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Intermittent demand forecasting for aircraft inventories: a study of Brazilian's Boeing 737NG aircraft´s spare parts management

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ABSTRACT
This paper aims to compare and evaluate five different methods for predicting intermittent demand using spare parts recorded series of the 737 Next Generation aircraft, manufactured by Boeing, of the largest Brazilian air fleet managed by VRG Airline Company S/A. The Winter, Croston, Single Exponential Smoothing, Weight Moving Average and Poisson Distribution Methods were tested on a history data of 53 spare parts, and each one has a demand history of thirty-six months (January 2013 to December 2015). The results showed that the Weight Moving Average, Poisson Distribution and Croston methods presented the best adjustments. Also, it was observed that most of the demands for spare parts presented a smooth pattern unlike the result obtained by the study of Ghobbar and Friend (2003) that presented a lumpy pattern. On the other hand, it showed that the Winter Method presented the worst adjustment in both studies. It was possible, therefore, to conclude that Weight Moving Average and Poisson Distribution methods are the most suitable to evaluate the intermittent demand for the VRG Airline Company S/A case.

RESUMO
Este estudo tem como objetivo avaliar cinco métodos de previsão para demanda intermitente usando uma série histórica de consumo de peças sobressalentes da aeronave 737 Next Generation, fabricado pela Boeing, da maior frota aérea brasileira gerenciada pela VRG Airline Company S/A. Os métodos de Winter, Croston, *Single Exponential Smoothing*, *Weight Moving Average* e Método de Distribuição de Poisson foram testados em um histórico de 53 peças sobressalentes e cada uma delas possui um histórico de demanda de trinta e seis meses (janeiro de 2013 a dezembro de 2015). Os resultados mostraram que os métodos *Weight Moving Average*, Distribuição de Poisson e Croston apresentaram os melhores ajustes. Além disso, observou-se que a maior parte das demandas por peças sobressalentes apresentaram um padrão *smooth* ao contrário do resultado obtido pelo estudo de Ghobbar and Friend (2003) que apresentou um padrão *lumpy*. Por outro lado, tem-se que o Método de Winter apresentou-se como o de pior ajuste em ambos os estudos. Conclui-se que os métodos de *Weight Moving Average* e Distribuição de Poisson são os mais adequados para avaliar a demanda intermitente para o caso da VRG Airline Company S/A.

1. INTRODUCTION

Delays in airline schedules have caused costly consequences to the airline network (Ahmad-Beygi, Cohn, Yihan Guan and Belobaba, 2008; Papakostas *et al.*, 2010; Wong and Tsai, 2012). Delays in airline schedules can be the result of many different causes, i.e., from January 2014 to September 2017, there were 21,533,005 total operations in the US airports with 246,099,313 delayed minutes. The delays were mainly caused by air carrier delay due to maintenance, crew, refueling or baggage transportation (34.10%), aircraft arriving late (36.45%), national aviation system delay (25.36%), weather (3.97%), and 0.12% for security reasons (Bureau of Transportation Statistics, 2017).

As shown above, attention has been given to the technical maintenance aspects (Wu and Wong, 2007). Delays caused by maintenance are based on poor maintenance services' planning, failures found during inspections and unavailable of spare parts in stock and unexpected glitches that occur at the time or near the time of the release of the aircraft for flight (Papakostas, Papachatzakis, Xanthakis, Mourtzis, and Chryssolouris, 2010). In fact, aircraft maintenance plays a significant role in reducing cost, which amounts up to about 13% of the total operating cost (Gu, Zhanga, and Li, 2015).

Brazil has the largest aircraft fleet, with a total of 21,905 airplanes, if compared to other Latin American countries (ANAC, 2017). Thus, most of the replacement parts are imported from the United States and Europe. The consequences are seen in a study presented by Machado, Urbina, and Macau (2016), in which airline companies fail to replace and control spare parts on time. This fact can significantly influence the maintenance costs. Also, the study shows that, with regards to maintenance support and control, the evaluation of suppliers is an essential activity for safety.

When aircraft parts fail, airline companies generate a demand request for spare parts which are supplied by the spare parts inventory department. If demands are satisfied immediately, the aircraft maintenance work can take place on schedule. Unfortunately, due to a spare parts shortage, it will probably lead to flight delay or cancellation which will incur extra cost.

According to Silva (2009), the demand for spare parts has very peculiar characteristics, and it is very different from that normally found in products, raw materials, and inputs for production lines. While the inputs have a high-turnover, a regular and predictable demand pattern, the spare parts can present demand patterns with characteristics varying in the size of the demand, in the periods of occurrence or both.

Spare parts represent a class of materials that exemplify a demand pattern known as intermittent. Its use usually follows the occurrences of aircraft failures frequencies, and these, in turn, have a non-regular pattern. The intermittent demand (ID) is defined as a random demand with a large proportion of null values or when a product experiences several periods of zero demand. ID is often experienced in industries such as aviation, automotive, defense and manufacturing; it also typically occurs with products nearing the end of their life cycle (Silver, Ho, and Deemer, 1971; Silver, Pyke, and Peterson, 1998).

Failures can occur due to normal or abnormal use of the materials used in the manufacturing of parts and components. The abnormal consumption can be related to harsh environments in which the equipment is operating or because of design problems. Abnormal use, which generally leads to premature failure of parts and components, causes consumption peaks and their occurrence may lead to distortions that are not interesting within a forecasting process (Tuomas, Eemeli, Ville, Kai, and Raimo, 2001; Vaughan, 2005; Wang, 2012).

Ghobbar and Friend (2003) argue that the difficulty in predicting the demand for aircraft spare parts maintenance is a problem that affects the aircraft industry worldwide. Reducing the uncertainty of forecasting these spare parts can be, according to the authors, the biggest challenge among planners within civil and military aviation companies. The great difficulty in forecasting intermittent demands lies in the high variability of demand, characterized by the size of the demand (quantity of items consumed by each demand) and by the interval of time between demands. Authors such as Croston (1972); Willians (1984); Willemain *et al*., (1994); Johnston and Boylan (1996); Botter and Fortuin (2000); Syntetos and Boylan (2001) have emphasized the importance of studies and methods to predict it.

Bredley (2011), shows a series of methods used to predict intermittent demands, such as: Poisson distribution (Ward, 1978; Mitchell, Rappold, and Faulkner, 1983; Dunsmuir and Snyder, 1989), Croston Method (Croston, 1972; Willemain, Smart, Shockor, and Desautels, 1994), the Holt-Winters (Winters, 1960), Weight Moving Average Method and Single Exponential Smoothing (Willemain, 1994).

Our research was motivated by following the work initiated by Ghobbar and Friend (2003) and taking into account the relevance of the discussed topic, we created predictions using the prediction methods known as Croston, Winters, Weight Moving Average, Single Exponential Smooth and Poisson for 53 intermittent demand spare parts inventory database used in a Brazilian airline company's Boeing 737NG aircraft. The originality of this research is in the fact that no other research has been done specifically for this kind of aircraft in the Brazilian aeronautical market. It is hoped, with this work, to encourage the study of aircrafts' intermittent demand spare parts inventory management in Brazil; to present tools that will allow planners to reduce uncertainty in forecasts with a consequent reduction in aircraft unavailability due to lack of spare parts.

Thus, this study aims to verify which method presents a better adjustment for the intermittent demand problem and also verify if the occurrences of aircraft failures cause demand peaks distorting any forecast and compare the results with the ones obtained in Ghobbar and Friend (2003).

This paper is organized as follows. The next section presents the literature review with regards to the problem. Section 3 explains the proposed methodology. An exhaustive case study of an airline carrier is discussed in Section 4. Finally, conclusions are given in Section 5.

2. LITERATURE REVIEW

The growing importance of maintenance has generated increasing interest in the development of adequate strategies to guarantee that the required spare parts are available at the right time. The main objective is to avoid prolonged stops due to the unavailability of some items through adequate forecasting methods. However, one of the major problems associated with spare parts inventory forecasting and control is the lack of past records to determine reliable estimates of historical consumption (Burden, 1969; Buffa, 1972, Mitchel, Raphael and Faulkner, 1983; Vasumathi and Saradha, 2013, Pennings, Van Dalen and Van der Laan, 2017).

Accurate forecasting of demand is one of the most important aspects of inventory management. However, the characteristic of spare parts makes this procedure especially difficult. Up to now, Croston's method is the most widely used approach for irregular demand forecasting. Companies maintain spare parts inventories to meet their demand, meet customer demand, or even meet market demands. Eaves (2002) addresses the need for companies to keep spare parts stored as a form of safety.

Traditional forecasting methods should not be applied to predict regular demand in spare parts management (Willemain, Smart and Schwarz, 2004). The reason is that the demand is stochastic resulting in inaccurate results (Morris, 2013; Shenyang, Zhijie, Qian, and Chen, 2017). Watson (1987) has shown that intermittent nature of demand makes forecasting especially difficult for spare parts. Inventory with irregular demands is quite popular in practice. An item with intermittent demand includes spare parts, heavy machinery, and high-priced capital goods. Data for such items is composed of time series of non-negative integer values where some values are zero.

Aircraft, like any other machine, exhibit irregular, and random failures, being susceptible to sudden stops due to breaks or damages caused by usage and tear on their components (Kennedy *et al.*, 2002). The intermittent nature of demand can present four features: Slow moving demand, strictly intermittent demand, erratic demand and lumpy demand (Ghobbar and Friend, 2003; Lowas III and Ciarallo, 2016).

The stock out is considered to be one of the main factors that cause operational delay and that directly affects the companies' punctuality indexes. The great dilemma is to have unnecessary quantities of materials in stock representing, therefore, high financial risks due to the parts obsolescence since they suffer modifications sporadically by the manufacturer, or the lack of these at the moment when they are necessary (Ghobbar and Friend, 2003).

Various studies have shown that forecasting demand has been an important issue for spare parts consumption (Kennedy, Patterson and Fredendall, 2002; Teunter, and Duncan, 2009; Hemeimat, Al-Qatawneh, Arafeh and Masoud, 2016; Shenyang, Zhijie, Qian and Chen, 2017). However, Ghobbar and Friend (2003) have identified that out of thirteen methods tested in the historical series of thirty-five aeronautical spare parts, four were highlighted, which are: The Croston Method, the Winters Method, Weighted Moving Average and the Single Exponential Smoothing. To evaluate the accuracy of the results and to determine the best software adjustment, the Mean Percentage Error (MAPE) method was used.

Gardner (2006) compared five studies on the Croston method and its variants. He concluded that the performance of the forecasting method could vary according to the error values and by the type of historical series that is used for forecasting. Teunter and Duncan (2009) argue that the accuracy of a forecast can be understood as the difference between current demand and expected demand. Predictions of low accuracy can cause the imbalance of the resupply process and the direct impact on materials' supply. Methodologies are used for the accuracy results analysis and these are: the Mean Square Error (MSE), the Mean Absolute Error (MAE) and the Mean Absolute Percent Error (MAPE) (Foote, 1993; Gross, 1981; Lewis 1997; Makridakis *et al.*, 1998; Ghobbar and Friend, 2003; Teunter and Duncan 2009).

Based on the work of Shenstone and Hyndman (2005) and considering that Y_t is the demand occurring in the time interval t; X_t the variable that indicates the number of periods in which the demand has a value other than zero; $X_t = 1$ when demand occurs in the period t e $X_t = 0$ when there is no demand occurrence; j_t is the number of demands with non-zero values during the time interval $[0, t]$; Y_t^* is the size of the period in which they occur from controls with values other than zero and Q_j is the interval between demands within the interval Y_{t-1}^* and Y_t^*; we have the following mathematical development:

$$Y_t = X_t X_t^* \tag{1}$$

Considering Z_j and P_j as the forecasts for the size of the demand and the intermittent interval respectively, we have the base equations for the Croston Method:

$$Z_j = (1-\alpha)Z_{j-1} + \alpha Y_j^* \tag{2}$$

$$P_j = (1-\alpha)P_{j-1} + \alpha Q_j^* \tag{3}$$

Considering α between 0 and 1 we have the forecast demand for period C_t:

$$C_t = \frac{Z_j}{P_j} \tag{4}$$

In order to use of this method, it was assumed that: (1) the distribution of demands that have values different from zero Y_j^* be normal, (2) that the interval between demands Q_j has a geometric distribution, (3) that the size of the demand Y_j^* and the interval between demands Q_j be mutually independent.

Contrary to these results, Syntetos and Boylan (2001) observed that the method presented a negative tendency that could extrapolate the predicted values, thus proposed the following changes:

$$E(C_t) = E\left[\frac{\widehat{Z_j}}{\widehat{P_j}}\right] \approx \frac{\mu}{P}\left(1 + \frac{\alpha}{2-\alpha}\,\frac{P-1}{P}\right) \tag{5}$$

In particular for α =1, there is:

$$E(C_t) = E\left[\frac{\widehat{Z_j}}{\widehat{P_j}}\right] = E\left[\frac{Z_j}{P_j}\right] = \mu\left[-\frac{1}{P-1}\ln\left(\frac{1}{P}\right)\right] \tag{6}$$

Based on (5) and ignoring the term $\frac{P-1}{P}$ Syntetos e Boylan proposed a new estimate that is presented in equation (7). It became known as the method of Syntetos and Boylan or method SB:

$$SB = \left(1 - \frac{\alpha}{2}\right)\frac{\widehat{Z_j}}{\widehat{P_j}} \tag{7}$$

Levén and Segerstedt (2004) tested the SB method and found that the problem of the trend on results still existed, thus proposed new changes that are presented in equation (8). According to the authors, such changes eliminated the trend problem in Croston.

However, Teunter and Sani (2006) argue that it persists.

$$E(LS_t) = \mu\left[-\frac{1}{P-1}\ln\frac{1}{P}\right] \tag{8}$$

Finally, Teunter and Sani (2006) compared all these variations of the Croston method with its estimation proposal presented in equation (9). In their results, they identified that this last version presented a smaller variation in the results when compared to the others.

$$TS_t = \left(1 - \frac{\alpha}{2}\right)\frac{\widehat{Z_j}}{\widehat{P_j} - \frac{\alpha}{2}} \tag{9}$$

As already presented, Simple Exponential Smoothing does not consider the trend smoothing and seasonality in its equations, being the simplest method among the others.

Considering that S_t is the forecast for the period *t+1*, α the smoothing constant, whose value is between 0 and 1 and S_{t-1} the value of the most recent forecast:

$$S_t = \alpha X_t + (1-\alpha)S_{t-1} \tag{10}$$

Expanding the equation (10) replacing S_t, S_{t+1}, S_{t+2} , ... S_{t+n} by its components comes the equation (11):

$$S_t = \alpha X_t + \alpha(1-\alpha)S_{t-1} + \alpha(1-\alpha)^2 S_{t-2} + \alpha(1-\alpha)^3 S_{t-3} + \cdots + \alpha(1-\alpha)^{t-1}S_t + (1-\alpha)^t S_t \tag{11}$$

This way we obtain the weighted average of all the values of the historical series under analysis. Hence, the name exponential smoothing (Makridakis *et al.*, 1998). Smoothing constants are also responsible for the random fluctuations of the method, sometimes causing some instability.

Another way of presenting the expression (11) is through equation (12). Makridakis *et al.,* (1998) argues that this equation allows one to state that the simple exponential smoothing model predicts the value of a time series by adjusting it by the error value.

$$S_t = S_{t-1} + \alpha e \tag{12}$$

Where,

$$e = \left(X_t - \hat{X}_{t-1}\right)$$

The Winters method can be divided in the multiplicative model and the additive model. The multiplicative model is described as follows:

The expressions for seasonality and trend are given by:

$$S_t = \alpha\left(X_t/I_{t-p}\right) + (1-\alpha)S_{t-1}R_{t-1} \quad (13)$$

$$R_t = \gamma(S_t/S_{t-1}) + (1-\gamma)R_{t-1} \quad (14)$$

Where:

$$I_t = \delta(X_t/S_t) + (1-\delta)I_{t-p} \quad (15)$$

$$\hat{X}_t(m) = (S_t R_t^m)I_{t-p+m} \quad (16)$$

$$S_t = S_{t-1} + \alpha e_t/I_{t-p} \quad (17)$$

$$T_t = R_{t-1} + \alpha\gamma e_t/S_{t-1}/I_{t-p} \quad (18)$$

$$I_t = I_{t-p} + \delta(1-\alpha)e_t \,/\, S_t \quad (19)$$

In these expressions α and δ are smoothing constants whose values are between 0 e 1, R_t is the seasonal smoothing index within the time interval t, I_t the smoothing trend index within the interval t. The seasonality, or the number of the interval subperiods, is represented by p.

The Weighted Moving Average (WMA) is shown as follows:

$$S_{t+1} = \frac{np_t + (n-1)_{p_{t-1}} + \cdots + 2p_{(t-1)+2} + p_{(t-n)+1}}{n + (n-1) + \cdots + 2 + 1} \quad (20)$$

Where: S_{t+1} - is the forecast for the period t +1

n – coefficient that interprets the weight of the observation.

p_t - observation in the time period t.

The Poisson distribution method can be expressed in the form of an equation (21). It is observed that it has only one parameter λ which is interpreted as the average of event occurrences. Thus, the probability of occurring £ events within a time interval is given by:

$$P(X = £) = \frac{\lambda^{£}e^{-\lambda}}{£!} \quad (21)$$

Where:

$$e \approx 2{,}7183$$

$$\lambda > 0$$

3. METHODOLOGY

VRG Airline Company S/A was founded in 2000 and started operations in 2001. It currently has a fleet of 107 Boeing 737NG aircraft, operating to 77 destinations, 63 of the domestic and 14 international and having 36.14% of the market. The fleet consists of 50 Boeing 737-800 SFP (Short Field Performance), 17 Boeing 737-800 and 40 Boeing 737-700 aircraft. VRG is the only company that operates with the 737NG aircraft in Brazil and is the largest in South America. Here 53 spare parts items were chosen, and each one has a historical demand of thirty-six months (January 2013 up to December 2015). The data was obtained directly from the company's stock control system, which is managed by ERP-AMOS. Once removed from the inventory control system, the materials were classified according to the Primary Maintenance Process (PMP) and Minimum Equipment List (MEL). Both allowed to differentiate the parts according to their importance for the aircraft's operation as well as the impact caused for its lack in stock.

The demand classification of each spare part was defined based on the calculation of the quadratic coefficient of variation (CV^2) and the intermittent interval (ρ). The matrix presented by Ghobbar and Friend (2003) served as a reference for the erratic, lumpy, intermittent and smooth classification regions, Figure 1. The breakpoints were calculated based on Eaves (2002). The prediction methods tested were: Croston, SES, WMA, Winters and Poisson distribution. The software used to simulate was the WESSA version 1.1.23-r7, and the accuracy of the results was measured using the methods: MSE, MAE, and MAPE. This methodology followed the steps presented in the studies related to Syntetos and Boylan (2001), Eaves (2002) and Ghobbar and Friend (2003).

The matrix shown in Figure 1 was used to classify the demand for each part that made up the historical basis.

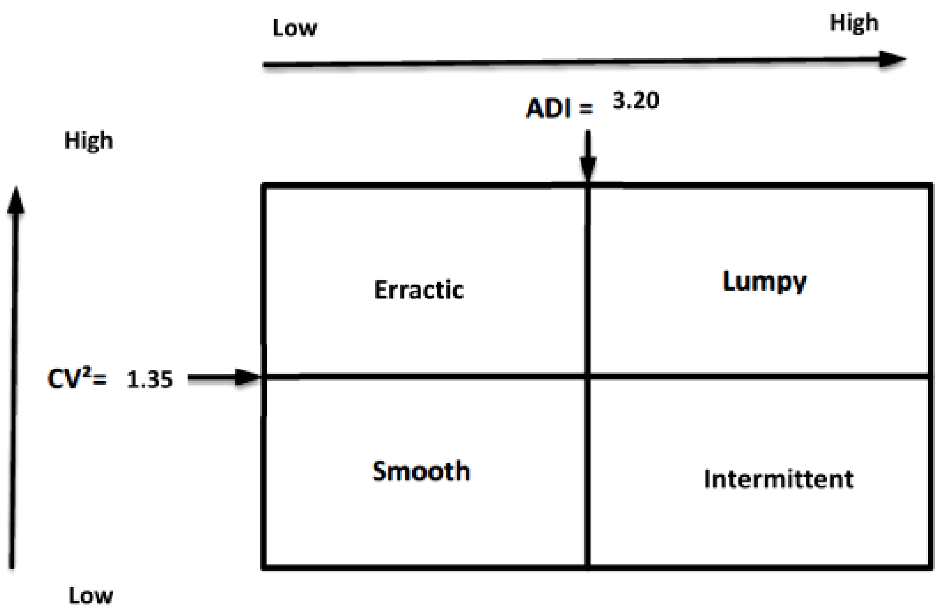

Figure 1: Demand Classification Matrix. Source: Research results

The values used in the damping coefficients α, β, and γ, remained between 0 and 1 and were established and introduced into the calculations automatically by the forecast software. According to Wessa's instructions, the coefficient values are calculated based on the profile of the input data, seeking the harmonic damping between seasonality and trend. This methodology followed the steps related in the literature for the prediction of materials and spare parts that have variability in their consumption. It is noteworthy to mention that they were used by authors such as Syntetos and Boylan (2001), Eaves (2002) and Ghobbar and Friend (2003).

4. RESULTS

Initially, we begin with the classification of each spare part. Table 1 presents important information about each one of them. The table shows the quantity of each part per aircraft, the number used for its purchase (Part Number), its Primary Maintenance Process (PMP) classification and its Minimum Equipment List (MEL) classification. Supply and purchasing teams consider them important information, because it helps them in planning the inventory replacement.

Table 1: Classification parts according to PMP and MEL database.

Item	Component Description	Part Number	Quantity per aircraft	PMP*	MEL release
1	ADF CTL PANEL	G7402-05	1	CM	3 Days
2	AIR MIX VALVE	398116-1-1	2	CM	NO GO
3	ALTERNATOR	85465-2	2	CM	NO GO
4	AOA SENSOR	0861FL1	2	CM	NO GO
5	APU ENG FIRE CTL MOD	69-37307-300	1	CM	NO GO
6	AUTO BRAKE SHUTTLE VALVE	2-7462-3	2	CM	NO GO
7	AUTO SLAT VALVE	65C26869-2	1	CM	NO GO
8	BRAKE METERING VALVE	2-7462-3	2	CM	NO GO
9	BRAKE METERING MODULE	71404-1	2	CM	NO GO
10	CABIN PRESS MODULE	7123-19973-03AB	1	CM	3 Days
11	EAU	7123-19973-01AA	1	CM	3 Days
12	EFIS CONTROL PANEL	285A1300-1	1	CM	3 Days
13	ELEVATOR FEEL COMPUTER	4082730-901	2	CM	10 Days
14	FIRST OFICER SEAT	162700-100	1	CM	10 Days
15	MARKER BEACON ANTENNA	3A296-0008-01-1	1	CM	10 Days
16	FUEL TEMP INDICATOR	441921-5	1	CM	3 Days
17	HMU	10037-0750	3	CM	3 Days
18	HYDRAULIC MOTOR	162BL801	1	CM	3 Days
19	LE SLAT ACTUATOR	1853M56P09	2	CM	3 Days
20	MODE CONTROL PANEL	761574B	2	CM	3 Days
21	AURAL WARNING MODULE	382000-1001	6	CM	3 Days
22	NLG ASSY	822-1567-102	1	CM	NO GO
23	OUTFLOW VALVE	69-78214-3	1	CM	NO GO
24	PARKING BRAKE VALVE	162A1100-5	1	CM	NO GO
25	POWER DRIVE UNIT	12D1010	1	CM	NO GO
26	SCU 245	EM91-79-5	1	CM	10 Days
27	SELCAL PANEL	256A3515-3	1	CM	10 Days
28	SCU 250	3289562-5	2	CM	10 Days
29	STARTER POWER UNIT	G7165-01	1	CM	10 Days
30	UNIT ANTISKID/AUTOBRAKE	1152426-245	1	CM	NO GO
31	VALVE HPTCC	1152466-250	1	CM	NO GO
32	WINDOW # 4	1152464-265	1	CM	10 Days
33	WINDOW # 5	42-935-2	1	CM	10 Days
34	AIR CICLE MACHINE	2206400-2	2	CM	10 Days
35	BLEED VALVE	109486-6-1	2	CM	03 Days
36	APU FUEL VALVE	AV16E1209D	1	CM	10 Days
37	APU START GENERATOR	171256-100C	1	CM	10 Days
38	FAN BLADE	1338M51P01	2	CM	NO GO
39	CONTROL DISPLAY UNIT	166891-01-01	4	CM	10 Days
40	DRIVE WXR	2041444-0401	1	CM	10 Days
41	FLIGHT CONTROL COMPUTER	10-62038-8	2	CM	10 Days
42	FUEL CONTROL UNIT	441921	1	CM	10 Days
43	FIRE DETECTOR	8970-01	2	CM	3 Days
44	FMC COMPUTER	168925-07-01	2	CM	10 Days
45	FUEL FLOW TRANSMITER	1853M48P03	2	CM	NO GO
46	HI STAGE REGULATOR	107484-7	2	CM	3 DAYS
47	FUEL NOZZLE	3830416-1	36	CM	NO GO
48	OXYGEN MASK	174290-41	4	CM	NO GO
49	STARTER VALVE	3289630-3	2	CM	NO GO
50	TRANSIENT BLEED VALVE	1821M60P04	2	CM	10 Days
51	VALVE	14330-050	1	CM	10 Days
52	VBV ACTUATOR	1211342-005	2	CM	10 Days
53	WXR ANTENNA	930-4301-001	1	CM	10 Days

Source: Research results

* CM stands for Conditioning Monitoring which is applied to components or systems that do not have a definite life limit, thus not falling under Hard-Time (HT) and On-Condition (OC) qualifications. This process involves monitoring the margin of failure, as measured by the number of individual component removals.

Table 2: Parts classification according to its importance in the aircraft operation

Parts Requirement	Quantity (# of parts)	Percentage
Parts that restrain aircraft to fly	19	35.85
Parts that require replacement in 3 days	13	24.53
Parts that require replacement in 10 days	21	39.62
Total	53	100.00

Source: Research results

Table 2 shows the proportion between the parts considering their importance for the aircraft's operation. Thus, 35.85% prevent the aircraft from flying if they fail, 24.53% should be replaced in up to three days, and 39.62% allows the aircraft to fly up to 10 Days. That means that 60.38% of the items have a direct impact on the aircraft operation.

Table 3: Calculated values of CV^2 and ρ for each component.

Item	Component Description	Variability in the size of demand CV^2	Variability in number of transactions (ρ)	Demand Classification
1	ADF CTL PANEL	0.3687	1.0976	Smooth
2	AIR MIX VALVE	0.8369	1.9899	Lumpy
3	ALTERNATOR	0.5840	0.9987	Smooth
4	AOA SENSOR	0.2556	0.0765	Smooth
5	APU ENG FIRE CTL MOD	0.5976	1.2567	Smooth
6	AUTO BRAKE SHUTTLE VALVE	1.0848	1.9459	Smooth
7	AUTO SLAT VALVE	0.8949	1.8333	Smooth
8	BRAKE METERING VALVE	1.1070	0.9843	Smooth
9	BRAKE METERING MODULE	0.5434	1.1983	Smooth
10	CABIN PRESS MODULE	1.2474	1.4871	Smooth
11	EAU	0.7997	0.9953	Smooth
12	EFIS CONTROL PANEL	0.7594	0.9745	Smooth
13	ELEVATOR FEEL COMPUTER	0.6014	0.9832	Smooth
14	FIRST OFICER SEAT	0.9262	0.0562	Smooth
15	MARKER BEACON ANTENNA	0.8332	1.7489	Smooth
16	FUEL TEMP INDICATOR	0.8051	0.6898	Smooth
17	HMU	1.5898	2.9782	Erratic
18	HYDRAULIC MOTOR	0.6575	1.6735	Smooth
19	LE SLAT ACTUATOR	0.5587	1.9867	Smooth
20	MODE CONTROL PANEL	0.7998	1.4876	Smooth
21	AURAL WARNING MODULE	2.1734	3.9678	Erratic
22	NLG ASSY	2.9245	3.1276	Smooth
23	OUTFLOW VALVE	0.5567	1.3279	Smooth
24	PARKING BRAKE VALVE	0.3487	0.9768	Smooth
25	POWER DRIVE UNIT	0.6827	1.6593	Smooth
26	SCU 245	0.4057	0.4536	Smooth
27	SELCAL PANEL	0.7733	1.3872	Smooth
28	SCU 250	0.6575	0.9834	Smooth
29	STARTER POWER UNIT	1.0579	1.8833	Smooth
30	UNIT ANTISKID/AUTOBRAKE	0.2736	1.0034	Smooth
31	VALVE HPTCC	0.202	0.4237	Smooth
32	WINDOW # 4	1.0690	1.2502	Smooth
33	WINDOW # 5	1.7606	2.1111	Erratic
34	AIR CICLE MACHINE	0.8893	0.1388	Smooth
35	BLEED VALVE	0.1944	1.0768	Smooth
36	APU FUEL VALVE	0.2222	1.3401	Smooth
37	APU START GENERATOR	1.2554	0.1944	Smooth
38	FAN BLADE	1.6432	0.1388	Erratic
39	CONTROL DISPLAY UNIT	1.0599	0.2777	Smooth
40	DRIVE WXR	0.9084	0.1110	Smooth
41	FLIGHT CONTROL COMPUTER	0.8134	0.1129	Smooth
42	FUEL CONTROL UNIT	0.8397	0.1113	Smooth
43	FIRE DETECTOR	1.0503	0.1388	Smooth
44	FMC COMPUTER	1.3788	0.2777	Erratic
45	FUEL FLOW TRANSMITER	1.0215	0.0555	Smooth
46	HI STAGE REGULATOR	0.9716	0.1666	Smooth
47	FUEL NOZZLE	0.9643	0.3656	Smooth
48	OXYGEN MASK	1.3572	0.2500	Smooth
49	STARTER VALVE	1.0129	0.2777	Smooth
50	TRANSIENT BLEED VALVE	0.8289	0.0032	Smooth
51	VALVE	1.6765	0.1388	Erratic
52	VBV ACTUATOR	1.4459	0.2500	Erratic
53	WXR ANTENNA	0.9537	0.1944	Smooth

In Brazil, the minimum time for importing parts of a 737NG aircraft, which are not subject to shipping restrictions by the customs authorities and which are available in the supplier's department at the time of purchase, runs around 10 Days. Thus, if we consider that 60.38% of the items penalize the operation of the aircraft below 10 Days, it is concluded that the lack of these materials in stock will cause serious inconvenience to the operation. Parts that fall between the "No Go" and 3 Days categories should receive special attention from the planners. For those cases, where this is not possible, companies will resort to the cannibalization process. In that case, cannibalization will allow the failed aircraft to return to operation in a shorter time interval than the purchase and import logistics of the part but will raise the maintenance costs.

Two factors that are considered important and clearly show the variability of these parts consumptions, are the quadratic coefficient of variation and the intermittent interval. The calculated values for the historical series are seen in Table 3. Note that items, such as the Aural Warning Module and HMU, have high values of CV^2 and ρ, thus producing high variability in their consumption. The mean value of CV^2 was 0.9287, and the mean ρ was 0.9927, which characterizes a historical series composed of demands of low variability. The breakpoints calculated for the boundary values of the demand classification matrix were: 1.35 (CV^2) and 3.20 (ρ). Through it, a large part of the database was classified as smooth presenting six occurrences of erratic demand and only one of lumpy demand.

Table 4 suggests that 86.79% of the database was classified as smooth, 11.32% was classified as erratic and only 1.89% as lumpy.

Table 4: Intermittent Nature of Demand

Intermittent nature of Demand	Quantity (# of parts)	Percentage (%)
Smooth	46	86.79
Erratic	6	11.32
Lumpy	1	1.89
Total	53	100.00

Regarding the consumption forecast, it was observed that all the data presented a good adjustment to the platform used, with no messages of errors that contributed to errors in the forecast.

Peaks in demand can cause surprises, as forecasts do not cover them. Table 5 shows the components of the historical series that presented such discrepancies.

A reduction on parts service life explains these results due to design problems or operational intemperance; reduction in the useful life of the parts led to changes in the maintenance program of the aircraft that demanded the greatest number of aircraft stops for maintenance; a need to replace parts considered to be obsolete by civil authorities or manufacturers; and the purchase of a larger number of parts for stock was required due to the high lead time of returned parts for repair.

Table 5: Components that presented consumption peak

Material	Period	Reason
Antiskid Auto Brake	Aug-14 /Apr-15/Nov-15	Repair problems
Brake Metering Valve	Oct-14/ Nov-14	Part modification
First Officer Seat	May-15/ Sept-15	Component wear
NLG Assy	Jan-13 - July-13	Component Wear
HPTCC	May-13/ Oct-13	Part modification
EFIS Control Panel	Feb-14/ Sept-15	Component wear

According to the VRG's material planning team, the time spent between the release of the material by the spare supplier for shipment to Brazil and its arrival into the company's inventory is around 20 days. It should be emphasized that this time does not contemplate the repair of the component that can vary according to the failure found by the repairer. For them, the biggest problem lies in the lack of national repairers, who would provide the reduction of the logistic lead time or in the high prices practiced by this modality in the national market. Thus, it is necessary to create a safety stock to meet the demand of the fleet, avoiding, in this manner, the operational impact in the absence of components.

In all, Table 6 presents the results of 155 simulations during the execution of the demand forecast processes. The table also shows the classification of the methods based on the number of simulations that produced the smallest quadratic errors. The Weighted Moving Average (WMA) method presented 44 simulations with the lowest MSE values followed closely by the Poisson method, which showed 43 simulations. This result corroborates with the results of Ghobbar and Friend (2003), who also identified WMA as the best fit method for a database that was mostly lumpy.

Table 6: Demand forecast methods classification

Method	Simulation	Classification
WMA	44	1st
POISSON	43	2nd
CROSTON	34	3rd
SES	25	4th
WINTERS	9	5th

Other authors also reinforce the results of this research. Manzini *et al.,* (2007) and Bredley (2011) point out that the Poisson Method, which was classified as the second best fit method, is used in the demand forecast of spare parts. It is important to note that Poisson was not part of the methods used in the study carried out by Ghobbar and Friend (2003). Croston was ranked third, maintaining its fame as a method indicated by the literature for the treatment of variable demands. Winters presented the worst adjustment, ranked last among the others. This result also corroborates with Ghobbar and Friend (2003). The superiority of the Croston method over SES was also verified according to studies by Croston (1972).

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The verification of these statements can be visualized in Table 7. In it, we can find all the values of the mean squared error, which were calculated for each spare part. In bold are the smallest error values that indicate the method that best fitted our historical series.

Table 8 compares the results obtained in our study with Ghobbar and Friend (2003). It shows the good fit of WMA for smooth and lumpy demands. This result also suggests that the WMA can be indicated for the aeronautical material demands forecasting analysis, which have these two forms of demand. The Croston method was also among the best, confirming its classic use for predicting aviation demands. Simple Exponential Smoothing (SES) appears in fourth place behind the Croston method, which confirms the superiority of this methodology over SES. The Winters method presented the worst adjustment, which also corroborates the conclusions of Ghoobar and Friend (2003).

Table 7: Prediction error values for best-fit methods.

			CROSTON	WINTERS	POISSON	SES	WMA
Item	Part Description	Demand Classification	MSE	MSE	MSE	MSE	MSE
1	ADF CTL PANEL	Smooth	0.9907	2.1040	1.0051	9.4013	1.0033
2	AIR MIX VALVE	Lumpy	2.5475	4.4176	2.4393	2.7487	2.3987
3	ALTERNATOR	Smooth	12.7806	32.6559	15.5707	14.1254	12.680
4	AOA SENSOR	Smooth	33.1619	37.3501	32.0239	32.8009	32.617
5	APU ENG FIRE CTL MOD	Smooth	5.5364	10.9286	5.6881	5.6139	10.491
6	AUTO BRAKE SHUTTLE VALVE	Smooth	5.1124	23.9286	6.2222	8.5649	6.4444
7	AUTO SLAT VALVE	Smooth	1.1784	2.4532	0.9877	1.0000	1.0000
8	BRAKE METERING VALVE	Smooth	2.6508	5.6638	2.3924	2.3211	2.3916
9	BRAKE METERING MODULE	Smooth	4.5213	16.7081	3.2539	3.1074	3.1074
10	CABIN PRESS MODULE	Smooth	1.4926	3.3094	1.3658	5.4488	1.4896
12	EAU	Smooth	4.2926	11.8943	5.2992	4.0281	4.0532
13	EFIS CONTROL PANEL	Smooth	6.4642	9.9007	6.1229	6.8348	6.0995
14	ELEVATOR FEEL COMPUTER	Smooth	1.2707	1.1651	1.1478	13.1163	1.1197
15	FIRST OFICER SEAT	Smooth	16.9526	12.3485	15.5162	7.6124	7.6124
16	MARKER BEACON ANTENNA	Smooth	1.8022	3.8758	1.5985	1.8159	1.8159
18	FUEL TEMP INDICATOR	Smooth	2.0784	3.7898	1.7288	13.8184	1.7451
19	HMU	Erratic	13.2937	26.0225	2.6118	15.449	22.769
20	HYDRAULIC MOTOR	Smooth	0.8137	1.7757	0.6674	0.6667	0.6667
21	LE SLAT ACTUATOR	Smooth	18.646	13.8631	10.327	23.1220	15.854
22	MODE CONTROL PANEL	Smooth	1.7333	1.4700	2.1150	1.6949	1.6949
23	AURAL WARNING MODULE	Lumpy	7.5012	9.8795	8.8889	13.2187	7.6382
24	NLG ASSY	Smooth	1.3444	2.4272	0.7970	3.3881	0.7998
25	OUTFLOW VALVE	Smooth	1.0235	1.6906	1.0563	1.0037	0.9572
26	PARKING BRAKE VALVE	Smooth	6.6489	7.6552	7.0429	7.1351	12.852
27	POWER DRIVE UNIT	Smooth	0.6677	1.3300	0.5441	0.5556	0.5555
28	SCU 245	Smooth	9.1881	6.8863	11.2571	37.0497	9.3463
29	SELCAL PANEL	Smooth	2.5270	6.2291	2.0550	2.0180	2.034
30	SCU 250	Smooth	1.6494	5.8550	1.7666	1.7028	4.9999
31	STARTER POWER UNIT	Smooth	1.5048	11.0272	1.3508	52.7873	3.372
32	UNIT ANTISKID/AUTOBRAKE	Smooth	10.3369	15.0143	14.9907	17.0981	10.993
33	VALVE HPTCC	Smooth	6.1221	33.1328	7.5199	6.8827	6.1966
34	WINDOW # 4	Smooth	1.1566	1.6004	1.0624	10.836	1.0275
35	WINDOW # 5	Erratic	1.9852	1.0188	0.6724	1.8940	0.4458
34	AIR CICLE MACHINE	Smooth	3.2456	6.3692	3.1639	2.8015	3.3792
35	BLEED VALVE	Smooth	2.5800	2.3025	2.2683	3.1437	2.5523
36	APU FUEL VALVE	Smooth	1.0599	5.399	1.0631	1.2802	1.1112
37	APU START GENERATOR	Smooth	19.8628	2.5150	1.8763	32.3628	2.9922
38	FAN BLADE	Erratic	0.4056	0.4404	0.3944	0.4034	0.4355
39	CONTROL DISPLAY UNIT	Smooth	7.3920	7.7191	5.6789	5.8119	7.3824
40	DRIVE WXR	Smooth	9.1839	13.4715	8.2959	11.0242	8.9128
41	FLIGHT CONTROL COMPUTER	Smooth	7.9329	2.7438	4.3467	282.9312	4.9424
42	FUEL CONTROL UNIT	Smooth	11.6384	17.8467	8.7298	37.4485	9.6552
43	FIRE DETECTOR	Smooth	4.6118	0.8904	0.9075	1.4620	0.9832
44	FUEL FLOW TRANSMITER	Erratic	5.1549	13.9825	6.4955	4.6834	5.7673
45	FMC COMPUTER	Smooth	1.8146	2.3600	1.8576	1.7876	1.8501
46	HI STAGE REGULATOR	Smooth	31.0817	37.5719	29.5818	72.23050	30.394
48	OXYGEN MASK	Smooth	16.0265	16.5692	15.0948	17.8987	15.757
49	STARTER VALVE	Smooth	16.5455	26.6865	17.7709	48.1593	18.885
50	TRANSIENT BLEED VALVE	Smooth	18.7527	30.2325	13.2719	38.6387	16.034
51	VALVE	Erratic	0.4448	0.5213	0.4362	0.8212	0.4701
52	VBV ACTUATOR	Erratic	1.8518	2.0832	1.7176	1.7636	1.9113
53	WXR ANTENNA	Smooth	2.4797	4.1400	2.2296	2.1539	2.2966

Table 8: Comparison between Ghoobar e Friend (2003) with this research

Factor	Ghoobar e Friend (2003)	Actual Research
Data	35 spare parts	53 spare parts
Parts composition in relation to different aircraft models.	*Various aircraft models*	*Only one aircraft model*
Demand pattern that covers the majority of the historical base	*Lumpy*	*Smooth*
Number of tested methods	13 methods	5 methods and 2 of them obtained the best results in the work of Ghoobar and Friend (2003)
Better adjustment methods	*WMA, Holt and Croston*	*WMA, Poisson, Croston*
Worst adjustment method	*Winters*	*Winters*

Finally, during the case study, it was observed that the company, as well as others around the world, has problems with forecasting the demand for variable consumption materials. It does not use a specific software package for forecasts of variable demands, and the future purchases are made based on consumption history and fault mapping. These last two criteria reinforce Ghoobar and Friend (2003) 's assertion on the use of these variables by airlines to forecast the purchase of materials.

5. CONCLUSION

The predictions presented satisfactory results and were consistent with the theory presented in the literature review, especially with the work of Ghoobar and Friend (2003). The results presented in this study, using a historical series composed of fifty-three units, corroborates with the same results presented by Ghoobar and Friend (2003).

The methods that obtained the best adjustments for the historical series were the Weight Moving Average (WMA), the Poisson Method and the Croston Method. Considering that the data used in the prediction models came from the largest fleet of 737NG aircraft´s consumption of spare parts in South America, as also being the only one in Brazil and that most of the demands were classified as smooth, it is possible to suggest that WMA and the Poisson method are the most suitable methods for the management of critical parts for the operation of the 737NG in Brazil.

A suggestion for future studies is to test a prediction timeline below a monthly basis for the most critical parts which affect the aircraft's capacity to fly. We also suggest a prediction considering the Seasonal Period Length (SPL) and the Holt method. Also, it is necessary to verify the behavior of the WMA method for the other demand patterns, the prediction methods used in this work with different damping coefficients and the testing of these methods using data from different aircraft models that are part of the Brazilian fleet.

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