Initial Electronic Spare Parts Stock and Consumption Forecasting

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Abstract

There is a consensus that conventional continuous demand distribution methods are not appropriate for forecasting replacement parts. However, many forecasting tools available in market still use them. This work presents an application of the Poisson distribution to forecast the needs of electronic spare parts. Using basic stock management notions and usual concepts of reliability, availability and the Poisson process, an alternative method is proposed for sizing the initial stock of replacement parts to be purchased along with a electronic equipment. The results from the application of the proposed method and its comparison to the SAGA method, which is based on time series and normal distribution, are presented. The analyses of results have shown that it is possible to reduce the forecast errors; hence the stock costs, and the number of stockouts, thus enhancing the operational availability.

Keywords: Replacement parts, spares, forecast, stock management, supply, time series, availability, reliability, Poisson.

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1 Introduction

The adequacy of the stock control type depends on the purpose for which the material is intended. Thus, when a spare item is seen from the manufacturer or the seller's point of view, it should be analyzed through an appropriate method for production or sales. However, if the same material is seen under the user's point of view, the appropriate method must serve the purpose of a "Maintenance Support Stock" (MSS).

Often, replacement parts are expensive, with long re-supply time, the stockout cost very high and the patterns of demand are not the same found in the retail sales and production. There is a consensus among researchers that the spare parts consumption forecast should not be made by traditional methods such as moving average and exponential smoothing. This is mainly due to the low consumption rate, the long time between demand occurrences, characteristic of spare parts. Moreover, the demand generating process depends on the number of equipment units in use and in some cases, on the intensity of use, which are usually well known data. When the reliability of the system is critical, manufacturers and users focus their attention on the failure probability, which is the time elapsed until it fails (MTBF - Mean Time Between Failure); for repairable parts, the average time to fail (MTTF - Mean Time To Failure); for disposable parts, the time between repairs (TBO - Time Between Overhaul), informed by the manufacturer. For these reasons, the management of parts must be based on the process that generates failures, which is endogenous to the system. However, the software most commonly used in the management of spare part stocks disregards these characteristics and use the exponential smoothing forecasting methods.

Another important feature related to spare parts in a MSS is the desired operational availability, Ao, of the associated equipment. The availability can be understood as the parameter that measures the proportion of the time the equipment is up and ready for use. Thus, the shorter the time off is, the higher the availability of the equipment and the better the level of service will be. However, for the availability be high, there should be spare parts ready for the replacement of the defective items in case of failures.

The literature on inventory management is rich in methods for controlling stocks in wholesale, retail sales and manufacture, but in what the supply of spare parts is concerned, it does not have the same coverage and is relatively scarce. In spite of its actual importance to many industries, engineering or business academic courses seldom address subjects approaching the management of replacement part inventories.

The purpose of this study is to present a real case of forecasting the consumption of electronic spare parts adequate for sizing stocks to cover the needs between acquisition epochs. The method is mainly aimed at the application in companies that provide services that need to maintain high operational availability of their equipment and thus to have stock of spare parts for the ready replacement of the defective items.

The next section will present a brief review of the literature on spare parts consumption forecasting. Following that, Section 3 will present details of the exponential smoothing forecasting method adopted by the SAGA System (Management and Support Automated System) used by the studied organization managing spare parts. Section 4, presents the proposal of an alternate methodology for forecasting the needs of electronic spare parts, as well as the present situation, and compares the expected results from both methodologies. Finally, in the last section, the benefits of the proposed methodology will be discussed.

2 Literature Review

Methods for forecasting and determining the re-supply of wholesale, retail and manufacture stocks are easily found in books and inventory management courses. In such cases, the demand and the response time frequently have good adherence to the normal distribution, and time series methods are adequate for forecasting the demand. However, in the case of spare parts for maintenance, the problem is clearly different. When compared with retail items, spare parts are usually more expensive, of sporadic need and low consumption rate; the availability is critical (high stockout costs). This intermittent demand rules out the normal distribution as a reasonable representation, and the time series methods, designed for continuous distribution, becomes inappropriate in face of high probabilities of zero demand.

Frequently, time intervals between failures are completely random, and many studies found in literature employ mainly Gamma and Poisson distributions to represent the demand for spare parts (CROSTON, 1972).

These distributions are associated with the known Poisson process characteristic of phenomena in which age or wear of the component does not affect the likelihood that it will fail, and also the fact that given that a failure has just occurred has no influence on the time elapsed until the next failure. A characteristic of the Poisson distribution (i.e. the probability distribution that, in a Poisson process, x failures will occur in a given time interval t), which makes it easy to use, is that its average is equal to its variance and is a parameter that completely characterizes the distribution. Therefore, if the failure process has the characteristics of a Poisson process, it is enough to use the average demand of historical data to estimate the probability of any given number of failures to occur in any time interval. Strijbosch et al. (2000) discuss the selection of adequate distribution for methoding demand distribution for spare parts for an (s, Q) control system, and use a compound Bernoulli distribution.

Studying the case of a manufacturer of electronic products in Taiwan, Yeh (1997) adopted the premise of the Gamma distribution for demand to determine the spare parts stock policy. As usual, the normal distribution proved to be inadequate by the fact that most of the items studied presented annual demand less than ten units. The Poisson distribution also showed little adherence to data since the variances and average historical demands were significantly different.

Wanke (2005) studied the case of a Brazilian manufacturer of agricultural equipments and used the Gamma distribution for methoding the consumption of spare parts adjusting the actual data to test alternative methods based on the key characteristics of the spare parts. In another study, Wanke (2006) noted that the demand for spare parts had good adherence to the Poisson distribution. He also pointed out that the properties of this distribution become particularly interesting when examining how different safety stock levels would affect the likelihood of lack of material, especially in environments where the annual consumption is between 1 and 300 units.

From the logistic point of view, spare parts systems can become extremely complex, especially when the company provides maintenance service for its customers. Some factors that may exacerbate the complexity are the geographic location and the existence of repairable items. Some interesting case studies are presented by Cohen, and Zheng Wang (1999) and by Fleischmann et al. (2003) for companies that offer service to their customers.

After checking the forecasting methods used by a central audio manufacturer, S.I.T.T.I.

(1999), by the France Telecommunications Committee, C.C.T. (1983), by a radar manufacturer, FIAR (1988) and by the authority responsible for the logistic development of equipments used for flight protection in Brazil, CISCEA (1994), it was found that all use the Poisson distribution in the methodology for estimating the initial purchase of spare parts.

The methodologies developed by Yeh (1997), and by Wanke (2005) were aimed at the stock of suppliers or manufacturers of spare parts. However, the methodologies employed by manufacturers of equipment S.I.T.T.I. (1999), FIAR (1988), CCT (1983), and mentioned by Wanke (2006) and CISCEA (1994), were developed for users of equipment maintainers. This latter seemed to be more adherent to the reality proposed in this work and was chosen to be the basis of its development.

3 The SAGA Stock Management Method

The SAGA System (Management and Support Automated System) is a software system containing a popular time series method (exponential smoothing) that allows forecasting demands of items based on its consumption records. The method is based on two main variables: the consumption average level (MI) and the growth trend (TI). For the calculation of future consumption, the past MI and TI values will be analyzed and used to calculate future values.

The procedures presented below have been taken from the technical documentation ISDS013 (PAME, 1986).

3.1 Presentation of the Method

The exponential smoothing method with trend can be described in two steps:

a) startup , and

b) (continuous) re-estimation of the parameters of the method.

3.2 Startup

In the startup step, the system provides starting values for α (smoothing coefficient for the average level estimate) and β (smoothing coefficient for the trend estimate) chosen from a set of pre-defined values that best represents the series. In other words, the pair that gives the smallest mean absolute deviation (MAD) value for a starting sample of the series of observed demands of the item (or, perhaps of some similar item, if the item has no history).

α	0.10	0.10	0.10	0.15	0.15	0.15	0.20	0.20	0.20	0.30	0.30	0.30
β	0.40	0.20	0.10	0.40	0.20	0.10	0.40	0.20	0.10	0.40	0.20	0.10

Adapted from PAME, 1986.

Table 1 – Initial values of α and β for the selection of the best pair

Different values of α and β can be entered manually.

Two situations are considered:

a) There is a historical series of consumption; in this case, the system methods the series and computes the mean absolute deviation (MAD) of the forecasts produced by each pair α and β. The pair selected will be the one presenting the lowest MAD; and

b) There is no historical series of consumption; in this case, the system estimates the future consumption considering α = 1 for the first forecast, α = 0.8 for the second forecast, α = 0.6 for the third forecast, α = 0.4 for the fourth forecast, α = 0.2 for the fifth forecast and α = 0.15 for the sixth forecast. In the seventh forecast, the system considers that there is already a historical series of consumption, and reevaluates the parameters accordingly.

3.3 Estimation of Model Parameters

The calculation of the consumption forecasts is done using the formulae described below:

$\hat{L}_t = \alpha Q_t + (1-\alpha)\hat{M}_t$ → level in month t

$\hat{T}_t = \beta(\hat{L}_t - \hat{L}_{t-1}) + (1-\beta)\hat{T}_{t-1}$ → trend in month t

$\hat{M}_{t+1} = \hat{L}_t + \hat{T}_t$ → consumption forecast for month t+1

Q_t → actual consumption in month t

3.4 Calculation of the Mean Absolute Deviation (MAD)

The MAD is calculated using the formula below:

$$EMA_{to} = \alpha\left|Q_{t0} - \hat{M}_{t_0}\right| + (1-\alpha)EMA_{t_0-1}$$

$\hat{M}_{t_0}$ → Average consumption forecast for the current month made in previous month.

Q_{t_0} → Actual consumption in the current month.

EMA_{t_0} → Mean absolute deviation estimate of the level estimates.

3.5 Estimation of Future Values

The estimation of future values is performed taking the optimum pair α e β, the last forecast and actual consumption as reference.

$\hat{L}_t$ → Level estimate in month t.

$\hat{T}_t$ → Trend estimate in month t.

$\hat{M}_{t+n} = \hat{L}_t + n\,\hat{T}_t$ → Consumption forecast for month t+n (made in month t).

The total consumption forecast for the next n months will be given by:

$\hat{C}_n = n \times \hat{L}_t + n(\frac{n+1}{2})\hat{T}_t$ → Consumption forecast for n future months.

3.6 Considerations on the SAGA

The system was developed in the 80's of the last century to manage around 100,000 different items. At that time, the computing resources in terms of memory, capacity and processing speed were quite limited when compared to today. Thus, programmers used tables and simplifications to avoid operations such as exponential, which consumed large processing time.

If the same system would be developed today, it would not be so worried about processing speed and could use procedures such as linear regression for the initialization of coefficients α and β, as well as the mean quadratic error instead of the MAD, making the calculations more accurate.

4 The Forecast Methodology Proposed

Modern electronic equipments present very low failure rates, something around one failure every 100,000 hours. This characteristic would lead us to think that electronic equipments would have long lifetime. However, one must consider another aspect: the obsolescence. There are two types of obsolescence: the operational obsolescence due to the emergence of new equipment providing greater convenience and operational performance, and the technical obsolescence due to the evolution of components, leading manufacturers to seek for components with better performance and lower cost. Obsolescence, even of reasonably large and expensive electronic equipment, has made the time to replacement that, not long ago was of 20 years, to drop to some 5 to 10 years.

It is then assumed that an electronic component does not wear during the lifetime of 5 to 10 years, and in this case, ruling out the phase of "infant mortality," the failures follow a stable stationary stochastic process. This assumption is fundamental for understanding the proposal made in this work, to use the Poisson distribution as an alternative to the use of time series to achieve better results in forecasting consumption of electronic replacement parts.

Initially, a brief review of the concepts that will support the methodology proposed will be presented followed by a methodology for calculating the initial purchase of spare parts used by the majority of suppliers of equipments.

4.1 Failure Rate λ

The failure rate of a given part can be defined as "the proportion of entities that having survived a certain time t failed within the time interval [*t,t+T*]", (VILLEMEUR, 1992). The failure rate can also be defined for a single item, by:

$$\lambda = \frac{f}{T}$$

$\lambda \rightarrow$ Failure rate

$f \rightarrow$ number of failures occurred in the time interval T

$T \rightarrow$ observation time interval,

and for N items installed in K equipments, by:

$$\lambda_{eq} = \frac{f}{KNT}$$

K $\rightarrow$ number of identical equipments containing the item,
N $\rightarrow$ quantity of the item installed in each equipment,

A variant of the failure rate, also widely used, is the MTBF (Mean Time Between Failures) and MTTF (Mean Time To Failure). For obvious reasons, the MTBF is customarily used to repairable items and the MTTF for disposable items.

$$MTBF = MTTF \frac{1}{\lambda}$$

4.2 Availability and Level of Service

The operational availability is related to the time to repair the equipment. It can also be seen as level of service and depends basically on the following:

a) Frequency and duration of the preventive maintenance, and

b) Quantity and duration of corrective maintenances.

Mathematically, the operational availability is the relationship between the operational time and the sum of the operation time and the time off (or, down time). A value of around one means maximum availability.

$$A_o = \frac{T_{ON}}{T_{ON} + T_{OFF}}$$

$A_o \rightarrow$ Operational availability

$T_{ON} \rightarrow$ Operational time

$T_{OFF} \rightarrow$ Time off

Time off is a function of several factors, of which, the most important are (C.C.T., 1983):

a) Constructive characteristics of the equipment:
- Devices for testing and locate failures
- Facilities for the removal of the defective item and its replacement;

b) Maintenance personnel:
- Quantity;
- Classification;

- Experience;

c) Technical documentation:
- Scope;
- Update;

d) Testing tools and equipment:
- Adequacy;
- State;
- Calibration;

e) Replacement parts availability:
- Adequacy;
- Quantity.

This work is focused on the issue of sizing spare parts inventory. The target stock should be such that the probability of no stockout (replacement parts availability) provides an operational availability index (level of service) specified for the equipment. Modeling the probability of no stockout as a function of available stock is, therefore, key issue on controlling operation availability. The model here proposed is based on the Poisson distribution.

4.3 Poisson Distribution

The Poisson distribution, whose concept was presented in Section 2, is used to method the occurrences of an event considered "rare" in a given period of time, (SHAPIRO, 1967).

Probability Density Function

$$f(k) = P(K = k) = (\lambda t)^k \frac{e^{-\lambda t}}{k!}, \; t > 0 \quad ,$$

λ → Failure Rate

λt → Mean failures in time period t

k → Number of failures in time period t

Cumulative Probability (probability of k or less failures)

$$P(K \leq k) = \sum_{i=0}^{k} (\lambda t)^i \frac{e^{-\lambda t}}{i!}, \; t > 0$$

4.4 Initial Purchase Forecast

The purpose of the initial purchase of spare parts is to minimize the probability that particular equipment becomes inoperable due to the lack of parts in the initial operation period. This is important because the cost of the additional parts at the time of acquisition is far lower than when it will be years latter when the part is already out of regular production.

Usually, the initial quantity of spare parts is purchased along with the equipment and is calculated according to the buyer's criteria and suggestion from the supplier. It is essential to maintain the availability of the equipment within the operation period in which the maintainability is estimated based on data from the manufacturer.

The problem is, essentially, to determine the number of spare component units to buy along with new equipment so that the probability of running out of stock is some given value.

4.4.1 Assumptions

The following assumptions are used in the inventory sizing method:

a) the defects due to the infant mortality were eliminated in the burn in process;

b) the components follow an exponential failures law;

c) there is no degradation of parts during the storage period (bottom of the "bath-tub" curve);

d) only the items damaged in the equipment are replaced by spare parts during the repair;

e) the failure rate is considered constant over the period forecasted for the stock, and the failures are resulting from stochastic and independent events, by intrinsic mechanisms of the own item (related to assumption (c) above);

f) the equipment is operating according to normal specification conditions, receiving all the recommended preventive maintenance, as well as all the corrective maintenance needed to restore it to original specification conditions and level of quality, and

g) the spare quantities of the item necessary for repairing failures, other than those resulting from the processes listed above, are supplied by additional stocks.

4.4.2 Mathematical Method

The cumulative Poisson distribution defined above gives the probability of not running out of stock during the maintainability period. With a notation and terminology more adequate to the application (CISCEA, 1994) it is presented below:

$$Ps(s) = \sum_{x=0}^{s} \frac{F^x}{x!} \times e^{-F},$$

s → number of units of the spare item bought with the equipment,

Ps(s) → also called the "probability of no stock disruption," is the cumulative probability that the number of failures, x, of the item is less than or equal to s.

Using the notation defined earlier:

F= $\lambda_{eq} t$ → mean number of failures of the item under consideration during a given a time interval t, assuming that all equipment units are identical:

$$F = K\, N\, M\, L\, T_d\,;$$

K → total number of units of equipment that contain the item,
N → quantity of the item installed in each unit of equipment,
M → (M < 1) average utilization rate of the KN items installed (M = 1 if under 24h a day, year-round operation),
L → failure rate of the item (failure per time unit), usually designated as λ,
T_d → time to decommissionement (or support, or maintainability period) forecasted as of the initial purchase.

4.5 Methodology Proposed

An item is considered critical when its failure puts the equipment, which contains it, out of operation. Hence, the first step in the stock-replacement methodology proposed is the identification of critical items. These items should have priority treatment in relation to others, regardless their value and quantity, because the consequences of the equipment breakdown will override other operational costs.

Once these critical items are identified, the non-critical items can be treated according to the usual cost benefit analysis, perhaps still methoding the demand as a Poisson, compound Poisson, gamma, or some other adequate distribution, in case the demand exhibits an intermittent generation process .

4.5.1 Operational Availability and Probability of no Stock Disruption

Usually, there is no simple direct relation linking the operational availability Ao with the probability of no stock disruption Ps, because as seen in Section 4.2, the time off, TOFF, depends on many other factors, especially on the supplier's lead time. However, ceteris paribus, the greater the Ps is, the greater the Ao will be. According to the experience with critical and complex electronic systems, Ps plays a dominant role in defining A0 due to the strict standards that usually focus on the other intervening factors mentioned above.

Table 2, below, shows a suggestion, based on experience, to associate Ps with Ao.

Ao	Ps
0.95	0.95
0.96	0.97
0.97	0.98
0.98	0.99
0.99	0.995

Table 2 – Ps suggested as a function of Ao

Ideally a very large Ao would be desirable; but very high values may be economically infeasible. Because the cost of failures and time-off are hard to assess in a formal way, the more realistic approach is to leave availability as a discretionary value left to managerial judgment.

4.5.2 Consumption Forecast

The methodology for forecasting the consumption in a given time period is described below:

a) Estimate time to decommissionement of the equipment, Td;

b) Identify the operational availability or level of service contracted for the equipment under analysis. Estimate the no stock disruption rate that provides the level of service, Ao, contracted (such as the Table 2);

c) Examine the failures of this item and the respective dates;

d) Calculate the failure rate estimate λ_{eq} during the observation time, T (symbols as defined earlier):

$$\lambda_{eq} = \frac{f}{KNT},$$

e) Calculate the number of parts s to be acquired for the desired probability of no stock disruption, where $F = \lambda_{eq}\, T_d$:

$$Ps(s) = \sum_{x=0}^{s} \frac{F^x}{x!} \times e^{-F}$$

It is important to stress that this approach calculates the probability of consuming no more than s units of an item during a given period of time. Therefore, it also useful for calculating the amount to be acquired to restore the stock, in case the initial stock is depleted.

5 Comparison between the SAGA method and the forecast method proposed

The forecast error measurement helps to assess the adequacy of method adopted by estimating the dispersion and the bias of the forecasted demand.

The forecast error, Et, is given by:

Et = Forecast – Actual Consumption

The Mean Absolute Deviation (MAD) is used to evaluate the forecast error, given by:

$$MAD = \frac{1}{n} \sum_{t=1}^{n} |E_t|$$

The MAD was used to compare the forecasts between SAGA method and the method proposed.

Another important aspect to measure in the performance of the method is the number of "insufficient forecasts." More so for maintenance jobs that will be stopped (in case of lack of spare part to replace the item that has failed) until the part required becomes available. The lack of replacement parts is one of the most important factors compounding the time off. It is special importance for parts with long acquisition lead times. Cases, where the acquisition time is more than 3 months are very frequent. Therefore, low occurrence of insufficient forecasts that lead to stockouts is an important performance measure.

The performances of the two methods were evaluated for three representative items of a flight protection system using historical data of four consecutive semesters. The values presented in Table 3 below show that the forecast method using the Poisson distribution presents smaller MAD when compared with the SAGA method. Using the Poisson model, no insufficient forecast was observed, while a total of nine occasions in two items were produced by the SAGA method in the period considered. In the case of the SAGA system, the stock manager would have to increase the safety stock to improve the availability of spare parts, meaning a substantial cost increase because, due to obsolescence, residual value of the leftover parts is negligible.

Item	Períod	Actual Consuption	Forecast SAGA	Forecast POISSON	Insufficient Forecast SAGA	Insufficient Forecast POISSON	MAD SAGA	MAD POISSON
Power Supply	2005-1	13	7	13	6	0	***7,25***	***4,5***
	2005-2	5	12	13	0	0		
	2006-1	8	24	15	0	0		
	2006-2	11	11	14	0	0		
	TOTAL	***37***	***54***	***55***	***6***	***0***		
Amp. Module	2005-1	8	7	10	1	0	***4,25***	***3,5***
	2005-2	6	4	9	2	0		
	2006-1	6	13	10	0	0		
	2006-2	5	12	10	0	0		
	TOTAL	***25***	***36***	***39***	***3***	***0***		
Local Oscill	2005-1	2	3	3	0	0	***1,5***	***1,25***
	2005-2	2	4	3	0	0		
	2006-1	3	3	3	0	0		
	2006-2	1	4	4	0	0		
	TOTAL	***8***	***14***	***13***	***0***	***0***		

Table 3 – Performance comparison: SAGA vs. POISSON

Conclusions

The objective of this study was to show an alternative method for use in sizing the initial stock of spare parts for expensive electronic control equipment. Consumption forecasts of critical electronic spare parts were based on the Poisson distribution as alternative to traditional methods that use classical exponential smoothing time series forecasting.

Through simulations of both methods applied in real cases, it was found that the simple and easy-to-implement methodology proposed may be considered more appropriate for forecasting the consumption of electronic parts, since it presented the smallest forecast errors when compared with the exponential smoothing method.

In addition, the alternative method provided considerable reduction of insufficient forecasts. The cost of insufficient forecasts is related to penalties for not meeting the operational availability contracted – due to the lack of spare parts for the ready operational recovery of the equipment – and, above all, to the company's image, which is priceless in complex systems maintenance business.

It is important to stress the importance of calculating the failure rate. When the manufacturer provides the failure rate of the equipment and its components, the value provided is obtained under standard conditions, and often does not match that found in the actual life of the item. In the case studied, the initial stock of replacement parts was dimensioned according to the failure rate informed by the manufacturer. However, after one year of operation, it was possible to reevaluate it to estimate future consumptions. The recalculated failure rate is an important forecast parameter and a description of the item behavior under the prevailing conditions. It should be noted, however, that the methodology proposed here assumes that the failure rate is stable. This means that the infant mortality phase and the wear out phase, of the "bath tube" shaped failure rate curve, are ruled out by an adequate burn in and by decommissioning the equipment before failure rate accelerates.

Future studies should consider the improvement of the failure rate calculation, especially in relation to the optimum calculation period and perhaps the application of a damping coefficient; so that failures occurred in a distant past have less weight than recent failures. Additionally, the operational availability as a function of the probability of no stock disruption also merits further investigation. The optimization of these factors could lead to results better than those already found with the application of the simple method proposed in this paper.

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