元 智 大 學

工業工程與管理研究所

碩士論文

**Application of Forecasting Methods to Slow Moving Demand Items: A Case Study**

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**TABLE OF CONTENTS**

[TABLE OF FIGURES 6](#_Toc75966256)

[TABLE OF TABLES 7](#_Toc75966257)

[CHAPTER 1 INTRODUCTION 8](#_Toc75966258)

[1.1. Research background 8](#_Toc75966259)

[1.2. Research motivation 9](#_Toc75966260)

[1.3. Research objectives 11](#_Toc75966261)

[CHAPTER 2 LITERATURE REVIEW 12](#_Toc75966262)

[2.1. Background about forecasting 12](#_Toc75966263)

[2.2. Categorization of demand patterns 13](#_Toc75966264)

[2.3. The Croston Method 16](#_Toc75966265)

[2.4. The Croston Method Modifications 18](#_Toc75966266)

[2.5. The Aggregate-Disaggregate Intermittent Demand Approach (ADIDA) and the Multiple Aggregation Prediction Algorithm (MAPA) 20](#_Toc75966267)

[CHAPTER 3 CASE STUDY 25](#_Toc75966268)

[3.1. Case Introduction 25](#_Toc75966269)

[3.3. Data Description 27](#_Toc75966270)

[3.4. Problem Formulation 28](#_Toc75966271)

[3.5 Application of forecasting methods for slow moving items 32](#_Toc75966272)

[PRELIMINARY RESULTS 36](#_Toc75966273)

[REFERENCES 39](#_Toc75966274)

# TABLE OF FIGURES

[Figure 1 Demand pattern classification 13](#_Toc75968026)

[Figure 2 William’s categorization scheme 13](#_Toc75968027)

[Figure 3 Demand pattern classification 14](#_Toc75968028)

[Figure 4 Demand patterns 15](#_Toc75968029)

[Figure 5 Croston’s method algorithm 16](#_Toc75968030)

[Figure 6 ADIDA forecasting framework 20](#_Toc75968031)

[Figure 7 Managerial and Systemic Viewpoint of the ADIDA framework 21](#_Toc75968032)

[Figure 8 Aggregation levels of a times series 22](#_Toc75968033)

[Figure 9 Forecasting and combination of a times series 23](#_Toc75968034)

[Figure 10 Agrosavia’s warehouses scheme 25](#_Toc75968035)

[Figure 11 Demand pattern of the items in Agrosavia 28](#_Toc75968036)

[Figure 12 Number of items by type of demand in Agrosavia 29](#_Toc75968037)

[Figure 13 BIP001271 demand pattern (erratic demand) 29](#_Toc75968038)

[Figure 14 BIP008013 demand pattern (intermittent demand) 30](#_Toc75968039)

[Figure 15 BIP005887 demand pattern (Lumpy demand) 30](#_Toc75968040)

[Figure 16 Scheme for evaluating the forecasting process of Agrosavia’s items 34](#_Toc75968041)

[Figure 17 Preliminary Croston method of the item BIP008013 35](#_Toc75968042)

[Figure 18 Preliminary SBA method of the item BIP008013 37](#_Toc75968043)

# TABLE OF TABLES

[Table 1 Monthly demand of Agrosavia’s 27](#_Toc75968085)

[Table 2 Preliminary results of Croston method for item BIP008013 36](#_Toc75968086)

# CHAPTER 1 INTRODUCTION

## Research background

Inventory management has been a long-standing topic in Operations Research. Silver (1981) mentions 8 major problems that are evident in this area of study, from deterministic or probabilistic demand, through the nature of the supply process, to the structure of inventory costs or the useful life of the stock, to mention some of them. However, most of the items that are analyzed in these problems present a constant demand, i.e. that within their variables there is demand in all the periods being analyzed. This is how the study of slow moving items enters the scene.

Firstly, slow moving items have a singular behavior as they have a slow demand, i.e. a demand that fluctuates from low to high during the periods in which it exists, but which has a large number of zeros in the periods under analysis. This can also be defined according to the analysis of the Coefficient of Variation presented by its demand, as well as the Average Inter-Demand Interval, which allows the classification of the demands of these items into smooth, intermittent, erratic and lumpy (Syntetos et al., 2005). Furthermore, this kind of items are very representative in the storages of companies, because they can represent, approximately, up to the 60% of references in a company (Williams, 1984 and Johnston et al., 2003)

With this in mind, the most used forecasting methods to know future demand have been very varied, being exponential smoothing one of them, thanks to the ease with which it can be calculated, as well as the certainty of its results (Gardner, 1985). However, in the case of slow-moving items with intermittent demands, it is not a successful method, because it presents irregularities in the performance of the results (Silver et al., 1998), as well as thanks to the appearance of many zeros during the periods, the forecast will tend towards this value (Wallstrom & Segerstedt, 2010).

For this reason, several forecasting models have been developed, based on the classification of demands. Thus, one of the most important and the one that gave rise to the most accurate results was the one proposed by Croston (1972). This method separates the probability in which the demand occurs and the size of this when it exists, so that it can avoid the bias that appears when using the exponential smoothing. Similarly, to reduce this bias, another variable is introduced, such as the estimated inter-arrival time each demand occurs.

However, some modifications have emerged from this method that have generated more precise results with fewer biases, such as the use of two previous periods, instead of one as in the original (Vinh, 2005). On the other hand, Croston method generated bias, mainly in how the smoothing constant was used, so that in Syntetos & Boylan (2005) the estimator of mean demand involves this constant to update the inter-demand intervals. This is then multiplied by the average demand of the period, based on the Croston method and, thus, correcting this bias. This can be found too in the correction done by Shale et al. (2006), where

On the other hand, there are also other methods that, like those mentioned above, generate results to predict intermittent demands. Such is the case of ADIDA (Aggregate-disaggregate Intermittent Demand Approach), in which the original time series are grouped in larger time units, i.e., monthly data are grouped into bimonthly or quarterly data, this new series is forecast and then it is disaggregated into the same original time unit (Nikolopoulos et al., 2011).

Based on these intermittent demand forecasting methods, there are several fields in which they can be used, not only in the study of the behavior of slow-moving items, but also in the occurrence of natural disasters or data analysis (Nikolopoulos, 2021).

## Research motivation

Most of the studies carried out to the Operations Research, specifically related to the management and control of the inventory, are applied to problems in which the companies are in charge of the production of spare parts or in the production of some article, because most of them respond to the reduction of production costs or the maximization of profits. However, many of them neglect the application of the models developed in this areas to other fields of action, such as companies that directly maintain inventories, but not for the production of articles. The case for which this research is to be carried out is of the Colombian company Agrosavia, which is in charge of developing and executing research, technology, and transfer of technological innovation processes to the agricultural sector and it would be a valuable opportunity to generate some recommendations so that its operation and inventory planning will be more optimal.

Similarly, it is important to highlight that forecasting is one of the most important tasks, within the planning of the operations of a company. Thanks to it, it is possible to anticipate what the future holds, due to the historical behavior of the data to be analyzed. In the case of the company to which this study will be the subject, the demand for basic operating supplies will be the main product to be analyzed.

Within the forecasting methods that exist today, all of them have been applied to environments where the demand has been constant, i.e., in each period there is a constant consumption of products, whose variation in the size of the demand is minimal. However, there are cases in which there are items, whose demand is sporadic or slow moving demand items. That is the case of the company to be studied, most of its products present this type of demand, which leads them to carry out purchase orders in a disorganized way, to have high inventories in periods where it is not necessary to have them, leading to increase their holding companies. costs.

In this way, the study proposes to evaluate the type of demand for basic operating products that Agrosavia has, through the Coefficient of Variation and the Average Inter-Demand Interval (ADI), so that certain forecasting models can be applied to items with slow moving demand, mainly those that are based on the Croston method, who was the pioneer in studying this phenomenon, and aggregation approaches. Besides, the methods based on Croston and aggregation generate more accurate forecasts than traditional methods, such as Simple Exponential Smoothing or methods related to Moving Average.

## Research objectives

The main objective of this research is to analyze the behavior of the demand for the supplies of the Agrosavia company inventory system, according to the forecast models applied to the most well-known slow moving demand problems in order to recommend to this company the application of the one that presents the best results. In this way, the specific objectives will be seen down below:

1. To classify the demands of the supplies in the Agrosavia inventory system.
2. To apply forecasting methods specifically designed for slow-moving demand patterns.
3. To measure the precision of these models, by comparing the errors they demonstrate
4. To recommend to the company the most practical method and to present the most accurate predictions.

# CHAPTER 2 LITERATURE REVIEW

## 2.1. Background about forecasting

The ability to forecast can be defined as the prediction of an event that may occur in the future. Usually, this tool can be used in various economic sectors, such as industry, businesses, government, environmental sciences, finance, among others, through the use of time series, or chronological observations of a specific variable, which can range from the viscosity of a product, until the demand for some item (Montgomery et al., 2016). In the same way, it is one of the most important tasks associated with Operational Research and Supply Chain Management, thanks to the fact that with forecasts, more accurate decisions can be made (Nikolopoulos, 2021).

Within Supply Chain Management, many of the actors that are within it seek to optimize their inventories, which is manifested in the reduction of their costs, i.e., improve the accuracy of forecasts and reduce their inventory levels, in addition to improve business competitiveness (Tliche et al., 2020). The lack of forecasting processes or their poverty can lead to situations of stock out or overstock, which would reduce profits and customer satisfaction (Steenbergen & Mers, 2020). For this, in some cases it is necessary that the method to be applied has to be simple and easy to apply and interpret (Stevenson, 2009 and Tliche et al., 2020). Some of these are so simple, such as Naive, where the predicted period is equal to the immediately preceding period (Stevenson, 2009; Ryu & Sanchez, 2003; Spithourakis et al., 2014), but with the high probability that its precision is not very adequate. On the other hand, there are more complex and widely used methods, in which the mean is used as a mechanism to smooth the variations in the data. Among these, there is the Simple Moving Average (SMA), the Weighted Moving Average (WMA), using different weights as the values are more recent, or the Simple Exponential Smoothing (SES), where each forecast is based on the previous one, adding a percentage of error to the difference between these two values (Croston, 1972; Gardner, 1985; Syntetos & Boylan, 2005; Billah et al., 2006; Stevenson, 2009; Wallstrom & Segerstedt, 2010).

However, in most cases where these methods are applied, the time series are constant or show a definite pattern, mainly in the forecast of demand. There are other scenarios where this indicator presents irregularities, so that the previously proposed methods are not enough to generate correct forecasts (Dunsmuir & Snyder, 1989; Johnston et al., 2003; Uzunoglu & Tamer, 2011; Santa Cruz & Corrêa, 2017)

## 2.2. Categorization of demand patterns

Within the issues related to inventory management, it is important to note that the classification of items that a system has facilitates the application of techniques or models to process them. The ABC classification, one of the best known, distributes in each of these letters the monetary weights and the quantity that an item represents in the inventory. However, the classification of items through the behavior of their demands shows those that have fast moving demand, which common forecasting methods would be applied (Syntetos & Boylan, 2005), and slow moving demand.

To categorize demand, Williams (1984) proposes a method in which he performs a partition of the demand variance during the lead time (DDLT), into smaller parts, that is, in the variance of the number of orders arriving, the variance of the size of these orders and the variance of the lead times, giving rise to the following equation:

(1)

Where *λ* is the mean of the number of demands, occurring at a random stream, is the mean of the lead time and *Cx*, is the coefficient of variation of the distribution of order size. Hence, the two products obtained can be explained separately: represents the mean number of lead times between demands, while represents the intermittence in demand. Thus, Figure 1 shows how the interaction of these two variables is observed, establishing 4 types of demands: type A or low sporadicity, B or slow-moving, C or frequent demand with large variable sizes, and D or with high sporadicity.

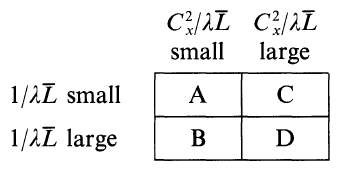


Figure Demand pattern classification (Williams, 1984)

To determine the maximum limits of lead times and intermittency at which an item could be in certain categories, Williams (1984) proposed Figure 2, which additionally shows a division of the items with type D demand into sporadic demand, D1, and highly sporadic demand, D2. (Syntetos et al, 2005).

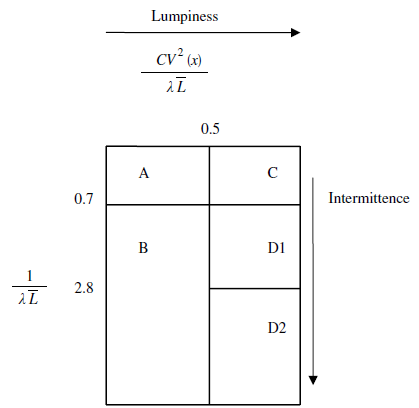


Figure William’s categorization scheme (Syntetos et al., 2005)

Later, the classification of demands would be modified a little. Thanks to the comparison of the EWMA, Croston and SBA methods (which will be explained later), mainly their MSEs, to establish which of them could better predict slow moving items, Syntetos et al. (2005) propose new cut-off points to the model proposed by Williams, which would be defined by calculating the square of the Coefficient of Variation and the Average Inter-Demand Interval (p). In the same way, it is evident in Figure 3 that the intermittent Williams demand patterns are consolidated into a single category (Boylan et al, 2008).

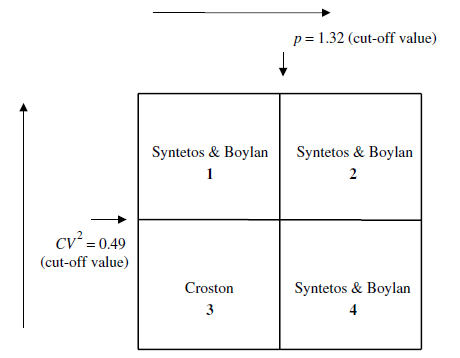


Figure Demand pattern classification (Syntetos et al. 2005)

As can be seen, the categories are practically divided in the same way as Williams. However, the names given to each of them are as follows:

1. Erratic, but not very intermittent.
2. Lumpy
3. Smooth
4. Intermittent, but not very erratic.

It is important to define each of them. An erratic demand means that the size of it is highly variable. On the other hand, intermittent demand has the characteristic that it occurs infrequently. As for lumpy, it could be said that it is the fusion of intermittent and erratic, that is, an intermittent demand that, when it occurs, is highly variable (Boylan et al., 2008). Meanwhile, smooth demand is the most constant of them. Observing it graphically, the classifications of the demand patterns can be similar to the following examples, where it can be seen the limit points of the squared Coefficient of Variation and the Average Inter-Demand Interval (ADI):

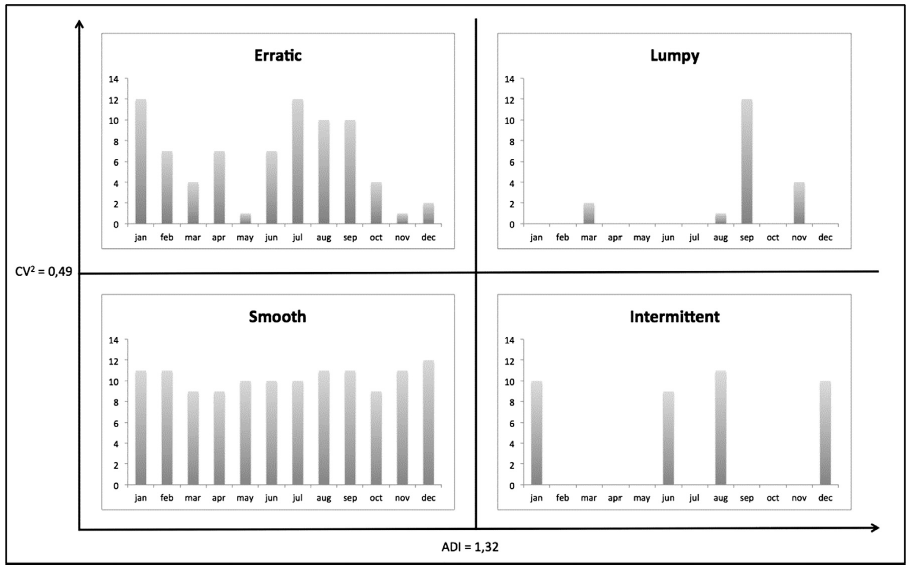


Figure Demand patterns (Costantino et al, 2018)

## 2.3. The Croston Method

Commonly, to forecast the demand for some product, one of the most used methods is Simple Exponential Smoothing. This tool is very popular, thanks to the ease that it can be executed and the generation of precise results (Gardner, 1981). However, when focusing on more specific problems, such as the forecast of slow moving items and the appearance of large amounts of zeros in the time series, the results may tend towards this value, losing all precision (Wallstrom & Segerstedt, 2010).

Croston (1972), proposes a two-part model that modifies the SMS to give more accurate results. These two parts are the size of the demand and the number of periods that occur between demands, i.e., the inter-demand interval. With these two variables, he establishes the following algorithm:

Start

Next t

End

No

Yes

Yes

No

Figure Croston’s method algorithm (Şahin et al., 2013 and Xu et al., 2012)

Where:

* : demand in period *t*
* : forecast of the next non-negative demand beyond the period *t*
* : Forecast of the average demand per period
* : forecast of demand interval
* : interval since the last non-negative demand
* : smoothing constant
* : smoothing parameter for inter-demand intervals

In this way, it can be seen in figure 5 that this method is only updated if there is demand in the period in which it is going to be forecast, i.e., if the demand in the period is equal to zero (), the forecast () will be the same value that was predicted in the previous period, similar to the forecast of the demand interval (). In the end, the ratio between () and () will be the average estimate of demand for the next period.

This method has been used in several cases where the problem of slow moving items exists. Xu et al. (2012) compiles several of the studies in which this method contributed to the study of the behavior of these items. Among them is the improvement in the results, compared with traditional methods such as EWMA (Willemain et al, 1994), mainly with ADI's higher than 1.25 (Johnston & Boylan, 1996) or using less than 0.15, because as this constant increases, there is an increase in the forecasting bias, which gave rise to the first modification to the Croston method or the SBA method, in honor of its authors (Syntetos & Boylan, 2005).

## 2.4. The Croston Method Modifications

One of the most interesting modifications that the Croston Method has undergone, explains that, instead of taking only the previous period with non-negative demand to make the forecast by demand period (), the last two should be taken . This would specify the effects of the forecast in general, besides that thanks to the irregular demand, the past trends would not affect the final result. This, when measured and compared with the Mean Square Errors (MSE) of the Croston method, showed greater precision (Vinh, 2005). This modification is calculated as follows:

(2)

This was applied too to the forecast of the demand interval (), resulting in this formula:

(3)

For the average demand per period , the ratio is calculated in the same way as in the Croston mode.

After having made the corresponding comparisons and evaluating the existing forecasting methods, Syntetos and Boylan (2005) find that the Croston method presents bias, mainly when calculating the average demand in the period (). In this way, they propose that the ratio between and be multiplied by the smoothing constant for inter-demand intervals divided by two and subtracted from 1, like this:

(4)

To verify that the results of the SBA model were solid, they were compared with the Croston method, SES and Simple Moving Average and, thanks to the evaluation of the performance of the Mean Signed Errors (thanks to its ease of calculation and its easy interpretation) and the Geometric Root Mean Square Error (since it immediately compares the level of precision of all the methods), it was unanimous that this new method corrected the bias and presented more accurate forecasts (Syntetos & Boylan, 2005).

However, the fact that these modifications exist does not prevent the Croston Method from being used. In some cases, it presents better performance when applied to items with smooth demands (Syntetos et al., 2005 and Kaya et al., 2020) or to items with intermittent demands (Kaya et al., 2020). Even other modifications to the Croston method were based on the correction of the smoothing factor proposed by Syntetos and Boylan, but extending the use to demands with Erlang and Gamma type distributions (Shale et al., 2006). In this last case, the correction factor replaces the one proposed in the SBA, hence the forecast of the Average Demand will be denoted by:

(5)

However, the study of forecasting models for slow moving items does not apply only to these mentioned ones. Leven and Segerestedt (2004) used the same Croston method, but this was updated as long as there was positive demand, which would update the predicted periodic demand, using the formula proposed by Croston. However, this method was not successful, as it continued to show bias (Boylan & Syntetos, 2007 and Segerstedt & Leven, 2019). On the other hand, another related method is the TSB, granted by the initials of its creators (Teunter et al, 2011), in which the demand is modeled and updated probabilistically, instead of the demand interval, which would allow the demand Each period will be updated, not only when a period has positive demand, so that the obsolescence of the items can be viewed more easily and how this affects their demand.

## 2.5. The Aggregate-Disaggregate Intermittent Demand Approach (ADIDA) and the Multiple Aggregation Prediction Algorithm (MAPA)

One of the least explored factors in the analysis of time series of items with slow moving demand is the possibility that these are subject to a temporal aggregation. This is understood as an activity in which a low-frequency time series, such as bimonthly or biannual, originates from a high-frequency one, such as monthly or weekly. The application of forecasts to series with high aggregation, usually, is more precise, than with its counterparts with low aggregation. If this is applied to a series in which the majority of periods are composed of zeros, the periods with demand would be closer, so the intermittency would be reduced and it would be easier to forecast with simpler methods. The ADIDA method (Aggregate-Disaggregate Intermittent Demand Approach) (Nikolopoulos et al., 2011) has within its philosophy this concept explained above. Additionally, this method tends to perform a non-overlapping aggregation.

The way in which the authors developed this method was exemplifying a monthly series with high intermittency. Later, it was added to a new time series on a quarterly basis, showing a much more uniform demand, but with inherent instability. In this way, a forecasting method is applied that allows the next period of the aggregated series to be extrapolated. Once this is done, the quarterly series is disaggregated into the original time units, for the following months, according to the same weights, i.e., if they are the next 4 months, 1/4. (Nikolopoulos et al., 2011)

The graphic form of this description can be seen in figure 6:

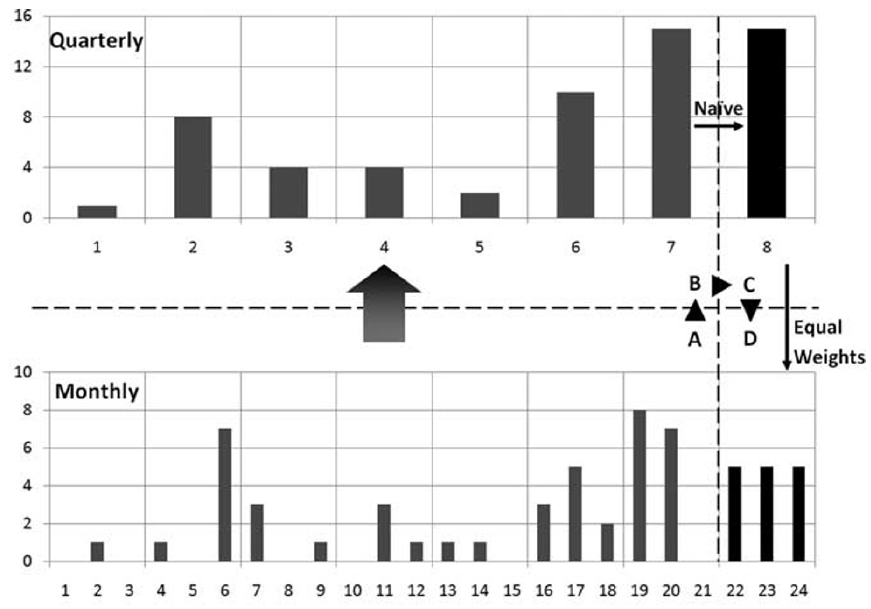


Figure ADIDA forecasting framework (Nikolopoulos et al., 2011)

Where (Spithourakis et al., 2014):

* (A) Obtaining the original data on its lowest timescale.
* (B) Performing the aggregation at a lower level. This step has nomenclature A for aggregation.
* (C) Application of forecasting method to extrapolate. This step has nomenclature F for forecasting.
* (D) Disaggregation of the forecast on the original time scale. This step has nomenclature D for disaggregation

Given that this method facilitates the flexibility of the use of other tools during the forecasting part, as well as its application to intuitive thinking, ADIDA can also be viewed from a systematic point of view (Spithourakis et al., 2014), where the aggregation steps (A) and disaggregation (D), have equivalences with the application of the Simple Moving Average (SMA) and the Weighted Moving Average (WMA), respectively. This can be seen in Figure 7.

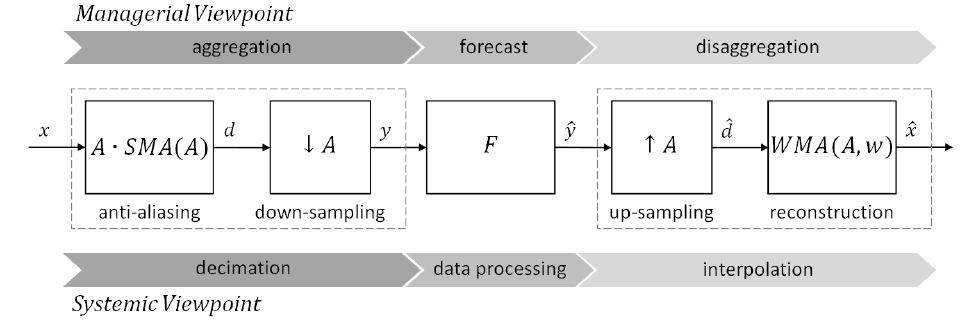


Figure Managerial and Systemic Viewpoint of the ADIDA framework (Spithourakis et al., 2014)

Where:

* : initial time series
* : averaged time series (i.e. series after SMA filtering)
* : aggregate time series
* : forecast model for aggregate series
* : downsampled aggregate forecast model
* : forecast model for initial series

The systematization of the ADIDA method facilitates the standardization of each of its steps, in a mathematical way, so that the data is reduced through a decimation process, preceded by the SMA, which becomes an anti-aliasing filter. By applying an extrapolation method to forecast (a method that can be used freely), data processing is performed. At the end, the aggregate series is interpolated, disaggregated by means of the WMA as a reconstruction filter (Spithourakis et al., 2014)

However, one of the main drawbacks of ADIDA's approach is to know what is the optimal level of aggregation to which the original series should adhere. Nikolopoulos et al. (2011) proposed that the best way was to use the lead time plus a review period, which would help improve decision-making for inventory control. In this way, to review and obtain a better optimization in the search for the level of aggregation, Kourentzes et al. (2014) proposed an algorithm called MAPA or Multiple Aggregation Prediction Algorithm, even combining it with slow-moving items forecasting methods (Petropoulos & Kourentzes, 2014). This method takes the philosophy of ADIDA, on aggregation and disaggregation, but instead of taking a single level, it considers time series subjected to several levels of aggregation simultaneously, obtaining the benefits that each of them can bring to the final forecast, and then combine them. all in a final forecast.

In principle, this algorithm has three stages: aggregation, forecasting and combination. In the first of them, taking the arithmetic mean as the aggregation operator, a time series is added at different levels of aggregation, that is, if it is monthly, it can be added to up to 12, so that this would be a level in which the data are grouped by year (which has 12 months), as seen in Figure 8 and the power indicators, showing where the seasonality or trends are visible. Having all the aggregation possibilities, these must be predicted.

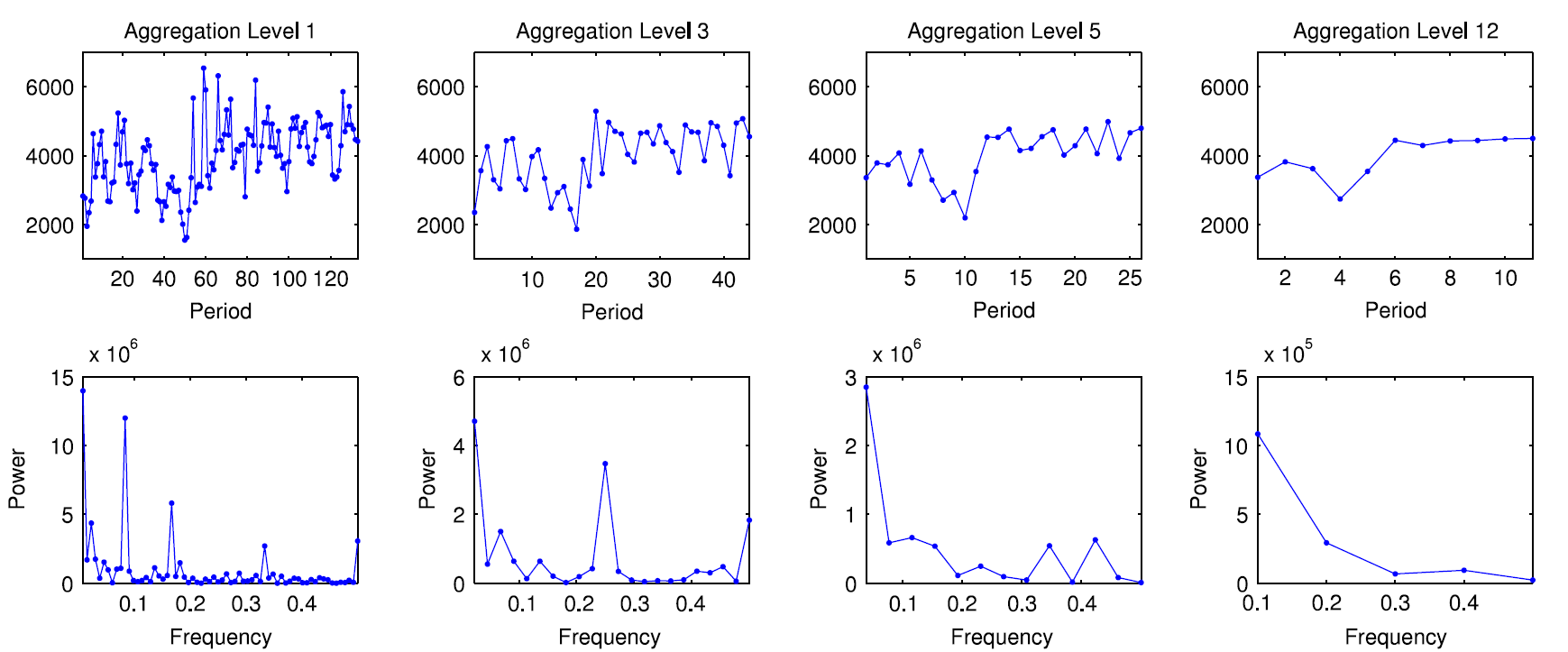


Figure Aggregation levels of a times series (Kourentzes et al., 2014)

Due to its flexibility and its wide use, the models based on the Simple Exponential Smoothing are applied to these time series, depending on the type of component that it presents, that is, if it has seasonality or trend. As it is seen in Figure 9, these components are transformed into others with additive characteristics, to later obtain the final components that will be combined in the last step. Finally, to combine them successfully, each component must be mixed independently of the others, without the need to adjust their level thanks to the use of the mean as an operator, through the unweighted mean and the median.

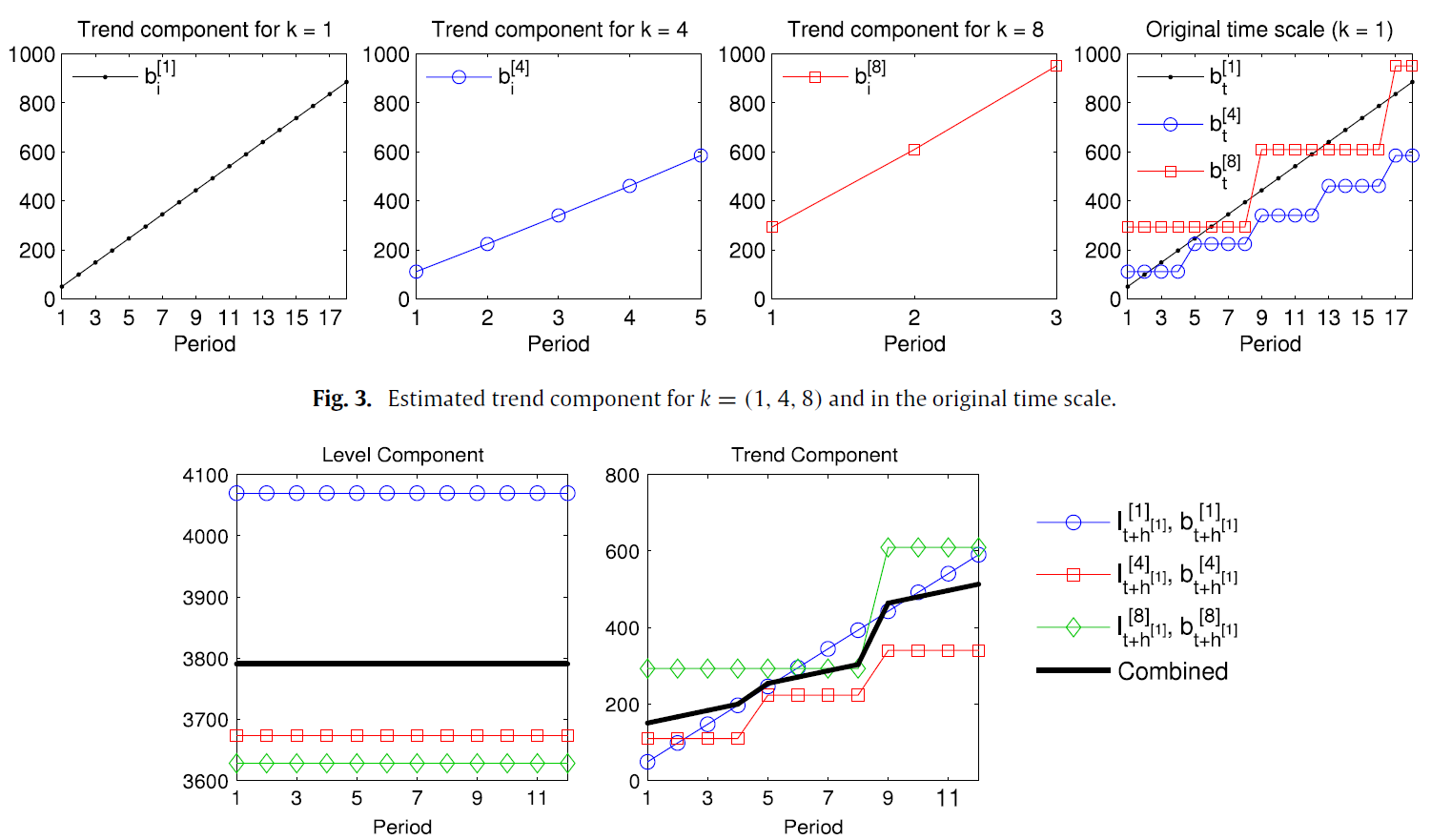


Figure Forecasting and combination of a times series (Kourentzes et al, 2014)

# CHAPTER 3 CASE STUDY

## 3.1. Case Introduction

As mentioned above, the company under study is the Agrosavia agricultural research center, which has several laboratories where the necessary experimentation processes are carried out. In addition, Agrosavia has several research centers throughout the country. However, where this research will focus is the main headquarters (Tibaitata), since it is the largest and where most of the research laboratories are located.

In relation to the subject of inventory, Agrosavia uses a great variety of materials, because each laboratory needs very specific chemical elements, which will only be needed at essential moments and will not be analyzed in this research. However, the materials that this entity calls "basic equipment" are those that the laboratories, as well as administrative and other areas, use to develop their basic operations, i.e., the ones that are ordered and consumed more frequently. It should be noted that some of them are also chemical elements, but these are materials that have a more common demand, because, although they are specific to each project, they are only ordered when starting or developing a project and, usually, these are different, which will make them last in the laboratory warehouse for a long time.

This company has a scheme of warehouses, divided into 3 echelons:

* A main warehouse, which conglomerates all the necessary supplies for the operation and distributes to the administrative units of the company
* An intermediate warehouse called "Cathedral", which receives supplies from the main warehouse and distributes exclusively to research laboratories.
* The laboratory storage, which receive the submissions from Cathedral and, to a lesser extent, from the main warehouse.

Principal warehouse

Cathedral

Figure Agrosavia’s warehouses scheme

In this way, the company has an ERP that allows it to manage internal processes, including requests for items that each laboratory needs. However, Agrosavia does not sell any of the items requested, because these are used for research. Besides, there is no control of the demand for items that are requested from the main warehouse. For this reason, there have been cases of products that remain in the main warehouse or in the Cathedral for a long time, generating cost overruns. For the development of this research, due to the lack of defined demand, the outputs of articles from the warehouses will be used as the demand for the corresponding item, because when an article leaves the warehouse, it is because it has been used.

**3.2. Problem Description**

The main inventory problem that this company has is that most of the items have very few outlets, that is, the demand for them is very slow. This indicates that the company does not adequately forecast the consumption of these supplies, in addition to the fact that conventional methods do not generate accurate results, due to the large number of periods that present demands equal to zero. Similarly, the company does not present a classification of these items according to its demand, so it would be inaccurate to apply a standard forecasting method to items with irregular behavior.

## 3.3. Data Description

The data that was used to do this research was provided directly from Agrosavia, from December 31, 2017 to November 2020. These two dates are taken, because the first marks the implementation of the new ERP system that the company hired, grouping all the previous balances as an initial inventory, while the second is the last record delivered by the company. On the other hand, the items used for the analysis are those that are part of the inventory of "basic equipment", because they are one of the items that Agrosavia most requests to carry out the main tasks within the administrative areas, as well as the basic tasks in laboratories. This classification does not take into account the individual demand for each product or those materials that laboratories use in specific projects, so they can be considered as supplies or “spare parts” of the main “production line”, which is the development of research services related with agriculture.

The number of items used was 79, because they were the ones that started 2018 with initial inventory. Each of these item has a specific and unique SKU (Stock Keeping Unit), which acts as an identifier of what and where is the item in the whole inventory system of the company. All the entries, transfers and exits found within each of the storages (main, Cathedral and the eight laboratories) were grouped to review the behavior of each of the items. Subsequently, the exits are taken as the demand for the items and aggregated in a low frequency time series, i.e., from daily to monthly data. In the same way, the number of zeros between periods and the months that are in demand is established, resulting in the following matrix (See Appendix A to see the whole data):

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Dec-17 | Jan-18 | Feb-18 | Mar-18 | Apr-18 | May-18 | Jun-18 | … | Total | Zeros | Months with exits |
| BIP001271 | 0 | 10 | 16 | 13 | 22 | 49 | 28 | … | 686 | 4 | 33 |
| BIP003819 | 0 | 0 | 36 | 0 | 36 | 31 | 3 | … | 1095 | 8 | 29 |
| BIP001998 | 0 | 1 | 8 | 0 | 7 | 7 | 4 | … | 838 | 8 | 29 |
| BIP002015 | 0 | 1 | 1 | 0 | 7 | 16 | 0 | … | 2098 | 8 | 29 |
| BIP002010 | 0 | 0 | 5 | 0 | 8 | 6 | 0 | … | 125 | 11 | 25 |
| BIP002898 | 0 | 0 | 0 | 0 | 0 | 6 | 5 | … | 96 | 15 | 22 |
| BIP001266 | 0 | 0 | 13 | 0 | 3 | 0 | 0 | … | 283 | 16 | 21 |
| BIP007983 | 0 | 0 | 9 | 4 | 7 | 0 | 0 | … | 94876 | 18 | 19 |
| BIP002983 | 0 | 0 | 0 | 0 | 10 | 6 | 0 | … | 304 | 19 | 18 |
| BIP005889 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | … | 99 | 20 | 17 |
| BIP008645 | 0 | 1 | 3 | 0 | 15 | 0 | 0 | … | 4829 | 20 | 17 |
| BIP005467 | 0 | 0 | 100 | 0 | 0 | 0 | 0 | … | 56101 | 20 | 17 |
| BIP008920 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | … | 4875 | 19 | 18 |
| BIP009107 | 0 | 0 | 0 | 0 | 0 | 170 | 50 | … | 1169 | 21 | 16 |
| BIP006806 | 0 | 0 | 0 | 1 | 0 | 6 | 0 | … | 41 | 22 | 15 |
| BIP005887 | 0 | 0 | 2 | 0 | 10 | 52 | 0 | … | 201 | 21 | 16 |
| … | … | … | … | … | … | … | … | … | … | … | … |
| BIP001964 | 0 | 0 | 0 | 0 | 0 | 2 | 0 | … | 29 | 28 | 9 |
| BIP008771 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | … | 25 | 35 | 2 |

Table Monthly demand of Agrosavia’s

## 3.4. Problem Formulation

Due to the lack of application of forecasting methods to the demand of the items belonging to “basic equipment: that Agrosavia has, the first step to develop precise methods is to classify the type of demand that these items have. In this way, the ADI (Average Inter-Demand Interval) and the Coefficient of Variation are calculated, applying the following equations respectively:

(5)

(6)

Where:

* *N*: Number of non-zero demand interval
* *ti:* time period between two consecutive demand periods
* *di:* demand value at time i of the item
* : average demand of the item

It is important to highlight that, to identify the type of demand that the Agrosavia inventory system has, only the average of the periods that have demand is taken into account and not the total periods, unlike the normal variation coefficient. This same situation can be identified in the calculation of the Average Inter-Demand Interval (ADI).

Figure Demand pattern of the items in Agrosavia

Thus, as can be seen in the figure 11, most of the items show a tendency to have intermittent demand (quadrant 4) and lumpy demand (quadrant 1). This is shown, because these items have an ADI higher than 1.32, that is, the average periodicity in which demand occurs is more than 1.32 periods or, in this case, months. This, when contrasting with the models of Syntetos et. al (2005), could justify the application of the method that Syntetos & Boylan propose (2005). Based on the above, Figure 12 shows the number of items that belong to each of the types of demand. It is important to note that, from the beginning, no item of the company has a constant demand, so no evidence of Smooth Demand will be shown.

Figure Number of items by type of demand in Agrosavia

To better illustrate how the demand types of some of the items are observed, Figures 13, 14 and 15 show the erratic, intermittent and lumpy patterns, respectively.

Figure BIP001271 demand pattern (erratic demand)

Figure 13 shows that there is a much more constant periodicity of demand, but the quantities of this are much more irregular, having some high peaks in May 2018, April and August 2019 and October and November 2020, and very small demands. in February and June 2019 and in June, August and September 2020 (these last two months with zero demand)

Figure BIP008013 demand pattern (intermittent demand)

Although the first months of figure 14 do not show any demand, in the subsequent months there is only an irregular peak, in December 2018, and more regular consumption in the following months. However, having a more stable demand in quantities, but less inconsistent in periods of occurrence, the characteristic intermittency of this pattern of demand is observed.

Figure BIP005887 demand pattern (Lumpy demand)

Finally, figure 15 shows two very high peaks of quantities, May 2018 and July 2019, but with quite low consumption in the previous, intermediate and subsequent months. Similarly, the occurrence of these two peaks is almost a year, for which the irregularity in the periods of demand is also evident. Knowing the behavior of the demand of the Agrosavia items, in part 3.5 the application of the chosen models to forecast these slow-moving demands will be expanded, as well as the error measurement mechanisms, so that in chapter 4 it will be possible to discuss about the accuracy of each model and conclude which is most beneficial to the company.

## 3.5 Application of forecasting methods for slow moving items

According to the number of items that were presented to analyze their demand patterns, some of them did not have enough data within the time series, i.e., they had 1, 2 or 3 demand periods, so it was decided not to use them within the application of forecasting methods for slow moving items. Thus, of the 79 initial items, 59 of them were taken to be analyzed by the Croston method (Croston, 1972), the SBA (Syntetos & Boylan, 2005), the Aggregate-Disaggregate Intermittent Demand Approach or ADIDA (Nikolopoulos et al, 2011) and the Multiple Aggregation Prediction Algorithm or MAPA (Kourentzes et al. 2014). Similarly, as seen in Figure 3, Boylan et al. (2008) had proposed the application of the Croston method and the SBA, depending on the type of demand that each of the analyzed items will present. However, in this study all the methods will be taken into account, to analyze which of them performs better in the entire Agrosavia system.

As mentioned, the Croston method was the pioneer in establishing a way to forecast items with irregularities in size and periodicity of their demands. In this way, Croston, based on Exponential Smoothing, decided to separate the components of this method in the demand size and the interdemand interval. Its modifications have focused on the reduction of the bias that this initial method presented, mainly taking two previous periods instead of one (Vinh, 2005), or in the approximation of the calculation of the average demand through the use of the smoothing constants (Syntetos & Boylan 2005 and Shale et al. 2006).

It is important to highlight that, for the application of these methods, the mathematical rigor that must be followed is important. In this way, calculations and predictions were carried out using the R programming language, which is quite accurate for statistical analysis. Additionally, there is a library designed by Kourentzes and Petropoulos (2016) called “*tsintermittent*”, specialized in forecast of intermittent time series, where the functions to be analyzed are already parameterized. In this way, it is important to show how each one of them works.

Using the crost () function of the previously mentioned library, the forecast can be obtained using the Croston method. What this function performs is to take the demand sizes that are different from 0, as well as the periods in which that demand occurs and each one is predicted by means of Exponential Smoothing. However, it differs from this method, as it mixes the two parameters as a whole. To execute it, it is necessary to specify the number of periods to be predicted, so for this study, 5 months will be established. Similarly, it is important to specify the value of the exponential smoothing, which will be 0.15, according to what was recommended in Syntetos & Boylan (2001) and Teunter & Duncan (2009). In addition, other 4 values for alpha will be executed, in order to diversify the analysis and consider more options for the final recommendation.

With the modifications, the process is similar, because it is the same Croston method, but adjusted to each of the concepts that they establish. Thus, to apply the approximation proposed in the SBA model, the type of modification must be specified in the crost () function, in this case 'sba'. The same occurs with the Shale-Boylan-Johnston (2006) correction, 'sbj'.

On the other hand, the library "*tsintermittent*" also includes a useful function to facilitate obtaining ADIDA. As explained in chapter two, this method adds a high-frequency time series into a low-frequency time series, then is forecasted, and this prediction is disaggregated into the original time series. Similarly, to find the "optimal" level of aggregation for the time series, Nikolopoulos et al. (2011) explain that lead time should be used plus a review period. However, as the lead time of the items in this study is not known, there will be a lead time of 1, so the temporary aggregation will be done bimonthly. Nevertheless, to implement the MAPE method, the process is very similar with ADIDA, but offering a much broader aggregation, testing several temporary aggregations simultaneously, resulting in the one that is more optimal for the original series. In this way, the imapa () function can be executed for the two scenarios outlined above: if the periodicity of the series is specified ('minumumAL =' parameter) and the "optimal" aggregation ('maximumAL =' parameter), the function will show the results for the ADIDA method. Otherwise, if no minimums or maximums are revealed, the function will calculate the MAPE method, by means of the actual optimal aggregation that it has found.

Finally, to evaluate the reliability of the forecasts made with each of the methods, 3 types of errors will be calculated: the Mean Error (ME), which will serve to identify the level of bias obtained by the forecast, the Mean Absolute Error (MAE), important to know how much variability the errors present, and the RMSE, which will facilitate the task of comparing the errors of the different models, demonstrating which of them present better precision. It is important to clarify that, due to the amount of zeroes within the time series, the calculation of MAPE will not be necessary, because being a proportion, it would give an undefined value (Montgomery et al. 2016)

Summarizing, the whole method applied to the data will be designated as it is seen in the Figure 16:

Classification of item’s demand patterns

Application of slow-moving demand forecasting methods

Measurement of the accuracy of the forecasting methods

Selection of the best forecasting method for each classification

Figure Scheme for evaluating the forecasting process of Agrosavia’s items

# CHAPTER 4 RESULTS AND DISCUSSION

First, it is important to highlight that the results obtained will be grouped according to the forecasting methods used and the 4 types of items with intermittent demand that have been described above and that comply with the parameters established by Syntetos & Boylan (2005). In this way, to facilitate the understanding of the outcome, an item will be taken from each of the types of intermittent demand identified and the analysis will be carried out, so that it will be generalized for the other items found in that classification. However, the application of forecasting methods and the measurement of errors was applied to all items provided by the evaluated company.

## 4.1 Croston’s and Exponential Smoothing Methods

For the development of these methods, five experiments were carried out evaluating different alphas per item, so that a much more diverse comparison could be made, not only evaluating the type of method, but also the consequences of changing the smoothing constant. In this way, the following values were chosen:

* α = 0.15, as it was recommended by Syntetos and Boylan (2001)
* α = 0.1, in order to review if values inferior as 0.15 would perform better, as Syntetos & Boylan (2001) said.
* α = 0.5, as a maximum value, to see how high values affect the methods and,
* α = “optimal”, which is calculated automatically by the function. This one can vary according to every method.

### 4.1.1 Erratic Items

Since, during the classification of items, none were found that had the type "smooth", the first classification of items to analyze is "erratic". For this situation, item BIP001271 was taken, which presents a relatively constant demand, except for 3 periods, but given the application of the ADI and the Coefficient of Variation, its demand is erratic. This can be demonstrated in Figure 17.

Figure 17 Item BIP001271 demand behavior

One of the main characteristics that this type of item presents is that they usually have an irregular demand size (since it does not have a constant or moderately similar demand), but its occurrence is much more constant. When applying the Croston and Exponential Smoothing methods, it is important to note that the forecast obtained is an average of the demand that will occur in the following periods, so it will be a constant (Croston, 1972; Vinh, 2005; Syntetos & Boylan, 2005; Shale et al., 2006; Teunter et al, 2011). Thus, Table 3 shows the smoothed results of each period using α = 0.1, as well as the forecast of the average demand per period (the complete table can be found in the annex)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| X | BIP001271 | SES\_bip1271 | cros\_smooth | SBA\_smooth | SBJ\_smooth |
| Dec-17 | 0 | 0 |  |  |  |
| Jan-18 | 10 | 0 |  |  |  |
| Feb-18 | 16 | 1 | 16.7873012 | 17.18181751 | 17.18182087 |
| Mar-18 | 13 | 2.5 | 16.75918329 | 17.11103829 | 17.10953779 |
| Apr-18 | 22 | 3.55 | 16.615703 | 16.92931923 | 16.92657029 |
| May-18 | 49 | 5.395 | 16.83475497 | 17.09086039 | 17.08586789 |
| Jun-18 | 28 | 9.7555 | 18.22586507 | 18.36493469 | 18.35458103 |
| Jul-18 | 15 | 11.57995 | 18.67401845 | 18.74252032 | 18.72926282 |
| Aug-18 | 7 | 11.921955 | 18.4959172 | 18.52474145 | 18.51021313 |
| Sep-18 | 13 | 11.4297595 | 17.9083697 | 17.91783246 | 17.90310529 |
| Oct-18 | 16 | 11.58678355 | 17.64461134 | 17.61863688 | 17.6028628 |
| Nov-18 | 29 | 12.0281052 | 17.55194887 | 17.48236342 | 17.46510578 |
| … | … | … | … | … | … |
| Oct-20 | 41 | 12.71635803 | 16.40118523 | 15.7257789 | 15.68779738 |
| Nov-20 | 60 | 15.54472223 | 15.75842652 | 15.0811569 | 15.04364941 |
| Fore. 1 |  | 19.99025 | 19.30151 | 18.43823 | 18.39108 |
| Fore. 2 |  | 19.99025 | 19.30151 | 18.43823 | 18.39108 |
| Fore. 3 |  | 19.99025 | 19.30151 | 18.43823 | 18.39108 |
| Fore. 4 |  | 19.99025 | 19.30151 | 18.43823 | 18.39108 |
| Fore. 5 |  | 19.99025 | 19.30151 | 18.43823 | 18.39108 |

Table 3 Smoothing and forecast of item BIP001217 with α = 0.1

Figure 18 Croston's and Exponential Smoothing forecasts of item BIP001271 with α = 0.1

Similarly, Figure 18 shows the graphic behavior of this procedure. In it, it can be seen that the Exponential Smoothing takes the previous values to perform its procedure (this will be seen in every experiment using these methods). However, due to the nature of the Croston method, in which it is only updated when there is demand, and given that all the items used within this study have initial demand of 0, the first value is not taken into account due to the uncertainty that exists related to the previous period in which there was demand other than zero (Petropoulos et al., 2016).

However, detailing the figure, it is possible to affirm that, although the Exponential Smoothing takes the demand values from the beginning, it tends to take time to smooth the data, so that its bias may be more accentuated compared to the Croston methods. Similarly, it seems that the latter show a fairly similar behavior, in such a way that it seems that there are imperceptible changes in their results. Given this situation, it is necessary to review the errors generated during the forecast, which appear in table 4.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | SES | Croston | SBA | SBJ |
| ME | 5.55 | 1.48 | 1.81 | 1.84 |
| MAE | 13.81 | 12.06 | 11.97 | 11.96 |
| RMSE | 17.46 | 15.58 | 15.57 | 15.58 |
| Error size | 3.65 | 3.52 | 3.61 | 3.61 |
| RMSE variation | | | | |
| SES |  | 12.05% | 12.13% | 12.12% |
| Croston | -10.76% |  | 0.06% | 0.06% |
| SBA | -10.81% | -0.06% |  | -0.01% |
| SBJ | -10.81% | -0.06% | 0.01% |  |
| MAE variation | | | | |
| SES |  | 14.54% | 15.41% | 15.47% |
| Croston | -12.70% |  | 0.76% | 0.81% |
| SBA | -13.35% | -0.75% |  | 0.05% |
| SBJ | -13.40% | -0.80% | -0.05% |  |

Table 4 Errors of item BIP001271 forecast with α = 0.1

As can be seen, there is a marked difference in the calculated MEs. This shows that there is a significant amount of bias in the forecast generated by Exponential Smoothing, which argues for the lack of precision that this method has, compared to Croston's. This is also demonstrated when calculating the MAE, with an increase of around 15%, and, ultimately, the RMSE, which is greater than the others around 12%. However, it is interesting to see that the Croston method has lower bias than the SBA and SBJ methods, although its RMSE and MAE present very close values, since their differences do not even reach 1%. In this way, it is possible to affirm that by having such small differences within their MAE and RMSE, the three Croston methods present a similar precision by having an alpha of 0.1, but they are much more precise than the Exponential Smoothing.

Figure 19 Croston's and Exponential Smoothing forecasts of item BIP001271 with α = 0.15

On the other hand, by increasing the alpha to 0.15, it can be seen in Figure 19 that, apparently, the Exponential Smoothing presents an improvement, by reducing its difference with the data presented. In the same way, the results of the Croston method can be better distinguished by an increase in the smoothing of the forecast, so increasing the alpha a little negatively affects the forecast accuracy of this method, at least for items with erratic demand. In the same way, when analyzing the errors of this iteration, Table 5 reiterates the improvement of the Exponential Smoothing, but it is still less effective, since its MAE is still greater than the Croston method by a little more than 11% (about 3 % improvement versus alpha = 0.1), and about 13% with the SBA and SBJ methods. Likewise, the former method presents a reduction of the RMSE, about 8% in relation to the other methods, but it is still high enough to demonstrate its ineffectiveness. On the other hand, although the Croston-type methods perform better, it is evident that the original Croston loses some efficiency against the other two (almost 2% for the MAE and although less than 1% for the RMSE). This justifies what was said by Syntetos and Boylan (2005) and by Teunter and Duncan (2009), related to the best performance of this method when the alpha used is a maximum of 0.15.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | SES | Croston | SBA | SBJ |
| ME | 4.08 | 1.47 | 2.14 | 2.16 |
| MAE | 13.66 | 12.26 | 12.05 | 12.04 |
| RMSE | 17.11 | 15.80 | 15.78 | 15.77 |
| Error size | 3.45 | 3.54 | 3.73 | 3.74 |
| RMSE variation | | | | |
| SES |  | 8.28% | 8.42% | 8.45% |
| Croston | -7.65% |  | 0.13% | 0.16% |
| SBA | -7.77% | -0.13% |  | 0.03% |
| SBJ | -7.79% | -0.16% | -0.03% |  |
| MAE variation | | | | |
| SES |  | 11.42% | 13.37% | 13.46% |
| Croston | -10.25% |  | 1.75% | 1.83% |
| SBA | -11.79% | -1.72% |  | 0.08% |
| SBJ | -11.86% | -1.80% | -0.08% |  |

Table 5 Errors of item BIP001271 forecast with α = 0.15

In reference to alphas greater than 0.15, it can be seen in Figure 20 that both the Exponential Smoothing and the Croston method tend to converge, except at times when demand is equal to 0 (periods of August and September 2020), due to the nature of the method. On the other hand, all the methods tend to resemble the behavior of the original data, although it is perceived that an increase in alpha reduces the precision of all the methods, especially the SBJ.

Figure 20 Croston's and Exponential Smoothing forecasts of item BIP001271 with α = 0.5

When reviewing the errors, the inaccuracy of the methods is evident as the alpha increases. Table 6 shows a small improvement in the forecast errors offered by the Exponential Smoothing, with variations that do not even reach 1% compared to the Croston and SBA methods. However, it is surprising that the SBJ method is the least accurate, when talking about the RMSE, since it has an increase of approximately 1.5% to almost 3%, compared to the other methods. It is interesting to review that the SES presents a better behavior of the RMS, but its MAE is not the best, as it increases in comparison with the Croston methods, while the SBJ method presents a totally opposite behavior. Thus, when the difference between the RMSE and the MAE is made, there is a much wider variation in the latter method than in the SES, even this method is the one that offers a more attenuated variation of errors, indicating that, although its mean errors are still usually high, the individual ones tend to vary to a lesser extent. However, when comparing the 4 methods, Croston is the one that shows the most favorable performance, having the lowest RMSE, as well as individual errors with lower variance.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | SES | Croston | SBA | SBJ |
| ME | 2.29 | 1.06 | 5.15 | 6.53 |
| MAE | 13.49 | 12.91 | 12.23 | 12.25 |
| RMSE | 16.98 | 16.78 | 16.92 | 17.26 |
| Error size | 3.49 | 3.87 | 4.69 | 5.01 |
| RMSE variation | | | | |
| SES |  | 1.19% | 0.34% | -1.63% |
| Croston | -1.18% |  | -0.84% | -2.79% |
| SBA | -0.34% | 0.85% |  | -1.96% |
| SBJ | 1.66% | 2.87% | 2.00% |  |
| MAE variation | | | | |
| SES |  | 4.47% | 10.29% | 10.12% |
| Croston | -4.28% |  | 5.57% | 5.41% |
| SBA | -9.33% | -5.28% |  | -0.16% |
| SBJ | -9.19% | -5.13% | 0.16% |  |

Table 6 Errors of item BIP001271 forecast with α = 0.5

Finally, the last iteration performed with the optimums suggested by the function, show smoother results than in the iterations using large alphas (0.5), since, as will be seen in Table 7, it uses alphas smaller than 0.1 for the case of Croston's methods. However, for the case of Exponential Smoothing, the alpha used is approximately 0.32, which indicates that this model generates more optimal forecasts using larger alphas, contrary to the former methods, as shown in Figure 21.

Figure 21 Croston's and Exp. Smoothing forecasts of item BIP001271 with α = “optimal”

Based on this and on Table 7, it can be seen that, in short, the alphas calculated for Croston's methods, which are less than 0.1, show a considerable improvement at higher alphas, unlike Exponential Smoothing, which responds better to increases in this parameter. Similarly, when comparing the "optimal" results, it can be seen that there is an improvement in the accuracy of the SES, specifically the RMSE, which indicates that, as the alpha increases, for this method, its effectiveness increases, since when comparing the results of the 4 tables, it starts with a maximum variation of about 12% with alpha = 0.1, goes through a variation of about 7% with optimal alpha of 0.32 and ends with almost 1% using an alpha of 0.5. However, although the MAE and RMSE in their last iterations seem to increase and decrease respectively, the size of SES errors offers a slight improvement in the case of optimal alpha, which suggests that individually its errors behave lighter, hence its prediction is more accurate. However, when generalizing the results of the four methods, the Exponential Smoothing, either with small or larger values of alpha, generates the least accurate results when forecasting erratic demand.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | SES | Croston | SBA | SBJ |
| α | **0.3248** | **0.0975** | **0.0832** | **0.0914** |
| ME | 2.68 | 2.45 | 2.49 | 2.40 |
| MAE | 13.58 | 12.24 | 12.31 | 12.14 |
| RMSE | 16.88 | 15.79 | 15.83 | 15.73 |
| Error size | 3.30 | 3.55 | 3.52 | 3.59 |
| RMSE variation | | | | |
| SES |  | 6.94% | 6.63% | 7.32% |
| Croston | -6.49% |  | -0.28% | 0.36% |
| SBA | -6.22% | 0.28% |  | 0.64% |
| SBJ | -6.82% | -0.36% | -0.64% |  |
| MAE variation | | | | |
| SES |  | 10.97% | 10.33% | 11.84% |
| Croston | -9.89% |  | -0.58% | 0.78% |
| SBA | -9.36% | 0.58% |  | 1.37% |
| SBJ | -10.58% | -0.77% | -1.35% |  |

Table 7 Errors of item BIP001271 forecast with α = “optimal”

On the other hand, it is surprising to note that what Syntetos & Boylan (2001) explained about the effectiveness of the Croston method with alphas lower than 0.15 is partially true. In other words, it is fulfilled, but not when its alpha decreases less than 0.1. As shown in Tables 4, 5 and 7, the best performance of this method is when using alpha = 0.1, since its MAE and RMSE is the lowest, as well as the variability of its individual errors. The same happens with the SBJ method, although it presents a tendency to increase its errors, hence to have a less accurate prediction, when alpha increases, although its behavior improves at optimal alphas. Finally, the method that presents the most favorable stability during all iterations is the SBA. It may be that during the optimal alphas it does not present the best behavior, since its errors are the highest with reference to the Croston methods, besides that all the methods present differences in the number assigned to alpha, but a remarkable improvement can be observed when comparing the results of its other iterations, evidenced in tables 4, 5 and 6. Thus, it is possible to admit that the method that works best with the erratic demand items, when comparing the alphas, is the SBA, although it is advisable to use an alpha equal to or higher than 0.1.

Similarly, during the analysis, the smoothing of the inter-demand intervals was taken into account, since this could predict when the next demand would occur or how many periods later it might occur. However, it is important to clarify that, although Croston type methods do not take this value individually to calculate their forecast, it could be taken into account in this analysis to identify how accurate the reading of this parameter could be. Thus, Table 8 shows the results of the smoothing of this parameter in all Croston methods, since the Exponential Smoothing does not make use of it for its execution. (For complete data, please see the annex)

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | 0.1 | | | 0.15 | | | 0.5 | | | opt | | |
|  | **Cro.** | **SBA** | **SBJ** | **Cro.** | **SBA** | **SBJ** | **Cro.** | **SBA** | **SBJ** | **Cro.** | **SBA** | **SBJ** |
| 17-Dec |  |  |  |  |  |  |  |  |  |  |  |  |
| 18-Jan |  |  |  |  |  |  |  |  |  |  |  |  |
| 18-Feb | 3.00 | 3.00 | 3.00 | 3.00 | 3.00 | 3.00 | 3.00 | 2.62 | 2.33 | 1.00 | 1.00 | 1.00 |
| 18-Mar | 2.80 | 2.80 | 2.80 | 2.70 | 2.70 | 2.70 | 2.00 | 1.81 | 1.66 | 1.00 | 1.00 | 1.00 |
| 18-Apr | 2.62 | 2.62 | 2.62 | 2.45 | 2.45 | 2.45 | 1.50 | 1.40 | 1.33 | 1.00 | 1.00 | 1.00 |
| 18-May | 2.46 | 2.46 | 2.46 | 2.23 | 2.23 | 2.23 | 1.25 | 1.20 | 1.17 | 1.00 | 1.00 | 1.00 |
| 18-Jun | 2.31 | 2.31 | 2.31 | 2.04 | 2.04 | 2.04 | 1.13 | 1.10 | 1.08 | 1.00 | 1.00 | 1.00 |
| 18-Jul | 2.18 | 2.18 | 2.18 | 1.89 | 1.89 | 1.89 | 1.06 | 1.05 | 1.04 | 1.00 | 1.00 | 1.00 |
| 18-Aug | 2.06 | 2.06 | 2.06 | 1.75 | 1.75 | 1.75 | 1.03 | 1.03 | 1.02 | 1.00 | 1.00 | 1.00 |
| 18-Sep | 1.96 | 1.96 | 1.96 | 1.64 | 1.64 | 1.64 | 1.02 | 1.01 | 1.01 | 1.00 | 1.00 | 1.00 |
| 18-Oct | 1.86 | 1.86 | 1.86 | 1.54 | 1.54 | 1.54 | 1.01 | 1.01 | 1.01 | 1.00 | 1.00 | 1.00 |
| 18-Nov | 1.77 | 1.77 | 1.77 | 1.46 | 1.46 | 1.46 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 18-Dec | 1.70 | 1.70 | 1.70 | 1.39 | 1.39 | 1.39 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 19-Jan | 1.63 | 1.63 | 1.63 | 1.33 | 1.33 | 1.33 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| … | … | … | … | … | … | … | … | … | … | … | … | … |
| 19-Mar | 1.51 | 1.51 | 1.51 | 1.24 | 1.24 | 1.24 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 20-Sep | 1.08 | 1.08 | 1.08 | 1.02 | 1.02 | 1.02 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 20-Oct | 1.08 | 1.08 | 1.08 | 1.02 | 1.02 | 1.02 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 20-Nov | 1.28 | 1.28 | 1.28 | 1.31 | 1.31 | 1.31 | 2.00 | 2.00 | 2.00 | 1.00 | 1.00 | 1.00 |

Table 8 Smoothed inter-demand interval of item BIP001271 (erratic demand)

As can be seen, for the cases in which the alpha is not optimal, the inter-demand interval forecast shows high values, from 3 to 2 approximately, in reference to the fact that it takes the values prior to the first demand and counts them as periods in which there is no demand, as indicated by (Petropoulos et al., 2016). However, when taking this parameter as a possible indicator to forecast the next period in which a demand will occur, given that the erratic type items are constant in their occurrence, but variable in the size of the demand, the period between demands is mostly at 1 (every period demand will occur). However, the periods in which there is no demand (August 2020 and September 2020), although it tends to reduce its forfecast, still tends to 1, so it is not very accurate in forecasting periods in which demand is zero. Therefore, for erratic items, forecasting the next period in which demand occurs, by revising the inter-demand interval, may lead it to show that all future periods will have demand.

### 4.1.2. Intermittent items

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# REFERENCES

Billah, B., King, M. L., Snyder, R. D., & Koehler, A. B. (2006). Exponential smoothing model selection for forecasting. *International Journal of Forecasting, 22*(2), 239-247.

Boylan, J. E., & Syntetos, A. A. (2007). The accuracy of a Modified Croston procedure. *International Journal of Production Economics, 107*(2), 511-517.

Boylan, J. E., Syntetos, A. A., & Karakostas, G. C. (2008). Classification for forecasting and stock control: a case study. *Journal of the Operational Research Society, 59*, 473-481.

Costantino, F., Di Gravio, G., Patriarca, R., & Petrella, L. (2018). Spare parts management for irregular demand items. *Omega, 81*, 57-66.

Croston, J. D. (1972). Forecasting and Stock Control for Intermittent Demands. *Operational Research Quarterly, 23*(3), 289-303.

Dunsmuir, W. T., & Snyder, R. N. (1989). Control of inventories with intermittent demand. *European Journal of Operational Research, 40*(1), 16-21.

Gardner, E. S. (1985). Exponential Smoothing: The State of art. *Journal of Forcasting, 4*(1), 1-28.

Johnston, F. R., & Boylan, J. E. (1996). Forecasting intermittent demand: a comparative evaluation of Croston's method. Comment. *International Journal of Forecasting, 12*(2), 297-298.

Johnston, F. R., Boylan, J. E., & Shale, E. A. (2003). An examination of the size of orders from customers, their characterisation and the implications for inventory control of slow moving items. *Journal of the Operational Research Society, 54*(8), 833-837.

Kaya, G. O., Sahin, M., & Demirel, O. F. (2020). Intermittent demand forecasting: a guideline for method selection. *Sadhana, 45*, 51.

Kourentzes, N., & Petropoulos, F. (2016). Forecasting with R. *International Symposium on Forecasting 2016* (p. 65). Santander: International Institute of Forecasters.

Kourentzes, N., Petropoulos, F., & Trapero, J. R. (2014). Improving forecasting by estimating time series structural components across multiple frequencies. *International Journal of Forecasting, 30*, 291-302.

Leven, E., & Segerstedt, A. (2004). Inventory control with a modified Croston procedure and Erlang distribution. *International Journal of Production Economics, 90*, 361-367.

Montgomery, D. C., Jennings, C. L., & Kulahci, M. (2016). *Introduction to Time Series Analysis and Forecasting.* Hoboken, New Jersey: John Wiley & Sons, Inc.

Nikolopoulos, K. (2021). We need to talk about intermittent demand forecasting. *European Journal of Operational Research, 291*(2), 549-559.

Nikolopoulos, K., Syntetos, A. A., Boylan, J. E., Petropoulos, F., & Assimakopoulos, V. (2011). An Aggregate-Disaggregate Intermittent Demand Approach (ADIDA) to forecasting: An empirical proposition and analysis. *Journal of the Operational Research Society, 62*(3), 544-554.

Petropoulos, F., & Kourentzes, N. (2014). Forecast combinations for intermittent demand. *Journal of the Operational Research Society, 66*(6), 914-924.

Petropoulos, F., Kourentzes, N., & Nikolopoulos, K. (2016). Another look at estimators for intermittent demand. *International Journal of Production Economics*, 154-161.

Ryu, K., & Sanchez, A. (2003). The Evaluation of Forecasting Methods at an Institutional Foodservice Dining Facility. *The Journal of Hospitality Financial Management, 11*(1), 27-45.

Sahin, M., Kizilaslan, R., & Demirel, O. F. (2013). Forecasting Aviation Spare Parts Demand Using Croston Based Methods and Artificial Neural Networks. *Journal of Economic and Social Research, 15*(2), 1-21.

Santa Cruz, R., & Correa, C. (2017). Intermittent demand forecasting with time series methods and artificial neural networks: A case study. *Dyna, 84*(203), 9-16.

Segerstedt, A., & Levén, E. (2020). *A study of different Croston-like forecasting methods.* Lulea, Sweden: Lulea University of Technology.

Shale, E. A., Boylan, J., & Johnston, F. R. (2006). Forecasting for intermittent demand: the estimation of an unbiased average. *Journal of the Operational Research Society, 57*(5), 588-592.

Silver, E. A. (1981). Operations Research in Inventory Management: A Review and Critique. *Operations Research, 29*(4), 628-645.

Silver, E. A., Pyke, D. F., & Peterson, R. (1998). *Inventory Management and Production Planning and Scheduling.* New York, United States of America: John Wiley & Sons, Inc.

Spithourakis, G. P., Petropoulos, F., Nikolopoulos, K., & Assimakopoulos, V. (2014). A systemic view of the ADIDA framework. *IMA Journal of Management Mathematics, 25*(2), 125-137.

Stevenson, W. J. (2009). *Operations Management.* New York: McGraw-Hill/Irwin.

Syntetos, A. A., & Boylan, J. E. (2001). On the bias of intermittent demand estimates. *Intenational Journal of Production Economics, 71*, 457-466.

Syntetos, A. A., & Boylan, J. E. (2005). The accuracy of intermittent demand estimates. *International Journal of Forecasting, 21*, 303-314.

Syntetos, A. A., Boylan, J. E., & Croston, J. D. (2005). On the categorization of demand patterns. *Journal of the Operational Research Society, 56*, 495-503.

Teunter, R. H., & Duncan, L. (2009). Forecasting intermittent demand: a comparative study. *Journal of the Operational Research Society*, 321-329.

Teunter, R. H., Syntetos, A. A., & Zied Babai, M. (2011). Intermittent demand: Linking forecasting to inventory obsolescence. *European Journal of Operational Research, 214*, 606-615.

Tliche, Y., Taghipour, A., & Canel-Depitre, B. (2020). An improved forecasting approach to reduce inventory levels in decentralized supply chains. *European Journal of Operational Research, 287*(2), 511-527.

Uzunoglu Kocer, U., & Tamer, S. (2011). Determining the Inventory Policy for Slow-Moving Items: A Case Study. *Proceedings of the World Congress on Engineering* (pp. 1-4). London: International Association of Engineers.

van Steenbergen, R. M., & Mes, M. R. (2020). Forecasting demand profiles of new products. *Decision Support Systems, 139*, 113401.

Vinh, D. Q. (2005). Forecasting irregular demand for spare parts inventory. *Department of Industrial Engineering, Pusan National University, Busan*, 609-735.

Wallstrom, P., & Segerstedt, A. (2010). Evaluation of forecasting error measurements and techniques for intermittent demand. *International Journal of Production Economics, 128*, 625-636.

Willeman, T. R., Smart, C. N., Shockor, J. H., & DeSautels, P. A. (1994). Forecasting intermittent demand in manufacturing: A comparative evaluation of Croston’s method. *International Journal of Forecasting, 10*, 529-538.

Williams, T. M. (1984). Stock Control with Sporadic and Slow-Moving Demand. *Journal of the Operational Research Society, 35*(10), 939-948.

Xu, Q. Z., Wang, N., & Shi, H. P. (2012). A Review of Croston’s Method for Intermittent Demand Forecasting. *9th International Conference on Fuzzy Systems and Knowledge Discovery* (pp. 1468-1472). Chongqing: IEEE.