Spare Parts Inventory Control for Non-Repairable Items Based on Prognostics and Health Monitoring Information

Leonardo Ramos Rodrigues[1] and Takashi Yoneyama[2]

[1] *EMBRAER S.A., São José dos Campos, São Paulo, 12227-901, Brazil*
leonardo.ramos@embraer.com.br

[2] *ITA – Instituto Tecnológico de Aeronáutica, São José dos Campos, São Paulo, 12228-900, Brazil*
takashi@ita.br

ABSTRACT

The application of PHM (Prognostics and Health Monitoring) techniques can provide a wide range of benefits to aircraft operators. Since the primary goal of PHM systems is to estimate the health state of components and equipments, as well as forecasting their RUL (Remaining Useful Life), they are often closely associated with the reduction in the number of unscheduled maintenance tasks. Indeed, the avoidance of unscheduled maintenance is a very important factor, but this technology may potentially lead to considerable further savings in other fields. The usage of PHM information by the logistics team for spare parts inventory control is a good example to illustrate that a PHM system can potentially provide benefits for other teams besides the maintenance team. The purpose of this work is to present a comparison between two different inventory control policies for non-repairable parts in terms of average total cost required and service level achieved. The well known [*R*, *Q*] (re-order point, economic order quantity) inventory model will be used as a reference. This model will be compared with a model based on information obtained from a PHM system. Discrete event simulation will be used in order to simulate and assess the performance of both models.

1. INTRODUCTION

PHM technology is recognized by the members of the aeronautical sector such as aircraft operators, MRO (Maintenance, Repair and Overhaul) service providers, aircraft manufacturers and OEMs (Original Equipment Manufacturers) as a relevant tool that may lead to important competitive advantages such as reduction in operational cost and increase in fleet reliability. However, quantifying PHM benefits is not a simple task. Hess, Frith and Suarez (2006) stated that cost-benefit models are the key to estimate the value of PHM technology.

In order to demonstrate the benefit of PHM technologies, many cost-benefit models have been proposed (Hess et al., 2006; Luna, 2009; Sandborn & Wilkinson, 2007; Feldman, Jazouli & Sandborn, 2009). Some of these works (Luna, 2009; Sandborn & Wilkinson, 2007) comprise discrete-event simulation models.

The objective of these models is to simulate the behavior of the maintenance or logistics departments when a PHM system is available for a set of components. Such models can be divided basically into three blocks: Fleet simulation, decision making and cost evaluation (Rodrigues, Gomes, Bizarria, Galvão & Yoneyama, 2010). Figure 1 shows how each simulation block interacts with others.

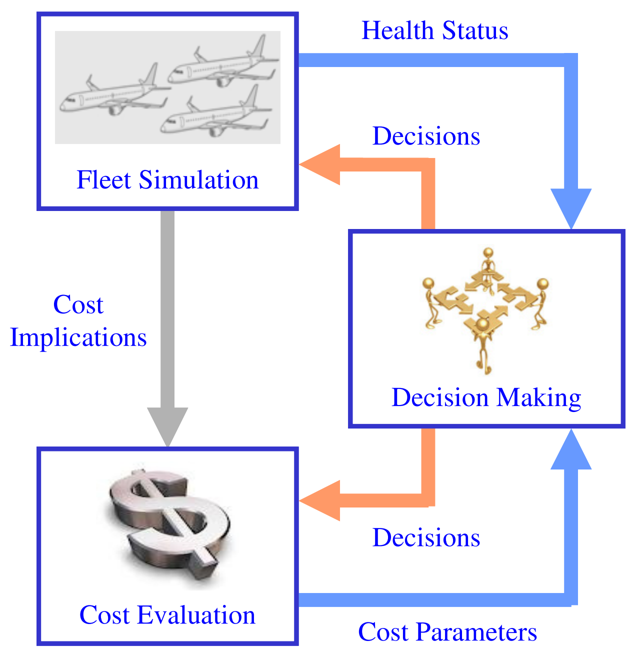

Figure 1. Simulation block diagram

The fleet simulation block comprises a simulation of a set of components that are monitored by a PHM system. Failures are inserted in the simulation based on historical rates and the PHM system is assumed to anticipate a given number of failures by providing PDFs (Probability Density Functions) of failure instant.

Based on that information, the decision making block is responsible for defining which actions should be taken in a certain moment in time. The logic of the decision making block depends on the activities covered by the simulation. When the maintenance planning is simulated, the decision making block can define the best time and the best location to perform maintenance. If logistics department is simulated, the decision making block can define the best moment to place a new purchase order for spare parts and the ideal number of spare parts to be acquired.

The cost evaluation block computes the total cost resulting from the actions taken during the simulation. Usually, this cost is compared to the cost obtained by using a conventional model in order to quantify the benefits due to the PHM system.

This work presents a spare parts inventory control policy for non-repairable items. The proposed policy is based on the health condition information obtained from a PHM system. A discrete event simulation is performed in order to compute the costs associated with the implementation of the proposed method. A comparison between the proposed method and the classical [*R, Q*] inventory control model is made in terms of average total cost required and service level achieved.

2. PHM Basic Concepts

PHM can be defined as the ability of assessing the health state, predicting impending failures and forecasting the expected RUL of a component or system based on a set of measurements collected from the aircraft systems (Vachtsevanos, Lewis, Roemer, Hess & Wu, 2006). It comprises a set of techniques which use analysis of measurements to assess the health condition and predict impending failures of monitored equipment or system.

The main goal of a PHM system is to estimate the health state of the monitored equipment and forecast when a failure is expected to occur (Roemer, Byington, Kacprzynski & Vachtsevanos, 2005). In order to accomplish this task, it is necessary to collect a set of data from the aircraft. The choice of the parameters that will be recorded is based on the type of equipment/system to be monitored (hydraulic, electronic, mechanic, structural, etc.) and the failure modes that shall be covered by the PHM system. These factors also guide the data collection specification (sample rate, flight phase, etc.).

A health monitoring algorithm must be developed for each monitored system. Each algorithm processes the relevant data and generates a degradation index that indicates how degraded the monitored system is. A degradation index can be generated for each flight leg or for a defined period of time (a day, a week, etc.).

In many cases it is possible to establish a threshold that defines the system failure. When the failure threshold is known, it is possible to extrapolate the curve generated by the evolution of the degradation index over time and estimate a time interval in which the failure is likely to occur (Leão, Yoneyama, Rocha & Fitzgibbon, 2008; Kacprzynski, Roemer & Hess, 2002). This estimation is usually represented as a probability density function, as illustrated in Figure 2. Due to the operational characteristics of some equipment – such as tires and the braking system – it can be useful to express the remaining useful life in terms of flight cycles. There is always a confidence level associated with the predicted time interval.

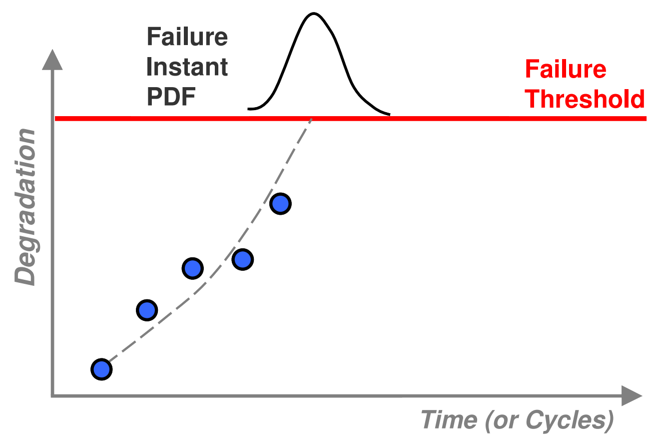

Figure 2. Degradation evolution and instant of failure prediction

The term IVHM (Integrated Vehicle Health Management) is commonly used when the information generated by a PHM system is used as decision support tool. IVHM can be defined as the ability of making appropriate decisions in both strategic and tactic levels based on diagnostics/prognostics information, available resources, logistics information and operational demand in order to optimize the efficiency of operation (Puttini, 2009).

3. CLASSICAL INVENTORY MODELS

Failure events occur during fleet operation and spare parts must be available to keep aircraft flying. To deal with these failure events and avoid AOG (Aircraft on Ground) situations, aircraft operators have to maintain a spare parts inventory. An inventory control program must be implemented in order to fulfill the highest possible number of spare parts demand at the least possible cost.

There is a set of classical inventory control models described in literature that can be used to establish an inventory policy. Most of these models define an inventory policy based on total cost minimization. Inventory cost can be broken down into the following factors (Ballou, 2006; Hillier & Lieberman, 2005):

Ordering Cost

The cost of ordering an amount of Q spare parts is presented in Eq. (1). It is composed by two main components: The acquisition cost C (directly proportional to the amount ordered) and a constant term K representing the administrative cost of placing a new purchase order.

$$OC(Q) = K + C \cdot Q \tag{1}$$

Where OC is the ordering cost, Q is the number of spare parts to be purchased, K is the administrative cost and C is the unit cost.

Holding Cost

Holding cost is also known as storage cost and represents the aggregated cost related to the storage of the inventory until it is used. It comprises the cost of capital tied up, warehouse space leasing, insurance, obsolescence, protection, inventory management labor, etc.

The holding cost can be computed either continuously or on a period-by-period basis. In the latter case, the cost may be a function of the maximum quantity held during the period, the average amount held, or the quantity in inventory at the end of the period. If holding cost is computed continuously, it can be calculate as indicated in Eq. (2).

$$HC = \int H \cdot X(t)dt \tag{2}$$

Where HC is the holding cost, H is the holding cost per unit per unit of time held in inventory and $X(t)$ is the number of spare parts held in inventory at instant t. In some cases, H is defined as a fraction of the unit cost.

Stockout Cost

Stockout cost is the cost of not having a spare part on hand when it is needed. In the event of a failure, if the failed component cannot be replaced due to the lack of a spare part, it may result in an AOG situation. In this case, the stockout cost represents the losses in the aircraft operator's revenue related to the aircraft unavailability.

Some aircraft operators outsource the spare part inventory management. In this case, the stockout cost is also known as penalty cost and represents possible contractual penalties for the inventory owner. Indirect costs such as company reputation and damage to customer relationship may also be included as part of the stockout cost.

Inventory simulation can adopt two different scenarios for stockout costs. In the first scenario, when a spare part is required and there are no spares on hand, the aircraft with the failed component remains unavailable until the inventory is replenished and demand for the failed component can be satisfied. This scenario is called backlogging.

In the second scenario, when a spare part is required and there are no spares on hand, the inventory is no longer responsible for satisfying that specific demand. In this scenario, this demand is considered to be met by a priority shipment. This scenario is called no backlogging.

In this work, the backlogging scenario is considered. The stockout cost is given by:

$$SC = \int P \cdot Y(t)dt \tag{3}$$

Where SC is the stockout cost, P is the stockout cost (or penalty cost) per unit per unit of time and $Y(t)$ is the number of spare parts requests not satisfied by the inventory at instant t. Sometimes, P is defined as a fraction of the unit cost.

3.1. Deterministic Models and Stochastic Models

Inventory models can be divided in two categories: Deterministic models and stochastic models, according to whether the demand for a specific period is known or is a random variable having a known probability distribution (Hillier & Lieberman, 2005).

Deterministic inventory models are used when the demand for future periods can be forecast with good precision. An inventory policy can be developed in order to satisfy all spare parts requests.

On the other hand, when it is not possible to forecast future demand with acceptable precision, stochastic inventory models are used. These models assume that future demand is a random variable having a known probability distribution. The inventory policy is designed based on the service level desired. Service level is the percentage of spare parts requests that are satisfied immediately.

In this work, demand is considered to be stochastic with a normal distribution.

3.2. Continuous Review and Periodic Review

Another common classification for inventory control models refers to whether the current inventory level is monitored continuously or periodically (Ballou, 2006).

In continuous review models, a reorder point is defined as the quantity that triggers the need for a new order. Then a new order is placed as soon as the stock level falls down to the reorder point.

In periodic review models, a maximum inventory level is defined and the current inventory level is checked at discrete intervals, e.g., at the end of each week or month. A new order is placed every time the inventory level is checked in order to replenish it to its maximum value.

In this work, the inventory level will be continuously monitored.

3.3. The [R, Q] Model

A continuous review inventory policy for a specific component normally will be based on two critical numbers: The reorder point (*R*) and the order quantity (*Q*). That is the reason for calling this the [*R, Q*] model. In this model, whenever the effective stock level of the component drops to *R* units, an order for *Q* more units is placed to replenish the inventory. The effective stock is the total of spare parts in the warehouse and replenishments ordered but not yet received.

In this work, a [*R, Q*] model will be simulated and the results will be compared with the results obtained when the proposed model used. The assumptions of the [*R, Q*] model used in this work are described as follows:

- Each [*R, Q*] model establishes the policy for a single component.
- The inventory level is under continuous review.
- There is a lead time between when the order is placed and when the order quantity is received. This lead time is considered to be fixed.
- The demand for withdrawing units from inventory during the lead time is uncertain. However, the probability distribution of demand is known.
- If a stockout occurs before the order is received, the excess demand is backlogged, so that the backorders are filled once the inventory is replenished.
- A fixed administrative cost *K* is incurred each time an order is placed (as described in Eq. (1)).
- There is no discount for large quantity order.
- A certain holding cost *H* is incurred for each unit in inventory per unit time.
- When a stockout occurs, a stockout cost *P* is incurred for each unit backordered per unit time until the backorder is filled.

To simulate an inventory model based on this policy, the only decisions to be made are to choose *R* and *Q*. The expression used to calculate *Q* is the EOQ (Economic Order Quantity) formula (Hillier & Lieberman, 2005):

$$Q = \sqrt{\frac{2 \cdot D \cdot K \cdot (H + P)}{H \cdot P}} \tag{4}$$

Where *Q* is the quantity of spare parts to be purchased when a new order is placed, *D* is the average demand per unit of time, *K* is the administrative cost of placing an order, *H* is the holding cost per unit per unit of time held in inventory and *P* is the stockout cost per unit per unit of time.

The reorder point *R* is determined based on the desired service level (*SL*). In this model, service level is related to the probability that a stockout will not occur between the time an order is placed and it is received (called lead time).

A managerial decision needs to be made on the desired service level. Since the demand probability distribution is known, *R* is chosen so that the area under the demand curve is at least equal to the defined service level. The procedure to determine *R* is illustrated in Figure 3.

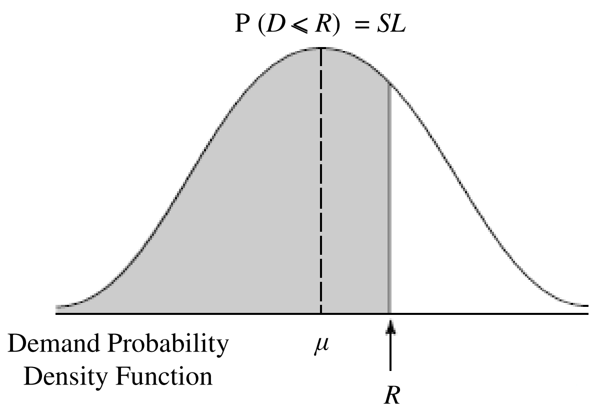

Figure 3. Reorder point definition for the [*R, Q*] model

3.4. Extensions of the EOQ Model

Several works exploring the EOQ formula and some extensions have been published by the Operational Research community over the last decades (Syntetos, Boyland & Disney, 2009). In most of these works, continuous demand is considered (Yong, Ying & Bing, 2011). Other techniques such as Lot for Lot Ordering (Omar & Supadi, 2003), Wagner-Within Algorithm (Wagner & Whitin, 1958), Least Period Cost Model (Ho, Chang & Solis, 2006) and Silver-Meal Algorithm (Omar & Deris, 2001) are also applied to deal with discrete demand problems.

Although demand for spare parts presents characteristics similar to a discrete pattern, many studies consider the assumption that spare parts demand is continuous and apply the EOQ formula (Sakaguchi & Kodama, 2009). It happens because the EOQ model is very easy to understand and simple to implement, while most of techniques developed to deal with discrete demand are complex and hard to implement.

Wongmongkolrit and Rassameethes (2011) proposed a modification to the EOQ model in order to adapt it to be used in discrete demand problems.

4. PROPOSED MODEL

This section describes the proposed model to control the spare parts inventory for a non-repairable item. All assumptions listed on section 3.3 for the [*R*, *Q*] model are valid for the proposed model, which also considers the following assumption:

- The proposed model receives information from a PHM system that systematically monitors the health status of the items installed on the fleet.

It can be noticed that the set of assumptions considered by the proposed model is very similar to the set of assumptions of the classical [*R*, *Q*] model presented in the previous section. In fact, the proposed model is essentially a [*R*, *Q*] model, but it differs from the classical [*R*, *Q*] model in how the reorder point *R* is calculated.

In the classical model, reorder point *R* is fixed. It is only necessary to calculate *R* at the beginning of simulation because it does not change unless desired service level or demand probability distribution change during the simulation.

However, in the proposed model, reorder point is obtained based on the information received from the PHM system. Since in this work PHM information is considered to be updated on a daily basis, the reorder point *R* will be also updated at the same rate.

Figure 4 illustrates the procedure to calculate the reorder point *R* for the proposed model. Since the reorder point is systematically updated, it will called *R(t)*.

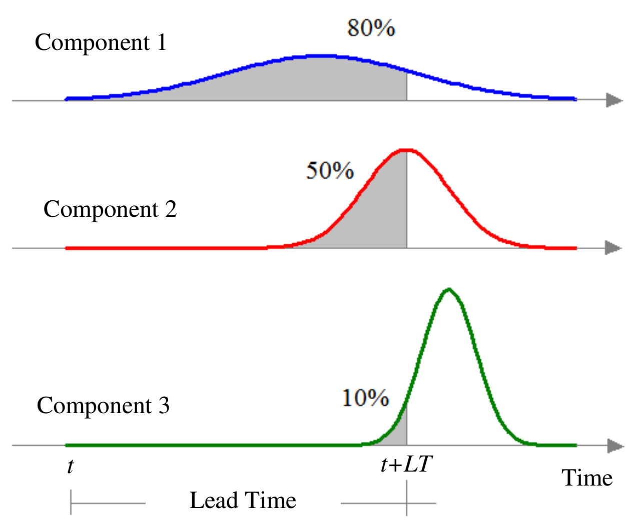

Figure 4. Reorder point definition for the proposed model

Let's assume that *t* is the current day and the curves showed in Figure 4 are the instant of failure probability density functions given by a PHM system for three similar components. The reorder point *R(t)* must be calculated in order to define whether a new order must be placed or not. An order placed on day *t* will be delivered on day *t+LT*, where *LT* is the lead time. The proposed model will calculate *R(t)* based on the probability that each component will fail before instant *t+LT*. These probabilities correspond to the gray area under each probability density function in Figure 4.

It can be seen that component 1 has a probability 80% of failing before instant *t+LT*. The probabilities for components 2 and 3 fail before instant *t+LT* are, respectively, 50% and 10%.

Based on this information, the model calculates the probability of *N* components fail before instant *t+LT*. For instance, in the example above the probability of all three components to fail before instant *t+LT* is obtained by multiplying the probability of each component to fail before instant *t+LT* (i.e. 80% x 50% x 10% = 4%). The complete fail probability table for this example is shown in Table 1.

Number of failures (N)	Probability that exactly N failures will occur before instant t+LT	Probability that at most N failures will occur before instant t+LT
0	9%	9%
1	46%	55%
2	41%	96%
3	4%	100%

Table 1. Fail probability table

The fail probability table and the desired service level are used to define the reorder point *R(t)*. Let's suppose that the desired service level for this example is 95%. The last column on the right in Table 1 shows that if there are 2 spare parts in inventory, there will be a probability of 96% that stockout will not occur. In other words, having 2 spare parts on the inventory corresponds to a service level of 96% (higher than the desired 95%). Since 2 is the lowest number of spare parts that satisfies the service level requirements, the reorder point *R(t)* is 2.

The EOQ formula will be used to calculate the number of parts to be purchased in the proposed model. The only difference between the proposed model and the classical [*R*, *Q*] model will be reorder point calculation.

5. Simulation

The spare part inventory control simulation is described in this section. As mentioned earlier, a comparison will be made between the classical [*R*, *Q*] model described in section 3 and the proposed model based on information obtained from a PHM system described in section 4.

In order to compare the performance of both inventory models, two identical fleets will be simulated. The classical [*R*, *Q*] model will be used to control the spare part inventory of the first fleet, while the other fleet will have its spare part inventory controlled by the proposed model.

5.1. Scenario Description

The spare parts logistic network considered in the simulation is illustrated in Figure 5. There is only one supplier and the spare parts are held in only one warehouse.

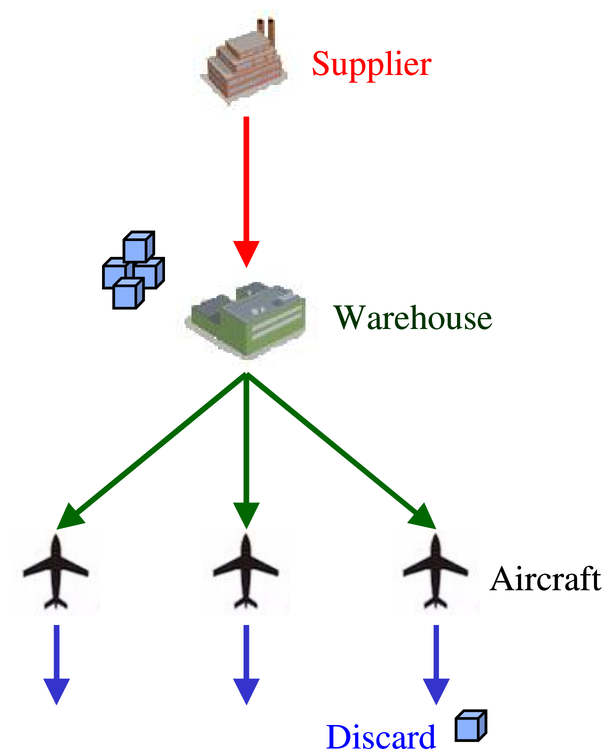

Figure 5. Spare parts logistic network

Spare parts enter the system when a new order is placed. Supplier always delivers the spare parts to the warehouse. Even if there is an aircraft waiting for the part, it is sent to the warehouse and then to the aircraft. There is a lead time between when the order is placed and when the order quantity is received.

When a failure occurs and a component has to be replaced, a spare part is supplied by the warehouse. Since components are considered to be non-repairable, faulty components are discarded.

If a failure occurs and there is no spare parts at the warehouse, the aircraft with the faulty component waits the next spare part delivery.

5.2. Simulation Parameters

In order to run the simulation, there are some parameters that must be set. A list of the parameters used during the simulation is shown in Table 2.

Parameter	Value	Unit
Administrative Cost (K)	50	Monetary Units (M.U.)
Unit Cost (C)	500	M.U.
Holding Cost (H)	1	M.U. per day per unit
Stockout Cost (P)	5	M.U. per day per unit
Fleet Size	10	Aircraft
Lead Time	15	Days
MTBF	180	Days
MTBF Standard Deviation	30	Days
Simulation Step	1	Day
Simulated Period of Time	15	Years

Table 2. Simulation parameters

5.3. Simulation Results

Five different service levels were defined (80%, 85%, 90%, 95% and 99%) and for each service level 15 simulations were run for each model (classical and proposed).

For the classical model, the economic order quantity Q is 3 units, calculated using Equation 4. The average demand used to calculate Q is the fleet size divided by the MTBF (Mean Time Between Failures). As mentioned earlier, the economic order quantity Q does not depend on the desired service level.

On the other hand, the reorder point R changes according to the service level. Figure 6 illustrates an example of how inventory level changed over time for the classical [R, Q] model during a period of 300 days. In Figure 6, the desired service level is 80% and the calculated reorder point is 0.84 units. In real systems, the reorder point is commonly rounded up. In this work, decimal values were kept.

When the effective stock (dashed green) is lower than the reorder point R (dotted red), a new order of 3 units is placed. The ordered units are immediately added to the effective stock (dashed green). The stock on hand (solid blue), however, only receives the ordered units after the lead time.

As mentioned earlier, in the proposed model the EOQ formula is used. So, the economic order quantity Q for the proposed model is also 3 units for all service levels considered in the simulation. The reorder point $R(t)$ is updated on a daily basis according to the information received from the PHM system. Figure 7 shows an example of how inventory level changed over time for the proposed model during a period of 300 days.

The desired service level in Figure 7 is 80%. When the effective stock (dashed green) is lower than the reorder point $R(t)$ (dotted red), 3 spare parts are ordered. These spare parts are immediately added to the effective stock and, after the lead time, they are added to the stock on hand (solid blue).

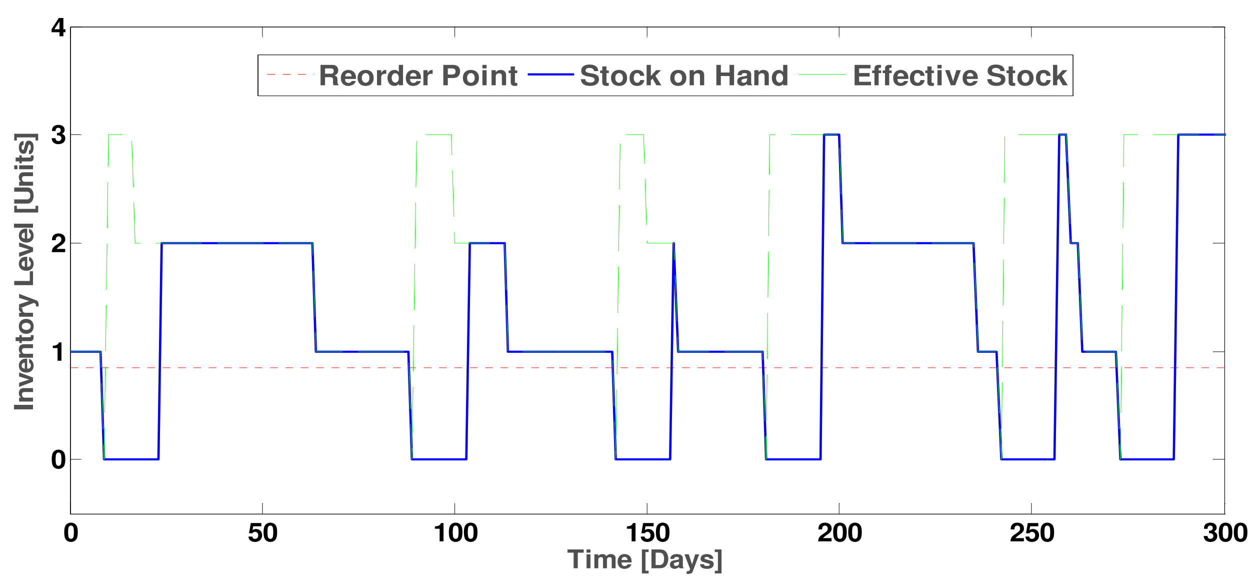

Figure 6. Inventory level evolution for the classical [R, Q] model

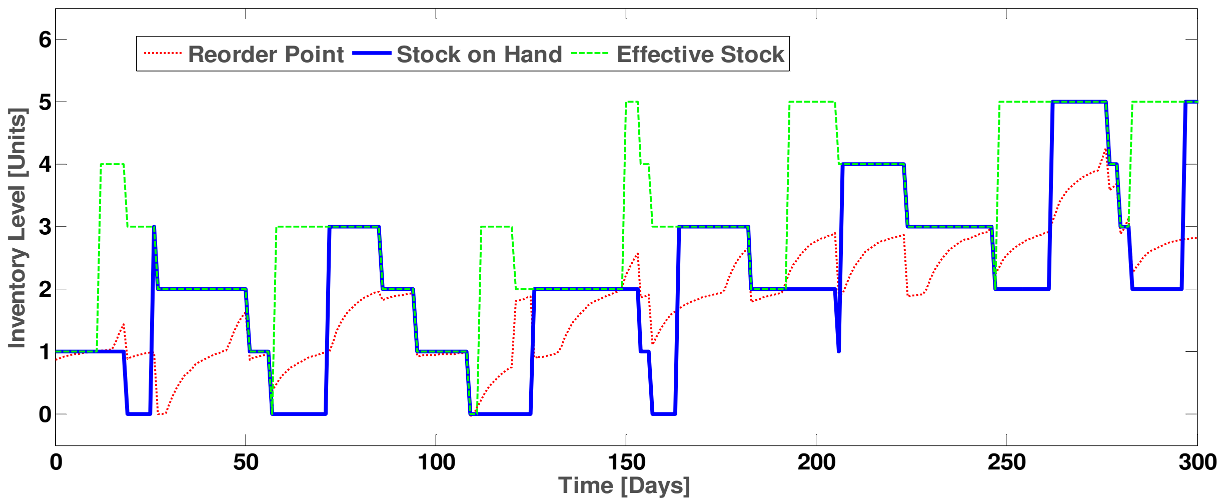

Figure 7. Inventory level evolution for the proposed model

For each simulation, the total cost required and the achieved service level were recorded for both classical and proposed models. Total costs are composed by ordering costs, holding costs and stockout costs. The results are shown in Figure 8.

For all desired service levels, the proposed model presented a lower average total cost. For high service levels, the better performance of the proposed model is more evident.

Figure 9 shows another comparison between the average total cost obtained during simulation of both classical [*R*, *Q*] model and the proposed model, where each cost component (ordering cost, holding cost and stockout cost) can be observed separately. For each service level in Figure 9, the bar on the left shows the average total cost obtained with the classical [*R*, *Q*] model, while the bar on the right shows the average total cost obtained with the proposed model.

For all service levels considered in this work, the average ordering cost obtained with both classical [*R*, *Q*] model and the proposed model were very similar. This result was expected, since the EOQ formula was used by the two models to determine the number of spare parts to be ordered. The average stockout cost values obtained with the two models were also very similar.

On the other hand, when the average holding costs obtained by simulating the two models are compared, it can be noticed that the proposed model allowed reducing this cost component in all service levels considered during the simulation.

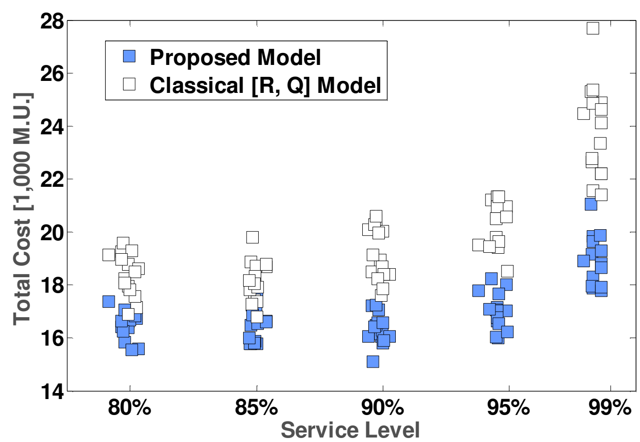

Figure 8. Total cost comparison

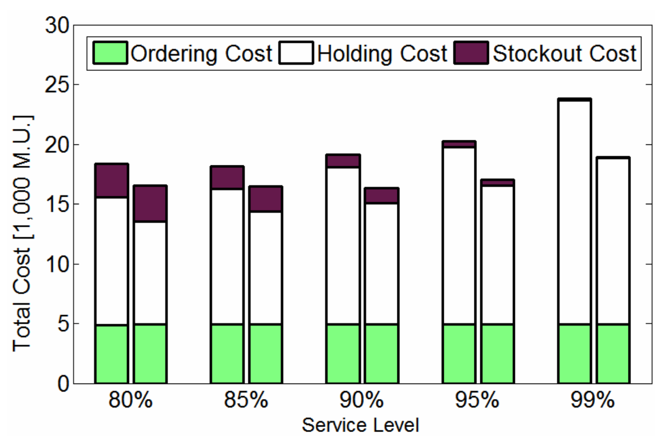

Figure 9. Average total cost components comparison

The proposed model differs from the classical [R, Q] model only in how the reorder point is calculated. This parameter determines when new spare parts shall be ordered and affects directly the average inventory level and the average holding cost. The information obtained by the PHM system allowed predicting future demands with better accuracy. Since parts are purchased closer to the instant when they will be used, the average period of time they stay in stock is reduced. Consequently, the average holding cost incurred is also reduced when compared to the classical [R, Q] model.

6. Conclusions

This paper presented a new inventory control model for non-repairable items, based on health condition data obtained from a PHM system.

The results obtained by simulating the proposed model and a classical inventory control model showed that the proposed model allows satisfying a defined service level with a lower average total cost. For high service levels, the proposed model showed itself even more efficient.

Future investigation could extend the idea presented in this paper by adapting the model to be used for repairable parts. Another opportunity to extend this work is to explore the performance of the proposed model when spare part inventories for multiple items are simultaneously controlled.

Acknowledgment

The authors acknowledge the support of FINEP (Financiadora de Estudos e Projetos - Brazil), CNPq (research fellowship) and FAPESP (grant 2011/17610-0).

References

Ballou, R. H. (2006). Gerenciamento da Cadeia de Suprimentos / Logística Empresarial. In *5th ed. Porto Alegre*.

Feldman, K., Jazouli, T. & Sandborn, P. (2009). A Methodology for Determining the Return on Investment Associated with Prognostics and Health Management. *IEEE Transactions on Reliability, Vol. 58, No. 2*.

Hess, A., Frith, P. & Suarez, E. (2006). Challenges, Issues and Lessons Learned Implementing Prognostics for Propulsion Systems. In *Proceedings of ASME Turbo Expo Power for Land, Sea and Air*.

Hillier, F. S. & Lieberman, G. J. (2005). Introduction to Operations Research. In *8th ed. New York*.

Ho, J. C., Chang, Y. L. & Solis, A. O. (2006). Two Modifications of the Least Cost per Period Heuristic for Dynamic Lot Sizing. Jounal of Operation Research Society, Volume 57.

Kacprzynski, G. J., Roemer, M. J. & Hess, A. J. (2002). Health Management System Design: Development, Simulation and Cost/Benefit Optimization. In *Proceedings of IEEE Aerospace Conference, Big Sky*.

Leão, B. P., Yoneyama, T., Rocha, G. C. & Fitzgibbon, K. T. (2008). Prognostics Performance Metrics and their Relation to Requirements, Design, Verification and Cost-Benefit. In *Proceedings of International Conference on Prognostics and Health Management, Denver*.

Luna, J. J. (2009). Metrics, Models, and Scenarios for Evaluating PHM Effects on Logistics Support. In *Proceedings of Annual Conference of the Prognostics and Health Management Society*.

Omar, M. & Deris, M. M. (2001). The Silver-Meal Heuristic Method for Deterministic Time-Varying Demand. Journal of Matematika, Volume 17.

Omar, M & Supadi, S. S. (2003). A Lot-for-Lot Model with Multiple Installments for a Production System under Time-Varying Demand Process. Journal Matematika.

Puttini, L. C. (2009). Gerenciamento da Saúde de Sistemas Aeronáuticos: Conceitos e Visão de Futuro. *In Proceedings of VIII Sitraer, São Paulo.*

Rodrigues, L. R., Gomes, J. P. P., Bizarria, C. O. Galvão, R. K. H. & Yoneyama, T. (2010). Using Prognostic System Forecasts and Decision Analysis Techniques in Aircraft Maintenance Cost-Benefit Models. In *Proceedings of IEEE Aerospace Conference, Big Sky.*

Roemer, M. J., Byington, C. S., Kacprzynski, G. J. & Vachtsevanos, G. (2005). An Overview of Selected Prognostic Technologies with Reference to an Integrated PHM Architecture. In *Proceedings of the First International Forum on Integrated System Health Engineering and Management in Aerospace*.

Sakaguchi, M. & Kodama, M. (2009). Sensitivity Analysis of an Economic Order Quantity for Dynamic Inventory Models with Discrete Demand. International Journal of Manufacturing Technology and Management, Volume 18.

Sandborn, P. A. & Wilkinson, C. (2007). A Maintenance Planning and Business Case Development Model for the Application of Prognostics and Health Management (PHM) to Electronic Systems. Microelectronics Reliability, Volume 47, Issue 12, Electronic system prognostics and health management.

Syntetos, A. A., Boyland, J. E. & Disney, S. M. (2009). Forecasting for Inventory Planning: A 50 Year Review. Journal of the Operational Research Society, Volume 60.

Vachtsevanos, G., Lewis, F. L., Roemer, M., Hess, A., & Wu, B. (2006). Intelligent Fault Diagnosis and Prognosis for Engineering Systems. In *1st ed. Hoboken.*

Wagner, H. M., Whitin, T. M. (1958). Dynamic Version of the Economic Lot Size Model. Management Science, Volume 5.

Wongmongkolrit, S. & Rassameethes, B. (2011). The Modification of EOQ Model under the Spare Parts Discrete Demand: A Case Study of Slow Moving Items. In *Proceedings of the World Congress on Engineering and Computer Science, Volume 2, San Francisco*.

Yong, Z. W., Ying, X. & Bing, S. (2011). Study on Spare Parts Inventory Control by Quantitative Analysis in the Environment of ERP System. In *Proceedings of the International Conference of Business Management and Electronic Information (BMEI)*.

BIOGRAPHIES

Leonardo Ramos Rodrigues holds a bachelor's degree in Electrical Engineering from Universidade Federal do Espírito Santo (UFES, 2003), Brazil, and a Master Degree in Aeronautical Engineering from Instituto Tecnológico de Aeronáutica (ITA, 2008), São José dos Campos, São Paulo, Brazil. He is currently pursuing his doctorate in Aeronautical Engineering at ITA. He is with EMBRAER S.A., São José dos Campos, São Paulo, Brazil, since 2006. He works as a Development Engineer in an R&T group at EMBRAER performing research on PHM technology for application to aeronautical systems. His current research interests are the application of health monitoring techniques for electronic components and the usage of PHM information for inventory optimization.

Takashi Yoneyama is a Professor of Control Theory with the Electronic Engineering Department of ITA. He received the bachelor's degree in electronic engineering from Instituto Tecnológico de Aeronáutica (ITA), Brazil, the M.D. degree in medicine from Universidade de Taubaté, Brazil, and the Ph.D. degree in electrical engineering from the University of London, U.K. (1983). He has more than 250 published papers, has written four books, and has supervised more than 50 theses. His research is concerned mainly with stochastic optimal control theory. Prof. Yoneyama served as the President of the Brazilian Automatics Society in the period 2004-2006.