

Advanced Prognostics for Aircraft Electrical Power Systems

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ABSTRACT

This paper describes a novel time-varying prognostic modeling framework for computing condition-based residual life distributions of partially degraded aircraft electrical power system (EPS) components. This advanced methodology is suitable for modeling the evolution of degradation signals acquired from aircraft electrical power system components through condition monitoring techniques. The evolution of the degradation signals is modeled as a stochastic process, with fixed and random parameters, and takes into consideration environmental covariates that capture the time-varying nature of the equipment's operating condition. The modeling methodology correlates the degradation signals with the underlying physical transitions that occur prior to component failures to estimate and update the residual life distribution of the system. Since these updated distributions capture current health information as well as the latest operating conditions, they provide precise remaining useful life (RUL) estimates.

INTRODUCTION

Most conventional failure models are developed on the premise that the prevailing environmental conditions either do not change in time or have no effect on the deterioration and failure process of the device [5]. While there have been some research efforts that addressed this problem, almost all of the research modeled the environmental conditions as randomly occurring shocks (for a survey see [13]). In [1], components were assumed to experience shocks that varied randomly in response to the environmental conditions. For example Klutke and Yang [7] modeled shocks as a Poisson process, where the shock magnitudes were assumed to be independent and identically distributed (*iid*) random variables. In [12], environmental conditions were modeled as a semi-Markov jump process. In some other cases, random effects of the field environments were captured by a unit-free environmental factor [14]. One popular concept was the estimation of a component's intrinsic age rather than its real age. Intrinsic age is defined as a measure of the cumulative

hazard accumulated over time in an environment with time-varying conditions [12]. Very few research efforts formally addressed the effect of environmental conditions on estimating residual life. Kharoufeh and Cox [6] assumed that degradation rate of the system was random and dependent on the external operating environment.

In this paper, we present a degradation modeling framework for computing residual life distributions of components operating under time-varying environmental conditions. The proposed methodology characterizes the stochastic nature of the degradation process and uses explicit coefficients to capture the effects of the changing environment. This is one of the important differences between this work and previous works published in [3, 4]. To do this, we leverage the advances in sensor and condition/health monitoring technology. Degradation-based sensory signals, such as vibration, acoustic emissions, temperature, etc, often exhibit characteristics patterns that are correlated with the underlying physical degradation processes. These patterns are known as degradation signals and can be used to assess the health of a system or its components [11]. A component is considered to have failed once its degradation signal reaches a predetermined failure threshold. The paper discusses experimental results and the work in-progress related to the application of the methodology to an aircraft integrated drive generator (IDG) system.

SENSOR BASED DEGRADATION MODELING

In this paper, degradation signals are modeled as continuous-time continuous-state stochastic processes. We define the amplitude of a degradation signal at time t_i , $A(t_i)$, as follows:

$$A(t_i) = \eta(x_{ij}; \Phi, \beta) + \varepsilon(t_i) \quad (1)$$

where, $\eta(\cdot)$ represents the functional form that

describes the path followed by the degradation signal. x_{ij} is an independent variable that may represent the operating time and environmental/operational parameters. Φ is a vector of deterministic coefficients, and β is a vector of stochastic coefficients. As mentioned earlier, the stochastic coefficients are assumed to follow specific prior distributions across the population of components with those of the individual components being an unknown “draw” from these distributions. The error term $\varepsilon(t_i)$ follows a normal distribution $N(0, \sigma^2)$ and captures environmental noise and other signal transients. Thus, at sampling epochs, $t_1 < t_2 < \dots < t_k$ the error terms $\varepsilon(t_1), \varepsilon(t_2), \dots, \varepsilon(t_k)$ are iid and follow a $N(0, \sigma^2)$ distribution. The assumption of an iid error term has been previously used by Lu and Meeker [10] and Gebraeel *et al.* [3].

As shown in Fig. 1, typically a database of historical degradation signals (**step 1**) is used to estimate the deterministic and distribution of the stochastic parameters of the model. The resulting model is a “generalized degradation model” that is used to evaluate the residual life distribution of a population of components (**step 2**). Evaluating the residual life distribution (hereafter referred to as RLD) is equivalent to computing the distribution of the time, T , required for the amplitude of the degradation signal to reach a predetermined failure threshold, η^* .

If we define T as a random variable that represents the remaining life of a component, then its distribution can be expressed as follows:

$$F_T(t) = P\{T \leq t\} = P\{\eta(x_{ij}; \Phi, \beta) + \varepsilon(t + t_k) \geq \eta^* | \beta\} \quad (2)$$

where t_k is the current time and t is the future time increment.

Next, assume that we have observed a partial degradation signal $A_1, \dots, A_k$, where $A_k = A(t_k)$. The partial degradation signal is used to update the distribution of the stochastic parameters of the degradation model in a Bayesian manner (**step 3**). Thus, the “generalized degradation model” is updated using component-specific degradation signals. Given the observed data, the conditional distribution of the stochastic coefficients can be expressed as;

$$p(\beta_k / A_1, \dots, A_k) \propto p(A_1, \dots, A_k / \beta) \pi(\beta) \quad (3)$$

where $p(\beta_k / A_1, \dots, A_k)$ is the posterior distribution of the stochastic parameters at the k^{th} updating epoch (time t_k), $p(A_1, \dots, A_k / \beta)$ is the likelihood function of the partial degradation signal, and $\pi(\beta)$ is the prior distribution of β .

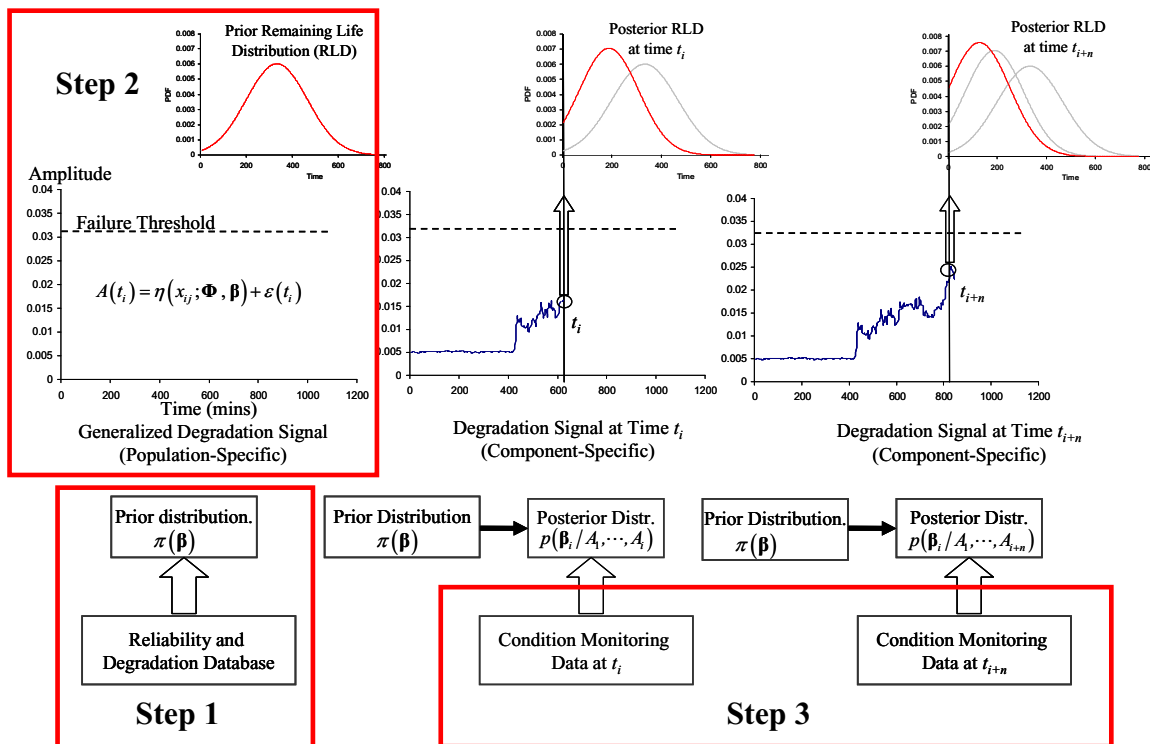


Fig.1 Overview of sensor-based degradation modeling methodology