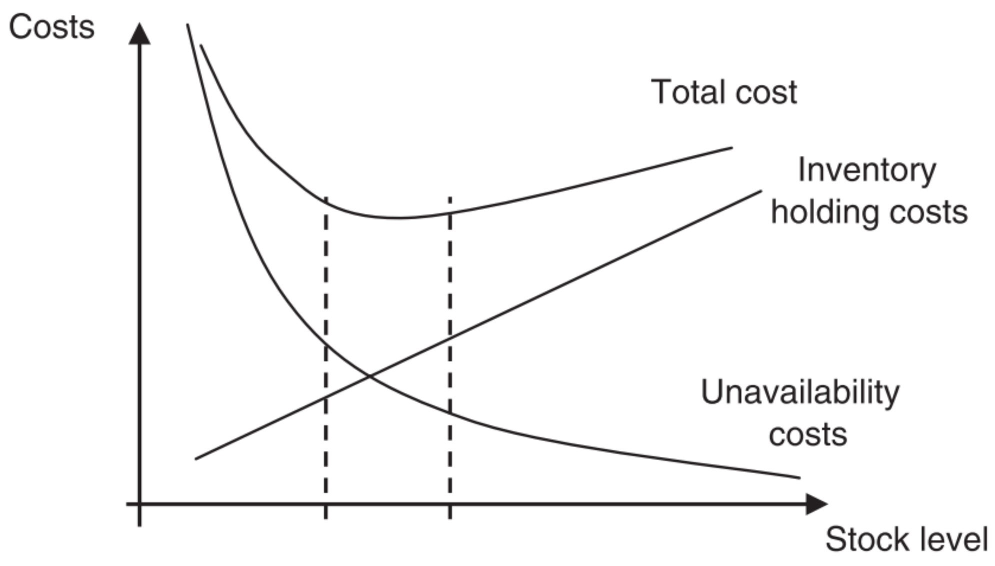


Figure 4: The spare parts management dilemma[1]

Due to the challenges on spare parts inventory previously brought up, finding such an optimum is not a simple matter. The high number of parts and their inventory holding costs restrict the possibilities to stock them all. Hence, unavailability has to be conceded for some parts. Therefore, the objectives of spare parts inventory is to answer the following questions:[2]

1. **Which spare parts have to be stocked?**
2. **Where?**
3. **In which quantity?**
4. **How to replenish the stocks?**

In a work to investigate on the gap between research and practice in spare parts management, a four-step decision-making process is suggested to implement a successful and profitable inventory management.[3] This model is actually very relevant in light of the research achieved to write this thesis. It is also now a standard practice adopted by most organizations which develop this kind of activity.

[1] Cavalieri, Garetti, Macchi and Pinto, 2008, p. 380
[2] Botter and Fortuin, 2000
[3] Bacchetti and Saccani, 2012

The concept is presented on the figure below.

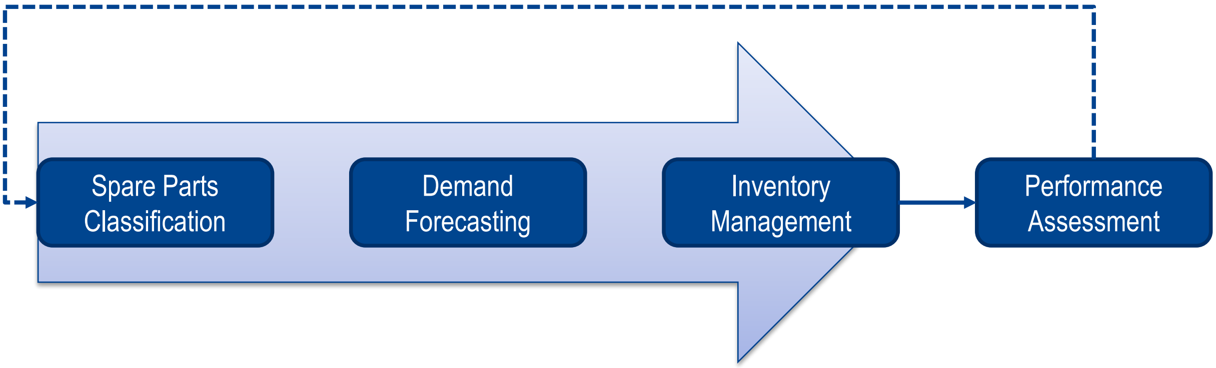


**Figure 5: An integrated approach to spare parts management**[1]

Spare parts management involves high amounts of parts, with various characteristics. It is therefore impossible to handle an inventory on a case-to-case basis. The idea of the concept is thus to cluster parts which share common characteristics in different groups (*classification*). Each group is then provided with an appropriate forecasting method (*demand forecasting*) and stocking policy (*inventory management*) that stem from the characteristics. The final step is to test and validate the achieved results and their benefits.

The table hereafter reviews the main steps towards spare parts management.[2]

| ***Step*** | ***Objective*** |
|---|---|
| **Spare Parts Classification** | **Chose the most relevant criteria to characterize each spare part according to diverse properties: technical features, criticality, value-usage, demand…**<br><br>The aim is to provide a way to distinguish or to gather parts into different classes delimited by predefined parameters, and so for each criterion.<br><br>Combining several criteria enables to build a *multicriteria classification*: the parts which share the same class for each criterion are clustered into groups.<br>A multicriteria classification is the basis for spare parts management. |

[1] Adapted from Bacchetti and Saccani, 2012, p. 733
[2] Cavalieri, Garetti, Macchi and Pinto, 2008

| | |
|---|---|
| **Demand Forecasting** | **Estimate properly the demand for each service part.**<br><br>The demand on spare parts is often intermittent and/or erratic, which makes the estimation highly unpredictable. Though, it exist specific forecasting methods dedicated to this type of variability.<br><br>The goal is to find the most adapted method for each group of the classification. |
| **Inventory Management** | **Define the inventory strategy for each group of parts, and give the concrete quantitative stocking decisions for each part.**<br><br>Following the two previous steps, a policy is assigned to every group: should the parts be stocked? If yes, where? How to replenish the stock?<br><br>The strategies are numerous, from a non-stocking policy to a very tight control on inventory levels. The accuracy on forecast takes on here its full meaning. Decisions focus on safety stocks, order quantities and re-order points. |
| **Performance Assessment** | **Test and validate the developed concept before its operative implementation in the organization.**<br><br>The final stage consists in demonstrating the relevance and the benefits of the results previously achieved. Simulations and comparisons with the current spare parts decisions within the company have to be performed.<br><br>If necessary, refinement and adjustments can be applied. |

Table 2: The four steps towards spare parts management

The general course of action to build and implement spare parts inventory management is now clear. This process is adopted for this research and conducts the remainder of the thesis, both in the theoretical (chapter 2) and practical part (chapter 3).

Now, each step towards spare parts management requires a close look on the existing techniques and methods that can be used.

## 2.2 Spare Parts Classification

As mentioned previously in the work, spare parts for the machinery industry are highly diverse due to their large number, the variability of their use and their complexity. A single inventory strategy can therefore not be specifically decided for each part within an inventory. The main objective of a classification is to set up groups of spare parts that share *similar characteristics* in order to assign for each group the most appropriated logistics (inventory) strategy. A secondary objective is to get a precise analysis of the inventory that allows to manage it efficiently.

So far, most organizations use a simple mono-criterion classification (usually the price or the frequency of the demand) which seems inefficient to deal with complex products.[1] It is therefore relevant and essential to select adequately the criteria to characterize one's inventory.

The appropriate criteria to characterize a spare parts are numerous and focus on a large range of aspects,[2] from technical properties to economic or supply considerations. The main criteria that can be found in the literature are presented hereafter, as well as the associated analysis method that determines the different classes.

***Value-Usage: ABC Analysis***

The most common and used in practice criteria is the value-usage. It measures the annual consumption of a spare part, based on its value and its annual demand.

$$Value\ Usage = Price * Annual\ Demand$$

**Equation 1: Value-Usage**

The method does not consist in classifying the parts according to cut-off values, but rather using the cumulative value-usage: the parts with the highest value-usage and

[1] Botter and Fortuin, 2000
[2] Bacchetti and Saccani, 2012

representing 80% of the total value-usage are A-parts. The Pareto Principle establishes that A-parts should represent approximately 20% if the items. B and C parts are defined as following:

| Class | % of total Value-Usage | % of total Items |
|---|---|---|
| **A** | 75 | 10 |
| **B** | 20 | 20 |
| **C** | 5 | 70 |

**Table 3: ABC Analysis[1]**

The determination of the cut-off values is of course arbitrary, and the percentage of items in each class will vary from an inventory to another. What is important is to have a similar distribution: few items represent the most important proportion of value-usage, whereas the majority of the items represent only a very small part of the total value-usage. In practice, such a distribution is usually observable and allows the inventory manager to know which items should require a specific attention, as they represent the most revenues. However, it is still a rough classification because big differences can exist between two items of the same class, such as the price or the frequency of the demand.

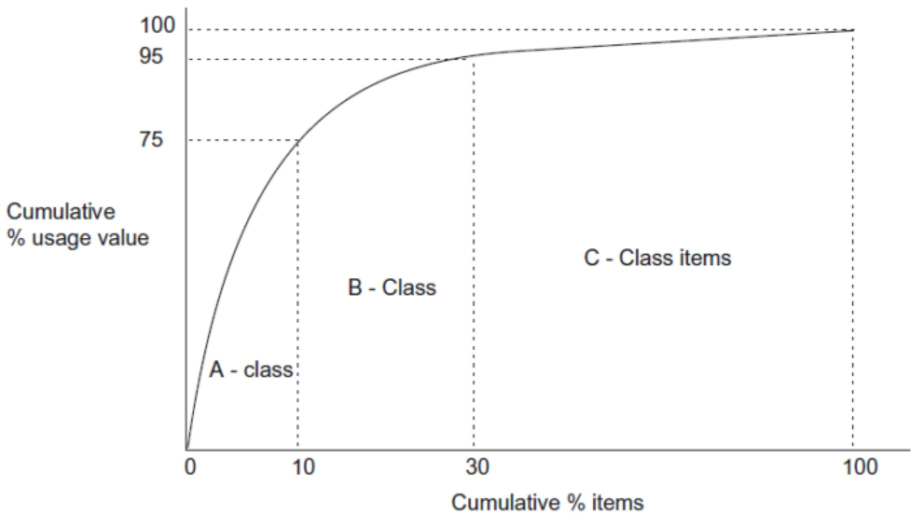


**Figure 6: ABC-Analysis presented in graphical form[2]**

[1] Chen, Li, Levy, Hipel and Kilgour, 2008
[2] Adapted from Chen, Li, Levy, Hipel and Kilgour, 2008, p. 36

### *Frequency of demand – FSN Analysis*

The frequency of demand is the number of orders on a spare part during a certain period of time. Usually, three classes are distinguished:[1]

- Fast-moving items (F) are frequently ordered
- Slow-moving items (S) are less used
- Non-moving-items (N) are items that are very rarely ordered

Cut-off values are also arbitrary and result from an analysis of the considered inventory. It is important to emphasize that this criterion does not measure the total ordered quantity whereas the number of orders in the period of time.

This classification is particularly suited for spare parts management as it gives a specific class for rarely ordered items (non-moving). In this way, this classification allows the manager to have a clear view on the most frequently ordered items.

### *Variability of demand – XYZ Analysis*

The criteria on variability estimates the predictability of the demand.[2] The measure is actually the coefficient of variation $\vartheta(x)$ of the demand, which normalizes the standard deviation $\sigma(x)$ with the arithmetic mean $\bar{x}$:

$$\vartheta(x) = \frac{\sigma(x)}{\bar{x}}$$

Equation 2: Coefficient of variation

| Class | Variability | Ability to schedule | Example |
|---|---|---|---|
| X | Very little variation | High | $\theta(x) < 1{,}5$ |
| Y | Some variation (trends, season) | Middle | $1{,}5 \leq \theta(x) \leq 3$ |
| Z | Unsteady | Low | $\theta(x) > 3$ |

Table 4: XYZ-Analysis

[1] Bošnjaković, 2010
[2] Stoll, Kopf, Schneider and Lanza, 2015

In this way, the higher the coefficient is, the more the demand varies, and thus the more unpredictable it is. Classes and example of cut-off values are presented in the previous table.

This measurement of variability is actually not very well suited for spare parts management because it only considers the demand quantities, and not in the interval of demand. Spare parts demands are indeed subject to a lot of “zero” demand (intermittent demand) which are periods where no item are ordered. A two-criterion classification for variability that considers interval periods is described later in the work (see section 2.4.1).

### *Unit Price – HML Analysis*

The price criterion does not request any calculation, but only arbitrary values to determine the different classes. These values will depend on the inventory.

| Class | Unit Price |
|---|---|
| **H** | High |
| **M** | Medium |
| **L** | Low |

Table 5: HML-Analysis

### *Availability Risk – KIC Analysis*

It is difficult to have a quantitative measure of the availability of an item on the market, such as the lead time. In this way, the availability risk criterion is a qualitative characteristic that focuses on the number of suppliers for an item,[1] which is easier to estimate. The classes are presented in Table 6.

| Class | Availability Risk | Characteristics |
|---|---|---|
| **K** | High (Key parts) | Few suppliers, made-to-order parts |
| **I** | Moderate (Industry specific parts) | More suppliers, easier to manufacture |
| **C** | Low (Commercial Parts) | Many suppliers, common bulk materials |

Table 6: KIC-Analysis

[1] Jouni, Huiskonen and Pirttilä, 2011

Key parts should then require the most attention concerning their inventory policy due to the small number of suppliers and therefore a high unavailability risk. On the opposite, there is no risk of unavailability with commercial parts, which therefore do not need strict monitoring.

***Lead Time (availability) – SDE Analysis***

Also considering the supply aspect, the lead time criterion is quantitative and considers directly the time needed by the supplier to provide the spare item. Such a classification is really relevant, especially concerning spare parts management, but requests a lot of investment: precise data on lead time are in general difficult to obtain.

| Class | Availability | Example |
|---|---|---|
| **S** | Scarce | More than 6 months |
| **D** | Difficult | Between 2 weeks and 6 months |
| **E** | Easy available | Less than two weeks |

Table 7: SDE Analysis

***Criticality – VED Analysis***

An item is said to be critical when following a breakdown, its “unavailability would result in severe consequences for the plant.”[1] The concept of criticality could appear very simple, but it is actually very complex and no common understanding has been reached. Indeed, everyone can derive its own definition of criticality and the qualitative judgement of this criteria makes it highly subjective.[2] Also, the criticality is often a combination of several factors, which make its determination rather complicated.

The VED analysis consist in finding methods to classify items in Vital, Essential and Desirable classes. The analysis can simply be established in an arbitrary and qualitative manner, which is then very subjective. To reduce the subjectivity of this classification, several methods have been developed and three of them are briefly presented in this section.

[1] Molenaers, Baets, Pintelon and Waeyenbergh, 2012, p. 570
[2] Bacchetti and Saccani, 2012

*Method 1*[1]

The criticality consists in assessing four sub-criticality parameters and to use a decision tree to determine the overall criticality of the considered spare part. The parameters are:

- *Plant production criticality*: qualifies the consequences of the failure of the part within the whole production process, from both qualitative and quantitative aspects.
- *Supply criticality*: this parameter is based on the lead time of the spare item.
- *Safety*: an assessment of the risk on the environment, health or operator safety.
- *Inventory:* some items are subject to deterioration during their inventory, or have specific storage conditions.

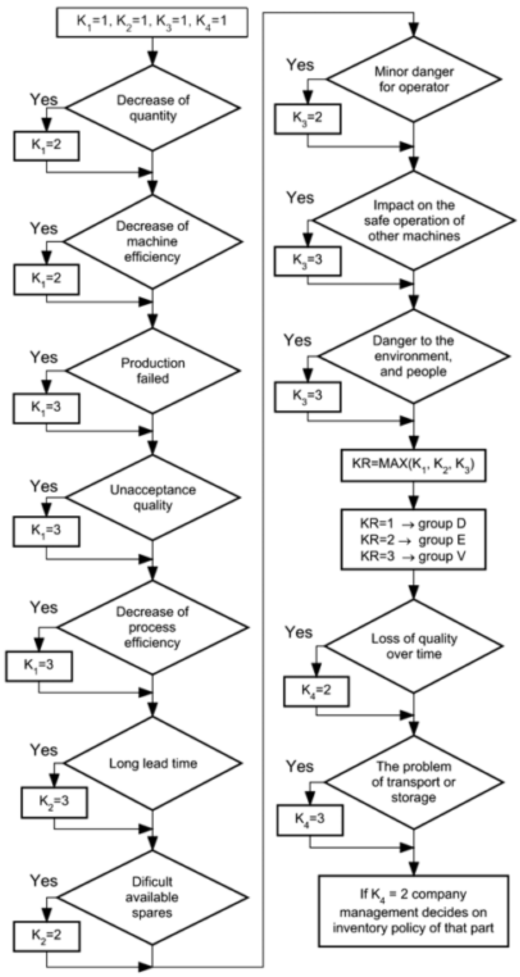


**Figure 7: VED Analysis**[2]

[1] Bošnjaković, 2010
[2] Bošnjaković, 2010, p. 501

Finally, each parameter is assigned with a value from 1 to 4 according to its assessment, and the general criticality is determined thanks to the procedure displayed on Figure 7.

*Method 2*[1]

This methods is based on the assessment of five different sub-parameters:

- Equipment criticality
- Probability of item failure
- Replenishment time
- Number of potential suppliers
- Availability of technical specifications

The last three attributes concern logistics aspects and are gathered in a general assessment through an Analytical Hierarchy Process (AHP). This process consist in weighing the three different attributes according to their relative priority. The determination of the weighs to assign is the results of expert judgments and of complex computations which are not presented here.

The final criticality assessment is determined with a decision cube, which distinguishes four classes.

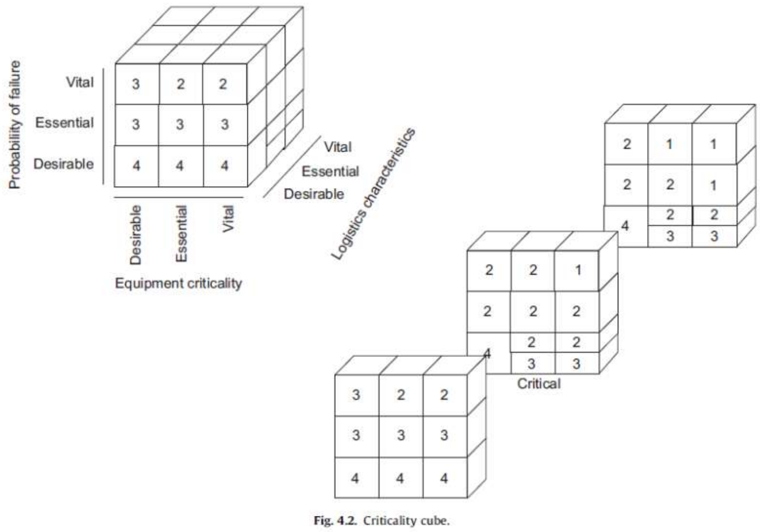


**Figure 8: Criticality Cube**[2]

[1] Molenaers, Baets, Pintelon and Waeyenbergh, 2012
[2] Molenaers, Baets, Pintelon and Waeyenbergh, 2012, p. 575

*Method 3*[1]

This method is different from the previous one as the sub-criticality parameters are not the same. However, the general idea is the same: an AHP is required to determine the priority between the parameters, and a decision tree is developed to assess the general criticality of each spare part. It is shown below.

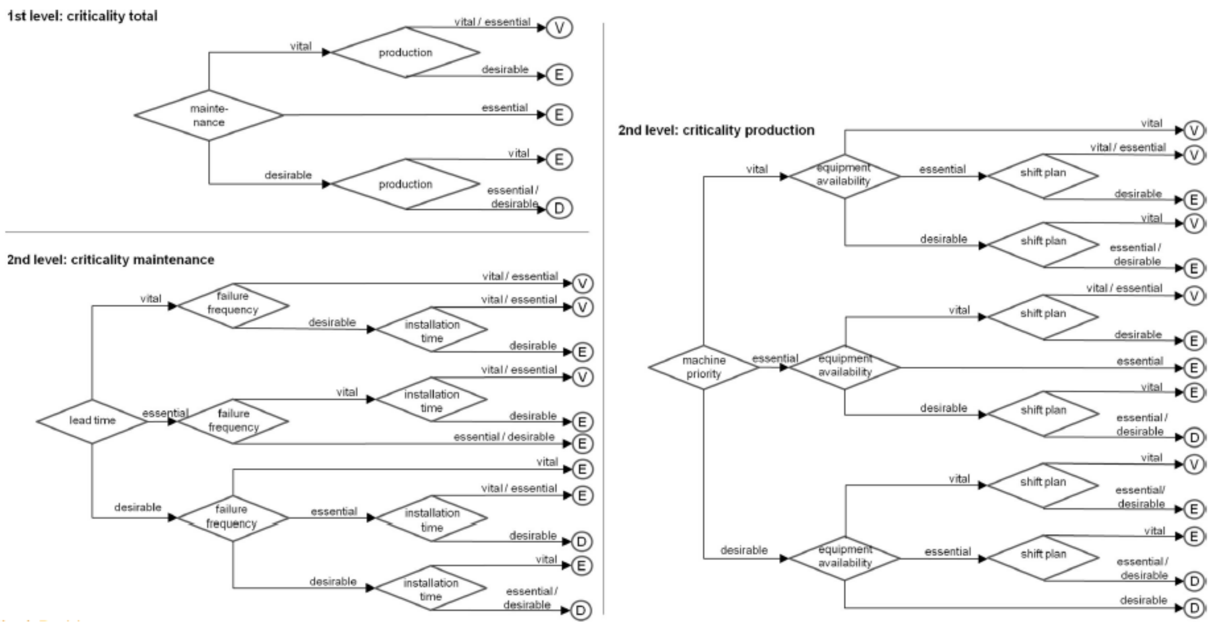


Figure 9: VED decision tree[2]

Finally, the exhibition of three criticality analysis shows the diversity of its assessment. The methods are numerous because the parameters and especially the procedures are very different. The result is that implementing a criticality analysis request a lot of investment because of the amount of requested data and the complexity of the procedure to custom. Also, all the processes are still marked by a high subjectivity although the results are accurate and relevant.

### *Life Cycle Phase – LCP Analysis*

The demand on spare parts is dependent on the life cycles of the equipment there are part of. For instance, the development of a new equipment induces the introduction of

[1] Stoll, Kopf, Schneider and Lanza, 2015
[2] Stoll, Kopf, Schneider and Lanza, 2015, p. 232

new spare parts in the catalog of the OEM. On the opposite, the obsolescence of an equipment over time implies the reduction and eventually the disappearance of the demand on certain items. The introduction of a dedicated classification is thus relevant, and is highlighted on an industrial case study.[1] Spare parts can be classified into Introduction, In-Use or Dismissed classes, according to their life cycle phase.

It is important to point out that this classification can be determined from a qualitative point of view with expert judgments on life cycles analysis, and from a qualitative point of view through a sale analysis over time. The classification is in the last case directly linked to the demand criteria (XYZ Analysis), and both can possibly merged into one single classification.

### *Conclusion on classification*

Table 8 recaps the different criteria and analysis that have been presented in this section. The aim is also to have an overview on their specificities, and on their relevance and the complexity of the analysis. Besides, the logistics consequences of each criterion is mentioned as an introduction to the next two sections (see 2.4 and 2.5). Such a comparison is essential when implementing a classification on a case study.

The “ability to measure” is a personal assessment of the difficulty to implement the classification given the availability to obtain the requested data and the complexity of the analysis. “High” stands for “easy to implement”, “low” for difficult”.

It is in practice impossible – and irrelevant – to use all of the criteria of the non-exhaustive list. The classification to develop will depend on the specificities of the organization: industry, product complexity, suppliers and distribution networks.[2] Besides, the classification will significantly depend on the investments that the organization is ready to put in. For instance, it has been shown previously that the development of a criticality classification implies new expert assessments that usually do not exist.

[1] Bacchetti, Plebani, Saccani and Syntetos, 2010
[2] Bacchetti and Saccani, 2012

| Criterion | Purpose | Analysis | Requested Data | Ability to measure | Logistics Consequences |
|---|---|---|---|---|---|
| **Value-Usage** | Sales | ABC | List of orders & Product Data | High | Stock levels. Replenishment. |
| **Demand Frequency** | Sales | FSN | List of orders | High | Stock levels |
| **Demand Variability** | Sales | XYZ | List of orders | Moderate | Demand Forecasting |
| **Price** | Product Life Cycle | HML | Product Data | High | Stock decision Replenishment |
| **Availability Risk** | Supply | KIC | Suppliers & product data | Low | Stock Decision |
| **Lead Time** | Supply | SDE | Supply Data | Low | Stock Decision |
| **Criticality** | Multipurpose | VED (multi-criteria) | Product Data Suppliers … | Low | Safety Stocks |
| **Life Cycle Phase** | Sales | LCP | List of orders or LCC Data | High or low | Demand Forecasting Stock decision |

Table 8: Classification criteria comparison (own research)

## 2.3 Strategy Mapping

The main goal of the classification is to provide the organisation with a generic analysis of characteristics for each spare part. The combination of the chosen criteria clusters the inventory into groups of parts that share the same characteristics. Then, it is possible to assign, for each group, a specific logistics strategy. The key elements of a spare parts logistics system are identified on Figure 10.

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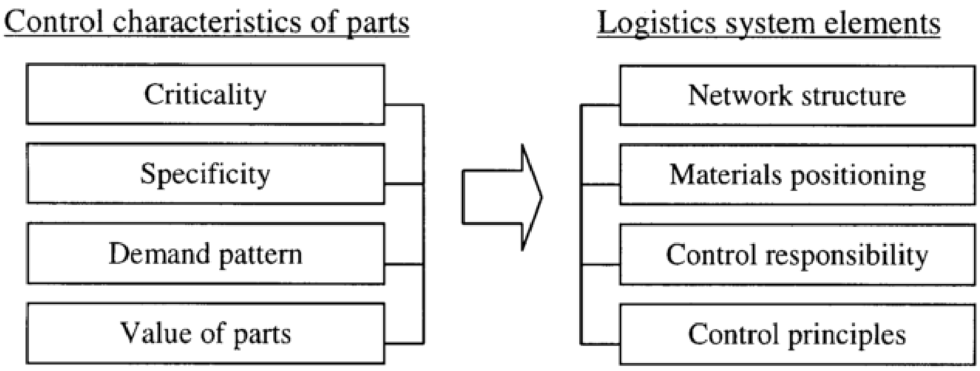



**Figure 10: Relevant control characteristics and logistics system elements**[1]

It appears that logistics strategies are firstly driven by the *structure of the network*, meaning the number of inventory echelons and locations in the system. *The materials positioning* refers to the choice of the location where to stock an item within a system. The *control responsibility and principles* are the operational directives to stock the material in the most efficient way: stock level, safety stock, lot size, reorder point…

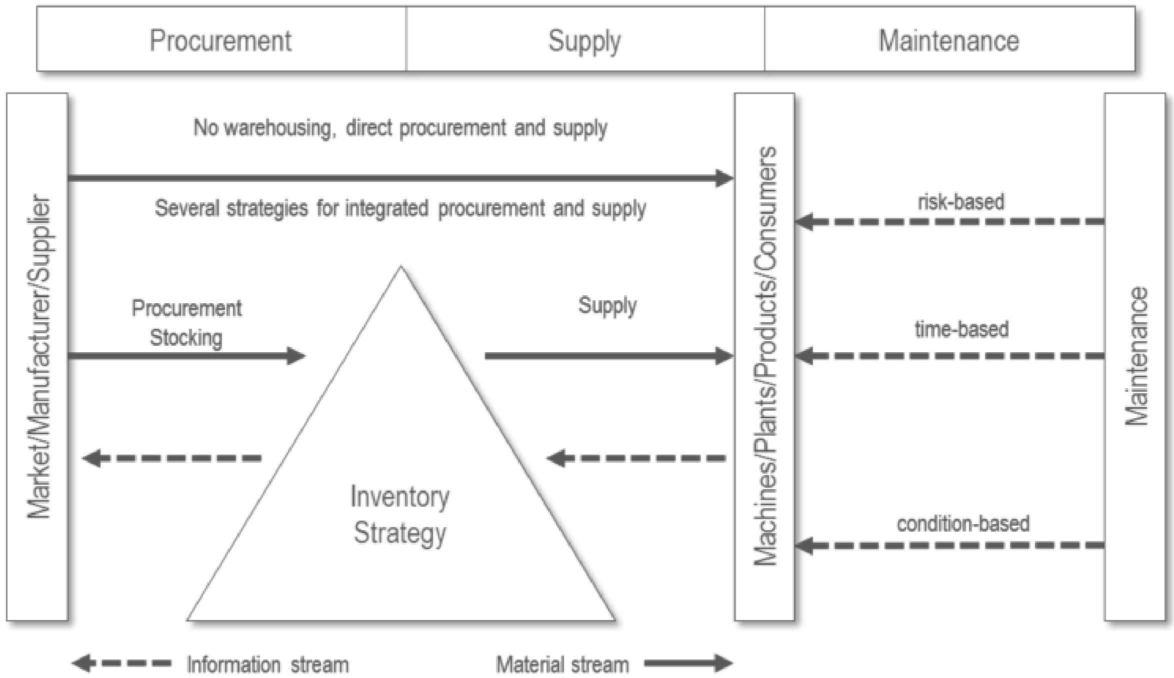



**Figure 11: Spare parts integrated inventory strategy**[2]

[1] Huiskonen, 2001, p. 129
[2] Adapted from Pawellek, 2013, p. 238

Focusing now on the network of the logistics system, it is indeed one of the most important factor in the strategy elaboration because it fixes the possibilities and the constraints on spare parts inventory. Figure 11 shows the place of spare parts inventory strategies within the organisation's network:

This figures highlights the dependence of inventory on the structure of its suppliers and consumers networks. It is important to point out the influence of the maintenance policy on the inventory strategy, to refer to the beginning of the work.

To be more specific regarding the logistics network, a common case is used for the remainder of this chapter; a 2-echelon model is considered to represent the network of warehouses (see figure below).

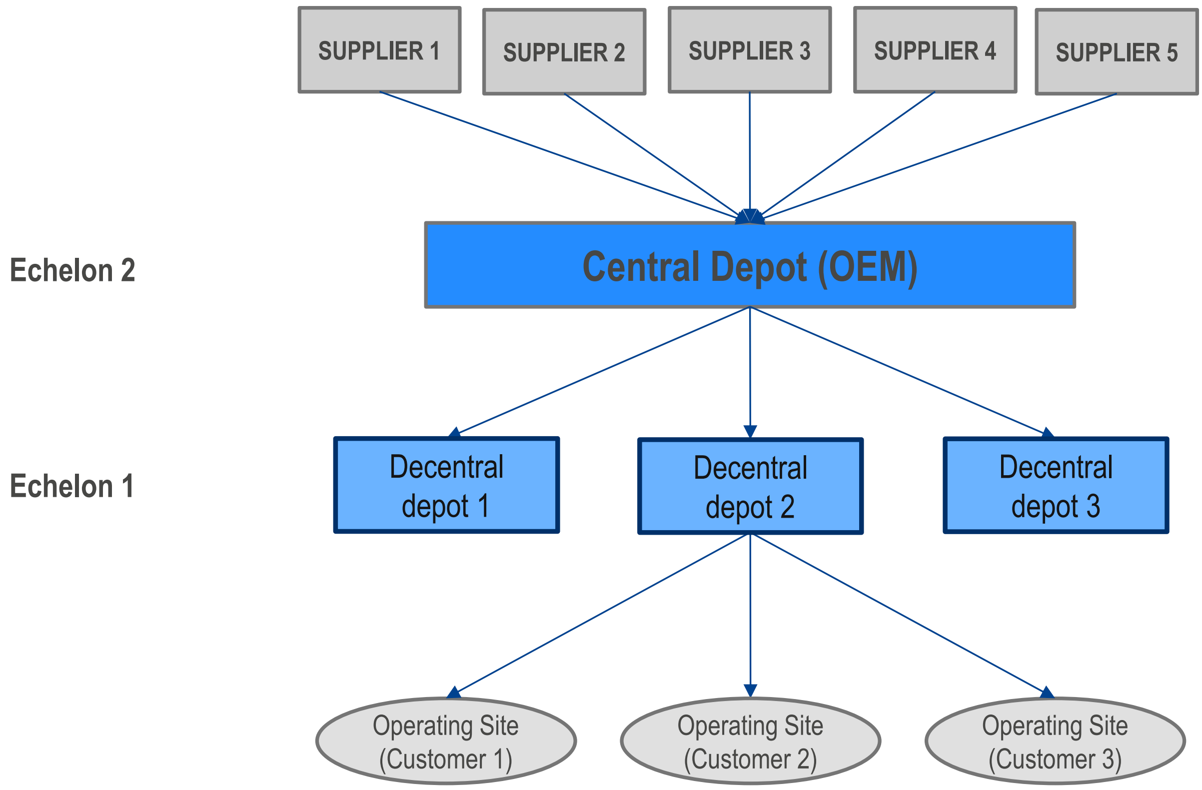



Figure 12: 2-echelon logistics network model (own illustration)

The type of warehouses from echelon 1 differ from one case to another, according to their size and importance within the structure of the organisation. They are for example called country warehouse or proximity stock.[1] Also, the number of echelons can be increased, according to the considered organisation. Such models make the inventory strategies more complex as it gives an additional possible storage location. For the simplicity of the rest of the section, and in prospect with the case study of the paper, the 2-echelon model is adopted

Spare parts suppliers only provide a central warehouse, usually the at the OEM site. The latter collects and stores the items before redistributing them on the warehouses of echelon 1. These locations are more local and are in charge to provide the customers of a specific area with spare parts. For example, a region, a country, or a continent. In this way, the process of spare parts supply may seem complex and very complex to face urgent situation because of the addition of storage and lead times. It is actually specifically oriented to give the maximum of service level, under the condition to manage properly the different inventories. This is the objective of the *strategy mapping*.

***Strategy***

Defining a spare part logistics strategy is answering the following questions:[2,3]

- **Does the part have to be stocked or not?**
  Not stocking implies a just-in-time supply of the item in case of demand, whereas stocking the part implies several inventory decisions.

- **Where the part should be stocked?**
  In the case of a multi-echelon network, items can be stored at one or several places. It is part of the strategy to decide whether to centralize or the stocks or not.

[1] Jouni et al. (2011)
[2] Botter and Fortuin, 2000
[3] Bošnjaković, 2010

- **How the part should be stocked?**

  The technical management of the strategy concern the inventory decisions: stock levels, safety stocks, type of control, order replenishment.

  All these techniques are presented in section 2.5.

***Mapping***

As previously mentioned in the section, strategy mapping consists in combining several classification criteria and to assign a logistics policy for each cluster. According to the chosen criteria (which depends on the available data and on the specificities of the industry) a decision guideline for logistics strategies is arbitrary built. Assigning a policy to a group of part is then subjective at first sight but is the result of a rational analysis.

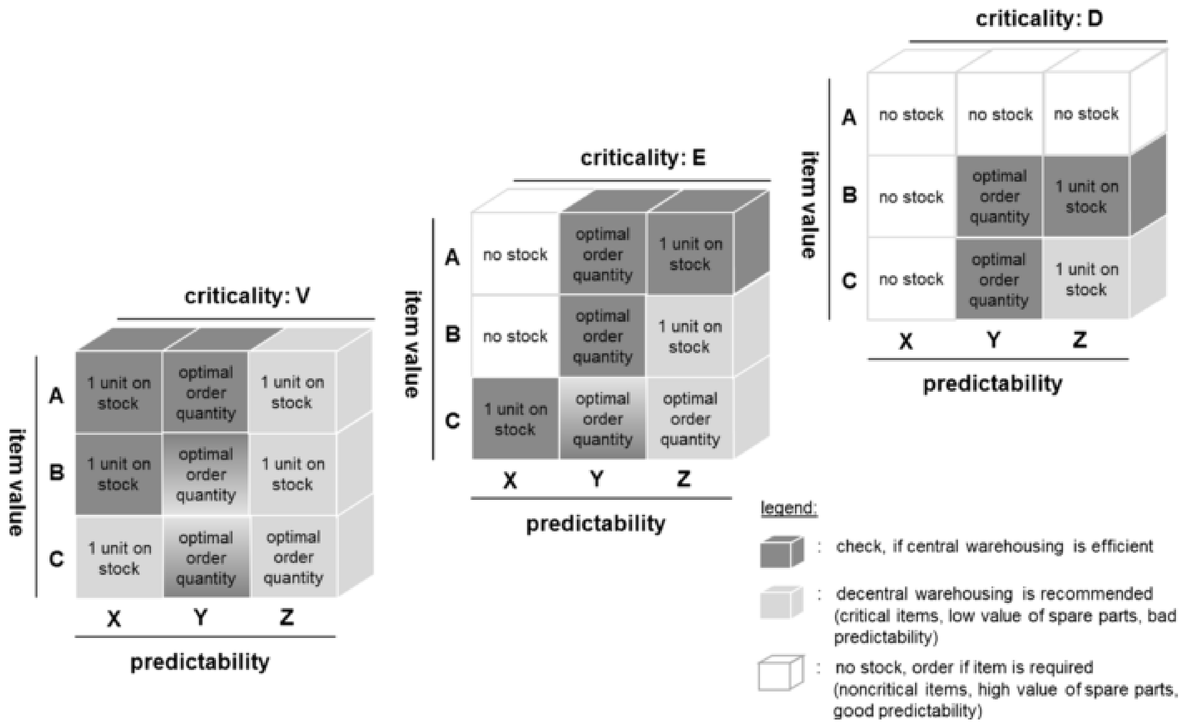



Figure 13: ABC-XYZ-VED strategy mapping[1]

One of the first strategy mapping method entails the combination of the value-usage criterion with the frequency criterion (ABC-FSN), which was proved to be an efficient

[1] Stoll, Kopf, Schneider and Lanza, 2015, p. 229

first approach towards efficient spare parts inventory management.[1] In the case of spare items, the prediction of the demand being rather uncertain, the criteria of demand predictability may seem also essential to develop specific strategies. Then, an ABC-XYZ mapping is also very relevant.[2] Even more specifically dedicated to spare parts management, the criticality parameter is unmissable when its assessment is possible. It is for instance combined with the frequency criterion in a two-dimensional VED-FSN strategy concept.[3]

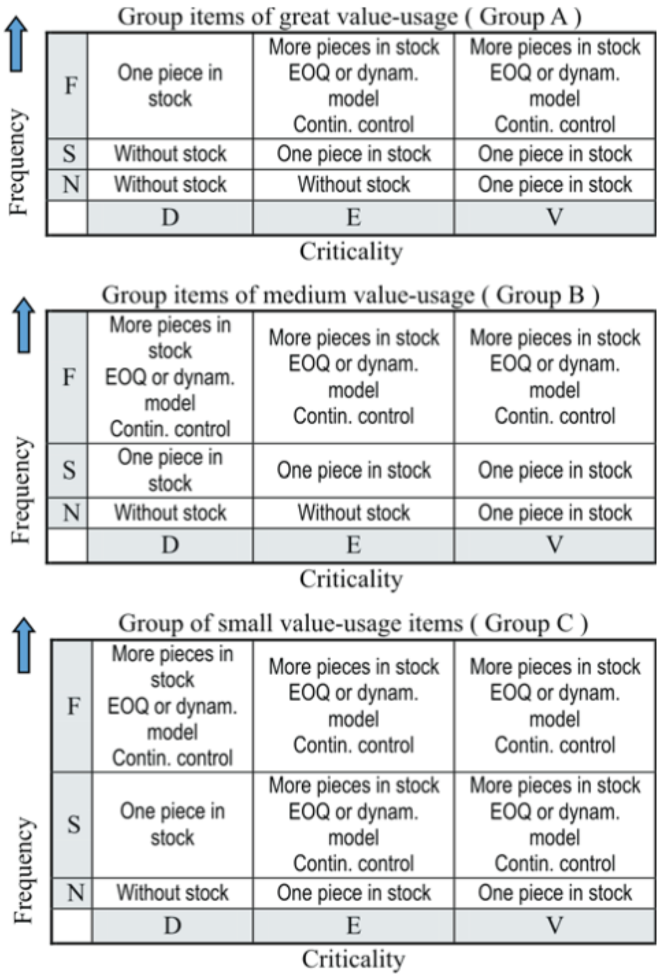



**Figure 14: ABC-FSN-VED strategy mapping[4]**

However, the diversity of spare parts on technical, economical or consumptions aspects tends to show the limits of a two-dimensional mapping.[5] Considering the

[1] Gelders and Van Looy, 1978
[2] Biedermann, 2008
[3] Botter and Fortuin, 2000
[4] Bošnjaković, 2010, p. 503
[5] Stoll, Kopf, Schneider and Lanza, 2015

value-usage (ABC) and the criticality (VDE) as main criteria for spare parts classification, both Bošnjaković (2010) and Stoll et al. (2015) propose a three-dimensional clustering method to strategy mapping. Both also use a demand characteristic as third criterion, the frequency for the first one, and the predictability for the second one. The assignation of logistics strategies for the different groups are visible on Figure 13 and Figure 14.

The two methods take into account only three criteria which may appear restrictive when dealing with large and diverse inventories. It is though unrealistic to consider more than three criteria to build a strategy map: three parameters having each three possible classes imply directly 27 groups of parts; four parameters induce 81 groups! The load of work to decide for each of them the optimal strategy is already substantial. Nonetheless, some authors present techniques to combine more than three criteria in their strategy mapping. The main idea is to reduce the number of final groups either by merging some of them, or by simplifying directly the strategies of some parts. For instance, one can decide that non-moving items should not be stocked. All the strategies related to non-moving items are in that case not considered, and the number of groups is reduced. An example of such a reasoning is presented below.

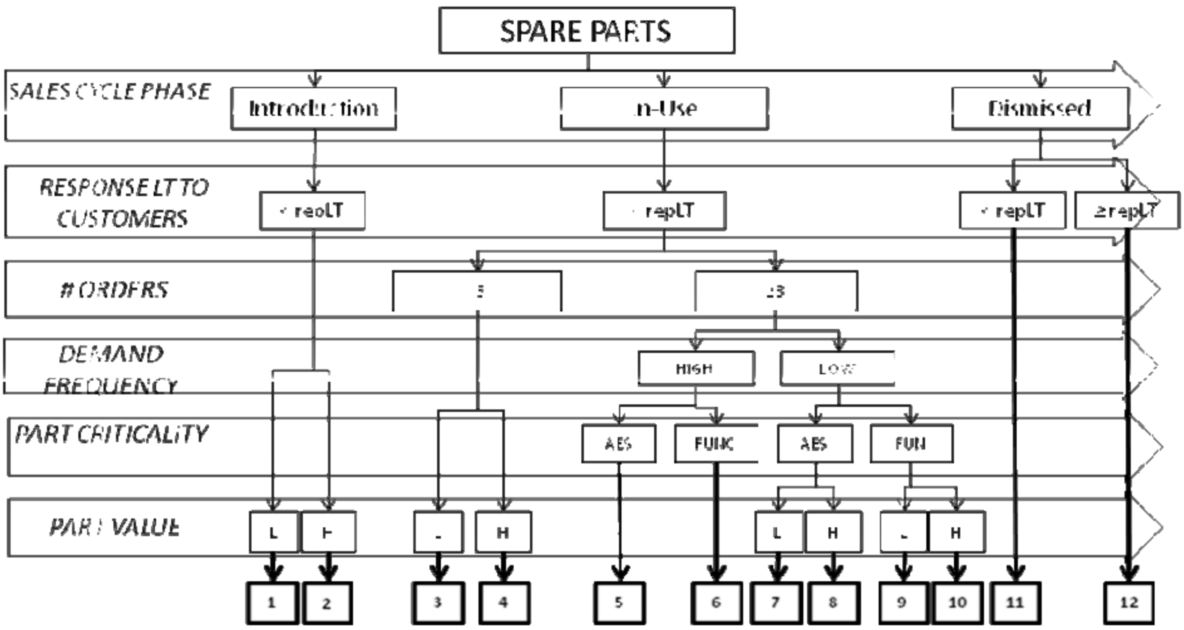



Figure 15: Proposed strategy mapping model[1]

[1] Bacchetti, Plebani, Saccani and Syntetos, 2010, p. 19

The authors developed a strategy mapping from 6 criteria, but only 12 different logistics strategies are identified. This is actually the result of simplifications in the parameters analysis and in the assignment of strategies. The benefits of such a mapping are plentiful:

- the classification is more refined and more accurate as it allows more criteria
- the decrease of the number of groups makes the mapping clearer to the managers
- it is also easier to apply such an approach in the practice due to the restricted number of strategies to define
- the construction of the model require more thought but has the benefit to provide a deep analysis of the inventory: prioritizing the criteria and building a smart decision procedure will contribute to the success of its application.

## 2.4 Spare Parts Demand Forecasting

The second step towards efficient spare parts inventory management is to develop relevant demand forecasts.[1] After classifying the items into groups that will follow the same logistics strategies, it is essential to have the most reliable forecasts to ensure that the operative directives are efficient: storing too few or too many quantities have immediate consequences on the revenues of an organisation. Though, the intermittency and the unpredictability of the demand for spare parts make the forecasts for spare parts completely different as for finished goods.[2]

This section underlines the specificities of the demand for spare parts in a first time. The different techniques for forecasting are presented afterwards.

[1] Bacchetti and Saccani, 2012
[2] Morris, 2013

### 2.4.1 Characterization of the Demand

The need for a spare item is very uncertain as it is the result of a maintenance activity. Depending the maintenance policy, the request for a spare parts is more or less predictable: a corrective policy in case of failure is unforeseen, whereas a predictive maintenance allows visibility on the needs.[1,2] The corrective policy is still the most in use in practice, due to the tremendous investments that requires a predictive maintenance. The result is that from the spare part provider point of view, the total demand on spare parts is very irregular: the demand on certain items is inevitably characterized by a high number of zeros.[3] However, some items like the fast-moving parts have a more regular demand which reflects a continuous need which is therefore not characterized in the same manner.

In order to characterize quantitatively the variability of the demand, a methodology has been developed.[4] Two values have to be calculated (considering that the demand over time for a spare part is given by the series $x$).

- **The squared coefficient of variation**

$$CV^2 = \left(\frac{Standard\ Deviation}{Mean}\right)^2 = \left(\frac{\sigma}{\bar{x}}\right)^2 = \left(\frac{\sqrt{\frac{\sum_{i=1}^{N}(x_i - \bar{x})^2}{N}}}{\bar{x}}\right)^2$$

**Equation 3: Squared coefficient of variation**

This coefficient (also known as squared relative standard deviation) is a standardized measure of dispersion of a statistical series. It gives a measure on *the quantity variability* of the demand.

Later on in this work, the squared coefficient of variation is referred to as *coefficient of variation*. Although it is a notation imprecision, it does not hinder the mathematical meaning of the concept.

[1] Biedermann, 2008
[2] Barkai, 2014
[3] Ghobbar and Friend, 2003
[4] Syntetos, Boylan and Croston, 2005

- **The average demand interval**

$$ADI = \frac{\sum_{i=1}^{N} t_i}{N}$$

Equation 4: Average demand interval

This attribute gives the mean interval between to non-zero demand periods. It measures the *variability over time* of the demand.

It is then possible to have a precise characterization of the demand, thanks to the ADI that gives a measurement of the intermittency, which is relevant for spare parts analysis. The Study of numerous case study led to identification of four different patterns of demand.[1] For both measurements, a cut-off value has been determined after accurate analysis and are now adopted by the academic community. They provide a classification for the parameters.

| Measurement | Cut-off value |
|---|---|
| Coefficient of variation | 0.49 |
| Average demand interval | 1.32 |

Table 9: Cut-off values for demand variability[1]

The figure hereinafter illustrates the four patterns for demand variability.

[1] Syntetos, Boylan and Croston, 2005

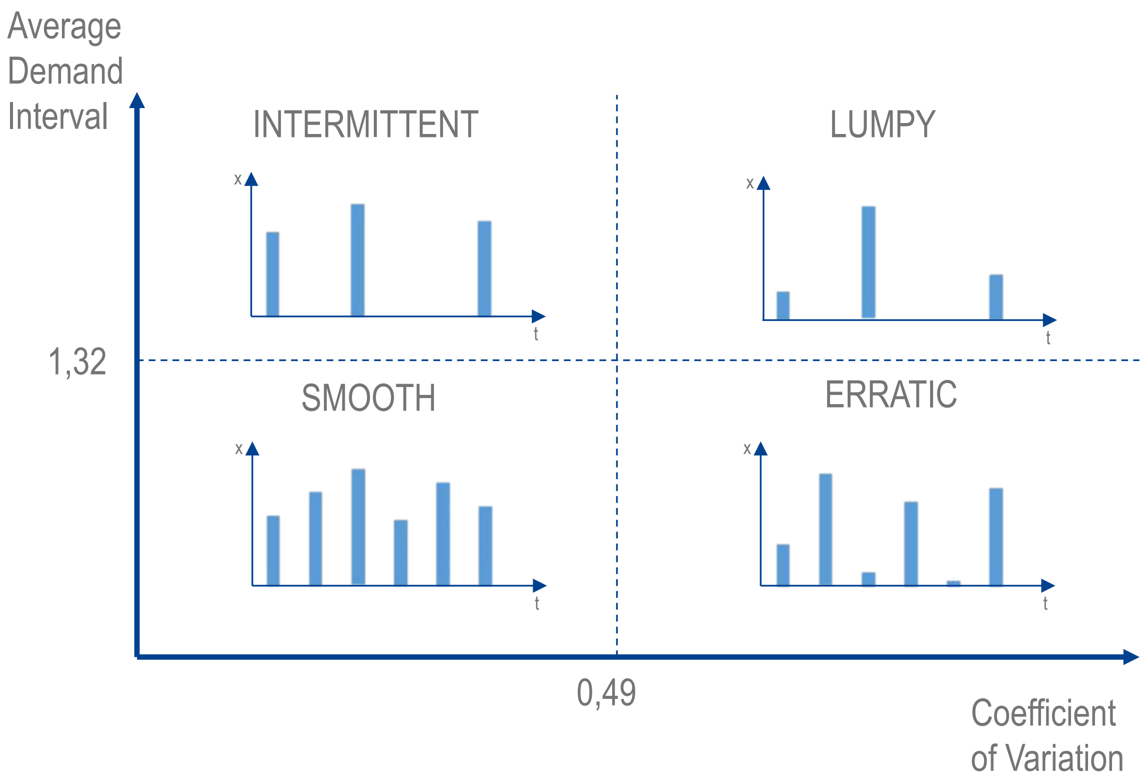



**Figure 16: Demand variability patterns (own illustration)**

Many different designation to qualify the demand variability appears in the literature. It is essential to agree on the vocabulary that will be used in the remainder of the paper.

- A demand is qualified as *smooth* when both variability parameters are below the cut-off values: the demand is happening regularly and has small variations concerning the quantities ordered.
- When a demand is *erratic*, significant variations on quantities are observable whereas the item is asked regularly.
- On the contrary, the variability on quantities is low with an *intermittent* demand but the ADI is high.
- The *lumpy* demand is characterized by extreme values of the parameters: the CV and the ADI are above cut-off values. The demand is therefore very variable on both quantities and frequency.

The recognition of variability patterns brings an additional classification for spare parts. Although it seems simplistic at first sight, it is a very relevant aspect towards efficient inventory management as it sets the base for demand forecasting.

### 2.4.2 Data Availability and Methods

Demand forecasting consists in predicting the future demand on products. The concept gathers techniques that allow to anticipate the sales via an estimation. In the specific case of spare parts inventory management, the notion of forecasting takes on its full meaning because of the high uncertainty of the needs. It has been mentioned previously that the reasons to ask for a spare parts are plentiful.

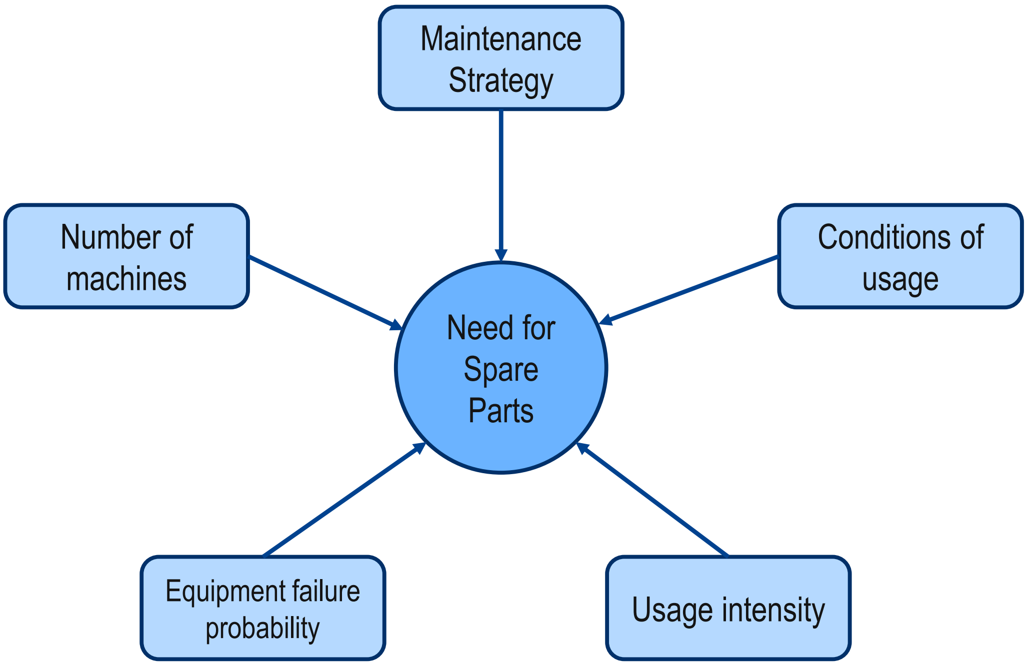



**Figure 17: Components of the spare parts demand**[1]

The figure above displays the different factors that influence the demand for spare items in an industrial context. All these factors generate different types of data, which have not the same level of acquisition investments. It is for instance more laborious to determine the mechanical behaviour of a material over time than to count how many hours it has been in use. Three sources of data are identifiable:[2,3]

- **Life-Cycle data** directly concern the properties of the products: failure behaviour, mechanical resistance, value, costs, etc.

[1] Adapted and translated from Pawellek, 2013, p. 224
[2] Biedermann, 2008
[3] Pawellek, 2013

- **Installed base data** gather the utilisation data: number of machines in use, number of operating hours, past maintenance activities…
- **Historic sales data** come from the past orders on spare parts: quantities, customers, prices, selling organisation…

The availability and the quality of every data varies according to its type and to its acquisition method. It is for example very demanding to collect data on installed base if not from the very beginning of their operating period. Consequently, the method to forecast the demand is depending on the available data. The forecasting methods are gathered in three groups (see Figure 18):

- *Deterministic forecasting methods* rely on the causes of a failure. It means they are used in the case of a predictive maintenance. Data from the product life-cycle (like the mean time before failure, or the failure behaviour) are necessary to lead such forecast. Also, the date collect on installed base are requested as they give an overview on the general demands. They are known in the practice as *reliability based forecasting* methods.

- *Stochastic forecasting methods* give a prediction based on statistics mathematical models. They are more easily applicable and request less data. Those are mainly historic data coming from the past sales, and the methods are therefore referred to as *time series* based forecasts.

- *Subjective forecasting methods* are qualitative methods to estimate a forecast thanks through intuition, thanks to experience or simple reasoning. This type of forecast is not used in practice and will not be discussed in this work.

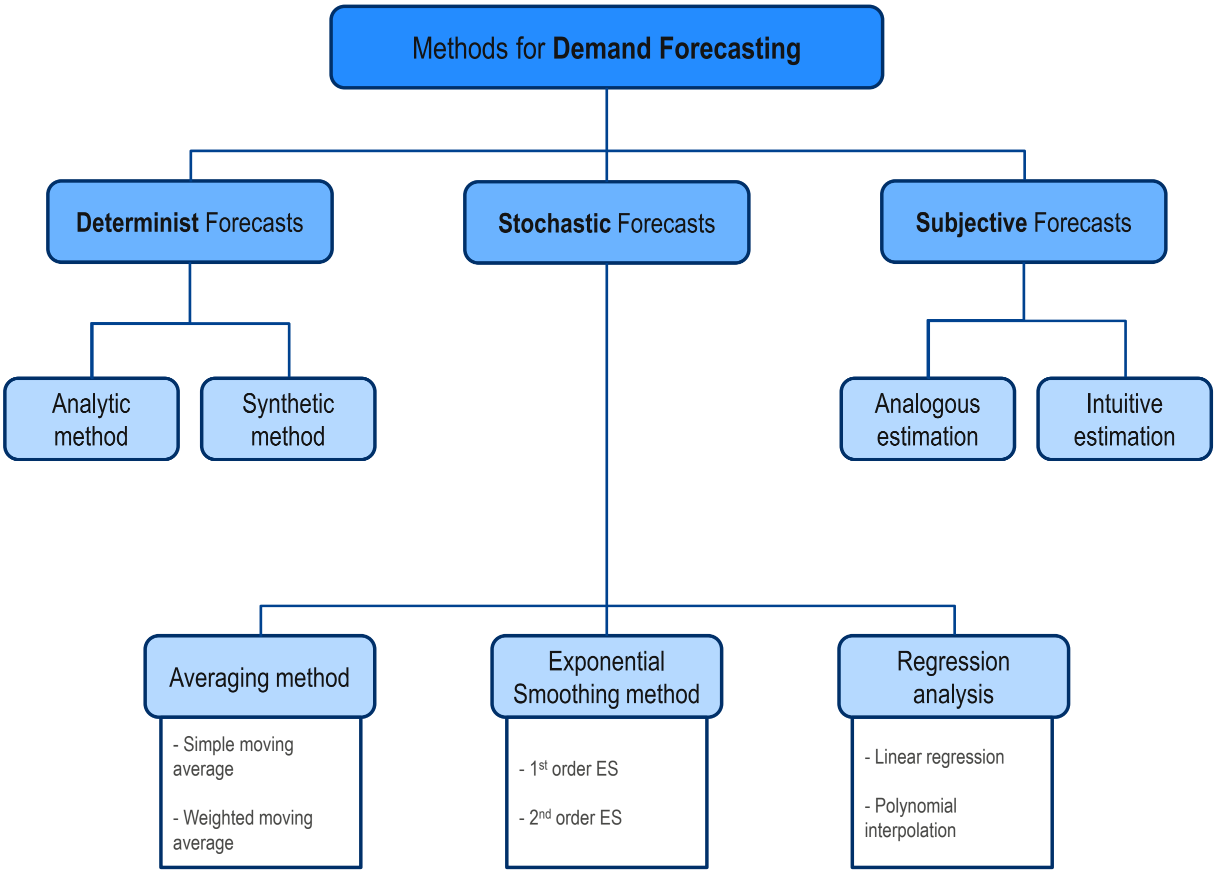



**Figure 18: Forecasting methods**[1]

Shortly, it exists forecasting methods to determine planned demand (deterministic methods) and others to determine unplanned demand (stochastic methods). Both can be combined to optimize the accuracy of the predictions.[2]

### 2.4.3 Reliability Based Forecasting

Deterministic forecasting methods firstly rely on life-cycle data of the considered part. The aim of such methods is to predict when to plan a maintenance activity considering its physical properties, and the time it has been in use. “Reliability is defined to be the probability that a component or system will perform a requested function for a given

[1] Adapted and translated from Biedermann, 2008, p. 35
[2] Driessen, Arts, Van Houtum, Rustenburg and Huisman, 2010

period of time when used under stated operating conditions."[1] In other words, it is the ability for a component not to fail over time. Assessing the reliability of a part involves systematically the development of mathematical models. Several techniques, offering several perspectives, are identified to compute reliability estimations;[2] the basis of these techniques are here briefly presented.

The *reliability function* of a component defines its probability to function properly over time, whereas the *cumulative distribution function* defines the probability that a failure occurs before time t. Then, the *probability density function* describes the shape of the failure distribution. The mathematical definition as well as an example of their representation are given below.

$$R(t) = Pr\{T \geq t\}$$
$$where\ T\ is\ the\ time\ to\ failure$$

Equation 5: Reliability function

$$F(t) = 1 - R(t) = Pr\{T < t\}$$

Equation 6: Cumulative distribution function

$$f(t) = \frac{dF(t)}{dt} = -\frac{dR(t)}{dt}$$

Equation 7: Probability density function

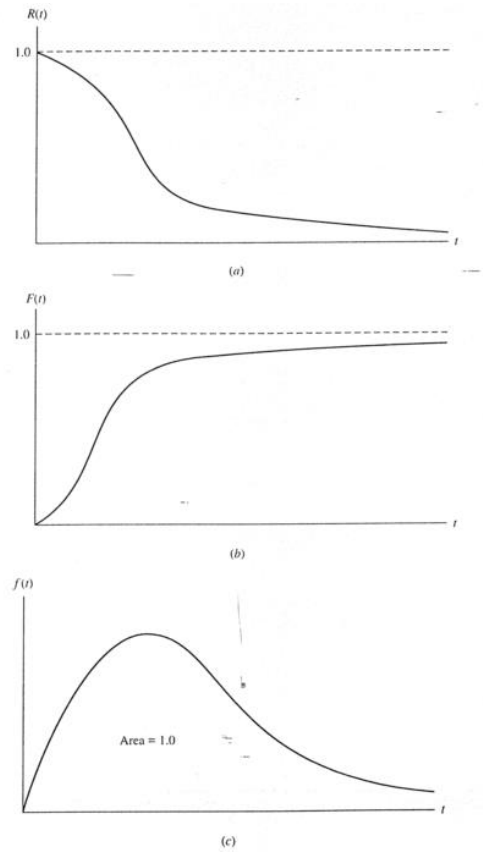


Figure 19: Reliability functions[3]

Logically, it appears that the reliability function and the cumulative distribution function are respectively decreasing and increasing over time: an item has more chance to fail as it gets older. Also, the probability density function provides a good visualisation of

[1] Ebeling, 1997, p. 5
[2] Ebeling, 1997
[3] Ebeling, 1997, p. 25

the probability of failure of a part; in that case the probability is maximum in an early stage of the life-cycle.

Besides, a "summary" measure of reliability stems from the probability distribution function. It is known as the *mean time to failure* (MTTF), and is defined by:

$$MTTF = E(T) = \int_0^\infty tf(t)dt$$

**Equation 8: Mean time to failure**

In addition to the probability functions, the reliability of an item can be assessed by the *failure rate* or *hazard rate function*, which provides an instantaneous (at time t) rate of failure.

$$\lambda(t) = \frac{f(t)}{R(t)}$$

**Equation 9: Failure rate function**

The failure behaviour of a component will be depicted as increasing, decreasing or constant, according to the behaviour of its associated failure rate function. Typical failure rate functions follow classic distributions such as the exponential, the gamma, the Weibull or the normal distribution. A specific case of failure rate function is often used in industrial contexts to describe the probability of failure of mechanical parts over time: the *bathtub curve*. The function is more complex as it is the combination of several basic functions (see Figure 20).

The curve is segmented into three phases:

- The "burn-in" phase corresponds to the beginnings of the component into its usage life. The decreasing profile highlights the early failures that can happen at the beginning of the life-cycle mostly due to manufacturing defects (welding flaws, cracks, poor quality control, etc.
- The "useful life" stage is characterized by a low and constant failure rate. The failures are due to random causes from the environment or the user. It is in principle the longest stage of the service lifetime.

- During the “wear-out” phase, the failure rate of the component increases significantly and reflects the wear of the material: aging, fatigue, corrosion…

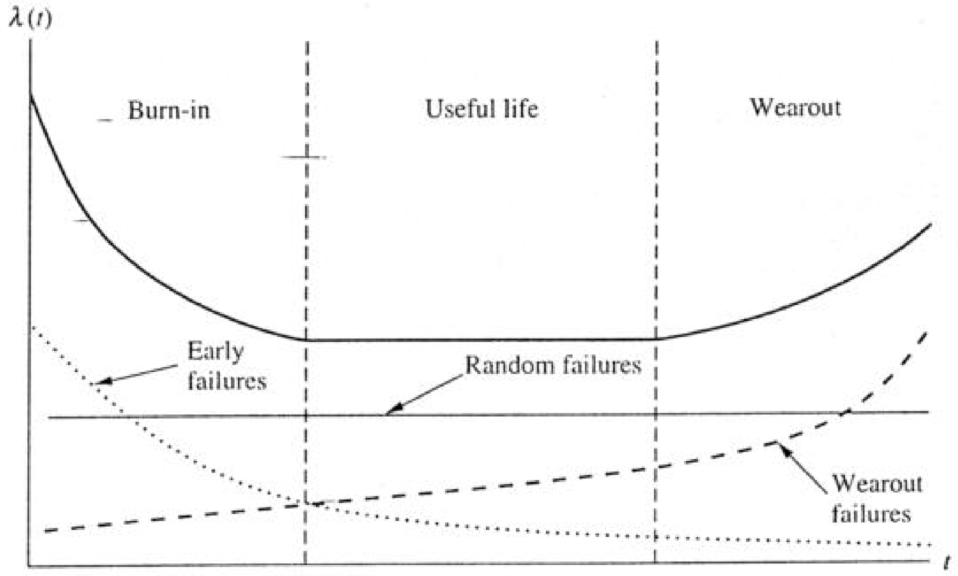



Figure 20: The Bathtub Curve[1]

The data produced by such curves are incentives to plan in advance maintenance activities, as they provide great knowledge on the remaining operational life of the equipment. Forecasting the global demand on spare parts is thus possible, under the condition to be in possession of the data related to the installed base:[2] acquiring and formatting these data is a tremendous effort which demands huge investments.

Additionally, reliability based forecasting is not an exact science and necessarily implies potential improvements. In order to refine the estimation of failure rates, and so to reduce the maintenance costs, more sophisticated methods including the development of efficient on-site data acquisition systems would bring up reliability based forecasting to a next level.[3]

[1] Ebeling, 1997, p. 31
[2] Driessen, Arts, Van Houtum, Rustenburg and Huisman, 2010
[3] Heng, Zhang, Tan and Mathew, 2009

### 2.4.4 Time Series Based Forecasting

Stochastic methods are more traditionally used to forecast spare parts demand, because of the facility to implement such techniques. Time series based forecasts only require historic sales data, which are in practice easily available. Typical techniques to forecast the demand are the exponential smoothing, the moving averages or the regression analysis. These methods have proven to be accurate for regular demand, but have shown limits when it comes to intermittent demand. The objective of this section is to present a quick review of the existing forecasting methods for time series, and especially the ones dedicated to intermittent demand.

***Traditional forecasting methods***

The most trivial method to forecast a demand is the **naïve method**: the estimated demand for the next period of time is the last actual demand. It is obvious that this kind of forecast is totally inappropriate for irregular demands, as it leads to huge errors when the demand varies quickly between two periods. The naïve forecast is however very useful to assess the performance of the different methods between each other (see the next section). The calculation of the naïve forecast is given by the following formula:

$$F_{t+1} = X_t$$

Equation 10: Naive forecast

Where:

$X_t$ is the actual value of the demand at the instant t;

$F_t$ is the forecast of the demand for the instant t;

The **moving average** forecast consists in averaging a certain amount of data points, which are continuously updated as the points are acquired. Several variants of the method exist, three of them are here presented. The simple moving average takes a fixed number of data points, the latter being the one of the last actual demand. The cumulative moving average takes all actual data in consideration that is to say from the first to the last actual demand. The weighted moving average and the exponential moving average are two more variations that gives more weight to the most recent data points. The moving average methods have advantages, especially to take seasonal trends into consideration. They are however not efficient regarding lumpy and intermittent demand patterns. Moving average forecasts are calculated in the following manner:

$$F_{t+1} = \frac{1}{N}\sum_{i=1}^{N} X_{t-i+1}$$

Equation 11: Simple Moving Average (N data points)

$$F_{t+1} = \frac{1}{t}\sum_{i=1}^{t} X_{i}$$

Equation 12: Cumulative Moving Average

$$F_{t+1} = \frac{2}{N(N+1)}\sum_{i=1}^{N} (N - i + 1) * X_{t-i+1}$$

Equation 13: Weighted Moving Average (N data points)

Another method to predict the future demand is the **linear trend estimation**, which, as its name implies, gives the forecast of the general trend of the time series. It is computed with the least-squares methods, which minimizes the sum of the squared errors in the data series. Also, the trend function is usually linear, and the method is in that case known as a simple linear regression:

$$F_{t+1} = at + b$$

$$Where\ (a, b)\ minimizes\ \sum_{t} [(at + b) - X_t]^2$$

Equation 14: Linear trend forecast

The three traditional forecasting methods are implemented on a realistic example that illustrates a lumpy demand (see

Figure 21). Thus, conclusions can already be drawn for the remainder of the paper.

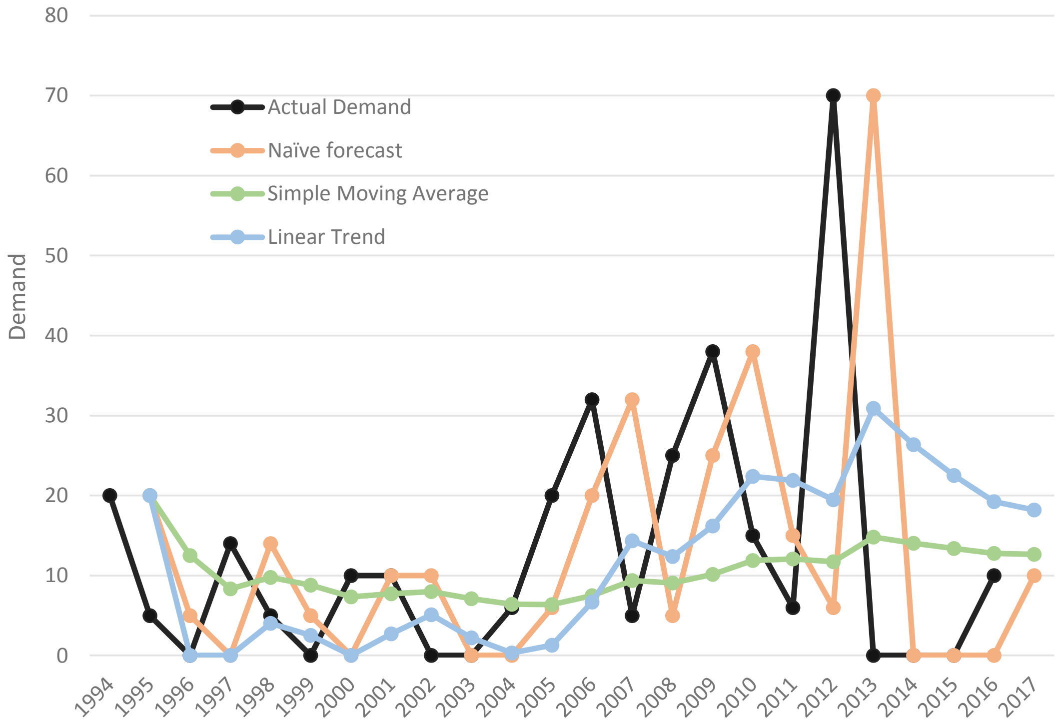



**Figure 21: Comparison of traditional forecasting methods (own illustration)**

The first observation is that the naïve forecast is very inappropriate when the demand varies excessively: the forecast is very "reactive" to variations and would directly implies wrong stocking decisions. On the opposite, the simple moving average smooths strongly every variation, and does not follow trends (for instance, from 2004 to 2013). This forecast is more suited too smooth demands with very few variations. Finally, the linear trend is an in-between method, reasonably reactive to variations, and reflecting trends. However, it tends easily towards zero, when the demand is decreasing (year 1994 to 2002). Such a behaviour may be prejudicial for stock levels decisions, namely that no units are kept in stock when the demand is only decreasing (no consideration for intermittency).

***Single Exponential Smoothing (SES)***

Exponential smoothing is in practice one of most used method to forecast intermittent demands.[1] The forecast is calculated with the last observed demand, as well as the last forecasted value. It means that it is "smoothed" over time because the value is permanently adjusted, with a weighing parameter. The formula is the following:

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

Equation 15: Single Exponential Smoothing forecast

where $\alpha$ is the smoothing parameter.

The exponential smoothing is less reactive to high variation in the demand, which explains its performance for intermittent or erratic demand. The smoothing parameter controls the reactivity to variations: it is low (meaning more weigh is given to the previous forecast) to soften the variations as much as possible, and high (meaning more weigh to the actual demand) in order to react easily to changes. The choice of the parameter is thus essential; the figure below illustrates the difference of forecast for 3 different smoothing parameters.

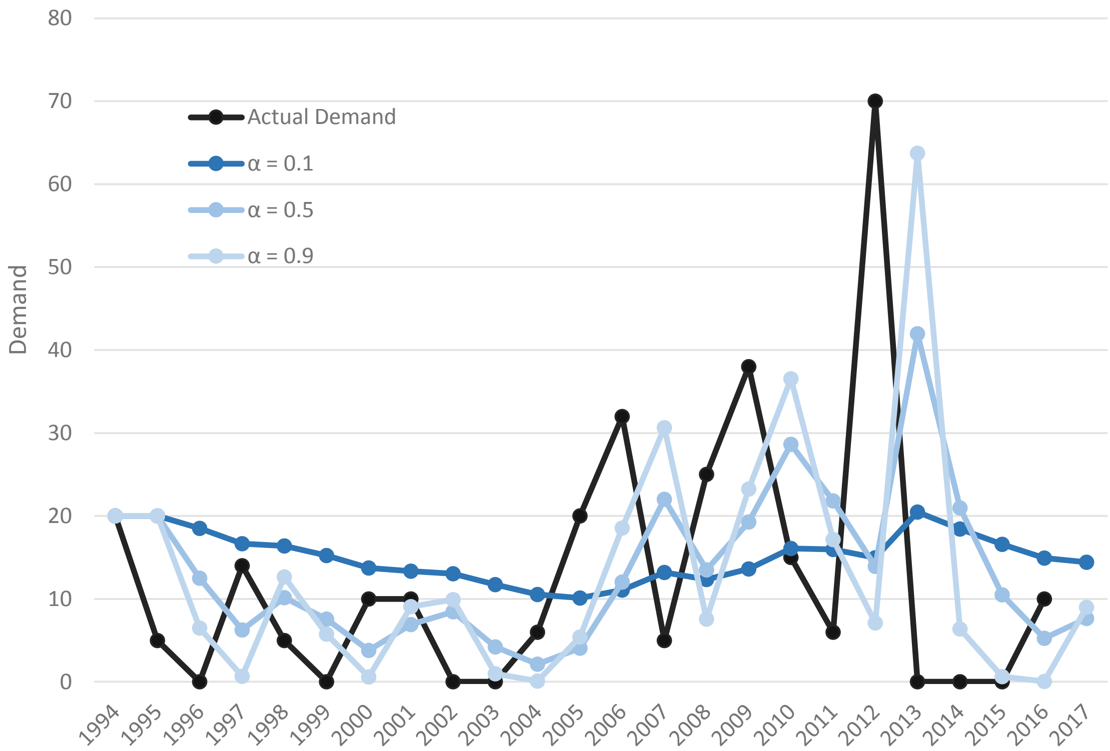



Figure 22: Smoothing parameter's influence for the SES forecast (own illustration)

[1] Syntetos and Boylan, 2004

***Croston's Method (CR)***

Croston[1] first remarked the limits of exponential smoothing methods applied to intermittent demands. His fundamental paper underlines the overstock appearing with single exponential estimations and lays the foundations of recent research on spare parts demand forecasting. He proposed a new approach, considering that both the size of the demand (i.e. the quantities) and the interval between two demands should be estimated separately, in order to provide an accurate forecast. The estimations of the two variables are achieved with a smoothing parameter. Additionally, the necessity to introduce two different values for the parameters has been highlighted.[2]

The algorithm is the following:

$$If\ X_t > 0, \begin{cases} Z_{t+1} = (1-\alpha)Z_t + \alpha X_t \\ K_{t+1} = (1-\beta)K_t + \beta I_t \end{cases}$$

$$If\ X_t = 0, \begin{cases} Z_{t+1} = Z_t \\ K_{t+1} = K_t \end{cases}$$

$$F_{t+1} = \frac{Z_{t+1}}{K_{t+1}}$$

**Equation 16: Croston's algorithm**

Where:

$X_t$ is the actual demand at the instant t,

$I_t$ is the actual interval between two non-zero demands at instant t,

$Z_t$ is the estimation of the demand size at instant t,

$K_t$ is the estimation of the interval between two non-zero demands at instant t,

$F_t$ is the forecast for instant t,

[1] Croston, 1972
[2] Schultz, 1997

$\alpha$ and $\beta$ are the two smoothing parameters.

The influence of the smoothing parameters is illustrated on the same previous example. Figure 23 and Figure 24 respectively displays the difference of the forecasts when the size and the interval smoothing parameters vary.

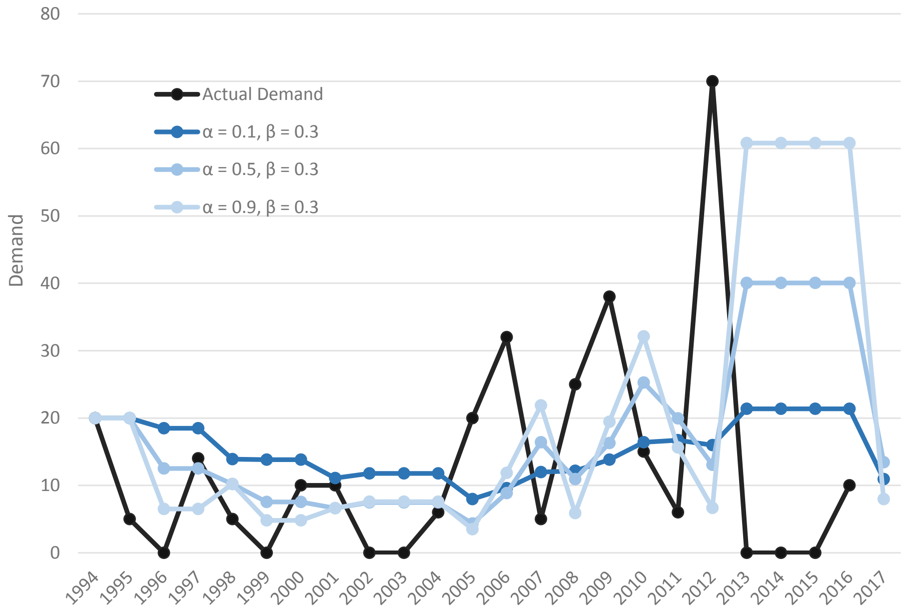



**Figure 23: Influence of the *size* smoothing parameter (α) for the CR forecast (own illustration)**

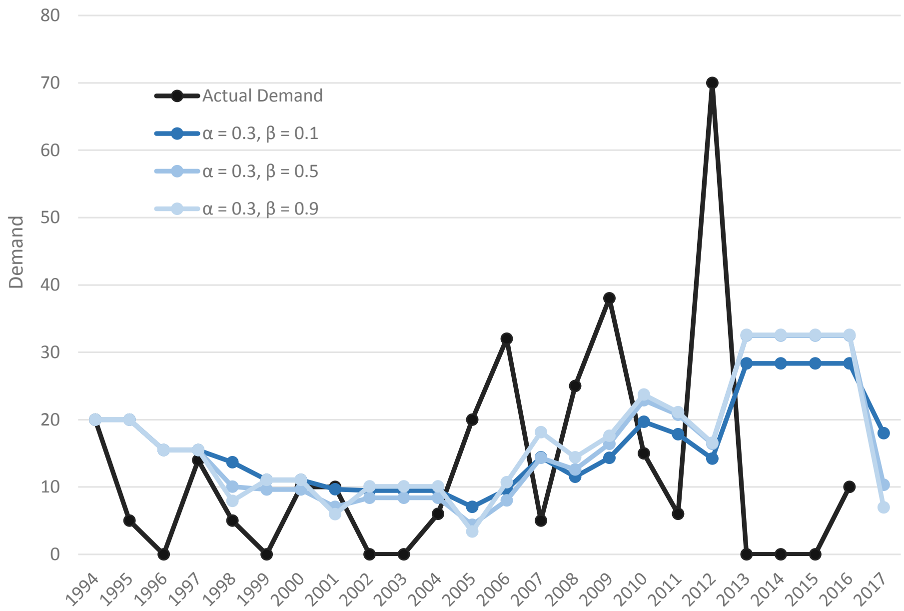


**Figure 24: Influence of the *interval* smoothing parameter (β) for the CR forecast (own illustration)**

As usual, the bigger the smoothing parameter is, the more the forecast is dynamic. The interval smoothing parameter has fewer influence on the forecast, but has still non-negligible effects. Besides, it is important to notice that the forecast remained unchanged with the previous period in case of no demand (year 2014 to 2016).

### *Syntetos-Boylan Approximation (SBA)*

Although the efficiency of Croston's method was proven on many case studies, Syntetos and Boylan revealed a bias in the forecast.[1] They also suggested a modification in the estimation of the forecast, the algorithm remaining exactly the same:[2]

$$F_{t+1} = \left(1 - \frac{\alpha}{2}\right)\frac{Z_{t+1}}{K_{t+1}}$$

**Equation 17: Syntetos-Boylan Approximation**

This new approximation gave the name to the SBA method. Also, a practical application showed that the parameters had great influence on the forecasts, and that they could be optimized to improve the result.[3] In this way, different sets of parameter are identified for each demand pattern (Smooth, Erratic, Intermittent, and Lumpy), providing an optimal forecasting method for each of them.

The figure hereinafter provides a comparison between Croston and SBA forecast with the same smoothing parameters. In light the mathematical expression of the estimations, it is logical to observe that the forecast given by the SBA is lightly smaller than CR. Besides, it appears that the latter is more reactive to high variations in the demand. This phenomenon can have harmful consequences on stock levels, and therefore illustrate a possible prevalence of the SBA over Croston's method.

[1] Syntetos and Boylan, 2001
[2] Syntetos and Boylan, 2005
[3] Syntetos, Boylan and Croston, 2005

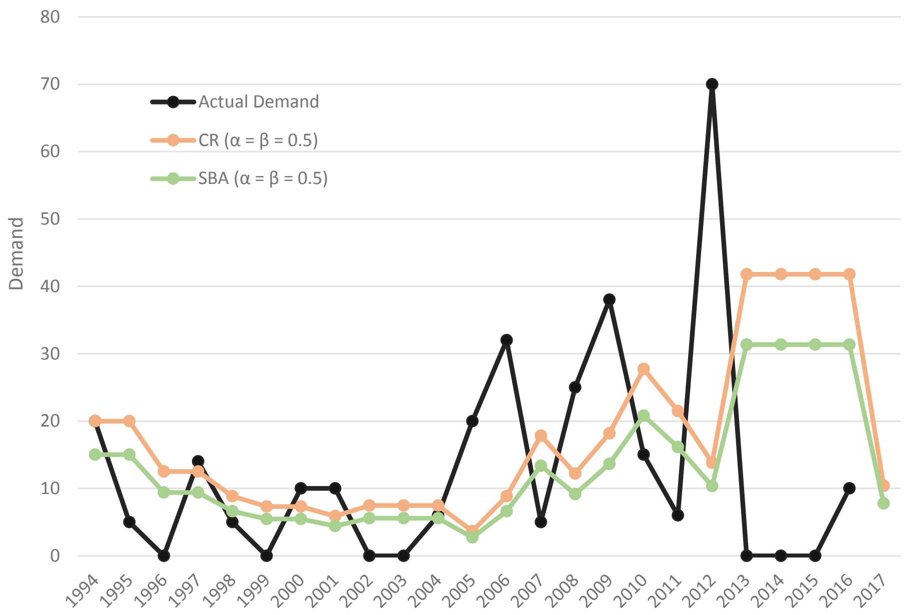



**Figure 25: Comparison of CR and SBA methods (own illustration)**

***Other Methods***

The scope of this section is not to provide an exhaustive list of forecasting methods, but rather to focus on the most relevant ones from a practical point of view. Therefore, from the amount of forecasting methods, only two other are here mentioned as they offer promising perspectives, but still need further practical applications.

A method using the *bootstrapping* technique was developed to deal specifically with intermittent and erratic demand patterns.[1] The traditional bootstrapping approach consists in taking several samples from a larger data series and to build up histogram of the distribution of inventory demands during lead time;[2] statistics are deduced from this distribution. Autocorrelation, frequent repeated values and relatively short series are considered additionally in order to apply the method to spare parts demand.[1] The method presents the advantage to be non-parametric, and applicable for small series, but requires intensive computations.

Finally, an alternative approach to spare parts forecasting uses *neural networks*. The seminal work on neural networks for spare parts forecasting was given by Gutierrez et

[1] Willemain, Smart and Schwarz, 2004
[2] Syntetos, Boylan and Croston, 2005

al.[1] Neural networks are adaptive statistical models, whose structure is analog to the human brain: the network is made of nodes (neurons) and create therefore a learning system able to estimate output data from input data. This approach seems to outperform Croston's methods and its variants in some cases, but shows limitations when the number of nonzero demand increases significantly. Neural networks forecasting are obviously not trivial to apply in practice, but definitely are representing a promising field of research.

***Conclusion on time series based forecasting***

Most comparative studies that aimed to apply spare parts forecasting to case studies have shown the superiority of Croston or SBA methods over traditional techniques.[2,3,4] These works outline however the non-consensus of the academic community on the topic. The lack of clear conclusive results have several reasons:[5]

- Studies were still not performed on relevant amount of data set
- Divergence in error metrics to compare the methods may affect the conclusions (see next section).
- Most studies do not differentiate precise demand patterns under the generic term of "intermittent demand"
- The research are usually made without a practical vision; the implementations difficulties are not considered (data availability and quality, users' skills, etc.)

The consequence is that very few companies are willing to implement forecasting methods due to the lack of practical application, and therefore stick to traditional or judgmental methods to estimate the demand on spare parts.[4]

[1] Gutierrez, Solis and Mukhopadhyay, 2008
[2] Eaves and Kingsman, 2004
[3] Gutierrez, Solis and Mukhopadhyay, 2008
[4] Teunter and Duncan, 2009
[5] Bacchetti and Saccani, 2012

### 2.4.5 Error Measurements and Methods Comparison

One essential aspect that has been mentioned in the previous section is the estimation of the accuracy of the forecasting techniques. Choosing a forecasting method is selecting the best among the other, and therefore implies a comparison. Hence, a measurement is needed to assess the accuracy of each method, in order to compare them between each other. The accuracy measurement of a forecast technique is given by a measurement of the error between the actual and forecasted values. Many different error measurements are applicable, but some are better suited when the demand is intermittent. Here is a review of the most common error measurements, mostly based on the work of Hyndman[1] who compares typical techniques and also introduces a metrics dedicated to intermittent demand (MASE).

The figure below recaps up the existing error metrics, which are clustered into four different groups.

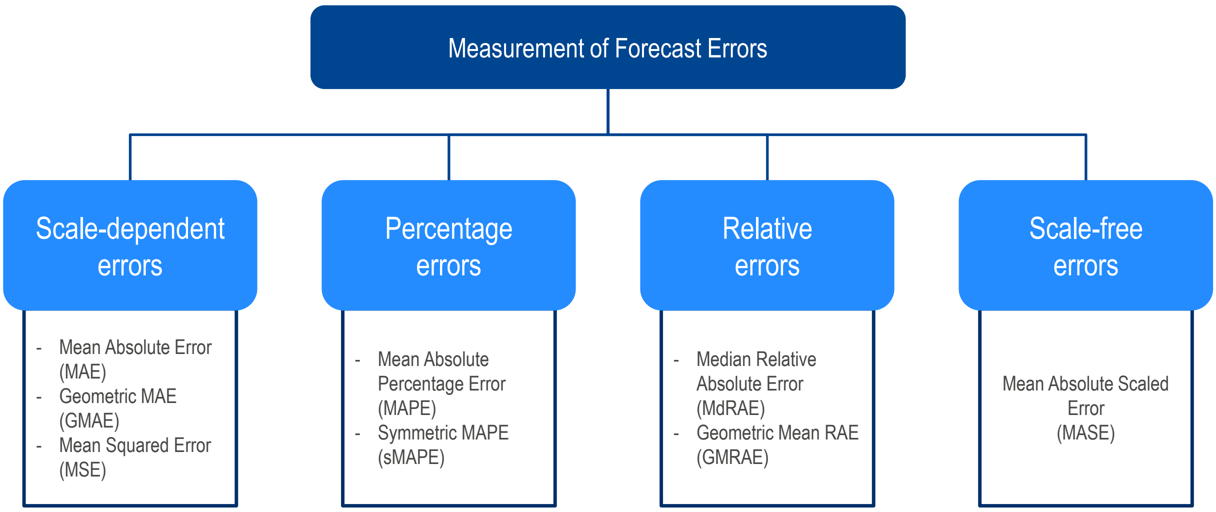



**Figure 26: Measurement of Forecast Errors (own illustration)**

For the remainder of this section, the notations are the following:

$Y_t$ is the actual demand at the instant t;

$F_t$ is the forecasted demand for the instant t;

[1] Hyndman, 2006

$e_t = Y_t - F_t$ is the forecast error at the instant t;

$p_t = 100\frac{e_t}{Y_t}$ is the percentage error at the instant t.

**Scale-dependent metrics** are the most basic forecast-error metrics, as they only rely on absolute or squared errors. These metrics are adequate to compare series that are on the same scale, are therefore not suited to assess forecast accuracy across multiscale series. The computations of the most common metrics are:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|e_i|$$

Equation 18: Mean absolute error

$$GMAE = \left(\prod_{i=1}^{n}|e_i|\right)^{1/n}$$

Equation 19: Geometric mean absolute error

$$MSE = \frac{1}{n}\sum_{i=1}^{n}{e_i}^2$$

Equation 20: Mean squared error

**Percentage metrics** allow the scale independency, and therefore the comparison across data series. The most commonly used metrics is the Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}|p_i|$$

Equation 21: Mean absolute percentage error

The big disadvantage of percentage metrics is that they introduce a division, which leads to infinite values for zero data-points in the demand series. Yet, it is impossible to use such a metrics for spare parts forecasting as the demand often has zero values.

Alternatively, **relative metrics** propose the also a scale-independent measurement of the error. It consists in dividing each error by the error obtain with a “benchmark” forecasting method. The usual benchmark method is the naïve forecast. The error metrics is then computed with a statistics operator like the median or the geometric mean (respectively MdRAE and GMRAE metrics). However, these methods are sometimes not relevant for intermittent series with small error as it implies to divide by zero.

Finally, it is suggested that a **scale-free metrics** is the most suited accuracy measurements because it does not imply calculation impossibilities.[1] The Mean Absolute Scaled Error is the ideal metrics. The MAE of the naïve forecast is used to scale the error, and cannot be equal to zero (except when all the data-points have the same value). The formula is thus the following:

$$MASE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{e_t}{MAE_{naïve}}\right|$$

**Equation 22: Mean absolute scaled error**

With

$$MAE_{naïve} = \frac{1}{n-1}\sum_{i=2}^{n}|Y_i - Y_{i-1}|$$

**Equation 23: Mean absolute error for naïve forecast**

Therefore, the MASE of the naïve forecast is always 1; a better forecast has a MASE below 1; a worse forecast is above 1.

The MASE is scale-independent and cannot take an infinite value. It is hence very relevant to compare forecasts accuracy across several data series and is to this date the most privileged forecast error measurement to deal with intermittent demand.[2] Though, this is this a very active field of research and further developments are to be

[1] Hyndman, 2006
[2] Boylan and Syntetos, 2007

expected. The Mean Arctangent Absolute Percentage Error (MAAPE) has for instance recently been suggested to improve the MAPE.[1]

Furthermore, it is important to keep in mind that error measurements are needed to *compare* forecasting methods. One approach is to find, for different patterns, the best method, implying that the sets of data are segmented. The large amount of data to achieve such analysis tends to erase the divergence between the error measurements. In this way, it is essential to use an appropriate but practical also technique.

| | **Scale-dependent errors** | **Percentage errors** | **Relative errors** | **Scale free errors** |
|---|---|---|---|---|
| **Example** | MAE,MSE | MAPE | MdRAE | **MASE** |
| **Scale dependence** | Yes | No | No | **No** |
| **Infinite Value** | No | Yes | Yes | **No** |

Table 10: Errors metrics comparison

## 2.5 Spare Parts Inventory Control

The notion of inventory management gathers all the operative directives that allow the monitoring of stocks. Concretely, the decisions must answer the following questions:

- How many units to keep in stock?
- How to review the stock?
- When to release a new order?
- How many pieces to order at once?

Answering these questions partly depends on the results given by the forecast of the **demand**. Besides, economic aspects are taken into account, as inventory management aims also to minimize the costs for the company. The challenge is then to find the right balance between costs minimization, and performance. This last step

[1] Kim and Kim, 2016

is determining for complete spare parts management process because it elaborates the final decisions of the reasoning. Neglecting this phase wrecks all the interest of the previous reasoning.

### *Stock-monitoring policies*

The first decision consists in choosing the stock control method. A monitoring policy is determined by two parameters:[1,2] one specifies the reorder point (namely the condition that generates the release of a new order) and the other gives a reference point for the quantity to be ordered. The most classic models are the following:

- **(Q, r) policy**: the review is continuous with a fixed reorder point (r), and a fixed order quantity. Namely, a new order is released when the stock falls under the given level r, and its volume is always Q. It is known as *the fixed order quantity* model.
- **(s, S) policy**: the review is also continuous with a fixed reorder point (s), but the order quantity varies for each order. The stock is refilled up to a target level (S). It is referred to as the *order-up- to level* model.
- **(S-1, S) policy**: this control is a variant of the (s, S), with the specificity that the reorder point is only one unit below the order-up-to level. The replenishment is thus one-for-one.
- **(T, R) policy**: the control is periodic (fixed interval T), and the quantity depends on the stock level (order-up-to level R).

More complex stocking policies additionally exist, but do not enter in the scope of this work, and are therefore not presented. The (Q, r) and the (s, S) policies are the most common in practice, and will be the only considered for the remainder of the thesis. It is assumed in this way that the inventory is under *continuous* review. The figure hereinafter displays the two policies, and also introduces the notion of safety stock.

[1] Cavalieri, Garetti, Macchi and Pinto, 2008
[2] Biedermann, 2008

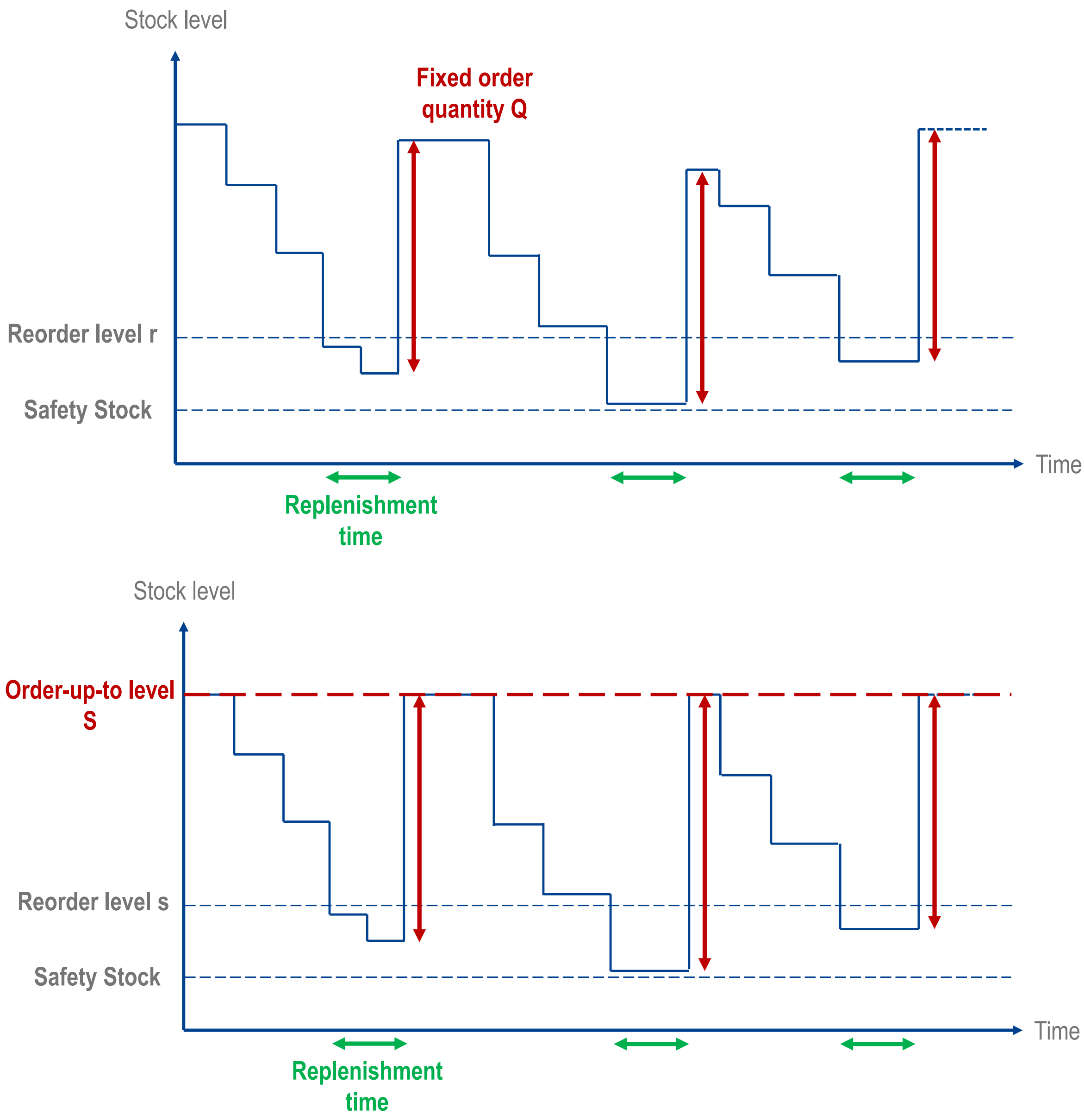



Figure 27: (Q, r) and (s, S) stock control (own illustration)

The decision between the two models is driven by the characteristics of the demands on one side, and the relative costs on the other side. If the demand is predictable, with small variations, and high frequency, the fixed order quantity model is better suited. The control on stocks is easy to handle (regular demand implies regular order), and brings costs advantages. Through the optimization of the order quantity (Economic Order Quantity, EOQ) the holding and ordering costs are minimized.

On the opposite the order-up-to level model presents the advantage to be more responsive to variations and thus more appropriate for intermittent demands.[1] Indeed, the target level ensures a full replenishment in case of high demand, and thus prevents from immediate stock out (in case of a peak in the demand).

It appears that choosing a logistics policy is not insignificant because it directly impacts the costs for the organization and the service level for the customer. An inappropriate policy can either conducts to stock outs or overstocks. However, the quantitative decisions related to these policies are equally, if not more, important.

***Stock-monitoring techniques***

The common parameter to any stocking policy is the determination of the **safety stock**. The latter is actually the basis of inventory control, and triggers all the next operative decisions. A safety stock is a buffer to prevent stock outs due to mismatch between forecasted and actual demand, and/or between expected and actual delivery time.[2] Determining a safety stock appears to be a complex task, that is why it is in practice mostly based on guts feelings or experience.[3] It is however argued that a mathematical approach has direct benefits on customer satisfaction, and costs.

Indeed, the service level directly influences the calculation of a safety stock. As a reminder, the service level is a precise measurement of the availability of a product. Aiming a service level of 90% means to ensure that the part will not be out of stock in more than 10% of the stock cycles (period of time between two replenishments). The higher the service level is, the higher the holing costs are. The service level is mathematically transposed into statistical figure, the Z-score (or standard score).[4] The Z-score increases disproportionally as the desired service level rises (see figure hereinafter).

[1] Cavalieri, Garetti, Macchi and Pinto, 2008
[2] Cf. http://www.businessdictionary.com/definition/safety-stock.html (read on 12/09/2017)
[3] King, 2011
[4] A z-score is the number of standard deviations from the mean a data point is. More technically it's a measure of how many standard deviations below or above the population mean a raw score is. A z-score is also known as a standard score and it can be placed on a normal distribution curve. Retrieved from http://www.statisticshowto.com/probability-and-statistics/z-score

| Desired cycle service level | Z-score |
|---|---|
| 84 | 1 |
| 85 | 1.04 |
| 90 | 1.28 |
| 95 | 1.65 |
| 97 | 1.88 |
| 98 | 2.05 |
| 99 | 2.33 |
| 99.9 | 3.09 |

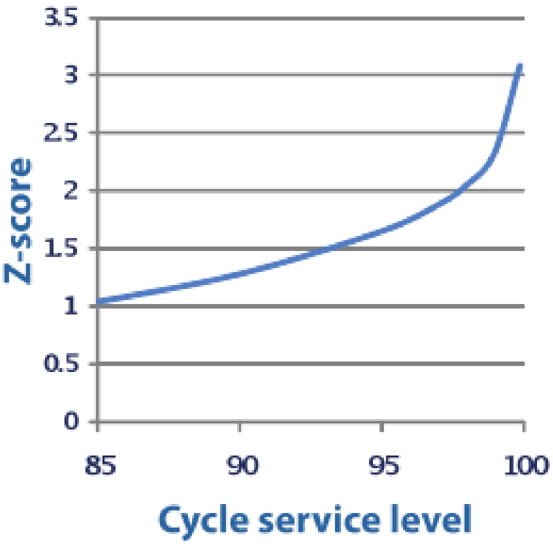



Figure 28: Relationship between desired service level and Z-score[1]

Basically, the Z-score is a multiplicative factor that generates extra inventory (in the safety stock calculation), in order to ensure the required service level. It is important to notice that the Z-score is not fixed because it depends on the targeted service level. The latter can evolve over time, according to the classification of the item.

- If the *variability in demand* is the primary concern, the safety stock is calculated as follows:

$$Safety\ stock = Z\sqrt{\frac{PC}{T_1}}\sigma_D$$

Equation 24: Safety stock with demand variability

Where Z is the Z-score; PC is the performance cycle (i.e. total lead time); $T_1$ is the time increment used to calculate $\sigma_D$ (standard deviation of demand).

- If the *variability on lead time* is the primary concern:

$$Safety\ stock = Z * \sigma_{LT} * D_{avg}$$

Equation 25: Safety stock with lead time variability

Where $\sigma_{LT}$ is the standard deviation of lead time, and $D_{avg}$ is the average demand.

[1] King, 2011, p. 34

- If both variabilities come into play:

$$Safety\ Stock = Z * \sqrt{\left(\frac{PC}{T_1}\ \sigma_D^2\right) + \left(\sigma_{LT} D_{avg}\right)}$$

**Equation 26: Safety stock with demand and lead time variability**

The investments to achieve such calculations are high because of the required data to execute them. Actually, the collection of lead time historical data is unusual, but makes sense in some contexts. Within the scope of spare parts management, it seems that the second formula is appropriate because it deals with the variability of demand.

Once the safety stock is determined, the **reorder point** (ROP) has to be computed. It represents the amount of units that must be in stock in order to stay above the safety stock during the time of replenishment. In other words, it is the addition of the safety stock with the potential consumption during replenishment time:

$$ROP = Safety\ Stock +\ Demand\ during\ lead\ time$$

$$= Safety\ Stock +\ Demand\ rate *\ lead\ time$$

The demand rate is a pace of demand, and is usually the average demand per day.

Finally, the last decision to determine is the **order quantity**. Less emphasis is given on this last decision but some hints are presented briefly.

In the case of a fixed order quantity policy, the most common method is to use the Economic Order Quantity (EOQ) that minimizes holding and ordering costs. It is calculated as follows:[1]

$$Q = \sqrt{\frac{2CD}{h}}$$

**Equation 27: Economic Order Quantity**

[1] Stoll, Kopf, Schneider and Lanza, 2015

With D the annual demand, C the order fixed costs, and h variable storage costs. Precise information on holding and replenishment costs are the prerequisites to determine the EOQ, and that makes it no easily implantable in practice.

In the case of the order-up-to level policy, the parameter to determine is the target level. Several techniques are applicable, but it happens in practice that the level S is mostly determined thanks to accumulated experience. In the example of spare items, S is usually an average of the forecasted demand over a certain period of time[1] (depending on the frequency of the item).



[1] Bacchetti, Plebani, Saccani, and Syntetos, 2010

# 3 Development of a Spare Parts Inventory Tool at Franz Haas Waffelmaschinen

## 3.1 Introduction

### 3.1.1 Company Presentation

The original incentive of this work is coming from a concrete need of the company Franz Haas Waffelmaschinen GmbH (hereafter referred to as FHW). Historically based in Vienna, the company is part of an industrial group (Haas Group) dedicated to the development and production of machinery for the making of wafers, biscuits, confectionery or dairy products. Backbone of the group, FHW is specialised in its core activity of wafers machinery, counts more than 600 employees for a revenue of 304M€ in 2016.[1] The firm is able to sustain its leading position thanks to its worldwide activities in more than 100 countries around the planet, representing 98% of the revenues. In order to provide specific market and reactive services, the group developed a network of sales and service centers whose responsibility is to ensure the efficient productivity of the customers thanks to a high service level. The service centers of FHW are based in Singapore (Haas Asia Pacific, HAP), Russia (HRU), Colombia (HCO) and Turkey (HTR), each of them being responsible for the installed base within a specific region.

Figure 29: Variety of wafer products[2]

[1] Cf. www.haas.com/en/haas-group/haas-group/facts-and-figures (read on 10/09/217)
[2] Retrieved from www.haas.com

The diversity of the possible end-products cooked by FHW machines (see figure above) makes the development of each plant a unique project. The specific requirements of each customer imply the production of custom-made machines. For instance, the process to make flat wafers is made of five different activities (mixing, baking, cooling, spreading and cutting), each of them having a dedicated equipment with specific features according to the end-product. The machines developed by FHW are consequently very complex due to their functionalities and thus to the very high number of components.

Besides, the products developed by FHW have very long lifecycles (up to several decades) as they are capital goods for the customers. To ensure their best productivity, the firm provides after-sales services which includes the supply in **spare parts**, which represent a major activity for the company. Ensuring a high service level is essential to win the customers' loyalty, and it is at the same time a very profitable source of revenues. The Sales and Service Department at FHW is responsible for the management of spare parts, and for the related activities. The present work has been achieved within this department, in helpful collaboration with the people in charge of spare parts monitoring.

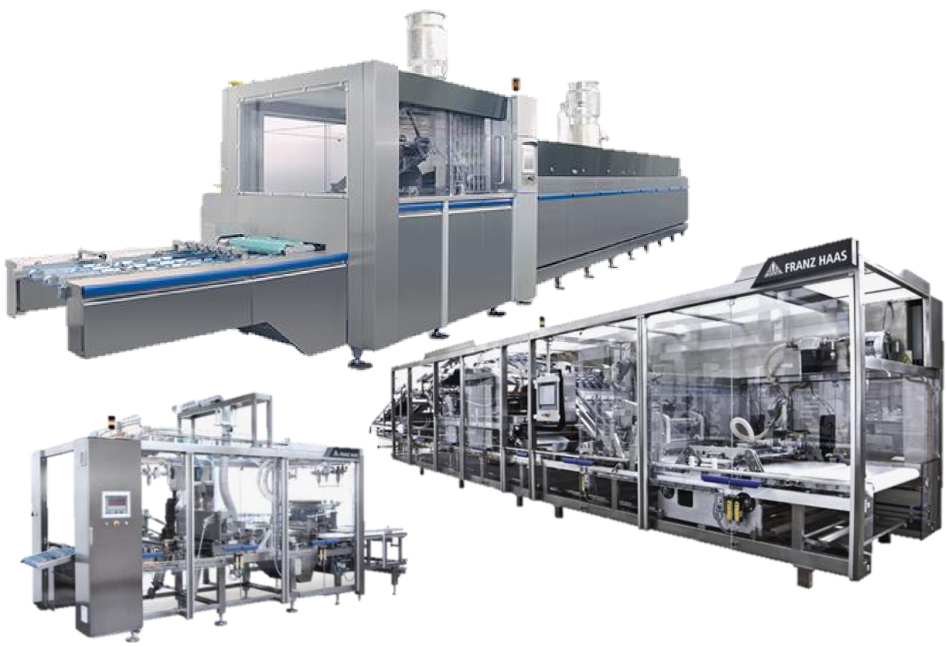



**Figure 30: Example of equipment developed by FHW[1]**

[1] Retrieved from www.haas.com

### 3.1.2 Spare Parts Management at FHW

As mentioned in the previous section, FHW has to deal with a tremendous number of spare parts: more than 42.000 items are referred to as “spare parts”. The complexity and the diversity of the equipment are the main reasons to this high value, which is also increased by long lifecycles and the custom-made aspect of the machines. The management of spare parts is made even more difficult by the worldwide distribution of the customers. But above all, the main factor that triggers logistics decision on spare parts is the criticality of the equipment. They represent capital goods for FHW’s customers and need therefore to be the most productive, as any downtime leads directly to significant losses in the revenues. The concept of **availability** is thus here essential as FHW is responsible for the supply of spare parts in the shortest time: in the ideal case, a requested item should be available anytime. However, holding costs as well as limited capacity does not allow a full availability for the whole spare parts catalogue; restrictive and smart decisions are the purpose of spare parts management. This section reviews the current situation regarding spare part management at FHW, from different perspectives.

***Logistics Structure***

The supply in spare parts is ensured by the different Service Centers (SC) which provide the installed base of their associated zone of activity Figure 31 displays the structure and the flows of spare parts through the organisation, from the suppliers to the customers. The logistics network to supply spare parts is composed of two echelons: one central depot at FHW, and several decentralized warehouses at the service centers. The function of FHW’s warehouse is threefold: to receive and stock the spare parts provided by *all* the suppliers, redistribute them to the different service centers, and supply the items to the installed base in Europe (there is no proximity warehouse for Europe). Additionally, some shipments between the service centers can occasionally occur but do not represent a significant part in the flows of items. Exchanges with the other firms or subsidiaries of the group are also possible but are not taken into account in the study because they do not concern to the same installed bases. In this way, each installed base is supplied by a specific warehouse.

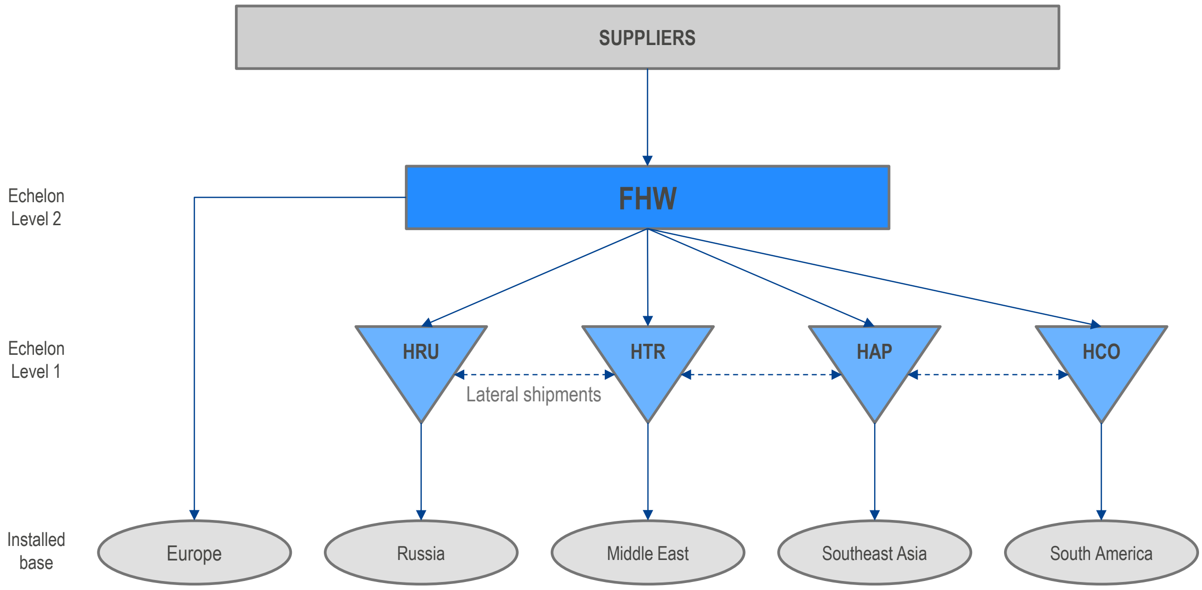



**Figure 31: Spare parts logistics network at FHW (own illustration)**

FHW currently leads a *corrective maintenance policy*, meaning that the demand for spare parts is unplanned and comes from the needs of customers (who may have an on-site preventive policy). In this way, the global demand on for spare items is the sum of the customers' needs and is thus unpredictable. The firm is now implementing a preventive maintenance policy in order to enhance their services to the customers, and to be able to control the demand for spare parts. This project is still in a development phase as it requires considerable investments but is certainly the future of maintenance activities at FHW.

***Processes***

Going further into details concerning the management of spare parts within the company, it is essential to understand how the supply process works, from the time of the demand to the delivery.

Following a failure (or an on-site preventive maintenance activity), the equipment owner submits a request to the responsible service center. The latter replies as quickly as possible with an **offer** to the customer; it is made of two different distinct data, the price of the spare part, and the delivery time. At this point, the customer has the choice to accept or to reject it. In the second case, this means that a competitor proposed a more satisfying offer. If the offer is accepted, the service center releases an **order** and can proceed to the delivery: the spare part is either directly shipped from the service center's warehouse if it is in stock, or asked to the central warehouse at FHW, or even ordered to a supplier when nowhere available. The following remarks are important for the remainder of the work:

- The **price** given on an offer is depending on several factors such as the location of the customer (currency exchange rate, customs fees) and the volume of the demand (which can imply bulk discount). In any case, the price is calculated with a reference price (P100) which is regularly updated into the global database.
- The **lead-time** suggested on the offer is an estimation of the total administration and transportation times (and occasionally the production time). It is calculated by summing the lead-times between the different echelons of the supply network.

Although the company has no feedback on the reasons for a rejected offer, it is assumed that from these two decision factors, the lead-time is by far the most prevailing. This assumption is completely relevant considering that most demands follow a corrective maintenance activity and that the equipment downtime has therefore to be minimized. Also, the costs of spare parts is usually way lower than the potential losses due to machine's inactivity.

***Data collection***

Any sales activity requires an efficient way to collect data for analytical purposes that steer managing decisions. FHW uses the Enterprise Resource Planning[1] (ERP) software SAP[2] that combines both the production and sales activities. Sales data from the different service center are in this way centralized into a single database. Besides,

[1] Enterprise Resource Planning is a process by which a company manages and integrates the important parts of its business. An ERP management information system integrates areas such as planning, purchasing, inventory, sales, marketing, finance and human resources. ERP is most frequently used in the context of software. As the methodology has become more popular, large software applications have been developed to help companies implement ERP.
(Retrieved from http://www.investopedia.com/terms/e/erp.asp)

[2] SAP is an ERP and data management software.

inventory data are included so that it is for instance possible to have an overview of the stock levels, and to adjust the safety stocks.

### *Inventory Management*

Although the data are centralized, each service center remains independent regarding their inventory management. This means that every service center is responsible for the supply in spare parts within their respective area of activity. The inventory decisions are only locally monitored and this implies consequently that each service center has developed its own methods to manage the demand on spare parts the most efficiently as possible. It has been observed for instance that the most prevailing criterion to establish a classification is not necessarily the same from a service center to the other one. The methods to forecast the demand or to set safety stocks may differ as well.

This work has been conducted on FHW's central site; the inventory management at this warehouse is therefore the case study for the remainder on the study. The current techniques for spare parts inventory management are briefly reviewed as follows:

- **Classification**: the classification is only based on the demand frequency criterion. According to the number of orders in the last year, each item is affected to a class (FSN). No other criterion is considered to classify the parts.

- **Strategy Mapping**: given the mono-criterion classification, it is very simple to assign a policy for each group: the F-parts require the most attention and have therefore to be stocked, whereas slow or non-moving parts are not kept in stock.

- **Demand Forecasts**: the estimations on the demand for the next year are established using a simple linear regression.

- **Inventory decisions**: decisions on stock levels are individual and manual for each part. Reorder levels are determined thanks to an estimation of the yearly demand. The review is not continuous and the replenishment frequency depends on the value of the item (low-price parts are ordered in bigger quantities, and not often). There is no optimal order-quantity calculation.

### 3.1.3 Problematics and Definition of the Objectives

Through the development of its services activities, FHW has observed a main issue regarding spare parts management: the percentage of offers converted into real orders is very weak. For instance, only 60% of the offers released by FHW's warehouse are transformed into orders. From this situation follows the following observations:

- A considerable amount of work is lost with the preparation of offers that will not be converted into orders. Releasing offers actually represents a significant workload for the sales department and thus, unfulfilled offers are directly considered as wasted work.
- On the other hand, the potential on spare parts sales is tremendous, as the improvement of the general success rate is very promising. Positive consequences on both the sales revenues and the service level enhancement are easily conceivable.

Referring to the previous section (Spare Parts Management at FHW) and thanks to the initial discussions to start the work, several reasons to explain the unsatisfactory sales on spare items have be identified:

- FHW's sales service suffers from high competition as spare parts are mostly standardized; customers have consequently several sources of supply at disposal. It is assumed that the customer's decision is made on the lead-time (and so on the availability) of the item, rather than on its price.
- In light of the current spare parts management situation at FHW, it appears that the inventory is handled with a too simplistic manner. The diversity and the complexity of the items results only in a simple classification; the forecasts are also overlooked. Such decisions have direct consequences on stocks decisions, and therefore trigger the availability of the parts.
- So far, no advanced analysis are performed on spare parts sales, resulting in a poor knowledge on the actual and especially potential revenues. The department does not have an easy interface at disposal to do so.
- The supply of spare parts is ensured through decentralized service center allowing proximity and reactivity to the customers' demands; however, no

coordination exists to plan and control stocks levels between the warehouses, which also use different stocking techniques.

In this way, many reasons highlight the need to develop a more sophisticated method to manage spare parts at FHW. So far, no dedicated analysis and monitoring tools have been developed; the purpose of this work was to address these issues.

### *Objectives*

In response to the problematics previously mentioned, the necessity to implement smart inventory techniques has concretely fallen on the development of a computer application. The latter could be used on a daily basis to support spare parts inventory decisions at FHW. The specifications are presented in the table below.

| | |
|---|---|
| ***Main Objectives:*** | - create a classification based on relevant criteria and with consistent parameters.<br>- implement appropriate and accurate methods to forecast the demand.<br>- differentiate realistic logistics strategies according to the classification (strategy mapping).<br>- suggest quantitative decisions to monitor the stocks. |
| ***Extended Objectives:*** | - create an automated database from specified SAP reports.<br>- provide sales and inventory analysis.<br>- include future functionalities (preventive maintenance)<br>- coordinate (and optimize) globally the stocks at the different warehouses. |
| ***Restrictions & Constraints:*** | - be easily and repeatedly usable (stay the most pragmatic as possible)<br>- be adaptable and modifiable |

| | |
|---|---|
| ***Form Expectations:*** | program the tool on MS Excel, using the VBA development possibilities |
| ***Expected Outcome:*** | show the potential benefits of the tool on sales and service level |

**Table 11: Specifications for the practical application**

## 3.2 Tool Development

In this section, the logical construction of the tool is depicted. The specific characteristics of the case study, the difficulties encountered as well as the reasoning to take the final decisions are presented. This work being both academic and practical, it aims to develop a generic procedure towards spare parts management optimisation.

### 3.2.1 Data Acquisition and Availability

The first step of development is to investigate which data are available and in the organisation. From there, it is possible to know which analysis are conceivable to lead. Also, it gives the direction of the reasoning.

It has been mentioned before that FHW handles the data flows and acquisition through an ERP (SAP) that allows to collect information on products, production and sales. Besides, the data are collected among the different organisations of the group and are therefore centralized. In the context of this work, the most relevant data have been quickly identified: sales data and product data. Considering the methods presented in the second chapter of this work, it is actually essential to analyse consumption data (sales) in order to forecast the future demand. On the other side, product data are useful when building a classification.

The required data have been specifically identified and acquired through reports from the ERP. After refining and discussing the most relevant data for the construction of the tool, the final reports have been established as depicted on Figure 32.

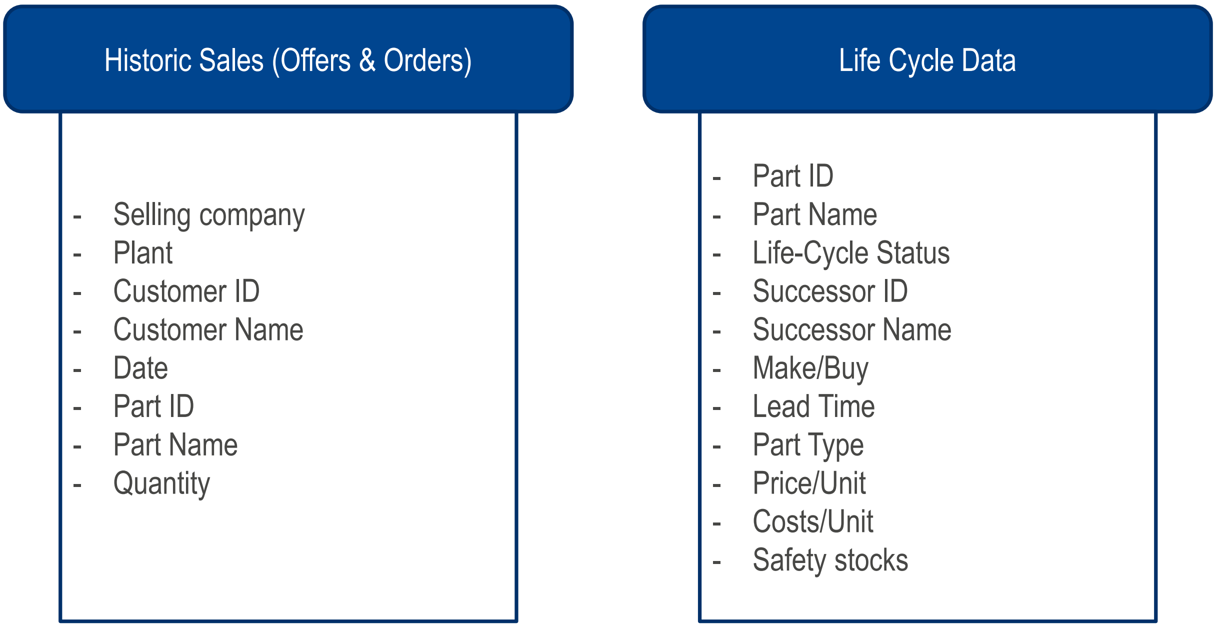



**Figure 32: Requested Data Reports (own illustration)**

***Clarification:**:*

- There is a distinction between the *selling company*, and the *selling plant* in an order (or an offer)*:* the first is the organisation that receives the demand whereas the plant performs the delivery. The two entries are usually the same a difference can happen, for example when a part is delivered by a different service center that the one which received the demand. It is important to take this distinction into account, and to notice that the selling plant is to be considered in the analysis as it gives the best estimation of the actual demand.
- The *quantity* is the number of units requested by the customer.
- The *Life Cycle status* of a part is its current state of usage; some parts become obsolete over time and are therefore dismissed. They are replaced by a new part (a *successor*) that fulfils the same function nut has a different ID (and usually a different lead time, price…). This concept of successor is essential for the remainder of the work.
- The *Lead Time* of a part is the time needed to supply it to the FHW's warehouse in case of a reorder. Each part is either a *make-part*, meaning that it is produced by FHW, or a *buy-part*, meaning that it purchased to one or several suppliers.

- The *Type* specifies if the part is a wear or a spare part. This distinction has however no effect on the decisions: spare and wear parts are generically considered as spare parts.
- The *price/unit* and *costs/unit* are actually reference values, as the actual selling price depends on the region and does not include transportation costs. Also, discounts are often applied. The price/unit is therefore very informative but cannot be used to determine the real revenues.
- Finally, the *safety stocks* at the different warehouses have been requested. They are essential to know what the current logistics policy for each part is.

The three distinct reports (historic offers, historic orders, and life cycle data) constitute the input of the tool. One can observe that there is no data concerning the criticality of the parts. Reliability data are currently not (or too few) available at FHW, and that has direct consequences on the development if the tool (see next sections). It is comprehensible as the collection of such data is very demanding and implies many investments. Also, it reflects the corrective maintenance policy that is now led by the organisation.

The quality of the data will be discussed progressively in the following sections, as it has often been a source of difficulties. The table below gives some hints on the amount of data to handle:

| | |
|---|---|
| Number of referenced Spare parts | **51.811** |
| Number of Selling Companies | **9** |
| Number of Customers | **1.968** |
| Number of Offers (2008-2017) | **285.656** |
| Number of Orders (2008-2017) | **223.380** |
| Total size of input data | **31 MB** |

Table 12: Input figures

### 3.2.2 General Structure and Functionality

The company has access to data back to the year 2000, providing more than 15 years of sales data. However, it has been assumed that 10 years of data would be enough to analyse and forecast the demand. The second reason to cut the tremendous amount of data is that the tool is developed with Microsoft Excel, which tends to be instable when the number of lines is too big. Considering sales data from 2008 still results in a 300.000 line-report, which is already enormous to handle for MS Excel. Besides, the Life Cycle Data (hereafter referred to as LCC Data) provide information on more than 51.000 parts, increasing considerably the total size of input data.

It is important to notice here the imperative need to combine the MS Excel application with a software dedicated to database treatment. This would be a first extension of the work. The total implementation of the application within the ERP of the company would eventually constitutes the final achievement of the project.

Originally, the tool was thought to both consolidate and analyse the data in a single file. Due to the amount of data from the input, it has been quickly decided to create a *Service Database* in which the inputs are manually added and automatically consolidated. Concretely, the service database is a separate MS Excel file, which is used as input for the *tool* itself. The advantages of such a split between the input data and the analysis tool are plenty:

- Historic sales data and LCC data are considerable and are therefore delicate to manipulate on MS Excel (instability). It is then relevant to use them separately.
- The consolidation of the data is in practice not a regular task: the user of the tool does not have to update the inputs frequently as the analysis are made on a yearly basis. The consolidation being very long and instable (on MS Excel), it is also practical to do it separately.
- In this way, the analysis tool is way more dynamic: the user can adapt easily the parameters of the analysis (for instance the number of years, or the selected organisation) and thus lead many different studies.

The general structure of the tool and its functionality is given on Figure 33. It is the result of the whole reasoning, and has therefore evolved progressively. The two big blue boxes embody the two MS Excel files. Each white box represents an MS Excel sheet.

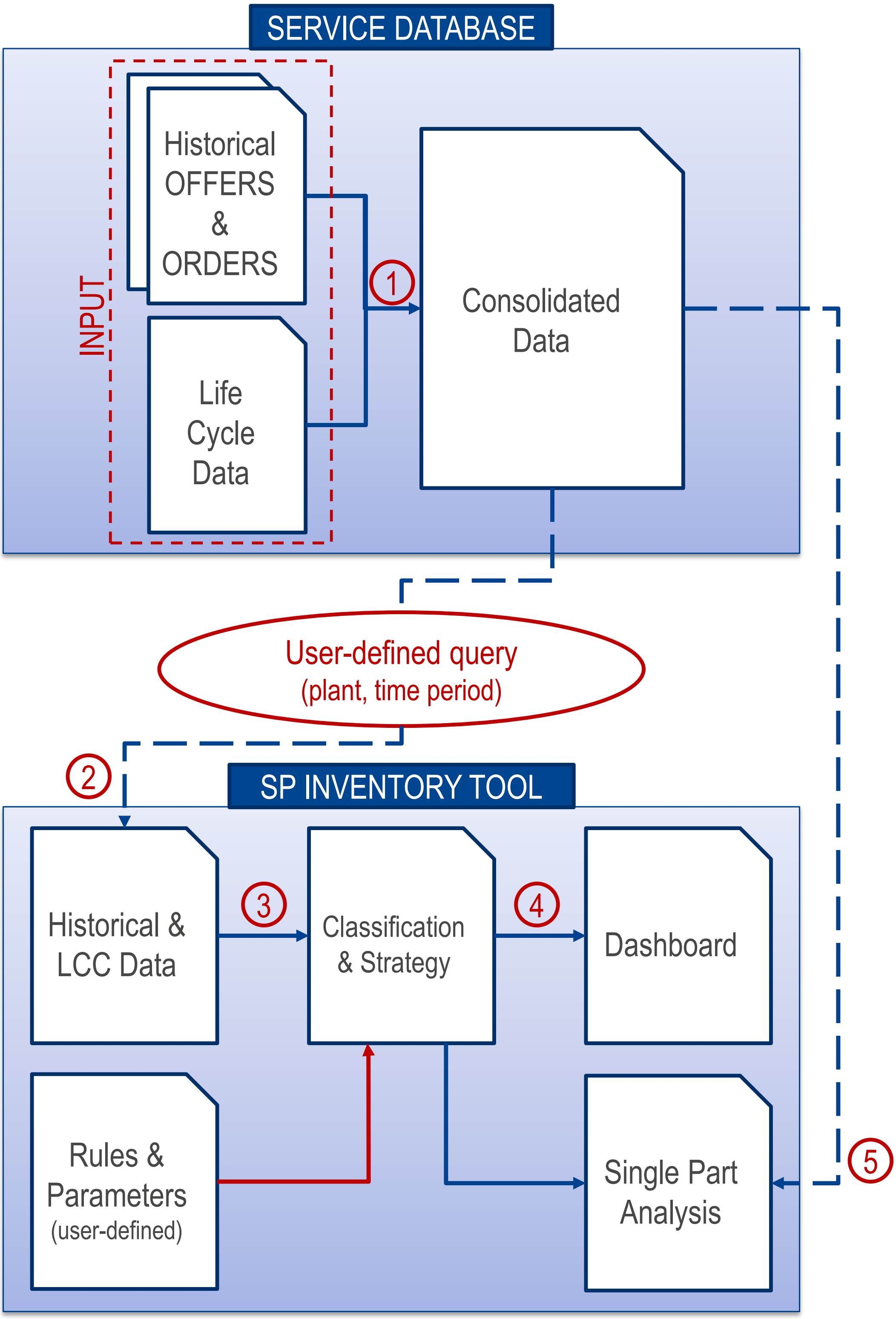



Figure 33: Structure of the tool (own illustration)

Five distinct steps are clearly identified; the figures also gives the flows of data (input and output) at every step. The function of each step is described hereinafter.

| | |
|---|---|
| *Step 1*<br>**Data Consolidation** | The consolidation consists in adding up the offers and the orders over time, in order to set up the total consumption (*frequency* and *quantity*) of each spare part. The result is the acquisition of 4 time series (one year time period): frequency and quantity in the demand for both offers and orders.<br>Additionally, the life cycle data are matched into the same sheet. |
| *Step 2*<br>**User-defined Query** | The purpose of the tool is to conduct analysis on the different service centers. The user has thus to choose the analysed organisation, in order to import the proper data (from the database) into the tool itself. |
| *Step 3*<br>**Classification & Strategy** | This step is the core of the tool. Based on the historical and LCC data (imported in the previous step) and on the user-defined Rules & Parameters, parts are classified according to several criteria. A relevant logistics strategy is affected, as well as quantitative suggestions for stocking. These decisions are made thanks to appropriate forecasts. |
| *Step 4*<br>**Dashboard** | The dashboard can be updated after an analysis. It provides the user with a visual overview of the analysis: distribution among classes, key figures, logistics summary… |
| *Step 5*<br>**Single Part Analysis** | This additional feature allows the user to select one specific spare part, and to conduct a global analysis on it. The result gives a comparison of the consumption among the different warehouses, and of the suggested logistics directives. |

**Table 13: The five steps of the application**

The next sections develop more specifically each of the steps. A bigger emphasis is given on the step 3 (Classification & Strategy) as it represents the core of the spare part inventory management process. The construction of a relevant multi-criteria classification and the determination of consistent forecasting methods constitute therefore the major part of the tool development.

Step 1, 2, 4 and 5 do not include important theoretical reasoning as in step 3, whereas mostly represent programming considerations. These steps are specific to the case study and thus not generic but still offer interesting issues that contribute to the overall reasoning.

### 3.2.3 Service Database Construction

The very first phase of the tool development is to organize the input data. The utility to separate and consolidate input data has been exhibited in the previous section. The service database aims to provide the user with "non-moving" data, meaning that they are rarely updated, and constitute a basis for the analysis. This phase is thus essential to give the most reliable data for the following steps.

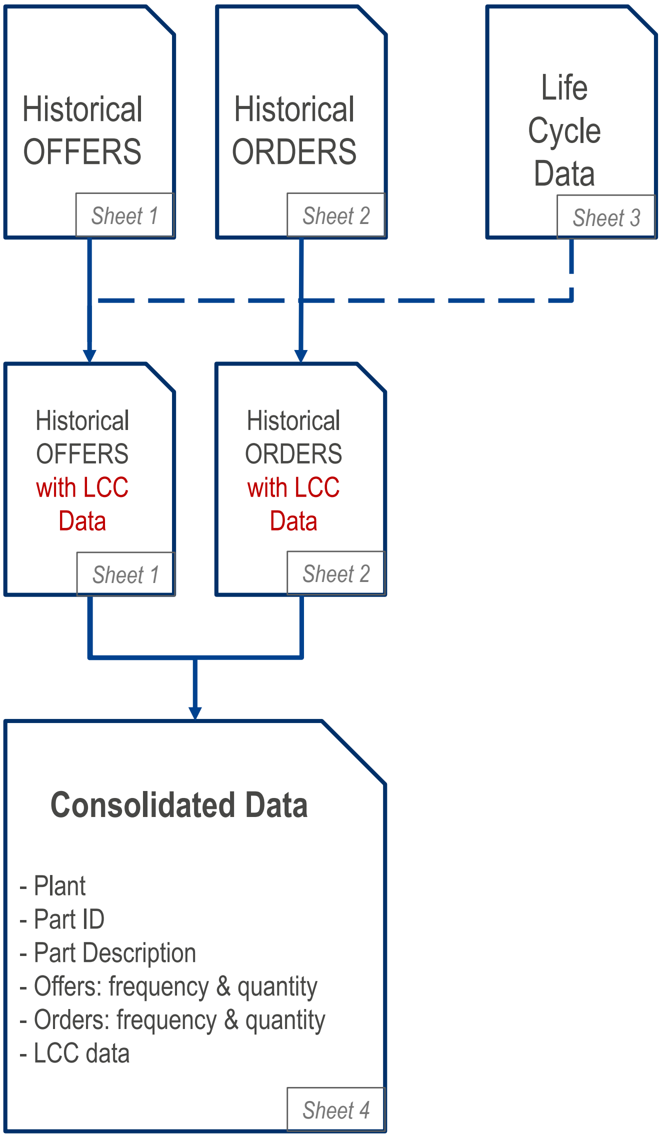



Figure 34: Consolidation Procedure (own illustration)

In the case study, the amount of data is considerable and so is the execution time to browse them all (several minutes). MS Excel shows indeed some limits when dealing with more than 100.000 lines, and the offers and orders data both have more than 200.000 lines. Consequently, and with a pragmatic vision, the construction of the database has to be smart and efficient. Hence the idea to match the LCC data into the consolidation: data from historic sales do not include LCC data (price, type, safety stocks…) and the programming function that allows to match two entries from two different sheets is time-consuming on MS Excel. The advantage of doing so is to that it will not be needed to access the LCC data in the next steps. For more clarity, the procedure of consolidation is displayed on Figure 34.

The consumption of a spare part is consolidated for each plant, meaning that a part can appear several times in the database, but for different plant of the organisation. The construction of such a database is actually only a formatting of the input data but the task is hampered by many specificities of the organisation:

- The parts which become obsolete can have a **successor** that fulfils the same function. In order to estimate the real consumption and need for a part, one must add the data of the related predecessor part. One more phase is then required into the consolidation to determine the “last” successor of a part because an item can have several successors. From a programming point of view, this matching is also time-costly because it requires to search the part into the LCC database.
- Some **parts ID** are not relevant for the analysis because they represent free-of-charge maintenance activities. These parts are therefore excluded of the consolidation.
- **Transversal shipments** between service centers can occur when a part is not available. In that case an offer is virtually set up to the plant that request the part. These offers must be excluded because they constitute a duplication of the original demand, and would skew the consumption data. The different plants are hopefully identifiable by a customer ID that allows to exclude their demand from the database.

The detailed algorithms of the consolidation is given in the appendix. Due to the specificities of the organisation describe above, the algorithm is very complex, but is actually one possibility among others.

In practice, the programming of this step took a significant amount of time due to the many difficulties encountered: instability of MS Excel on big database, long execution time, basic programming skills, complexity of the loops, etc. It is here important to point out that the efficiency of the algorithm can probably be enhanced by a programming expert. Also, the construction of such a database could be done externally by a dedicated software (further development).

The key figures of the consolidation are the following:

| | |
|---|---|
| Execution time | **12 min 35s** |
| Total file size (with Input data) | **61 MB** |

**Table 14: Consolidation figures**

As previously mentioned, the database is global, meaning that it gathers the data from all selling entities of the companies. The goal being to optimize the stocking strategies at each warehouse, the user has the possibility to define manually a data quest within the tool (step 2 on Figure 33). The quest includes the name of the considered plant, and the first year of the required data. Consequently, a program has been developed to import the requested data from the database to the tool itself, without opening the Service Database file. At this point, it is then possible to start the core analysis of the data.

Following the process developed in the theoretical chapter, the approach to smart spare part management is the following:

- Classification & Strategy Mapping
- Demand Forecast
- Inventory Management

The next sections exhibit the reasoning that led to the adequate choices of this case study.

### 3.2.4 Classification and Strategy Mapping

***Classification***

Building up a classification is essentially based on the data at disposal. In the case of FHW, the maintenance policy is currently corrective, meaning that maintenance data are not easily available, or of poor quality. Besides, the company does not have access to installed base data yet (number installed machines, hours of operations, achieved maintenance activities). It is then impossible to develop a classification and the related forecast based on a preventive maintenance. Therefore, the main data only come from the historic sales, and from the life-cycle data.

The relevance to estimate the **criticality** has been underlined in the theoretical chapter, as well as the numerous possibilities to assess it. In respect of this practice case, this criterion has been moved aside because no criticality assessment (even very subjective) is currently implemented. The criticality in the supply process is also very demanding to estimate, and appears irrelevant in this case.

The majority of the data coming the historic sales, the classification is necessarily based on the analysis of the **demand**. Several criteria allow to qualify the demand in a quantitative or qualitative manner: value-usage, frequency, variability. The implementation in practice of a classification reveals that the classification varies according to the parameters that are chosen and to the calculation methods. Indeed, the parameters to distinct a class from another are usually determined arbitrary, but may have an influence on the final decisions. It is therefore essential to choose wisely the parameters considering the specificities of the application. Additionally, the assessment of the values like the value-usage or the demand frequency is also an arbitrary decision. Taking the example of the demand frequency, one can chose to use a mean value over a certain number of years (to define) or to forecast the value (with a method to define as well).

<table>
<tr><th>Criterion</th><th>Assessment</th><th>Class Parameters</th></tr>
<tr><td>Supply</td><td>Raw data.</td><td>Make<br>Buy</td></tr>
<tr><td>Lead Time</td><td>Raw value.</td><td>Long: >21 days<br>Intermediate: 8-21 days<br>Short:0-7 days</td></tr>
<tr><td>Price</td><td>Raw value.</td><td>High: >1.000 €/unit<br>Medium: 100-1.000 €/unit<br>Low: <100€/unit</td></tr>
<tr><td>Profitability</td><td>$\frac{\text{Price} - \text{Costs}}{\text{Costs}} * 100$</td><td>P1: >500%<br>P2: 200-500%<br>P3: <200%</td></tr>
<tr><td>Life-Cycle Phase<br>(Offers AND orders)</td><td>Frequency time series analysis.</td><td>Nonexistent: No demand<br>Dead: No demand over the past 4 years<br>New: 1st demand in the previous year<br>In-Use: When none of the previous class.</td></tr>
<tr><td>Value-Usage</td><td>Mean value over the last 4 years on the real consumption (i.e. orders time series)</td><td>A: <80% of cumulated VU<br>B: 80-95%<br>C: >95%</td></tr>
<tr><td>Demand Frequency<br>(Offers AND orders)</td><td>Forecast on the whole frequency time series for the next year.</td><td>Very Fast-moving:>12/year<br>Fast-moving: 7-11/year<br>Slow-moving: 4-6/year<br>Non-moving: 0-3/year</td></tr>
<tr><td>Demand Variability<br>(Offers AND orders)</td><td>Only for “In-Use” parts.<br>Determination of the coefficient of variation and the Average Demand Interval over the last 6 years (quantity time series).</td><td><table>
<tr><th></th><th>CV²<br>0,49</th><th>ADI<br>1,32</th></tr>
<tr><td>Smooth</td><td><</td><td><</td></tr>
<tr><td>Erratic</td><td>≥</td><td><</td></tr>
<tr><td>Intermittent</td><td><</td><td>≥</td></tr>
<tr><td>Lumpy</td><td>≥</td><td>≥</td></tr>
</table></td></tr>
</table>

**Table 15: Classification criteria and parameters**

One main issue when implementing a spare part classification is to estimate the value of the criteria with the most appropriate manner, implying systematically a part of free will in the decisions. The adopted criteria in the case study (and the assessment method) are displayed in the previous table.

The table requires some important explanations and remarks:

- **Life-cycle phase**: One issue of spare part management is to deal with long life-cycles, especially within the machinery industry. The consequence is that every year, a significant number of parts becomes obsolete (replacement by a successor, or simply obsolescence of the equipment); and many new references are added on the other side (new products). In both cases, the stocking strategy is a special case that must be dealt carefully with. Hence the distinction with “In-use” parts. The limit for “Dead” parts has been set to 4 years thanks to the experience of life-cycle specialists at FHW.

- The **Value-Usage** estimates the consumption of parts in terms of revenues for the company. The calculation is made with the price within the LCC database (P100), meaning that the value does not reflect the actual revenues, which depend on the sales region and on the discounts. The aim is actually to compare the parts between each other and to estimate roughly the ones that bring the most revenues to the company, and which consequently need a strict inventory strategy. The class parameters are chosen according to the classic Pareto distribution, at first.

- Concerning the demand analysis (**Frequency** and **Variability**), the classification is conducted on offers and on orders. A simple classification on one or the other set of data could seem sufficient, but it is necessary in that case study to have both analysis. In fact, the main problematic encountered by FHW is the poor success rates on some items. Differentiating the analysis on the two data sources generates a very accurate knowledge on the demand, and thus provides good information to implement corrective directives.

- The **demand frequency** is estimated on the whole time series, in order to provide the most accurate value as possible. The forecasting methods that have been developed for the tool are detailed in section 3.2.5. Still, it is essential to point out that a variability analysis is conducted within the program to determine the most appropriate forecasting method.

- The **demand variability** provides the user with a qualitative assessment of the quantity variations on a 6-year period of time. The reason of a shorter time series is to give more importance to recent data.

***Strategy mapping***

Once the classification criteria are identified and that the techniques to assess them are determined, the following step is to create groups of parts that will be affected with the same logistics strategy. Each group (or cluster) gathers parts that shares the same classes for the different criteria of the classification. 8 criteria have been identified in the previous section, with three or four classes for each. It is conceivable to combine all the criteria and to assign for each cluster a specific strategy. The examples exhibited in the theoretical chapter provide hints to develop a smart strategy mapping. With a pragmatic perspective, one must chose the most relevant criteria according to the situation, and prioritize them. Also, it is not necessary to use every criteria for every part. For instance a spare item whose life-cycle phase is “Dead” will not need any further sub-classification as a non-stocking policy is directly the most appropriate strategy. Finally, some criteria can be used as “secondary” criteria and not appear in the strategy mapping. However, it makes sense to use them to refine the qualitative decisions.

The demand criteria have been already emphasized in this chapter. They are indeed the basis of the analysis and therefore the criteria that must be prioritized in the strategy mapping. A first approach consists in defining clusters based on the following criteria: life-cycle phase, frequency, value-usage and price. Lead time and profitability are considered firstly as “secondary” criteria that will be considered in the elaboration of quantitative decisions.

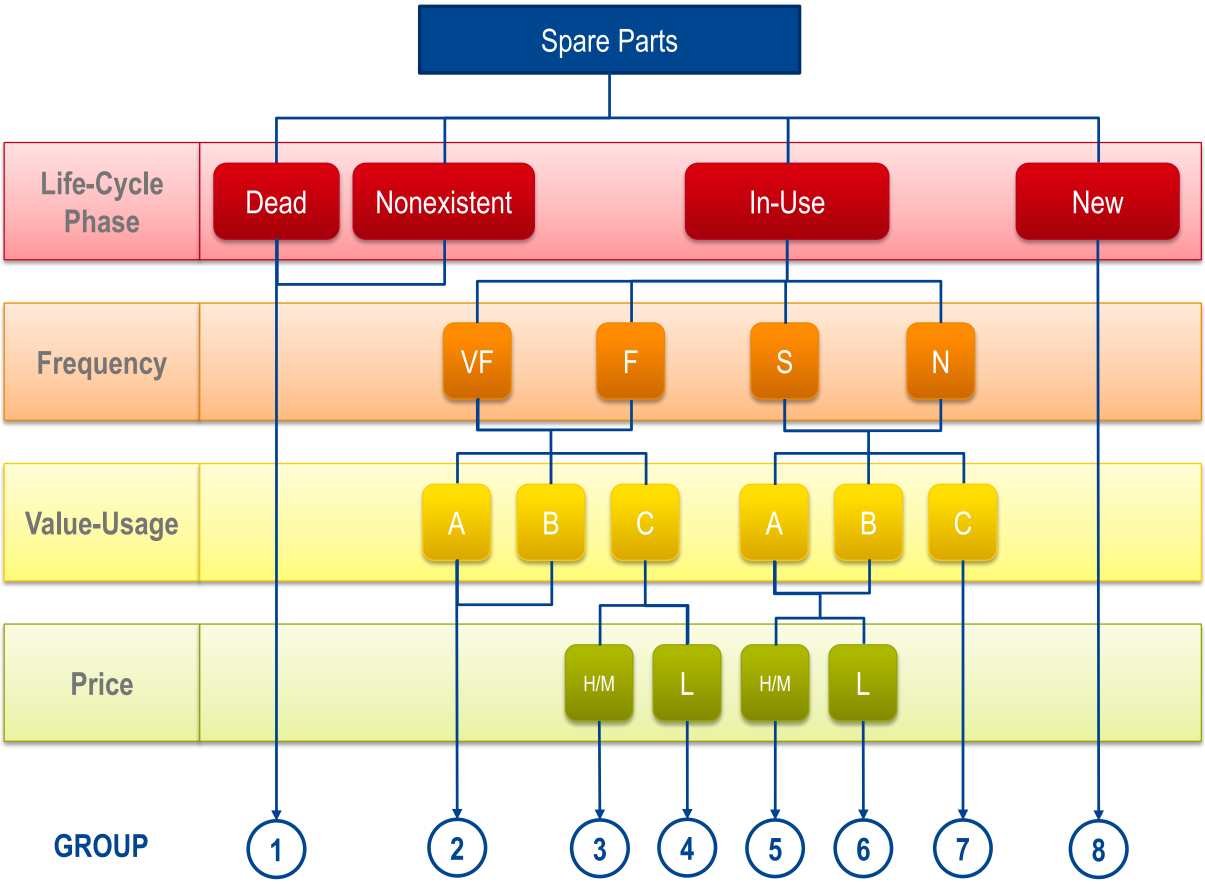



Figure 35: Suggested Strategy Mapping (own illustration)

Figure 35 displays the strategy decision-making process for FHW, according to the chosen criteria for the classification. It is worth noticing that classes are often merged in order to reduce the number of groups. For instance, Very Fast and Fast-moving items are considered as a unique class. The aim of the tool is indeed to implement smart strategies, which constitutes the first part of spare part management. A more subtle analysis (implying the increase of clusters) could be developed eventually to optimize the stocking strategies.

For now, it is assumed that a dozen of clusters is sufficient to conduct effective improvements for inventory management. A logistics strategy is then assigned to each group. As a reminder, the possible policies are the following:

- No part kept in stock: the demand is satisfied from order.
- (Q,s) policy: stock with fixed reorder point and fixed order quantity (EOQ)
- (s,S) policy: stock with fixed reorder point but order-up to level replenishment.

In the case where the part is kept in stock, the decision to set a safety stock is also to be determined. The review is considered to be always continuous. The results of the strategy allocation is given hereafter (Table 16).

| ***Group*** | ***Logistics Policy*** | ***Safety Stock*** |
|---|---|---|
| **1** | No stock | - |
| **2** | (Q,s) | Yes |
| **3** | (Q,s) | No |
| **4** | (Q,s) | Yes |
| **5** | (s,S) | No |
| **6** | (s,S) | Yes |
| **7** | No Stock | - |
| **8** | No stock | - |

**Table 16: Suggested logistics policies**

The **group 1** gathers parts whose demand is either “dead” or nonexistent. Even though a demand may still occur in the future, it makes sense not to keep these items in stock.

**Groups 2, 3 and 4** cluster very fast and fast-moving items. The demand for these items is very high (more than 7 times per year). The forecast are normally rather accurate, it is therefore recommended to control the stocks with a fixed order quantity and a safety stock when the value-usage belongs to class A and B. These parts bring the most important revenues and require strict inventory measures. A distinction is made for C-parts: if the price is low, meaning that the quantities ordered are important, a safety stock becomes necessary. On the opposite, a high or medium price means that the quantities ordered are small; a safety stock is therefore not required.

**Groups 5 and 6** gather slow and non-moving items. A and B-parts are stocked either with a safety stock if the price is low (meaning high quantities), and without if the value of the part is high or medium. The order-up to level replenishment should be preferred as it allows more dynamism and flexibility to face irregular demand. C parts are not kept in stock because of they represent small revenues and are unpredictable to forecast.

It has been decided that new parts (**Group 8**) should not be kept in stock. Indeed, a part that has been ordered only once in the previous year will not necessary ordered the following year. New demands are tied with new equipment, meaning the beginning of a life-cycle.

Finally, a first suggestion has been built up on a theoretical basis. This model can obviously eventually refined in thanks to practical observations. This is the purpose of the last chapter of the work.

### 3.2.5 Demand Forecasting

Spare parts inventory management rests on appropriate strategies on one side, and on consistent quantitative decisions on the other side. Concretely, these decisions concern stock sizing and replenishment quantities, and are based on the prediction of the demand. Spare parts demand follows specific patterns which have been exhibited in section 2.4.1. Consequently, the techniques to forecast intermittent or erratic demand must be adapted. It has been observed that in most cases the techniques to forecast the demand for spare items do not differ from the methods used traditionally. The demand for consumer goods or production items follows more regular – and thus more predictable – patterns. Traditional techniques like the moving average or the single exponential smoothing are inappropriate to forecast a demand with many zero values. In the end, the consequences on quantitative logistics decisions, and further, on the revenues, can possibly take on tremendous dimensions: stock-outs or overstocks have a direct impact on revenues and on client satisfaction.

FHW uses for example a simple linear regression to estimate the future demand. Even though the method can provide good predictions when the demand is smooth, it is legitimate to challenge its accuracy for intermittent patterns. The objective of this section is to find the most appropriate forecasting techniques, in light of the case study. Many different time-series based forecasts are indeed at disposal to estimate future demand (see section 2.4.4).

The following benchmarking compares:

- the simple moving average method (**MA**)
- the linear trend approximation (**LT**)
- the single exponential smoothing (**SES**)
- Croston's method (**CR**)
- the Syntetos-Boylan Approximation (**SBA**)

Reliability based forecasts are in that case no possible to implement, due to the unavailability of the needed data. Other time-series based techniques like the bootstrapping method or the neural networks have been straightaway moved aside: very few practical studies prove the benefits of such methods over the other ones, for now. Also, they present more difficulties to be set up.

***Approach***

The procedure to determine the most suited forecasting technique is inspired from the work of Syntetos et al.[1] The authors investigate the distinction in the demand variability patterns to determine the "best" forecasting method. A technique is then assigned for each pattern. Such a process is very relevant for spare parts because of the variability in the demand behaviors. In this way, no general forecasting method is determined, whereas several methods that fit better to the demand of parts that share the same pattern.

The four demand patterns have been already identified: smooth, erratic, intermittent or lumpy. The membership of a group is defined through the calculation of the coefficient of variation, and the average demand interval. Realizing such a study requires the use of a significant amount of data, in order to provide the most consistent results. The data consolidated in the Service Database furnish good material to conduct the analysis and the latter has been realized with the historical values from the *offers*. Parts with a "nonexistent" or "dead" pattern have been removed from the dataset. Table 17 displays the distribution of the parts among the four variability groups.

[1] Syntetos, Boylan and Croston, 2005

| *Variability* | *Number of parts* | *%* |
|---|---|---|
| **Smooth** | 1606 | 12,6% |
| **Erratic** | 1034 | 8,2% |
| **Intermittent** | 8611 | 67,6% |
| **Lumpy** | 1482 | 11,6% |
| ***Total*** | *12733* | *100%* |

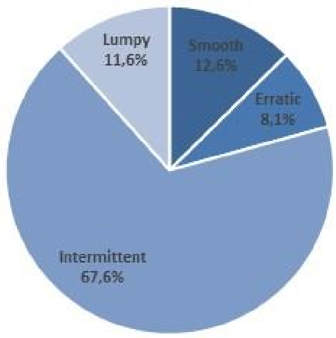



Table 17: Dataset variability distribution

The predominance of intermittent patterns in the dataset is coherent given the analysis of the demand for spare parts: few parts follow a lumpy pattern, whereas the majority have intermittent demand. Also, this confirms the consistency of the cut-off values used to distinguish the patterns (retrieved from the literature). Finally, even though the parts following a smooth, erratic or lumpy pattern are fewer, it is here assumed that more than 1.000 entries are sufficient to produce good results.

Comparing forecasting methods consist in comparing the error with the real demand. The metrics to measure the errors have been previously presented (see section 2.4.5) and it appears that only one measurement is appropriate to compare spare parts forecasts. It is the Mean Absolute Scaled Error (MASE) that is the most appropriate metrics because it is scale-independent (and thus allows comparison between non-related time series) and cannot take infinite value. As a reminder, the formula to calculate the MASE of a forecast method over a time series is:

$$MASE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{e_t}{MAE_{naïve}}\right|$$

Equation 22: Mean absolute scaled error

Where

$MAE_{naïve}$ is the Mean Absolute Error of the naïve forecast:

$$MAE_{naïve} = \frac{1}{n-1}\sum_{i=2}^{n}|Y_i - Y_{i-1}|$$

Equation 23: Mean absolute error for naïve forecast

For each entry in the data set, the best forecasting method is the one that has the lowest MASE. If all the MASE are greater than 1, this means that the best forecast comes from the naïve method. Assigning the most suited forecasting method to a variability group amounts to determine which method is most often the most accurate.

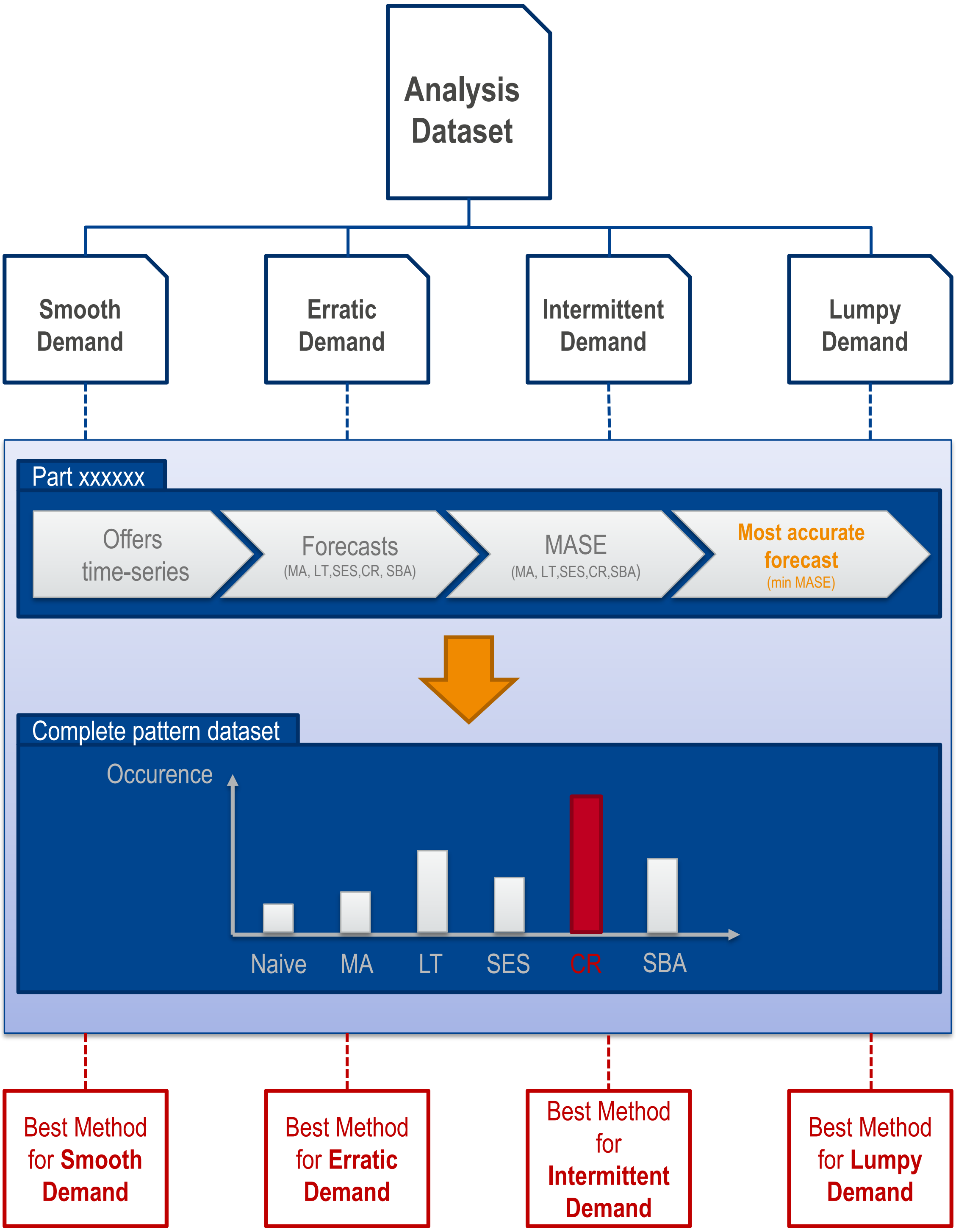



Figure 36: Procedure to determine the best forecasting method (own illustration)

Figure 36 displays the procedure that is set up to determine the best forecasting method, for each of the four demand patterns.

Among the five forecasting methods on the benchmark, three of them include at least one variable parameter (SES, CR, and SBA). A quick study on the influence of the parameters on the forecast accuracy has shown that their choice is far from insignificant. Hence the need to conduct a parameter optimization for the concerned methods, and to inject the results for the comparison.

***Optimization for parametric methods***

The SES method have one smoothing parameter, whereas the CR and SBA methods have two smoothing parameters (one for the quantity variations, and the other for the inter-demand interval). The three methods are considered as “smoothing” method because the forecast of the future demand is a weighted value between the actual demand at instant t, and the forecast for the instant t. In this way, the role of a smoothing parameter is to give more or less importance to the actual demand or to the last forecast. Giving more importance to the actual demand (high value of the parameter) tends to furnish a forecast very reactive to variations. On the opposite, the smaller the parameter is, the more the variations are “smoothed”. The choice of the smoothing parameters has therefore a direct influence in the accuracy of the predictions.

Following these considerations, it is logical to think that the optimal parameters differ from on demand pattern to another. For, instance a lumpy demand is characterized by important variations in quantities and inter-demand interval; a forecast reactive to these variations can be assumed to be more suited to fit the demand more properly.

An optimization program has been developed on MS Excel. It consists in evaluating the MASE of the forecasts, for different values of the parameters, and to calculate the mean MASE of the complete set of data (accordingly to the demand pattern). The optimal parameters are then the ones that minimize the mean MASE.

The **Single Exponential Smoothing** has only one parameter, the optimization is therefore unidirectional. The parameter varies from 0.05 to 1 with a 0.05 interval. It is assumed that this interval is sufficient to reach concluding results. The results of the optimization are given on the charts below.

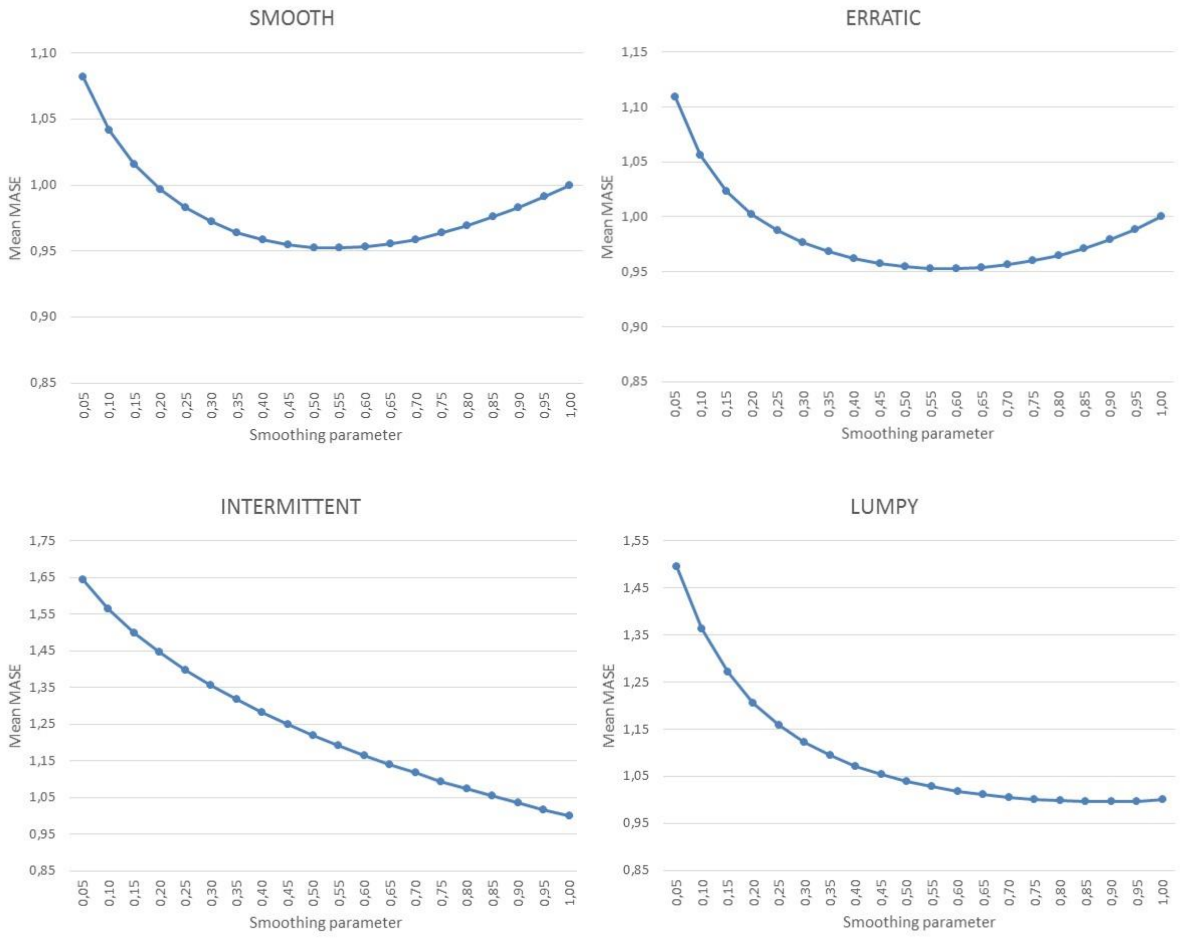



Figure 37: Smoothing parameter optimization for SES method (own illustration)

Visually, it appears that the optimization is converging for three patterns (smooth, erratic and lumpy) because the mean MASE reaches a minimum. An optimal parameter can be consequently determined. The intermittent pattern provides however a non-concluding result as the optimization furnish no minimum for the mean MASE. This means that the latter is maybe reached with a value greater as 1, which has no mathematical signification (the smoothing parameter must be smaller than 1). Finally, the optimal parameter for intermittent patterns is arbitrary chosen equal to 0.9. The final optimal parameters taken on for the remainder of the study are given in Table 18.

| ***Demand Pattern*** | ***Optimal smoothing parameter*** |
|---|---|
| Smooth | 0.55 |
| Erratic | 0.60 |
| Intermittent | 0.90 |
| Lumpy | 0.90 |

**Table 18: Optimal smoothing parameters for SES method**

Optimizing **Croston's method** and the **Syntetos-Boylan Approximation** is more elaborate because there are two smoothing parameters (α and β). The principle is the same as for the SES, but with a bidirectional optimization. Both parameters vary from 0.05 to 1 with a 0.05 interval. The visualization of the results for the optimization of CR's smoothing parameters is shown on Figure 38.

The same observation is remarked as for the SES optimization. Smooth, Erratic and Lumpy patterns reach a minimum within the parameters' range, whereas the optimization on intermittent patterns tends to happen outside the boundaries (α is too big). An arbitrary decision is taken to ensure coherent results. The fixed parameters for the remainder of the work are gathered in Table 19.

| ***Demand Pattern*** | ***CR Optimal smoothing parameters*** | | ***SBA Optimal smoothing parameters*** | |
|---|---|---|---|---|
| | ***α*** | ***β*** | ***α*** | ***β*** |
| Smooth | 0.55 | 0.20 | 0.40 | 0.10 |
| Erratic | 0.60 | 0.35 | 0.80 | 0.20 |
| Intermittent | 0.90 | 0.75 | 0.90 | 0.80 |
| Lumpy | 0.65 | 0.90 | 0.90 | 0.70 |

**Table 19: Optimal smoothing parameters for CR and SBA methods**

| α\β | 0,05 | 0,10 | 0,15 | 0,20 | 0,25 | 0,30 | 0,35 | 0,40 | 0,45 | 0,50 | 0,55 | 0,60 | 0,65 | 0,70 | 0,75 | 0,80 | 0,85 | 0,90 | 0,95 | 1,00 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0,05 | 1,08 | 1,08 | 1,08 | 1,08 | 1,08 | 1,08 | 1,08 | 1,08 | 1,08 | 1,08 | 1,08 | 1,08 | 1,08 | 1,08 | 1,08 | 1,08 | 1,08 | 1,08 | 1,08 | 1,08 |
| 0,10 | 1,04 | 1,04 | 1,04 | 1,04 | 1,04 | 1,04 | 1,04 | 1,04 | 1,04 | 1,04 | 1,04 | 1,04 | 1,04 | 1,04 | 1,04 | 1,04 | 1,04 | 1,04 | 1,04 | 1,04 |
| 0,15 | 1,02 | 1,02 | 1,02 | 1,02 | 1,02 | 1,02 | 1,02 | 1,02 | 1,02 | 1,02 | 1,02 | 1,02 | 1,02 | 1,02 | 1,02 | 1,02 | 1,02 | 1,02 | 1,02 | 1,02 |
| 0,20 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 |
| 0,25 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 |
| 0,30 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 |
| 0,35 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 |
| 0,40 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 |
| 0,45 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 |
| 0,50 | 0,95 | 0,95 | 0,95 | 0,95 | 0,95 | 0,95 | 0,95 | 0,95 | 0,95 | 0,95 | 0,95 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 |
| 0,55 | 0,95 | 0,95 | 0,95 | **0,95** | 0,95 | 0,95 | 0,95 | 0,95 | 0,95 | 0,95 | 0,95 | 0,95 | 0,95 | 0,95 | 0,95 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 |
| 0,60 | 0,95 | 0,95 | 0,95 | 0,95 | 0,95 | 0,95 | 0,95 | 0,95 | 0,95 | 0,95 | 0,95 | 0,95 | 0,95 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 |
| 0,65 | 0,96 | 0,96 | 0,95 | 0,95 | 0,95 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 |
| 0,70 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 |
| 0,75 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 |
| 0,80 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 |
| 0,85 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,98 |
| 0,90 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 |
| 0,95 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 |
| 1,00 | 1,00 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 |

Mean MASE for smooth demand

| α\β | 0,05 | 0,10 | 0,15 | 0,20 | 0,25 | 0,30 | 0,35 | 0,40 | 0,45 | 0,50 | 0,55 | 0,60 | 0,65 | 0,70 | 0,75 | 0,80 | 0,85 | 0,90 | 0,95 | 1,00 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0,05 | 1,11 | 1,11 | 1,11 | 1,11 | 1,10 | 1,10 | 1,10 | 1,10 | 1,10 | 1,10 | 1,10 | 1,10 | 1,10 | 1,10 | 1,10 | 1,10 | 1,10 | 1,10 | 1,10 | 1,11 |
| 0,10 | 1,06 | 1,06 | 1,06 | 1,06 | 1,06 | 1,06 | 1,06 | 1,06 | 1,06 | 1,06 | 1,05 | 1,06 | 1,06 | 1,06 | 1,06 | 1,06 | 1,06 | 1,06 | 1,06 | 1,06 |
| 0,15 | 1,03 | 1,03 | 1,03 | 1,03 | 1,03 | 1,03 | 1,03 | 1,03 | 1,03 | 1,03 | 1,03 | 1,03 | 1,03 | 1,03 | 1,03 | 1,03 | 1,03 | 1,03 | 1,03 | 1,03 |
| 0,20 | 1,01 | 1,01 | 1,01 | 1,01 | 1,01 | 1,01 | 1,01 | 1,01 | 1,01 | 1,01 | 1,01 | 1,01 | 1,01 | 1,01 | 1,01 | 1,01 | 1,01 | 1,01 | 1,01 | 1,01 |
| 0,25 | 1,00 | 1,00 | 1,00 | 1,00 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 1,00 | 1,00 | 1,00 | 1,00 |
| 0,30 | 0,99 | 0,99 | 0,99 | 0,99 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,99 | 0,99 | 0,99 | 0,99 |
| 0,35 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 |
| 0,40 | 0,98 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 |
| 0,45 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 |
| 0,50 | 0,97 | 0,97 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,97 | 0,97 | 0,97 |
| 0,55 | 0,97 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 |
| 0,60 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | **0,96** | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 |
| 0,65 | 0,97 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 |
| 0,70 | 0,97 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,97 | 0,97 |
| 0,75 | 0,97 | 0,97 | 0,97 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,96 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 |
| 0,80 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 |
| 0,85 | 0,98 | 0,98 | 0,98 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,97 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 |
| 0,90 | 0,99 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,98 | 0,99 | 0,99 |
| 0,95 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 | 0,99 |
| 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 | 1,00 |

Mean MASE for erratic demand

| α\β | 0,05 | 0,10 | 0,15 | 0,20 | 0,25 | 0,30 | 0,35 | 0,40 | 0,45 | 0,50 | 0,55 | 0,60 | 0,65 | 0,70 | 0,75 | 0,80 | 0,85 | 0,90 | 0,95 | 1,00 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0,05 | 1,71 | 1,70 | 1,69 | 1,68 | 1,67 | 1,67 | 1,66 | 1,66 | 1,66 | 1,66 | 1,65 | 1,65 | 1,65 | 1,65 | 1,65 | 1,65 | 1,65 | 1,65 | 1,65 | 1,66 |
| 0,10 | 1,71 | 1,70 | 1,68 | 1,68 | 1,67 | 1,67 | 1,66 | 1,66 | 1,66 | 1,65 | 1,65 | 1,65 | 1,65 | 1,65 | 1,65 | 1,65 | 1,65 | 1,65 | 1,65 | 1,65 |
| 0,15 | 1,71 | 1,69 | 1,68 | 1,67 | 1,67 | 1,66 | 1,66 | 1,66 | 1,65 | 1,65 | 1,65 | 1,65 | 1,65 | 1,65 | 1,65 | 1,65 | 1,65 | 1,65 | 1,65 | 1,65 |
| 0,20 | 1,71 | 1,69 | 1,68 | 1,67 | 1,67 | 1,66 | 1,66 | 1,65 | 1,65 | 1,65 | 1,65 | 1,65 | 1,65 | 1,64 | 1,64 | 1,64 | 1,64 | 1,65 | 1,65 | 1,65 |
| 0,25 | 1,70 | 1,69 | 1,68 | 1,67 | 1,66 | 1,66 | 1,66 | 1,65 | 1,65 | 1,65 | 1,65 | 1,65 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,65 | 1,65 |
| 0,30 | 1,70 | 1,69 | 1,68 | 1,67 | 1,66 | 1,66 | 1,65 | 1,65 | 1,65 | 1,65 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,65 |
| 0,35 | 1,70 | 1,69 | 1,67 | 1,67 | 1,66 | 1,66 | 1,65 | 1,65 | 1,65 | 1,65 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,65 |
| 0,40 | 1,70 | 1,68 | 1,67 | 1,67 | 1,66 | 1,66 | 1,65 | 1,65 | 1,65 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,65 |
| 0,45 | 1,70 | 1,68 | 1,67 | 1,66 | 1,66 | 1,65 | 1,65 | 1,65 | 1,65 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 |
| 0,50 | 1,70 | 1,68 | 1,67 | 1,66 | 1,66 | 1,65 | 1,65 | 1,65 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 |
| 0,55 | 1,70 | 1,68 | 1,67 | 1,66 | 1,66 | 1,65 | 1,65 | 1,65 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 |
| 0,60 | 1,70 | 1,68 | 1,67 | 1,66 | 1,66 | 1,65 | 1,65 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 |
| 0,65 | 1,69 | 1,68 | 1,67 | 1,66 | 1,66 | 1,65 | 1,65 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 |
| 0,70 | 1,69 | 1,68 | 1,67 | 1,66 | 1,65 | 1,65 | 1,65 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 |
| 0,75 | 1,69 | 1,68 | 1,67 | 1,66 | 1,65 | 1,65 | 1,65 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,63 | 1,63 | 1,63 | 1,64 | 1,64 | 1,64 | 1,64 |
| 0,80 | 1,69 | 1,68 | 1,67 | 1,66 | 1,65 | 1,65 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,63 | 1,63 | 1,63 | 1,63 | 1,63 | 1,64 | 1,64 | 1,64 |
| 0,85 | 1,69 | 1,68 | 1,67 | 1,66 | 1,65 | 1,65 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,63 | 1,63 | 1,63 | 1,63 | 1,63 | 1,63 | 1,64 | 1,64 | 1,64 |
| 0,90 | 1,69 | 1,68 | 1,67 | 1,66 | 1,65 | 1,65 | 1,64 | 1,64 | 1,64 | 1,64 | 1,64 | 1,63 | 1,63 | 1,63 | 1,63 | 1,63 | 1,63 | 1,63 | 1,64 | 1,64 |
| 0,95 | 1,69 | 1,68 | 1,67 | 1,66 | 1,65 | 1,65 | 1,64 | 1,64 | 1,64 | 1,64 | 1,63 | 1,63 | 1,63 | 1,63 | 1,63 | 1,63 | 1,63 | 1,63 | 1,64 | 1,64 |
| 1,00 | 1,69 | 1,68 | 1,66 | 1,66 | 1,65 | 1,65 | 1,64 | 1,64 | 1,64 | 1,64 | 1,63 | 1,63 | 1,63 | 1,63 | **1,63** | 1,63 | 1,63 | 1,63 | 1,64 | 1,64 |

Mean MASE for intermittent demand

| α\β | 0,05 | 0,10 | 0,15 | 0,20 | 0,25 | 0,30 | 0,35 | 0,40 | 0,45 | 0,50 | 0,55 | 0,60 | 0,65 | 0,70 | 0,75 | 0,80 | 0,85 | 0,90 | 0,95 | 1,00 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0,05 | 1,58 | 1,53 | 1,50 | 1,48 | 1,46 | 1,44 | 1,43 | 1,42 | 1,42 | 1,41 | 1,41 | 1,40 | 1,40 | 1,40 | 1,40 | 1,40 | 1,40 | 1,41 | 1,41 | 1,42 |
| 0,10 | 1,56 | 1,51 | 1,48 | 1,46 | 1,44 | 1,43 | 1,42 | 1,41 | 1,40 | 1,39 | 1,39 | 1,39 | 1,39 | 1,39 | 1,39 | 1,39 | 1,39 | 1,39 | 1,40 | 1,41 |
| 0,15 | 1,55 | 1,50 | 1,47 | 1,44 | 1,43 | 1,41 | 1,40 | 1,39 | 1,39 | 1,38 | 1,38 | 1,38 | 1,38 | 1,38 | 1,38 | 1,38 | 1,38 | 1,38 | 1,39 | 1,40 |
| 0,20 | 1,53 | 1,49 | 1,46 | 1,43 | 1,42 | 1,40 | 1,39 | 1,39 | 1,38 | 1,37 | 1,37 | 1,37 | 1,37 | 1,37 | 1,37 | 1,37 | 1,37 | 1,37 | 1,38 | 1,39 |
| 0,25 | 1,52 | 1,48 | 1,45 | 1,43 | 1,41 | 1,40 | 1,39 | 1,38 | 1,37 | 1,37 | 1,36 | 1,36 | 1,36 | 1,36 | 1,36 | 1,36 | 1,36 | 1,37 | 1,37 | 1,38 |
| 0,30 | 1,51 | 1,47 | 1,44 | 1,42 | 1,40 | 1,39 | 1,38 | 1,37 | 1,37 | 1,36 | 1,36 | 1,36 | 1,35 | 1,35 | 1,35 | 1,36 | 1,36 | 1,36 | 1,37 | 1,38 |
| 0,35 | 1,51 | 1,46 | 1,43 | 1,41 | 1,39 | 1,38 | 1,37 | 1,36 | 1,36 | 1,36 | 1,35 | 1,35 | 1,35 | 1,35 | 1,35 | 1,35 | 1,35 | 1,36 | 1,36 | 1,37 |
| 0,40 | 1,50 | 1,45 | 1,42 | 1,40 | 1,39 | 1,38 | 1,37 | 1,36 | 1,35 | 1,35 | 1,35 | 1,35 | 1,34 | 1,34 | 1,35 | 1,35 | 1,35 | 1,35 | 1,36 | 1,37 |
| 0,45 | 1,49 | 1,45 | 1,42 | 1,40 | 1,38 | 1,37 | 1,36 | 1,35 | 1,35 | 1,35 | 1,34 | 1,34 | 1,34 | 1,34 | 1,34 | 1,34 | 1,35 | 1,35 | 1,35 | 1,36 |
| 0,50 | 1,49 | 1,44 | 1,41 | 1,39 | 1,38 | 1,37 | 1,36 | 1,35 | 1,34 | 1,34 | 1,34 | 1,34 | 1,34 | 1,34 | 1,34 | 1,34 | 1,34 | 1,35 | 1,35 | 1,36 |
| 0,55 | 1,48 | 1,44 | 1,41 | 1,39 | 1,37 | 1,36 | 1,35 | 1,35 | 1,34 | 1,34 | 1,33 | 1,33 | 1,33 | 1,33 | 1,33 | 1,34 | 1,34 | 1,34 | 1,35 | 1,36 |
| 0,60 | 1,47 | 1,43 | 1,40 | 1,38 | 1,37 | 1,36 | 1,35 | 1,34 | 1,34 | 1,33 | 1,33 | 1,33 | 1,33 | 1,33 | 1,33 | 1,33 | 1,34 | 1,34 | 1,34 | 1,35 |
| 0,65 | 1,47 | 1,43 | 1,40 | 1,38 | 1,36 | 1,35 | 1,35 | 1,34 | 1,33 | 1,33 | 1,33 | 1,33 | 1,33 | 1,33 | 1,33 | 1,33 | 1,33 | 1,34 | 1,34 | 1,35 |
| 0,70 | 1,47 | 1,42 | 1,40 | 1,38 | 1,36 | 1,35 | 1,34 | 1,34 | 1,33 | 1,33 | 1,33 | 1,32 | 1,32 | 1,32 | 1,33 | 1,33 | 1,33 | 1,33 | 1,34 | 1,35 |
| 0,75 | 1,46 | 1,42 | 1,39 | 1,37 | 1,36 | 1,35 | 1,34 | 1,33 | 1,33 | 1,33 | 1,32 | 1,32 | 1,32 | 1,32 | 1,32 | 1,33 | 1,33 | 1,33 | 1,34 | 1,35 |
| 0,80 | 1,46 | 1,42 | 1,39 | 1,37 | 1,36 | 1,35 | 1,34 | 1,33 | 1,33 | 1,32 | 1,32 | 1,32 | 1,32 | 1,32 | 1,32 | 1,32 | 1,33 | 1,33 | 1,34 | 1,34 |
| 0,85 | 1,46 | 1,42 | 1,39 | 1,37 | 1,36 | 1,34 | 1,34 | 1,33 | 1,33 | 1,32 | 1,32 | 1,32 | 1,32 | 1,32 | 1,32 | 1,32 | 1,33 | 1,33 | 1,33 | 1,34 |
| 0,90 | 1,46 | 1,42 | 1,39 | 1,37 | 1,35 | 1,34 | 1,34 | 1,33 | 1,33 | 1,32 | 1,32 | 1,32 | **1,32** | 1,32 | 1,32 | 1,32 | 1,32 | 1,33 | 1,33 | 1,34 |
| 0,95 | 1,46 | 1,42 | 1,39 | 1,37 | 1,36 | 1,34 | 1,34 | 1,33 | 1,33 | 1,32 | 1,32 | 1,32 | 1,32 | 1,32 | 1,32 | 1,32 | 1,32 | 1,33 | 1,33 | 1,34 |
| 1,00 | 1,46 | 1,42 | 1,39 | 1,37 | 1,36 | 1,35 | 1,34 | 1,33 | 1,33 | 1,32 | 1,32 | 1,32 | 1,32 | 1,32 | 1,32 | 1,32 | 1,33 | 1,33 | 1,34 | 1,34 |

Mean MASE for lumpy demand

**Figure 38: Bidirectional parameters optimisation for CR Method (own illustration)**

To conclude on the optimization of parametric methods, the results are very satisfactory because the analysis provide consistent observations. Intermittent and lumpy patterns are better forecasted when the smoothing parameters are close to 1, whereas smooth patterns require lower values. The optimization is rather basic but one must keep in mind a pragmatic vision. The aim is to determine the forecasting technique that fit to the majority of the parts that follow one demand pattern.

### *Methods comparison*

The parametric methods being optimized for the four different demand patterns, it is then possible to conduct the comparison presented in the approach of this section. The results of the comparison are displayed in Table 20. The figures given in the first table represent the number of times one method is prevailing over the other ones. For example, the CR method is the most accurate method in 313 cases out of the 1497 following a smooth pattern. The second table exhibits the corresponding percentage for each variability class, and fort the complete dataset (in green).

| | Naive | MA | LT | SES | CR | SBA | *Total* |
|---|---|---|---|---|---|---|---|
| **Smooth** | 144 | 325 | 69 | 49 | 313 | 597 | *1497* |
| **Erratic** | 71 | 318 | 38 | 28 | 104 | 475 | *1034* |
| **Intermittent** | 405 | 183 | 3592 | 51 | 144 | 4236 | *8611* |
| **Lumpy** | 102 | 273 | 191 | 39 | 23 | 854 | *1482* |
| ***Total*** | *722* | *1099* | *3890* | *167* | *584* | *6162* | *12624* |

| | Naive | MA | LT | SES | CR | SBA | *Total* |
|---|---|---|---|---|---|---|---|
| **Smooth** | 9,6% | 21,7% | 4,6% | 3,3% | 20,9% | 39,9% | *100%* |
| **Erratic** | 6,9% | 30,8% | 3,7% | 2,7% | 10,1% | 45,9% | *100%* |
| **Intermittent** | 4,7% | 2,1% | 41,7% | 0,6% | 1,7% | 49,2% | *100%* |
| **Lumpy** | 6,9% | 18,4% | 12,9% | 2,6% | 1,6% | 57,6% | *100%* |
| ***Total*** | *5,7%* | *8,7%* | *30,8%* | *1,3%* | *4,6%* | *48,8%* | *100%* |

Table 20: Methods benchmarking with optimized parameters

The conclusions stemming from these results are the following:

- Firstly, the SBA method provides the majority of the most accurate forecast for the four different demand patterns. This confirms practically what has emerged from the literature review, namely that this method outperforms any other method when the time-series are very unpredictable.

- For smooth demand, the MA and the CR forecast have also good results (more than 20%); this observation is explained by the low average demand interval of the time-series from this group. MA is indeed known to perform well for this type of demand.

- The LT estimation has surprisingly good results when the demand is intermittent. A reason for that could be the low variabilities in the quantities, which are rather well estimated thanks to the linear regression.

- The SES presents very poor results for every category. It is important to notice that this method gives exactly the same forecast as the CR method when the average demand-interval is 1. This is the case for most of the time-series from the smooth and erratic classes. In such as situation, the priority is given to the CR method. However, the method is clearly less efficient when the demand is more intermittent.

- Finally, the effectiveness of the SBA method is most visible for lumpy patterns (almost 60% of the most accurate forecasts). This confirms the relevance to use this prediction for the most unpredictable demands.

Nota: The same analysis has been conducted with non-optimized parameters for the SES, CR and SBA methods (all smoothing parameters set on 0.3). The results are displayed in Table 21. The aim of this comparison is to show the benefits of the parameters' optimization, and the results are convincing. The SBA is significantly less performant for the four demand categories. Hence the necessity to determine in a first time the most suited parameters for the different patterns.

| | Naive | MA | Linear Trend | SES | CR | SBA | *Total* |
|---|---|---|---|---|---|---|---|
| **Smooth** | 212 | 260 | 83 | 67 | 353 | 522 | *1497* |
| **Erratic** | 191 | 235 | 78 | 35 | 111 | 384 | *1034* |
| **Intermittent** | 522 | 246 | 4283 | 128 | 189 | 3243 | *8611* |
| **Lumpy** | 199 | 283 | 395 | 133 | 26 | 446 | *1482* |
| ***Total*** | *1124* | *1024* | *4839* | *363* | *679* | *4595* | *12624* |

| | Naive | MA | Linear Trend | SES | CR | SBA | *Total* |
|---|---|---|---|---|---|---|---|
| **Smooth** | 14,2% | 17,4% | 5,5% | 4,5% | 23,6% | 34,9% | *100%* |
| **Erratic** | 18,5% | 22,7% | 7,5% | 3,4% | 10,7% | 37,1% | *100%* |
| **Intermittent** | 6,1% | 2,9% | 49,7% | 1,5% | 2,2% | 37,7% | *100%* |
| **Lumpy** | 13,4% | 19,1% | 26,7% | 9,0% | 1,8% | 30,1% | *100%* |
| ***Total*** | *8,9%* | *8,1%* | *38,3%* | *2,9%* | *5,4%* | *36,4%* | *100%* |

Table 21: Methods benchmarking with non-optimized parameters

***Conclusion on demand forecasting***

The previous analysis provide conclusive results for the rest of the study, as the SBA method largely outperforms the other forecast, and that for the four demand patterns. The choice of this method is then fixed (with the adequate parameters) and has been implemented into the tool. Besides the analysis has shown the weakness of the Linear Trend approximation, which is currently used to determine future demand at FHW. Although the comparison does not exhibit the benefits of a more suited method, the implementation of the SBA estimation can be considered as a good improvement towards spare parts inventory optimization.

### 3.2.6 Inventory Management

The very last step of the spare parts management process is to determine the quantitative inventory decisions. The multi-criteria classification produces the strategies to follow, and the inventory management aims to provide operative decisions on stock levels and replenishment quantities. Such operational directives are triggered by the estimation of the demand, whose techniques are developed in the previous section.

### *Adjusted demand estimation*

One redundant problematic encountered by FHW is the poor ratio of offers that are converted into orders (meaning real sales and their related revenues). The main objective of this work is to improve the **success rates** of the parts that suffer from competition, because of their unavailability. It is indeed assumed that the main reason that prevent a customer to accept an offer is the delivery time: when the item is not in stock, the time to supply the spare part is necessarily steeply increased.

The data at disposal allow accurate analysis on historic sales and on the behaviour of customers regarding their availability. The predictions for the future sales are only based on time-series data, hence the necessity to find the most realistic estimation of the demand for FHW. There is actually a shade of difference between the demand resulting from the *offers*, and the one estimated with the *orders*. The first reveals the need coming from the market, whereas the second expresses the actual consumption through FHW's sales. When the success rate is high, the two estimations are almost the same. If the success rate is not good, the estimations can significantly differ. Consequences on stocks levels are immediate, hence the relevance to develop a smart estimation of the demand.

The idea is to refine the forecasts given by the predictions from the historic sales, by setting up a realistic and business-oriented estimation of the demand. Explanations:

- Monitoring the stocks based on the predictions from the offers may lead to overstocks because of the behaviour of customers that stand down an offer (due to unavailability, or other reasons).

- Calculating the stocks from the orders' prediction is at the opposite risky because it does not reflect the reality of the needs. The consequence is an underestimation of the actual demand, and thus an increased risk of stock-outs.

- *Refining the demand* consists in finding a middle ground between offers and orders forecasts, using the knowledge of the success rates. The objective of smart spare parts inventory management is to enhance the success rates of parts that present poor sales results, meaning concretely the improvement of their availability. To do so, the idea to overestimate the orders' forecasts has been developed in this work. The predictions on the orders are reasonably overstated so that stock levels are sensibly increased, and so is the availability.

An example is given hereafter for illustrative purposes (Figure 39). The selected part is an angular ball bearing; the mean success rate is 65% over the last four years.

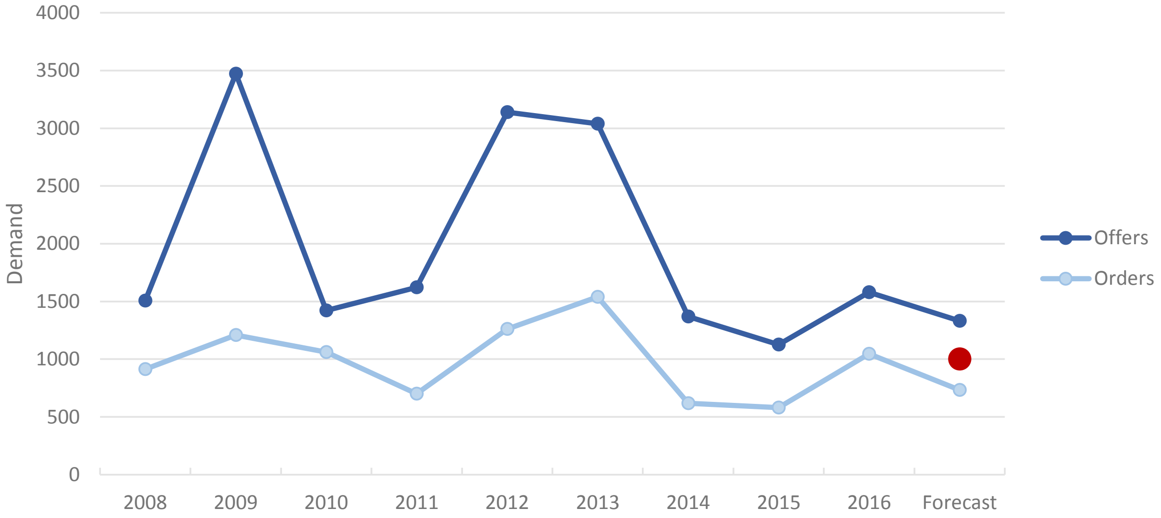



Figure 39: Example: demand for an angular ball bearing (own illustration)

The gap between the quantities offered and eventually ordered is easily noticeable on this example. The same gap is logically observed for the predictions. The estimated demand on which the stock levels rely on is to be found between the two forecasts (red point). Several ideas have emerged as for the calculation of the adjusted demand that can be determined with a mean or weighted value. Finally, a solution involving the success rates has been selected.

The idea is to set a “target” success rate for each part in order to enhance progressively the real success rate. The adjusted demand is calculated by the proportional quantity that corresponds to this target. By doing so, the stocks are consequently perceptibly overestimated in comparison to the calculations coming from the order’s predictions.

The calculation of the adjusted forecast is the following:

$$Adjusted\ forecast = orders'forecast * \frac{Target\ Success\ Rate}{Real\ Success\ Rate}$$

Equation 28: Adjusted forecast

With:

$$Real\ Success\ Rate = \frac{number\ of\ orders\ in\ the\ last\ 4\ years}{number\ of\ offers\ in\ the\ last\ 4\ years}$$

Equation 29: Success rate

Additionally, a rule is set up to determine the target success rate. It is displayed in Table 22 and has been elaborated only from a theoretical point of view, meaning it is bound to evolve in practice.

| Real Success Rate ranges from… | …is increased by… |
|---|---|
| **0 to 20%** | 20% |
| **20 to 40%** | 15% |
| **40 to 60%** | 10% |
| **60 to 80%** | 5% |
| **80 to 100%** | 3% |

Table 22: Rule for target success rate determination

Such a rule seems relevant in several respects. The additional rate is regressive so that more efforts is to be made on low-success rate parts. Also, the rate are relatively low to avoid abrupt variations concerning stocks monitoring. The real success rate is actually a mean on four years, and thus, varies slowly. Enhancing the success rate is a long term challenge.

*For instance, with the previous example:*

Real success rate = 65%

Target success rate = 70%

Forecasts on orders = 732 units

**Adjusted forecast = 732 * 70 / 65 = 788 units**

Important remarks have to be highlighted:

1. The success rate is a very relevant performance indicator; however, the accuracy of its calculation is altered by several specificities of the case study. There exists no connection between offers and orders at FHW, meaning that no data indicates the outcome of an offer (acceptance or rejection, and its reason). The calculation is then only statistical, and does take into account the delays from one year to the other. For example, if an offer is released in December, and the corresponding offer appears only in January the following year, the demand is affected at different times. Hence the necessity of a statistical measure (a mean over 4 years) that is supposed to smooth such irregularities.

2. In some cases, spare parts are sold without any offer. This happens when the customer and the sales service directly handle a sale by joint agreement. Such practices directly affects the quality of sales data, and thus of the forecasts. Success rates can be greater than 100%, which has no signification.

3. The success rates are determined on the frequency of the demands. Due to the reasons previously explained, it is not possible to estimate a success rate on quantities, which would refine the analysis.

The implementation of success rate in the calculation of an adjusted demand is, to conclude, delicate because of the quality of the input data. It must be therefore manipulated carefully not to skew the final results. It is in any case a very good indicator that can possibly be used to refine the strategy mapping.

***Stock control***

The very last lest of the general approach for smart spare part management is the implementation of judicious stocking directives. In reference to the theoretical part of this focusing on this theme (see section 2.5), this phase has not to be neglected as it directly impact the real storage costs and the achieved service level. All the previous efforts are annihilated if such decisions are underestimated.

For the items which have to be kept in stock, the first operative decision is the determination of the **safety stock**. The current practices are not automated, resulting in a manual process, which includes rounding values, and case-to-case decision. Such practices are for now not bound to change rapidly, that is why only an assistance to safety stock calculation is here suggested. The idea is to implement the concept of *service level;* the possibilities are numerous (see section 2.5) but some data are lacking (lead time standard deviation). The suggestion is therefore the following:

$$Safety\ Stock = Z * D_{avg}$$

Equation 30: Suggestion for safety stock calculation

Where Z is the Z-score of the item and $D_{avg}$ is the monthly average demand over a year. The Z score by default set up on 1.65 (representing a service level of 90%). Eventually, a calculation with the standard deviation of the demand would be more judicious, as the patterns are mostly very intermittent.

The same observation is made for demand quantity, only suggested directives are given in this work, as they require the collection of new data for the company. In the case of the (Q, r) policy, the recommended order quantity is the EOQ. This necessarily implies the collection of ordering and holding costs data. In the case of the (s, S) policy, a proposition is to set the target level with the quarterly average consumption.

To conclude on inventory control, an extension of this is worth to be developed to focus on the operative aspect of spare parts management. Also, it is essential to combine theoretical techniques with practical possibilities. The implementation of new control methods is above all a pragmatic process.

## 3.3 Outcome and Evaluation

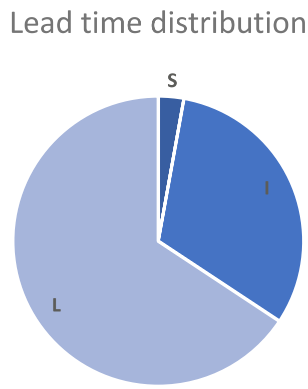
The last part of the work consists in conducting an evaluation of the results coming out of the present achievement. It aims to apply on a real example the spare parts management concept which has been elaborated. By doing so, the implemented techniques can either be validated or adjusted. Secondly, the performance of the tool is assessed through a simulation that compares real stocking decisions to the ones suggested by the tool. It then possible to show the benefits brought by the tool and therefore the relevance to operative implementation. Finally, the whole work is discussed under various perspectives in order to give a critical review of both technical and resulting aspects.

All the following analysis and figures are related to FHW's warehouse (data from 2008 to 2017), which represents a consistent and realistic example to assess the work.

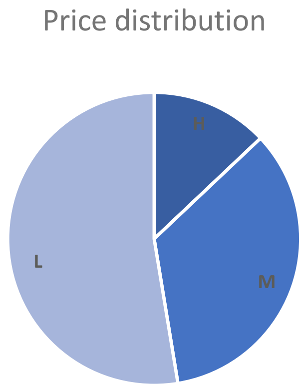
### 3.3.1 Inventory Analysis and Adjustments

First of all, an examination of the inventory is conducted in order to have an overall overview of the parts distributions among the different classes. The results of the examination are given in the tables below.

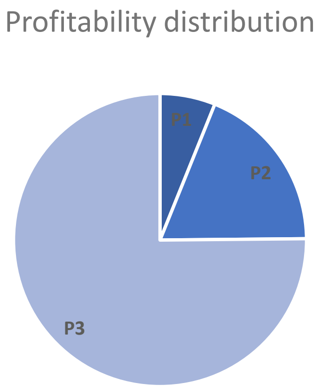
| **Lead Time** | *Number* | *Absolute %* | *Relative %* |
|---|---|---|---|
| **S**hort | 633 | 2,7% | 2,8% |
| **I**ntermediate | 7031 | 29,7% | 31,5% |
| **L**ong | 14674 | 62,0% | 65,7% |
| *Total* | *22338* | *94,3%* | *100%* |
| No Data | 1338 | 5,7% | - |
| *Total* | *23676* | *100%* | - |



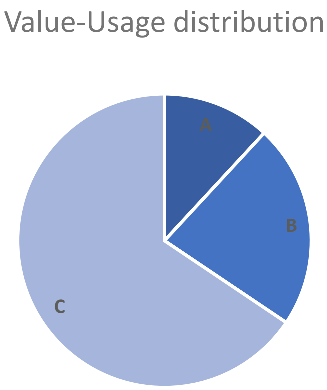

| **Price** | *Number* | *Absolute %* | *Relative %* |
|---|---|---|---|
| **H**igh | 2891 | 12,2% | 12,9% |
| **M**edium | 7698 | 32,5% | 34,5% |
| **L**ow | 11749 | 49,6% | 52,6% |
| *Total* | *22338* | *94,3%* | *100%* |
| No Data | 1338 | 5,7% | - |
| *Total* | *23676* | *100%* | - |



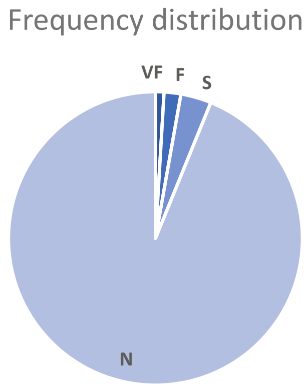
| **Profitability** | *Number* | *Absolute %* | *Relative %* |
|---|---|---|---|
| **P1** | 1250 | 5,3% | 6,1% |
| **P2** | 3840 | 16,2% | 18,8% |
| **P3** | 15389 | 65,0% | 75,1% |
| *Total* | *20479* | *13,5%* | *100%* |
| No Data | 3197 | 13,5% | - |
| *Total* | *23676* | *100%* | - |




| **Value-Usage** | *Number* | *Absolute %* | *Relative %* |
|---|---|---|---|
| **A** | 883 | 3,7% | 11,9% |
| **B** | 1674 | 7,1% | 22,5% |
| **L** | 4872 | 20,6% | 65,6% |
| *Total* | *7429* | *31,4%* | *100%* |
| No Data | 16247 | 68,6% | - |
| *Total* | *23676* | *100%* | - |




| **Frequency** | *Number* | *Absolute %* | *Relative %* |
|---|---|---|---|
| **V**ery **F**ast moving | 85 | 0,4% | 0,9% |
| **F**ast moving | 167 | 0,7% | 1,8% |
| **S**low moving | 305 | 1,3% | 3,4% |
| **N**on moving | 8500 | 35,9% | 93,9% |
| *Total* | *9057* | *38,3%* | *100%* |
| Dead | 9085 | 38,4% | - |
| Nonexistent | 5534 | 23,4% | - |
| *Total* | *23676* | *100%* | - |




| **Variability** | *Number* | *Absolute %* | *Relative %* |
|---|---|---|---|
| Smooth | 1095 | 4,6% | 14,3% |
| Erratic | 560 | 2,4% | 7,3% |
| Intermittent | 5389 | 22,8% | 70,2% |
| Lumpy | 638 | 2,7% | 8,3% |
| *Total* | *7682* | *32,4%* | *100%* |
| New | 1176 | 5,0% | - |
| Dead | 4295 | 18,1% | - |
| Nonexistent | m10523 | 44,4% | - |
| *Total* | *23676* | *100%* | - |

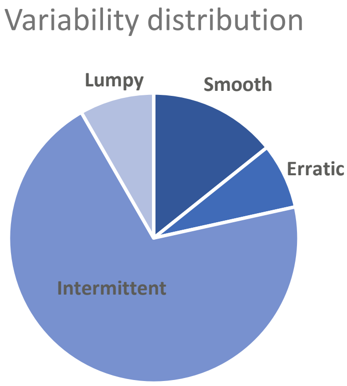



Table 23: Classes distribution at FHW's warehouse

For each classification, some parts do not have the required data, and are therefore excluded of the relative distributions. It appears in this way that **5,7%** of the parts handled by FHW are not registered in the LCC catalogue yet. No value-usage analysis can be determined for these parts, which have to be managed on a case-by-case basis according to their frequency analysis.

The first observation is that the class definition (cut-off parameters) is well suited to FHW's inventory. Price and profitability classes are well balanced: the class that requires most attention is the smallest one, and vice-versa. Also, the ABC classification meets the theoretical distribution (Pareto's principle). The analysis on frequency brings out more unbalanced classes with very small items being very fast, fast or slow moving. This result is yet coherent because it emphasis already the parts that will require the most attentions. Also, this is an expected result for a spare parts inventory as it reflects the very small demand on most items. The choice of the different parameters is then validated, but is still bound to evolve in practice.

Secondly, the strategy clustering has to be assessed. Referring to Figure 35, the distribution among logistics groups is displayed in the table below.

| **Life-Cycle Phase** | Dead or Nonexistent | In-Use | | | | | | New |
|---|---|---|---|---|---|---|---|---|
| **Frequency** | - | VF / F | | | S / N | | | - |
| **Value Usage** | - | A / B | C | | A / B | | C | - |
| **Price** | - | - | H/M | L | H/M | L | - | - |
| **Group** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
| **Number of parts** | **14818** | **205** | **0** | **42** | **1259** | **528** | **3242** | **3582** |
| **%** | **62,2%** | **0,9%** | **0%** | **0,2%** | **5,3%** | **2,2%** | **13,7%** | **15,1%** |

**Table 24: Inventory distribution among logistics groups**

The first observation is that group 3 is empty, which is actually normal because a part cannot have small value-usage with a high or medium price, when the demand is very frequent. Groups 2, 3 and 4 are therefore merged.

Group 5 is quite substantial with more than 1200 items. A closer examination shows that many parts within this group have a very low adjusted demand: more than 1000 items (out of the 1259) have an adjusted demand lower than 5. The (s, S) policy with no safety stock is therefore very judicious, all the more so as many parts will be stocked in small quantities.

A programming mistake explains the amount of parts in group 7: no exception is planned for parts whose value-usage is not assessed. The code assigns these parts mistakenly in group 7 (2406 items). In few cases, this is due to the lack of data (119 items), but the main reason is that these parts have a success rate equal to zero. The actual consumption (corresponding to the orders) is non-existent but the demand still exists. A special group is created for these parts, with a default non-stocking policy which can be adjusted manually by the user.

The adjusted strategy mapping is given in the table below. The groups are rebalanced.

| **Life-Cycle Phase** | Dead or Nonexistent | In-Use | | | | | New |
|---|---|---|---|---|---|---|---|
| **Frequency** | - | VF / F | | S / N | | | - |
| **Value Usage** | - | A / B / C | Non-assessed | A / B | | C | - |
| **Price** | - | - | - | H / M | L | - | - |
| **Group** | **1** | **2** | **3** | **4** | **5** | **6** | **7** |
| **Number of parts** | **14818** | **247** | **2406** | **1259** | **528** | **3242** | **1176** |
| **%** | **62,6%** | **1,0%** | **10,2%** | **5,3%** | **2,2%** | **13,7%** | **5,0%** |

**Table 25: Adjusted inventory distribution among logistics groups**

The final observation is that only 8.5% of the total amount of items require a stocking policy (groups 2, 4 and 5). This figure is actually substantial but is to analyze with a step back considering that the stocks are determined with the adjusted demand quantity which is in many cases close to zero. This means that a significant number of parts whose suggested policy is to be stocked have in practice no actual stock.

### 3.3.2 Performance Assessment

The very last step of the work is to conduct an evaluation of the developed application through the comparison of the current practices at FHW with the suggested decisions provided by the tool. The aim is to show the potential benefits generated by the approach developed in this work. A simulation is carried out on the available set of data of FHW's warehouse from 2008 to 2016; the logistics policies are given for the year 2017. The results are displayed in the table below.

| **Group** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | ***Total*** |
|---|---|---|---|---|---|---|---|---|
| Number of items | 14818 | **247** | 2406 | **1259** | **528** | 3242 | 1176 | *23676* |
| **Current** number of items to stock | 167 | **211** | 87 | **359** | **259** | 568 | 10 | *1661* |
| **Suggested** number of items to stock | 0 | **244** | 0 | **151** | **511** | 0 | 0 | *906* |

Table 26: Stocking policy comparison for the year 2017

The table presents the number of parts that request a stocking policy among the different classes. A part follows a stocking policy when the re-order level is *strictly* bigger than 0. Both current and suggested policies are displayed. The

The first observation is that currently a significant number (167) of items or stocked despite a nonexistent or "dead" demand (group 1), which results in unnecessary holding costs that are avoided with the present approach. This phenomenon is also observable with parts of group 6 (low frequency and low price). It has been here suggested no to stock these parts which are currently partly stocked (568 out of 3242) because their demand is rather unpredictable. The risk of overstock prevails over a stock out.

It appears then that the items that require most attention (group 2) have very close results for current and suggested decisions. This observation confirms the performance of the developed approach in respect of actual decisions, meaning that the decisions provided by the application are very realistic.

The very low number of items to stock for group 4 (151 out of 1259) is due to the large number of parts that have a suggested re-order point of 0, meaning that they to do appear as “parts to stock”. However it is important to notice that a very small number of parts with high value-usage but weak frequency of demand are currently stocked (359 out of 1259). This is suggests a strong idea of improvement for FHW that would results in the generation of more revenues. The same remark appears for group 5 but in different proportion: only half of the parts are currently kept in stock.

The performance assessment conducted in this work only focuses on qualitative decisions. Indeed, the analysis only compares current and suggested stocking policies among the different groups of items. However, a more sophisticated approach to exhibit the benefits from a quantitative point of view has to be carried out. The lack of data is the one of the reasons to the limited evaluation provided in this work. Some important remarks and findings are developed as follows:

- Showing the quantitative benefits of the application relies on the estimation and achieved service level and inventory costs.[1] When assuming that the data of historical stocks levels, holding and replenishment costs are available, it is possible to determine quantitative values to compare costs and service levels. Such an assessment is obviously complex to set up but provides beneficial results on potential revenues and savings.

- The performance assessment presented here is therefore restricted to qualitative observations. No real time data on stock levels, holding and replenishment costs are available. It is then impossible to measure the efficiency of quantitative decisions (reorder levels and quantities). The knowledge of stock levels at any time provides for example the reason of a rejected offer (unavailability or another reason). Consequently, no conclusion on potential revenues and savings are drawn from the present study. Such results can either be obtained thanks to the collection of new data, or thanks to the direct introduction of the application into a practical context.

[1] Bacchetti, Plebani, Saccani, and Syntetos, 2010

### 3.3.3 Benefits and Limitations

This sections provides conclusions on the outcomes of this work from different perspectives. The case study of FHW gives a good example to apply theoretical research in practice, as is directly reveals the advantages of such practices, as well as the difficulties encountered to set them up.

***Benefits***

The elaboration of a concept to manage spare parts with a smart vision has shown the following benefits:

- The major achievement of this work is the development of a **general approach** towards an efficient spare part inventory management. With regard to the current situation at FHW, the application of new concepts is a successful innovation from the outset. Indeed, very little interest is currently dedicated to the improvement of managing methods for spare parts, even though efficiency issues are perceptible.

- The first concrete outcome is the development of a **multi-criteria classification** that allows an accurate knowledge of the inventory. Considering the available data, the classification is for now guided by consumption and value aspects. The parameters to distinguish classes have been identified and validated through the analysis of the parts' distributions.

- A **mapping** for the different logistics strategies is suggested. Even though it is still very basic (only 7 different groups), it provides a first decision-making step that did not exist before. The distinction between "in-use", "dead" or "new" parts brings a very convincing input.

- One main improvement is the introduction **forecasting techniques** that are suited to intermittent patterns. The benchmarking conducted in section 3.2.5 shows the unequivocal superiority of the SBA method over traditional techniques. Also, the optimization of parameters provides concrete values adapted to the study case.

- The consideration of the **success rates** for stock levels calculations appears to be a good finding, as it deals with the main issue encountered by FHW regarding spare parts sales.

- Finally, the **results** of the simulation conducted in the performance assessment are very promising. Expected outcomes are firstly observable: the parts that need the most attention represent a very small share of the overall catalogue, hence the necessity to handle them carefully (strict inventory management). Secondly, the simulation points out the current inappropriate logistics policies for some parts. The consequence is the existence of stock outs or overstocks that have direct impact on revenues of the company.

***Limitations***

On the other hand, the formulation of the work unveiled the following constraints:

- Building a spare parts management concept depends firstly on the **data at disposal**. It has been shown in that case that a criticality criterion (essential regarding spare parts inventory) was not easily measurable, and therefore moved aside.

- Furthermore, the **quality of the data** often restricts the accuracy and the consistency of the results. The absence of a link between the offers and the orders is in that case a good example.

- The outcome of the work concretely suggests the techniques that should be implemented *firstly* when developing a spare parts management program: multi-criteria classification, strategy mapping and forecasting methods. The second stage consists in focusing on replenishment methods as they also have great influence on costs optimization.

- **Computer knowledge** has often been an obstacle to the rapid progression of the application. The elaboration of the Service Database illustrate the difficulties encountered with the numerous exception of the case study, and therefore the necessity to implement the application within the ERP. Also, this reveals the absolute need to involve dedicated IT resources in such a substantial project.

- Arbitrary decisions have been a permanent feature throughout the whole work (class parameters, forecasts data, strategy mapping, etc.). Even though such decisions are based on rational reasoning and experience knowledge, the approach is tinted with a high degree of **subjectivity**. The proposed approach reveals only one possible reasoning that can be modified through numerous parameters. The final deliverable is actually a starting point which is bound to evolve throughout its practical application.

### 3.3.4 Outlook on Further Developments

This section gathers all the potential extensions and future developments of this project that have been mentioned along the work. Also it gives firstly hints on particular aspects that must be dealt in depth.

Concerning the classification, the introduction of a consistent **criticality criterion** seems to be inevitable, especially in a highly intermittent context. The benefit for the company would be a finer analysis of the inventory, and consequently a more elaborate strategy mapping. Results on customers' satisfaction are in the long run to be expected, but this involves investments in terms of resources. More simply, the determination of logistics groups proposed here is bound to evolve quickly in practice.

Also, the maintenance is for now mostly corrective, a big step forward is to couple the current practices with a **predictive maintenance**. A better knowledge of the installed base, and the collection of accurate life-cycle data generate more a more predictable demand, and thus more reliable forecasts. Benefits on stock control are certain with such a combination.

Very little emphasis is given on the operative **control of the inventory**. More sophisticated and especially more adapted techniques are to be developed. Even though it requires the collection of new data (like the ordering and holding costs), the potential benefits on costs minimization are tremendous. This aspect is definitely the priority to complete this work.

Besides, the designed tool has been developed to work for the different warehouses of the organisation. It aims indeed to standardize the practices among the services centers. Further, the objective would be to synchronize the logistics decision on the central warehouse at FHW. For now, no logistics optimization is conducted along the whole chain of supply of the company. A **multi-echelon inventory management** would provide benefits on efficiency and costs.

In the same connection, assuming a very high level of data collection (and quality), a mathematical **optimization of stock levels** would bring spare parts inventory management up to the next level. The concept is to elaborate an objective function that provides decisions through the minimization of the costs, under fixed constraints. The development this type of decision process is complex and demanding but represents the promising future of logistics.

Finally, a main extension of the work relates to its **integration into a computer program**. Indeed, the approach delivered through this work aims to show the potential benefits of a smarter spare parts inventory management. But the final deliverable (the MS Excel application) appears not to be sufficient in a practical working context. Due to the quantity of data required, a reliable and stable database treatment program is vital. Also, the concept must eventually finds its place within the organization's activities, and therefore be easily accessible and usable. Therefore, the implementation of a module dedicated to spare parts management into the ERP software of the company is the probable extension of this work.

# 4 Conclusion

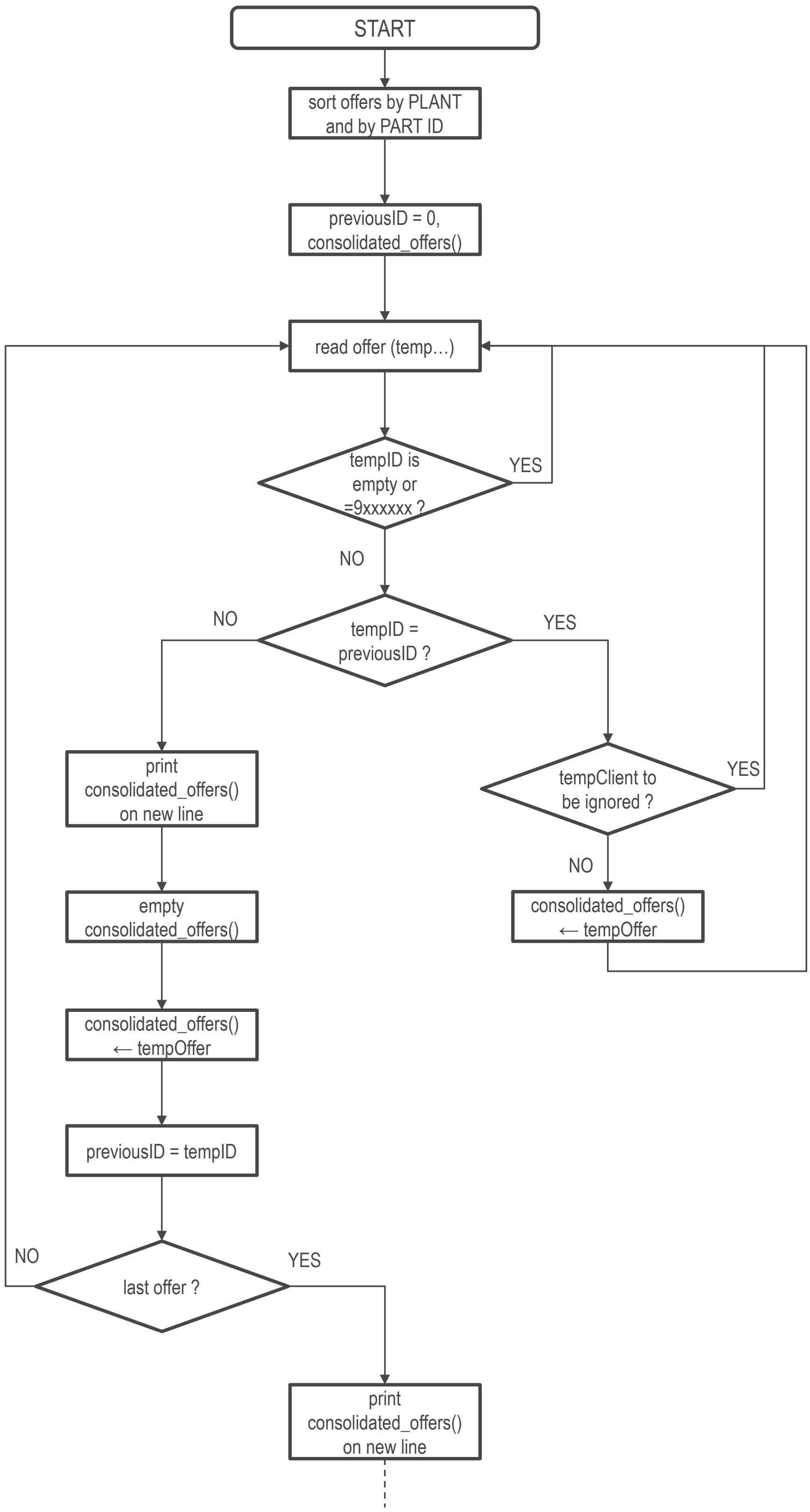
The work conducted through the development of this thesis makes all sense in the current industrial context. In response to both economic and competitive factors, it is vital for capital goods producers to strengthen their after sales activities. Hence the relevance to look at the very profitable management of spare parts. The study realized on a real industrial case enables to draw general findings as for the handling of spare items. Although the academic literature provides a high variety of methods and techniques, practical applications to encourage such practices are missing.

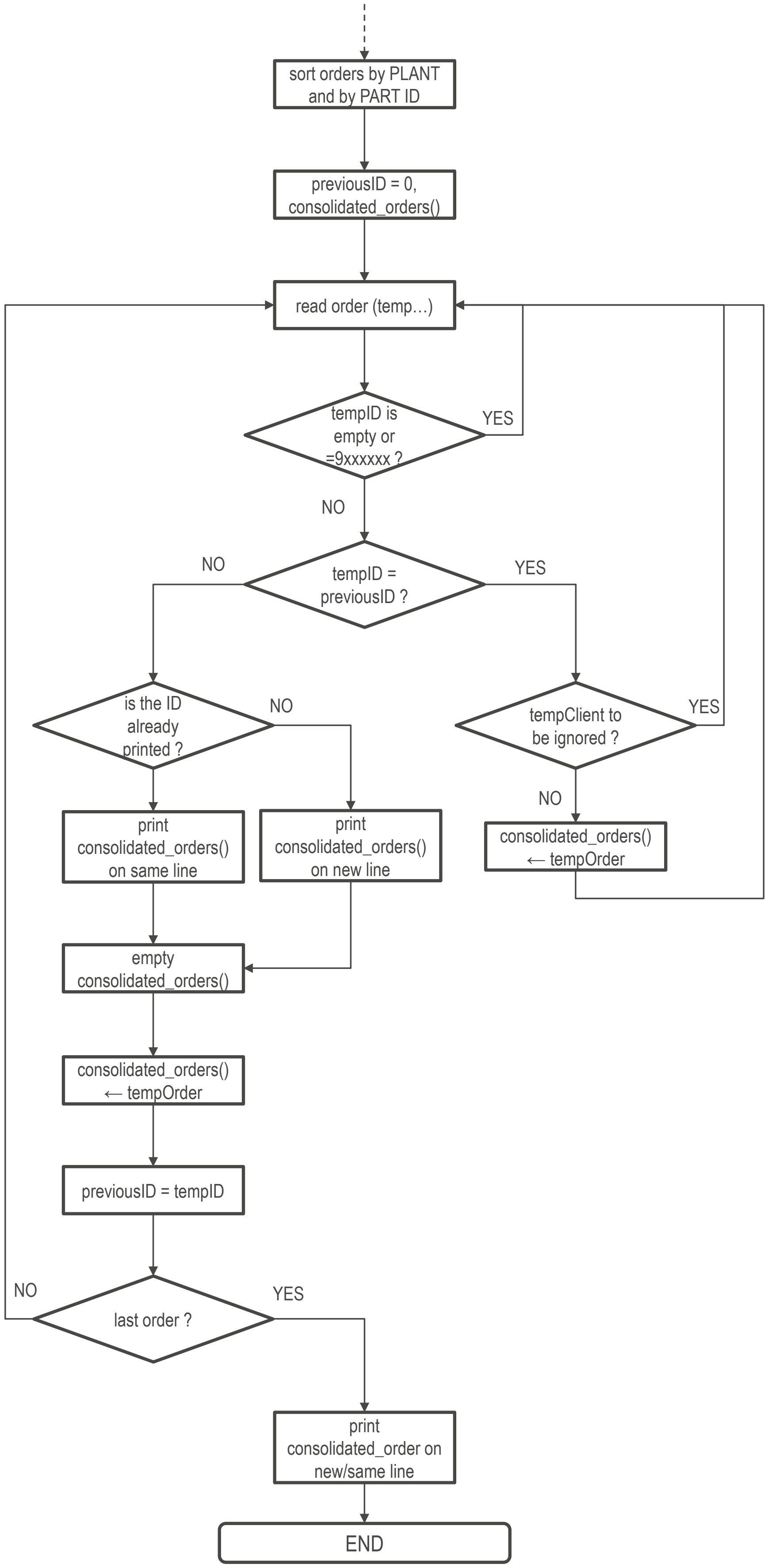
The first key finding of the thesis is that the introduction of a spare parts management approach depends above all on the **data at disposal**. Quality data ensure the reliability of the concept, and their variety allows to implement more sophisticated – and thus more performant – techniques. Hence the necessity to invest in efficient data systems. A second essential observation of the work is that the **field of possibilities** is tremendous, due to the amount of parameters to consider. The advantage is that the range of decisions is very wide, and so, includes more potential. On the other hand, it is sometimes an obstacle to decision-making. The result is that spare parts management is constructed on a high degree of **human judgment**, and consequently, of subjectivity. This feature is related to the specificities of the context: uncertainty and unpredictability. One main input of the work is the practical application of **dedicated forecasting methods** to face, at best, such demand patterns.

It appears also that developing a spare parts concept is a **case-to-case process**, which depends on the special features of the organization: industrial context, type of products, organisational structure, current practices, etc. In this way, the results provided by this work are not replicable as such. The final achievement of the thesis is indeed to propose a **practical procedure and methods** to tend towards efficient and profitable spare parts management. Additionally, it furnishes hints to introduce the very first steps of such directives. It is obvious the introduction of new techniques must be gradual and needs to show actual benefits for the company. The application of a complete, operational and effective system is a long way that requires considerable investments and organizational adjustments. However, the potential benefits are well known, and this should definitely encourage managers to embark upon that path.

# 5 Appendix

## Algorithm for Service Database consolidation




sort orders by PLANT and by PART ID
previousID = 0, consolidated_orders()
read order (temp…)
tempID is empty or =9xxxxxx ?
YES
NO
tempID = previousID ?
NO
YES
is the ID already printed ?
NO
tempClient to be ignored ?
YES
NO
print consolidated_orders() on same line
print consolidated_orders() on new line
consolidated_orders() ← tempOrder
empty consolidated_orders()
consolidated_orders() ← tempOrder
previousID = tempID
NO
last order ?
YES
print consolidated_order on new/same line
END

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# 7 List of Figures

# 8 List of Tables

# 9 List of Equations

# 10 List of Abbreviations

| | |
|---|---|
| ABC | Value-Usage classification |
| ADI | Average Demand Interval |
| AHP | Analytical Hierarchy Process |
| CBM | Condition Based Maintenance |
| CR | Croston's forecast |
| CV | Coefficient of Variation |
| EOQ | Economic Order Quantity |
| ERP | Enterprise Resource Planning |
| FHW | Franz Haas Waffelmaschinen GmbH |
| FSN | Fast, Slow, Non-moving. Frequency classification |
| GMAE | Geometric Mean Absolute Error |
| GMRAE | Geometric Mean Relative Absolute Error |
| HML | High, Medium, Low. Price Classification |
| KIC | Key, Industrial or Commercial part |
| LCC | Life-Cycle Costing |
| LCP | Life-Cycle Phase |
| LT | Linear Trend |
| MdRAE | Median Relative Absolute Error |
| MA | Moving Average |
| MAAPE | Mean Arctangent Absolute Percentage Error |
| MAE | Mean Absolute Error |
| $MAE_{naïve}$ | Mean Absolute Error for naïve forecast |
| MAPE | Mean Absolute Percentage Error |
| MASE | Mean Absolute Scaled Error |
| MSE | Mean Squared Error |
| MTTF | Mean Time To Failure |
| OEM | Original Equipment Manufacturer |
| PM | Planned Maintenance |
| (Q, r) | Fixed order quantity policy |
| ROP | Re-Order Point |
| (s, S) | Order-up-to level policy |
| SBA | Syntetos-Boylan Approximation |
| SES | Single Exponential Smoothing |
| SDE | Scarce, Difficult, Easily available |
| VED | Vital, Essential, Desirable |
| XYZ | Variability classification |