A Data-Driven Health Assessment Method for Electromechanical Actuation Systems

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Abstract

The design of health assessment applications for the electromechanical actuation system of the aircraft is a challenging task. Physics-of-failure models involve non-linear complex equations which are further complicated at the system-level. Data-driven techniques require run-to-failure tests to predict the remaining useful life. However, components are not allowed to run until failure in the aerospace engineering arena. Besides, when adding new monitoring elements for an improved health assessment, the airliner sets constraints due to the increased cost and weight. In this context, the health assessment of the electromechanical actuation system is a challenging task. In this paper we propose a data-driven approach which estimates the health state of the system without run-to-failure data and limited health information. The approach combines basic reliability theory with Bayesian concepts and obtained results show the feasibility of the technique for asset health assessment.

1. Introduction

Initially, many aircraft health monitoring applications were focused on the fault detection and reconfiguration of failure modes before they cause a system-level unrecoverable failure (Bieber, Noulard, Pagetti, Planche, & Vialard, 2009). The advance of prognostics and health management approaches contribute to expand the scope of health monitoring systems in aircrafts (Vachtsevanos, Lewis, Roemer, Hess, & Wu, 2007). These applications provide potential benefits such as extended useful life and condition-based maintenance strategies (e.g., see (TATEM, 2008; ACTUATION2015, 2015)).

Airframers demand more sophisticated health monitoring approaches in the scope of the More Electrical Aircraft (Rosero, Ortega, Aldabas, & Romeral, 2007). The purpose of these techniques is to stimulate the introduction of Electromechanical Actuator (EMA) technology in the next generation aircrafts, providing fault detection and health monitoring capabilities. However, the aggregation of health monitoring mechanisms on the electromechanical actuator affects the cost and weight of the aircraft. Accordingly, these constraints hinder the aggregation of additional assets such as sensors or electrical/mechanical components for an improved health monitoring system (Todeschi & Baxerres, 2014).

Due to the rapidly growing interest in prognostics and health management, researchers have developed a number of different applications for health assessment and prediction of remaining useful life (Aizpurua & Catterson, 2015). Defining a system-level health assessment model for electromechanical actuators in aeronautics is a challenging task. On the one hand, model-based approaches require the physics-of-failure degradation equation of the asset under study (e.g., see (Daigle, Saha, & Goebel, 2012)). However, the complexity of physics-of-failure laws increases at the system-level involving interactions between different assets. On the other hand, traditional data-driven techniques require run-to-failure tests to determine the remaining useful life of assets (e.g., see (Goebel, Saha, & Saxena, 2008)). Run-to-failure data is hardly available in the aeronautic engineering arena and this situation prevents the application of existing data-driven health assessment approaches.

Electromechanical actuators can be used in a wide range of applications such as flight control, high lift, landing gear or engine control. They can be rotary or linear and they include different types of sensors, motors or speed reducers. Electromechanical actuators can be designed as single channel, dual channel or they can incorporate disconnection devices in order to improve the fault tolerance of the system. Figure 1 shows a typical linear actuator configuration. It consists of a Power and Drive Electronics module which drives an electrical motor as torque generator. This torque is multiplied in a speed reducer and transmitted to a ball/roller screw mechanism where it is converted into linear force. The linear bearings support the axial loads and a position sensor provides a position signal.

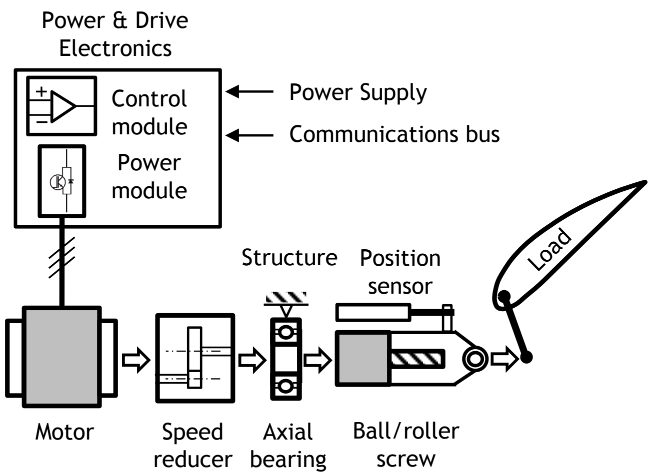

Figure 1. Linear actuator configuration.

The main functions of the health monitoring mechanism of electromechanical actuator systems are (Todeschi & Baxerres, 2014):

- Fault detection and isolation.
- Health assessment of electrical and mechanical components which require preventive maintenance.
- Update health estimations.
- Store operational data in the system database (e.g., load reversal or number of cycles).

In this paper we present a data-driven health monitoring approach for electromechanical actuator systems. The main contribution of the proposed work is the evaluation of the health state of electromechanical actuator systems without run-to-failure data and limited health state information. The proposed health monitoring approach evaluates the reliability of the electromechanical actuator system using degradation information and enables the implementation of condition-based maintenance actions.

The potential benefits of the proposed approach are: (i) accurate health estimation of the system; (ii) improvement of the aircraft availability by the reduction of the corrective maintenance actions; and (iii) reduction of the operational cost through the implementation of condition-based maintenance strategies, instead of periodic preventive maintenance strategies.

The remainder of this paper is organized as follows: Section 2 presents the proposed health monitoring architecture, Section 3 defines the health assessment approach, Section 4 applies the approach to a ball screw case study, and finally Section 5 draws conclusions and identifies future prospects.

2. HEALTH MONITORING ARCHITECTURE FOR ELECTROMECHANICAL ACTUATOR SYSTEMS

Certification of health monitoring systems is a challenging task. In the case of electrical actuation systems there is no certification process for health monitoring systems due to the recent introduction into service of electrical actuations systems in commercial aircrafts.

When designing a health monitoring application for the electromechanical actuation system the use of additional assets is limited (e.g., sensors, electrical or mechanical devices). One feasible alternative is to allocate the health monitoring application in the electromechanical actuator control board and reuse already existing signals (e.g., phase current, rotary/linear position, winding temperature, force, commanded voltage) for fault detection and diagnostics (Iturrospe, Abete, Isturiz, & Viñals, 2014; Arellano-Padilla, Gerada, & Summer, 2015).

Figure 2 shows the proposed health monitoring architecture. The architecture is built into the EMA Power and Drive Electronics and it shares the signals and the communication bus with the Flight Control Computer.

EMA signals are captured by the health monitoring hardware module. These signals are used to compute the *Usage* and to execute the *Health Monitoring algorithms*. Usage data can be expressed as operational hours, number of turns/cycles, or average load. Each health monitoring algorithm is responsible for monitoring one or more failure modes of one or more components. The output of the algorithm for each monitored failure mode is defined as *Health Index (HI)*, which can be expressed as simple physical variables, percentages, or the overcoming of predefined thresholds. The *Health Assessment* module takes as input all Health Index values, together with the Usage information and it performs the system diagnostic estimating the *health state* of the EMA system. This information is sent to the *Flight Control Computer*.

The health monitoring architecture estimates the up-to-date health state of the system. This information helps to improve periodic maintenance strategies through condition-based main-

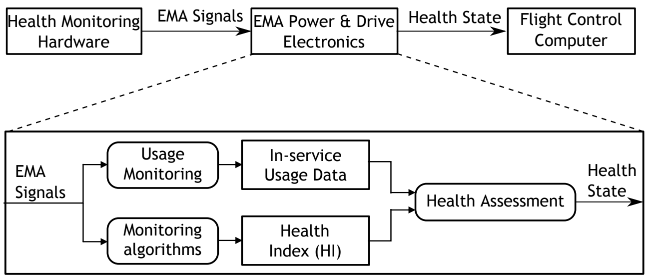

Figure 2. Simplified health monitoring architecture for the electromechanical actuator system.

tenance mechanisms.

3. HEALTH ASSESSMENT APPROACH

The proposed data-driven health assessment approach takes as input in-service usage data and health index values of the monitored failure modes and estimates the health state of the system under study (cf. Figure 2).

This data capture approach presents two main advantages compared to the classical estimation of health assessment based on the number flight hours:

- Data reliability. The data reflects the real usage of the EMA during its whole operational life; taking into account the actual influence of the external factors such environmental conditions during flight and the work carried out by the actuator.
- Health assessment adaptability. EMA usage data updates the parameters of the health monitoring algorithm. As this data has been acquired during real flight conditions, it is the most representative and accurate data source. Moreover, data from both scheduled and corrective maintenance operations also increase the accuracy by updating the health assessment algorithm.

The operationalization of this approach not only requires the development of the theoretical framework (cf. Subsection 3.1), but also the implementation of data-gathering tests to extract the required data according to the theoretical framework (cf. Subsection 3.2).

3.1. Theoretical Framework

Reliability is defined as the ability of an item to perform a required function under stated conditions for a stated period of time (Hamada, 2008; Rausand & Høyland, 2003). Given a continuous random variable T representing time to failure of the system, reliability $R(t)$ is defined as the probability that the system is still working at time t. Alternatively, it is possible to use a probability density function $f(t)$ to define the reliability of the item at time t as follows (Hamada, 2008; Rausand & Høyland, 2003):

$$R(t) = Pr(T > t) = \int_t^\infty f(s)ds \tag{1}$$

In Eq. (1) we can see that the use of the classical reliability definition for health assessment requires run-to-failure data so as to evaluate the probability of being operative at any time instant. However, in this paper we propose the reliability calculation with respect to a particular damage or degradation level of different failure modes of the components. This approach provides a suitable information for a timely health assessment and does not require end-of-life tests.

In order to calculate the reliability related to a particular damage at a particular operation time, we discretize the damage magnitude into N bands denoted L_i where $i = \{1, 2, \ldots, N\}$. For example, a first damage band, L_1, can comprise measured damage values between 0 and an arbitrary value; a second damage band, L_2, can range from the higher limit of L_1 to a higher arbitrary damage value; until the entire range of measured damage values is covered with N damage bands. The idea of dividing the damage into discrete bands is similar to the idea of Lebesgue sampling (Zhang & Wang, 2014; Yan, Zhang, Wang, Dou, & Wang, 2016). In Lebesgue sampling prognostics predictions are based on the Lebesgue sampling model whose states are predefined according to the quantization level.

Based on Bayesian concepts, we can use a predictive distribution to define the relationship between operation times, discrete set of damages, and the damage magnitude estimation (Hamada, 2008; Rausand & Høyland, 2003):

$$p(T|\widehat{D}) = \sum_{L_n} p(T|L_n)p(L_n|\widehat{D}) \tag{2}$$

where T is the operation time, L_n denotes N discrete damage bands and $\widehat{D}$ represents the damage magnitude assessment.

The solution of Eq. (2) consists of two dependent steps:

1. Distribute all measured damage values into N damage bands (L_n), and determine the distribution of operation times (T) related to each damage level: $p(T|L_n)$.
2. Calculate the damage band distribution (L_n) given a particular damage indicator value ($\widehat{D}$): $p(L_n|\widehat{D})$.

The solution of the second step requires two intermediate calculations. Firstly, we calculate the distribution $p(D|\widehat{D})$ using the measured damage data (D) and the corresponding damage estimations ($\widehat{D}$). This distribution approximates the distributions of the measured damage values given each particular damage indicator value and it specifies the error incurred by the damage estimation. Namely, if there is no error in the damage estimation, the expected value of the distribution of the measured damage values coincides with the damage indicator value.

Subsequently we determine the damage band distribution (L_n) given a particular damage indicator value, i.e., $p(L_n|\widehat{D})$. Let $D_{L_n}^{(min)}$ and $D_{L_n}^{(max)}$ denote the minimum and maximum damage values from band L_n, respectively. Eq. (3) defines the distribution of the damage bands (L_n), given a damage indicator value ($\widehat{D}$):

$$\begin{aligned} p(L_n|\widehat{D}) &= \int_{D_{L_n}^{(min)}}^{D_{L_n}^{(max)}} p(D|\widehat{D})dD \\ &= \int_{D_{L_n}^{(min)}}^{\infty} p(D|\widehat{D})dD - \int_{D_{L_n}^{(max)}}^{\infty} p(D|\widehat{D})dD \end{aligned} \tag{3}$$

Once both distributions $p(T|L_n)$ and $p(L_n|\widehat{D})$ are determined, the distribution of operation times given a damage indicator value can be achieved by using Eq. (2). This distribution of operation times is used to estimate the component reliability function with respect to an estimated damage magnitude, instead of component failure.

The reliability at some particular operation time, T_0, given a damage indicator value, $\widehat{D}$, can be determined applying Eq. (1) as follows:

$$R(T_0)_{\widehat{D}} = \int_{T_0}^{\infty} p(T|\widehat{D})dT \tag{4}$$

The expected value of the distribution resulting from Eq. (4) represents the most probable operation time at which the component reaches that specific damage magnitude. This estimation can help to program maintenance tasks. For instance, achieving such an estimation of damage magnitude at a time higher or lower than the expected value of the distribution will provide useful information about the current component deterioration process, i.e., current component deterioration process could be running slower or faster, in relation with the expected one. Then, the designer can adopt condition-based maintenance decisions to improve availability and reduce maintenance costs.

3.2. Practical Framework: Data Gathering Tests

The proposed approach requires a preliminary double characterization test campaign to obtain data for health assessment. Accordingly we correlate different variables and extract corresponding probability distributions:

- *Degradation-usage distribution*: tests for determining the correspondence between the degradation level of each failure mode and the usage data.
- *HI-degradation distribution*: tests for determining the correspondence between the output of the health monitoring algorithms (i.e., health index) and the degradation level.

During the characterization tests the degradation level of the monitored failure mode is measured and stored. Figure 3 describes the characterization process.

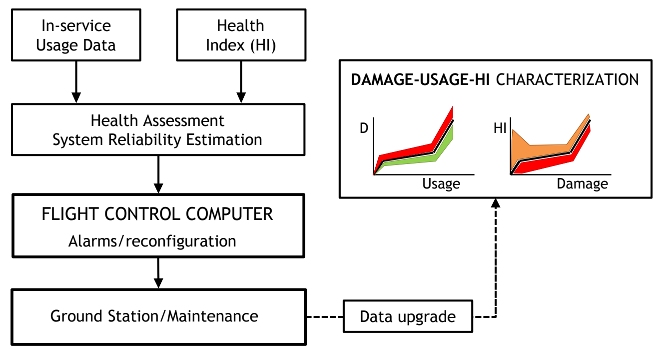

Figure 3. Health assessment data flow.

The data relating real damage measurements with damage indicator estimations and operation times are gathered from a experimental test bench. The test operation follows a programmed schedule which measures the real magnitude of the component deterioration (D) using the damage magnitude assessment ($\widehat{D}$) and the operation time (T).

One benefit of the described approach is that the tests are not required to be extended until a complete failure occurs. The usage and health index data are useful for the health assessment even corresponding to low levels of degradation. The second benefit is that all the data coming from any maintenance action can be fed into the system characterization data base once the failed components are inspected and analyzed.

4. NUMERICAL SIMULATIONS

The validation of the proposed methodology is presented by means of numerical simulations implemented in Matlab. In particular, we use data extracted from tests of ball screws of the same type and same manufacturer. With numerical simulations we assess the reliability of the ball screw at a specific operation time given a damage indicator value.

The damage indicator defines the gradual component damage. The values for backlash threshold and distribution parameters depend on the type of ball-screw and the initially designed backlash. Typically, the backlash threshold value corresponds to the beginning of the wear out degradation phase. This phase is characterized by an exponential increase of the component failure probability. In this article, the threshold and distribution parameters are determined based on life tests carried out in a specific ball-screw. Accordingly, an indicator higher than 45.0 μm is defined as the condition from which a ball screw starts to fail.

The range of possible damage values is arbitrarily divided into nine uniform bands, L_i, i=$\{1, 2, \ldots, 9\}$. Table 1 displays the specification of the damage bands. For each band L_i its corresponding value ranges and mean and variance values of the operation times T are specified assuming that they are drawn from a Normal distribution.

Table 1. Damage bands specification.

Damage Bands	**Range (μm)**	**Mean (hours)**	**Variance (hours)**
L_1	5-10	1000	150
L_2	10-15	1500	200
L_3	15-20	2000	300
L_4	20-25	2500	400
L_5	25-30	3000	500
L_6	30-35	3500	400
L_7	35-40	4000	300
L_8	40-45	4500	200
L_9	45-50	5000	100

Figure 4 shows time to damage data samples for some damage bands (L_1, L_3, L_5, L_7, L_9).

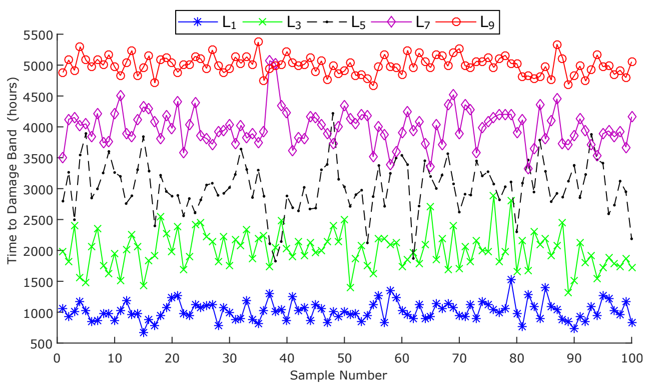

Figure 4. Time to damage band (L_i) data samples.

The distributions $p(T|L_n)$ are obtained from damage measurements shown in Figure 4 and parametrized in Table 1. Figure 5 shows the nine corresponding distribution estimations.

Without loss of generality in this work we assume that the distribution of the real damage values given a damage indicator value (i.e., $p(D|\widehat{D})$) follows a Normal distribution with an expected value equal to $\widehat{D}$ and a typical deviation equal to 8.0 μm. Gaussian distributions are used for simplicity because they facilitate the analytical treatment as in (Benton, 2009). However, it should be noted that this assumption does not limit the practicality of the proposed approach because the model developed in this paper is applicable to any type of distribution.

The distribution of damage bands given a damage indicator value is determined applying Eq. (3) as follows:

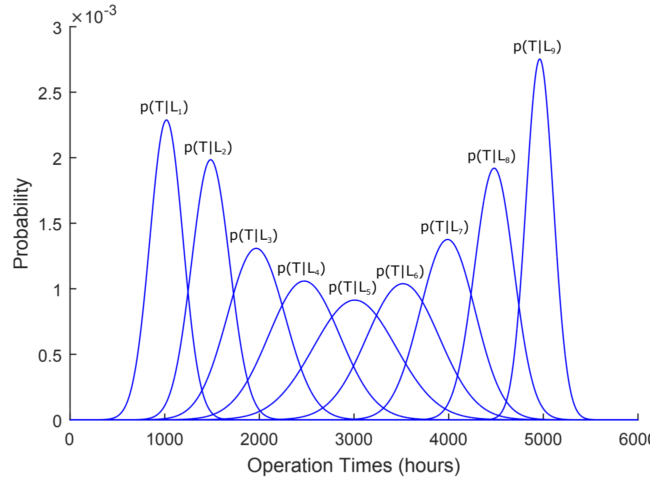

Figure 5. Distributions $p(T|L_n)$ obtained from draws of Normal distributions.

$$
\begin{aligned}
p(L_n|\widehat{D}) &= \int_{D_{L_n}^{(min)}}^{\infty} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{D-\widehat{D}}{\sigma})^2} dD - \\
&\int_{D_{L_n}^{(max)}}^{\infty} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{D-\widehat{D}}{\sigma})^2} dD \\
&= Q(\frac{D_{L_n}^{(min)} - \widehat{D}}{\sigma}) - Q(\frac{D_{L_n}^{(max)} - \widehat{D}}{\sigma})
\end{aligned} \tag{5}
$$

where $Q(.)$ is the Q-function, defined as (Rausand & Høyland, 2003):

$$
Q(z) = \int_{z}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} dy \tag{6}
$$

The distribution of operation times given a damage indicator value, $p(T|\widehat{D})$, is determined through Eq. (2), and this result enables the calculation of the reliability related to some particular estimated damage magnitude at specific operation times. For a damage indicator value of 26.0 μm, the probabilities of the damage bands (a discrete distribution) are given in Table 2.

Table 2. Probabilities of the damage bands given a damage indicator value of 26 μm.

Bands	$p(L_n\|26)$
L_1	0.02
L_2	0.06
L_3	0.14
L_4	0.22
L_5	0.24
L_6	0.18
L_7	0.09
L_8	0.03
L_9	0.01

The sum of the resulting distributions for each damage band from the product $p(T|L_n)p(L_n|26)$ yields the distribution of operation times given a damage indicator value $p(T|\widehat{D})$ (cf. Eq. (2)). Subsequently, we use this expression for the reliability calculation according to Eq. (4). For the case of an operation time of 2100 hours, the component reliability, given damage indicator value of 26.0 μm, is equal to 0.79.

Figure 6 shows the distribution of $p(T|26)$ with an expected value of 2850 hours.

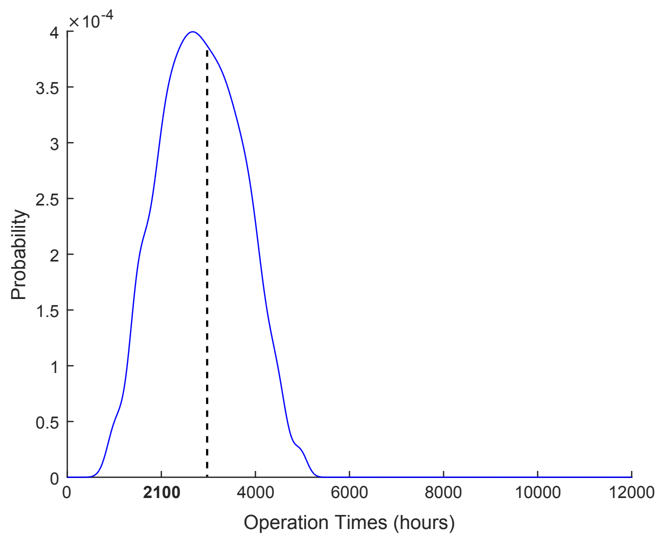

Figure 6. Distribution of $p(T|26)$.

Since an estimation of damage magnitude of 26.0 μm was attained at an operation time of 2100 hours, we can deduce that the deterioration process is running faster than expected. Therefore, a special attention must be paid to the component operation.

The proposed work can also be extended to the analysis of the reliability behavior as the component usage or operation time varies (Eq. (4)). For example, Figure 7 shows the reliability for three different damage indicator values: 9.0 μm, 26.0 μm and 43.0 μm.

Based on the results, the main added-value of the proposed approach is twofold. On the one hand, this approach is useful to detect the premature degradation of both mechanical and electrical components of the EMA, thus increasing the system reliability and reducing unscheduled maintenance actions. On the other hand, the operational life of the EMA could be gradually extended based on the reliability analysis of the obtained data.

5. CONCLUSION

In this work a data-driven health monitoring architecture was proposed taking into account the limitations of the application of condition-monitoring strategies on aircrafts.

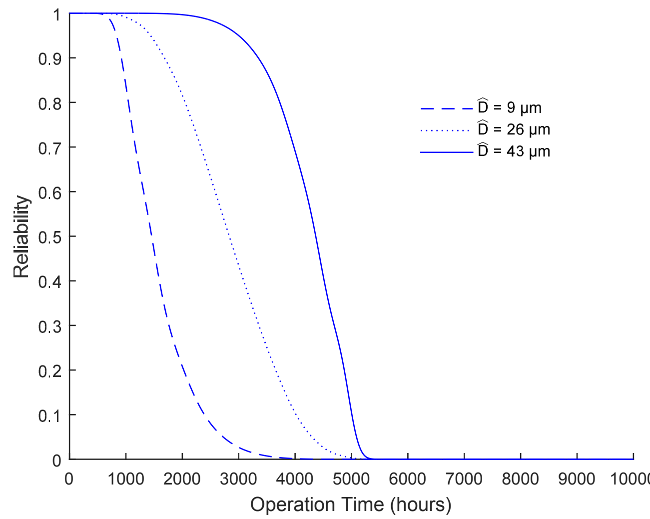

Figure 7. Reliability of the damage indicator values.

We have proposed a method for calculating the reliability related to a particular damage magnitude of a component at certain operation time. The proposed approach does not require run-to-failure data and enables the evaluation of the condition-based health state of the system. The proposed approach has been validated through numerical simulations.

According to proposed approach it is possible to define condition-based maintenance strategies. Namely, we can use the distribution of operation times given an estimation of the component damage magnitude for component maintenance programming. The comparison between the expected value of this distribution and the time instant in which the component reaches the same level of damage magnitude provides information about the speed of the deterioration process.

As for the future research goals, it would be interesting to analyse the improvement on system availability and cost as a result of condition-based maintenance strategies. To this end, we can use the results obtained from the proposed approach and compare them with respect to periodic preventive maintenance strategies.

NOMENCLATURE

$R(t)$	Reliability at time instant t
$f(t)$	Probability density function
L_i	Discretized i-th damage band
D	Real damage magnitude
$\widehat{D}$	Estimated Damage Magnitude
T	Operational Time
$R(t)_{\widehat{D}}$	Reliability at time instant t given $\widehat{D}$
$Q(\cdot)$	Q function

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BIOGRAPHIES

Aitor Isturiz is M.Sc. Mechanical Engineer and with ten years of work experience, more than five years as Project Engineer of projects and developments related with the Prognostic and Health Monitoring (PHM) technologies, aeronautical and vehicles business and actuation and control systems. As participant in the European project Actuation 2015, he coordinates the Work Package dedicated to the Prognostic, Usage and Health Monitoring.

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Javier Viñals is M.Sc. Mechanical Engineer and with twenty six years of work experience, more than twenty years as Project Manager and Technical Director of projects and developments related with the simulation of materials behaviour and processes, space, new technologies, aeronautical and vehicles business and actuation and control systems. External Evaluator in R&D European Projects in Brussels. Associated Professor in the UPV-ETSII (Bilbao). Subject: Mechanic. Two doctorate courses in the Mechanical Department of the Bilbao Engineering School. Research Sufficiency Title in the UPV-ETSII (Bilbao). SENER representing in the Executive Committee of the Basque Country Cluster in Aerospace (HEGAN). Technical secretary of the Research and Development Committee (GTID) of the Basque Country Aerospace Cluster (HEGAN). Representing in the Mechanical Engineering Department Committee, that groups all the departments, sections and centres of the University of the Basque Country (UPV). Cooperating researcher in the Computational Mechanics of the Bilbao Engineering School.