TREND ANALYSIS FOR PROGNOSTICS AND HEALTH MONITORING

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Abstract. *This paper discusses conceptual aspects of prognostics and health monitoring (PHM) and presents an overview of PHM approaches applied to aircraft systems. More specifically, the present work is concerned with trend analysis and regression techniques for estimation of the future condition of the system and prediction of the time-to-failure. A technique for obtaining confidence bounds of such a prediction on the basis of Monte Carlo technique is described. The proposed approach is versatile and can be easily applied to any system, for which health state indicators are monitored. For illustration, a case study involving actual data from an aircraft system is presented.*

Keywords: *Prognostics, trend analysis, Monte Carlo.*

1. INTRODUCTION

In recent years the aircraft market has seen an increasingly competitive scenario regarding low cost operation. Therefore, new technologies or procedures that can reduce operational and maintenance costs are highly desirable by aircraft operators. This is the case of prognostics and health monitoring (PHM) [31]. PHM comprises a set of techniques which use measured data to assess health state and predict impending failure of a given equipment [24]. PHM is aimed at anticipating failure events that could be avoided if the monitoring solution is available to the operator [02].

In aircraft systems where PHM concepts are not yet applied, the end user has to deal with unscheduled maintenance or waste of useful life to some extent. In fact, maintenance actions are scheduled for an average component running under average environmental and stressing conditions. For example, a component may be scheduled to be replaced when it reaches 80% of its mean time between failures (MTBF). Therefore, whenever a component in this population presents lower-than-average strength characteristics or is operated in a higher-than-average stress condition, it will likely fail before the population mean, and the end user would face an unscheduled removal. To reduce the rate of unscheduled removals, the maintenance policy could establish lower (more conservative) replacement thresholds, at the cost of a greater waste of useful life [23].

For this reason PHM has become an important field of research, with the potential of generating technical and financial benefits in different application areas [02]. More specifically, PHM benefits include:

- improved troubleshooting (condition-based maintenance scheduling);
- decrease in the operations/maintenance logistics footprint;
- improvement of aircraft dispatch reliability;
- reduction of maintenance and operational costs;
- reduction of the number of delays and unscheduled stops;
- safety augmentation; and
- better exploitation of the useful life of equipments.

On the other hand, PHM systems may require the deployment of additional sensors and recording devices in aircraft, as well as the availability of maintenance and operational field data [24], [18], [03], [29]. This task is currently and gradually being accomplished, as more and more field data become available, correlated with the failure reports and the maintenance actions history [23], [10], [11], [12], [13].

An important observation is that Health Monitoring defines the systematic collection and analysis of parametric flight data from sensors distributed over aircraft systems in order to provide advanced failure diagnostics and prognostics. Health Management is the use of such diagnostics and prognostics functionalities to implement Condition-

Based Maintenance (CBM) concepts, and thus produce economical benefits on engineering, maintenance, logistics and operations [18].

The present work presents an overview of some generic PHM methodologies, with emphasis on prediction methods for prognostic assessment. For illustration, a simple trending technique for predicting the time-to-failure with confidence bounds is described. This technique involves the use of Monte Carlo method in a regression framework.

This paper is organized in six sections. Section 2 contains an explanation of the PHM methodologies. Section 3 presents in more details the prognostics methods. Section 4 describes a case study, explaining the prognostics methods used. The results obtained in the study are presented in Section 5. Concluding remarks are given in Section 6.

2. PHM METHODOLOGIES

The major high-level requirements for a PHM system are to provide precise health information for all the systems and components within the scope of the PHM solution, in the most automatic way that is economically viable, to allow the optimization of maintenance activities [23].

The PHM system architecture can be formalized by using the OSA–CBM (Open System Architecture for Condition Based Monitoring) standards. These standards were defined on the basis of technical, industrial, commercial, and military trends. Their purpose is to allow the development of an effective open systems architecture that will promote the rapid, cost-effective deployment of known monitoring diagnostics and prognostic technologies [09]. OSA-CBM comprises six layers with interfaces defined in Unified Modeling Language (UML) language. Figure 1, therefore used as reference, presents a brief functional description of the OSA-CBM layers, from the sensor measure up to the advisory generation. Benefits of adopting international standards are ease of integration, possibility of exchanging modules and reduction of development times and costs [23].

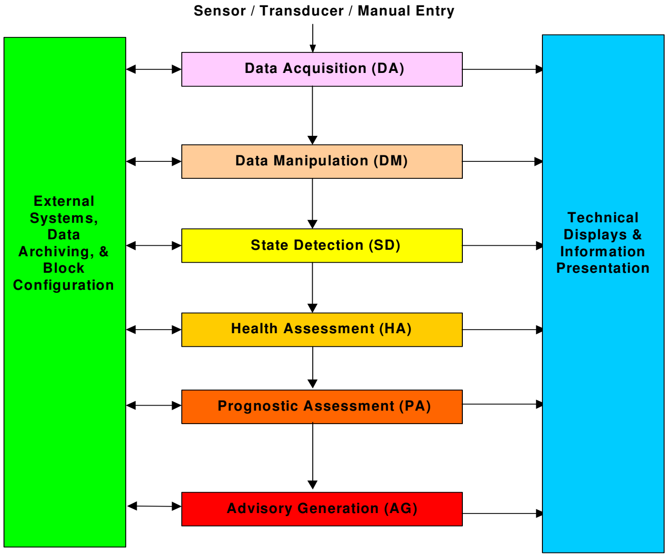

Figure 1 - Condition Assessment Data Processing & Information Flow Blocks [09]

The OSA-CBM layers consist of the following [09]:

1) Data acquisition (DA): conversion or formatting of analog output from transducer to digital signal;
2) Data manipulation (DM): signal processing, provides low-level computation or sensor-data;
3) State detection (SD): conditioning monitoring gathers DM data and compares to specific predefined features;
4) Health assessment (HA): use historical and SD values to determine current health;
5) Prognostics assessment (PA): considers health assessment, employment schedule, and models/reasoners that are able to predict future health with certainty levels and errors bounds; and
6) Advisory generation (AG): presentation layer, interface.

PHM implementation methodologies can be classified into three main groups: experienced-based or statistical-based, trend-based or data-driven and model-based. Diverse techniques can be used in an isolated or combined manner in any or all of the three main methodologies, in only one step or in the whole process [24]. These techniques range from Bayesian estimation and other probabilistic/statistical methods to artificial intelligence tools and methodologies based on notions from the computational intelligence arena [29], [26]. Specific approaches include multi-step adaptive Kalman filtering [19], auto-regressive moving average models [20], stochastic auto-regressive integrated moving average models, Weibull models [14], forecasting by pattern and cluster search [11], and parameter estimation methods

[21]. From the artificial intelligence domain, case-based reasoning, intelligent decision-based models and min-max graphs have been considered as potential candidates from prognostic algorithms [01]. Other methodologies, such as Petri nets, neural networks, fuzzy systems and neuro-fuzzy systems have found ample utility as prognostic tools as well [28], [24], [03].

Figure 2 summarizes the range of possible prognostic approaches as a function of the applicability to various systems and their relative implementation cost. Depending on the criticality of the Line-replaceable Unit (LRU) or subsystem being monitored, various levels of data, models and historical information are needed to develop and implement the desired prognostic approach [24], [03].

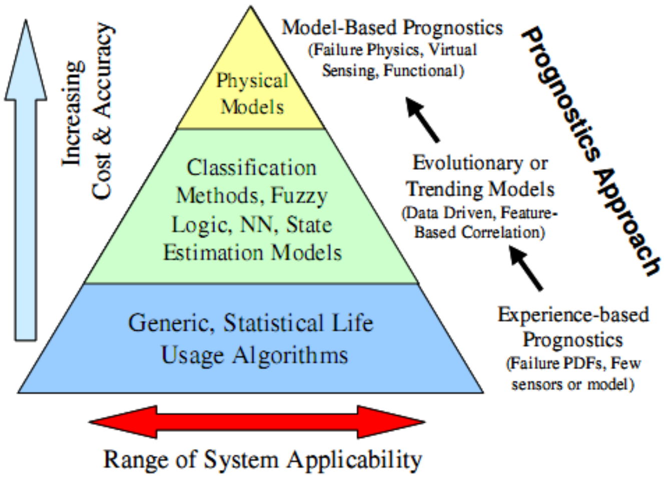

Figure 2 - Hierarchy of PHM approaches [24]

2.1. Experience-based prognostics

In situations where sophisticated prognostic models are not warranted due to the lower level of criticality or low rates of failure occurrence and/or there is an insufficient sensor network to assess health condition, a statistical reliability or usage-based prognostic approach may be the only alternative. This form of prognostic algorithm is the least complex and requires component/LRU failure historical data of the fleet and operational usage profile data. Although simplistic, a statistical reliability-based prognostic distribution can be used to drive interval-based maintenance practices that can then be updated on regular intervals [24]. Typically, fault and inspections data are compiled, and employed to fit a probability distribution of time-to-failure. Weibull distributions are typically employed for this purpose [14].

2.2. Evolutionary/ trending models or data-driven approaches

If the health reference is not well established and a model for the physics of failure is not available, a data-driven approach could be performed [31]. This approach relies on the ability to track and trend deviations and associated change rates of specific features or measurements from their normal operating condition. This approach requires that sufficient sensor information is available to assess the current condition of the system or subsystem. Once these features are obtained, they can be tracked and trended over the life of the component and compared with remaining useful life estimates to provide corroborative evidence of a degrading or failing condition [24].

2.3. Model-based techniques

Physics-based models provide a means to calculate the health state of the components as a function of operating conditions and assess the cumulative effects in terms of component life usage. This technique relies on the availability of a good dynamic model of the system [29]. By integrating physical and stochastic modeling techniques, the model can be used to evaluate the distribution of remaining useful component life as a function of uncertainties in component strength/stress properties, loading or lubrication conditions for a particular fault.

Model-based approaches to prognostics differ from trending approaches in that they can enable identification of parameters that reflect the actual physical characteristics of the system [04], facilitating the failure mode identification.

3. PROGNOSTICS ASSESSMENT

This study focuses on the Prognostics Assessment (PA) layer of OSA-CBM. The prognostic ability consists of predicting accurately and precisely the remaining useful life of a failing component or subsystem, based on current information and on history of past states [29]. It is worth noting that PA differs from Health Assessment (HA) in that the HA layer provides an index of degradation for a given system or component, whereas PA is intended to predict the future degradation with an associated level of confidence [02]. This level of confidence can be expressed by probability distributions of the degradation at given times in the future. Moreover, a probability distribution of the predicted time-to-failure is also desirable to guide CBM decisions [06], [05],[17].

Some methods that could be applied to prognostics are described below.

3.1. Artificial intelligence methods

Computational intelligence methods, such as artificial neural networks (ANNs) and fuzzy inference systems, may be used for forecasting purposes [16]. For this purpose, known transitional or seeded fault degradation paths of measured or extracted features can be used. A neural network, for example, can then be trained by using features that progress through a failure. The resulting predictor could be used to forecast the progression of the features for a different test under similar operating conditions [25].

Generally, ANNs can be viewed as one of many multivariate nonlinear and nonparametric statistical methods. The main problem of ANNs is that the reasoning behind their decisions is not always evident. Nevertheless, they provide a feasible tool for practical prediction problems [26].

3.2. Bayesian estimation

Bayesian estimation techniques can be of much value in fault diagnostics and failure prognostics to exploit the availability of models and measured data [26]. The Kalman filter incorporates the signal embedded with noise and forms what can be considered a sequential minimum mean square error estimator (MMSE) of the signal or prediction. The standard Kalman filter formulation, however, assumes that the state and observation equations are linear and the noise is Gaussian. If these conditions are not met, the resulting prediction may not be optimal. A number of alternatives have been proposed to address problems involving nonlinear dynamics and/or non-Gaussian noise [08]. In this context, particle filters have become a popular technique for long-term prognostics [29].

3.3. Support Vector Machines

Recently, SVMs have been proposed as a novel technique for time series forecasting. SVMs are a very specific type of learning algorithms characterized by the capacity control of the decision function, the use of kernel functions and the sparsity of the solution. Established on the unique theory of the structural risk minimization principle to estimate a function by minimizing an upper bound of the generalization error, SVMs are shown to be very resistant to the over-fitting problem, eventually achieving high generalization performance in solving various time series forecasting problems. Another key property of SVMs is that training SVMs is equivalent to solving a linearly constrained quadratic programming problem so that the solution of SVMs is always unique and globally optimal, unlike other networks training which requires non-linear optimization, which typically exhibits local minima [13], [31], [27], [15], [07].

3.4. Regression

Regression is a generic term for all methods attempting to fit a model to observed data in order to quantify the relationship between two groups of variables. In statistics, regression analysis refers to techniques for the modeling and analysis of numerical data consisting of values of a dependent variable (also called a response variable) and of one or more independent variables (also known as explanatory variables or predictors) [10]. The fitted model may then be used either to merely describe the relationship between the two groups of variables, or to predict new values. A simple regression-based technique for Prognostics Assessment will be presented in the next section.

4. A SIMPLE REGRESSION-BASED METHOD FOR PROGNOSTICS

Empirically, the relationship between the time t and a degradation index y can be approximated as

$$y = \beta_0 + \beta_1 t + \varepsilon \tag{1}$$

where β_0 is the linear coefficient ("intercept"), β_1 is the angular coefficient ("slope") and ε is the model residue. The coefficients β_0 and β_1 are unknown but constant. The residue is also unknown, but it is different for each y observation. Estimates of β_0 and β_1 can be obtained by least-squares, as described elsewhere [10]. It may be argued that the long-term evolution of degradation with time will seldom be linear, as assumed in equation (1). However, this simplified model may be adequate for medium and short-time predictions, which may be enough for CBM purposes.

For estimation purposes, the following notation will be employed:

$$b_0 = \hat{\beta}_0 \,,\; b_1 = \hat{\beta}_1 \quad \hat{y} = b_0 + b_1 t \tag{2}$$

where $\hat{y}$ denotes the predicted value of y for a given t. Thus, given a failure threshold L for the degradation index, the predicted time of failure $\hat{t}_f$ can be calculated as

$$\hat{t}_f = \frac{L - b_0}{b_1} \tag{3}$$

Once the coefficients b_0 and b_1 have been obtained, it is interesting to analyze whether the linear trend observed in the data is statistically significant, as described below.

4.1. F-test for significance of regression

The significance of the linear trend (or, more precisely, the significance of regression) can be assessed by an analysis of variance (ANOVA). Such an analysis is based on the following identity:

$$\sum_{i=1}^{n} (y_i - \bar{y})^2 = \sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2 + \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{4}$$

Where:

$$\bar{y} = \frac{1}{n} \sum_{i=1}^{n} y_i \tag{5}$$

and n denotes the number of available observations. The terms in Eq. (4) can be disposed in standard ANOVA format as shown in Table 1.

Table 1. Terms involved in the analysis of variance for the regression [10].

Source of variation	Degrees of freedom	Sum of squares (SS)	Mean Square (MS)
Due to regression	1	$\text{SSReg} = \sum_{i=1}^{n}(y_i - \bar{y})^2$	MS_{Reg}
About regression (residual)	$n-2$	$\text{RSS} = \sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2$	s^2
Total	n – 1	$S_{YY} = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2$	$s_y^{\ 2}$

The significance of the regression can be evaluated by comparing MS_{Reg} e s^2. Under usual assumptions for linear regression [30], it can be shown that the ratio

$$F = \frac{MS_{\text{Reg}}}{s^2} \tag{6}$$

follows an F-distribution with 1 and $(n-2)$ degrees of freedom if $\beta_1=0$. This fact can thus be used as a test for the null hypothesis H0: $\beta_1 = 0$ (no linear trend), versus H1: $\beta_1 \neq 0$. Comparing the ratio (6) with the $100(1-\alpha)\%$ point of the tabulated $F(1, n-2)$ distribution, it is possible to determine whether β_1 can be considered nonzero. In addition, a p-value can be obtained as the area under the tail of the distribution F (1, n-2) for $F > F_{calculated}$. The p-value can be interpreted as the chance that the observed trend is fortuitous [10].

4.2. Probability distribution of the regression coefficients

Under the usual assumptions for linear regression [30], the estimate b_0 follows a normal distribution with mean β_0 and variance given by

$$\sigma^2\left[\frac{1}{n}+\frac{\bar{t}^2}{S_{TT}}\right] \tag{7}$$

σ^2 is the variance of the residue ε, $\bar{t}$ is the mean value of t. The mean and variance of estimated b_0 and b_1 are given by:

$$b_0 \sim N\left(\beta_0, \sigma^2\left[\frac{1}{n}+\frac{\bar{t}^2}{S_{TT}}\right]\right) \tag{8}$$

$$b_1 \sim N\left(\beta_1, \frac{\sigma^2}{S_{TT}}\right) \tag{9}$$

S_{TT} is:

$$S_{TT} = \sum_{i=1}^{n}\left(t_i - \bar{t}\right)^2 \tag{10}$$

Eq. (7) shows that the accuracy of the estimates may be improved by reducing the noise level, increasing the number of observations and increasing the timespan of the historical record. A covariance value for b_0 and b_1 can also be calculated [30]. As in practice the value of σ is not known, it can be replaced with the standard error (s) obtained as

$$s = \sqrt{\frac{RSS}{n-2}} \tag{11}$$

In this case, a Student-t distribution for b_0 and b_1 would have to be used [10]. However, for large values of n, the Student-t distribution may be approximated by a normal distribution.

4.3. Confidence interval for time failure t_f

In order to obtain a probability distribution for the time of failure, t_f, it is possible to use a Monte Carlo simulation method, a class of algorithms based on repeated random sampling. Using a multivariate random number generator, it is possible to obtain random values of b_0 and b_1 that are distributed as described above. The random number generator can also be employed to obtain different realizations of the residue ε over a sequence of future time instants. For each pair (b_0, b_1) and each realization of the residue, a sequence of future degradation values is obtained. The failure time is then defined as the earliest instant for which the degradation is larger than the failure threshold L. By repeating this kind of simulation, it is possible to obtain a probability distribution around the predicted failure time [32], and assuming that this distribution is Normal or Weibull, for instance, the confidence interval can be obtained.

5. CASE STUDY

In order to illustrate the technique described in the previous section, a case study involving actual data from an aircraft system will be presented. The degradation index was obtained from features related to measurements of fluid content in equipment. In this case, the degradation represents the fluid consumption. Appropriate prognostics of such consumption would be of value to schedule a maintenance intervention (replenishment of the reservoir) for a convenient time. The data consists of a historical record of 250 values for degradation index, acquired over time, as can be seen in Fig. 5.

An algorithm was used in order to provide the results [32]. Briefly, it first calculates values for b_0 and b_1, by least square linear regression method, refer to equation (2). Secondly, values for $MS_{\mathrm{Re}g}$ and s^2 are obtained, refer to Table 1. An F-test was initially carried out to assess the significance of the linear regression. The critical value of the F distribution, for α = 0.05, was calculated as F_{crit} = 3.9. The F-value obtained by using (5) was 1727, which is considerably larger than F_{crit}. Therefore, the null hypothesis (there is no linear tendency) can be rejected with $100(1-\alpha)\% = 95\%$ of confidence. The associated p-value was very close to zero, which means that one can be quite sure that the trend observed in the data record is not fortuitous.

Latter, to obtain the probability distribution of the estimated coefficients, the algorithm uses equations (8), (9) and (10). In addition, the failure time forecasts are simulated by Monte Carlo technique, as described in section 4.3. For each interaction, a failure time is taken from a linear extrapolation with noise. A vector with the simulated failure times is provided.

Figure 5 presents the results obtained with the linear regression, indicated by the red line, and the failure times resulting from the Monte Carlo iterations, indicated by the black crosses. The algorithm also displays three probability distributions for these failure times: a Normal distribution, a Weibull distribution and an approximated distribution obtained by non-parametric estimation, based on a normal kernel function [33].

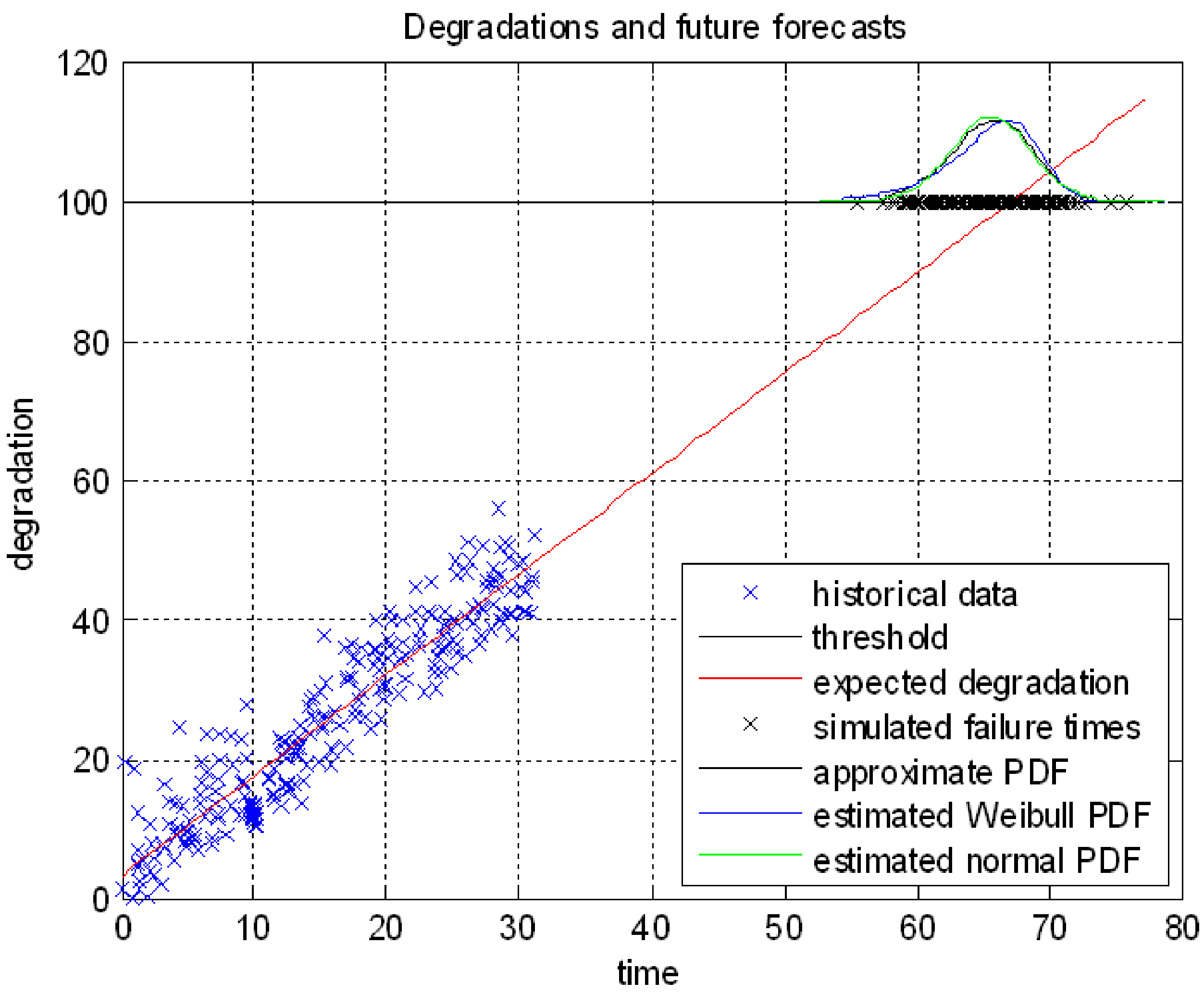

Figure 5 – Monte Carlo simulation result

The probability densities obtained by the proposed technique may be used, for instance, to calculate the probability of failure within a given time window in the future. Such a result could be used to drive a cost-benefit analysis in order to establish maintenance recommendations.

6. CONCLUSION

This paper has briefly reviewed the PHM concepts, describing in more detail some generic prognostic approaches and introduced the theoretical and notional foundations associated with probabilistic predictions. Moreover, a regression-based technique was presented and illustrated by a case study simulated with real data from an aircraft system. The failure instant was calculated and the confidence associated with this estimation was evaluated by using a Monte Carlo technique.

It is worth noting that all applicable methodologies must be carefully studied and analyzed prior to deciding which prognostics approach should be adopted for a given aircraft subsystem. If possible, the results of using different methodologies and data sources should be combined to obtain more reliable forecasts.

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