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Methodologies for system-level remaining useful life prediction ☆

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ABSTRACT

While most prognostics approaches focus on accurate computation of the degradation rate and the remaining useful life (RUL) of individual components, it is the rate at which the performance of subsystems and systems degrade that is of greater interest to the operators and maintenance personnel of these systems. We develop a comprehensive methodology for system-level prognostics under different forms of uncertainty in this paper. Our approach combines an *estimation scheme* with a *prediction scheme* to compute the RUL as a stochastic distribution over the life of the system. We compare two prediction methods: (1) stochastic simulation and (2) the inverse first order reliability method (inverse-FORM). We compare the computational complexity and the accuracy of the two approaches using a case study of a system with several degrading components.

1. Introduction

System-level prognostics encompasses two distinct but related problems: (1) *estimating* the current system state and the degradation rates of individual components and (2) *predicting* future system performance by deriving system RUL functions. This approach provides a framework for condition-based maintenance and system survivability. However, nonlinear system models, uncertainties in the model structure and parameter values, unknown environmental elements that affect the system operations, and measurement noise can affect the accuracy and convergence properties of the estimation and prediction tasks. Much of the past research in RUL prediction have adopted a component-centric view [1,2], but recently, Gomes et al. [3] have developed a system-level approach that assumes the PDFs of the RUL of individual components are known. Recent reliability analysis methods have studied system components whose failure is dependent because they are linked to common causes [4,5]. Liu et al. [6] have studied preventive maintenance policies for systems with multiple components that degrade in a continuous manner.

In practice, small amounts of degradation in several components can combine to produce much larger effects on system performance. Therefore, system end of life (EOL) computation is more than a simple combination of individual component failures. Direct extrapolation of the component RULs to the system RUL can lead to over- and under-estimation problems. Daigle et al. [7] have developed a distributed stochastic simulation approach to compute system EOL as a violation of pre-specified constraints on system behavior projected to individual subsystems. In this method, the system RUL is the minimum of all the distributed subsystem RULs.

Our system-level prognostics approach develops an analytic framework for combining the degradation rate of individual components to predict the change in system performance over time. We define the estimation problem in system-level prognostics and extend a particle filtering (PF) based stochastic simulation approach to estimate component degradation rates and system state simultaneously. Prediction is developed as a stochastic process that derives system-level RUL from system performance. To model uncertainty, we extend two approaches for component-level prediction to system-level prediction: (1) stochastic simulation and (2) inverse-FORM to propagate the uncertainties through the system degradation model and compute *credibility bounds* [8] of the system-level RUL. We perform a comparative analysis of the computational complexity and performance of the two prediction methods using a case study of a system with multiple degrading components. In this framework, we do not assume that the components degradation processes are independent.

Abbreviation: **RUL**, remaining useful life; **EOL**, end of life; **PF**, particle filtering; **PDF**, probability density function; **CDF**, cumulative distribution function; **FOSM**, first-order second moment method; **FORM**, first-order reliability method; **PCs**, possible conflicts; **EKF**, extended Kalman filters; **LSE**, least squares estimation; **ARIMA**, auto regressive integrated moving average; **UT**, unscented transform; **SIR**, sampling importance resampling; **MPP**, most probable point

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The rest of the paper is organized as follows. Section 2 reviews the literature. Section 3 illustrates the complexities of system-level prognostics using an example. Section 4 formulates the system-level prognostics problem. Section 5 discusses our proposed system-level prognostics approach. Section 6 presents the case study using an electric rectifier with several degrading components. Section 7 presents conclusions and discusses the future work.

2. Review of prognostics methodologies

Broadly, prognostics approaches fall into three primary categories [9,10]: (1) data driven techniques, (2) model based and (3) hybrid approaches. Data driven methods use statistical [11] or machine learning algorithms [12] to derive degradation characteristics of components from measurements, and typically rely on run-to-failure data. This kind of data is rarely available. Moreover, the data available may apply under certain conditions only, limiting the generality of the derived model. Model-based prognostic approaches attempt to address this by developing parameterized analytic degradation models from first principles [13,14]. Hybrid approaches combine model-based and statistical approaches. Neerukatti et al. [15] propose a hybrid approach for damage state prediction that starts with a simple crack growth model and investigate two different regression techniques, least absolute shrinkage and selection operator (LASSO) and relevance vector machine (RVM) to update the model using the measured data. They show that even with a simple physics model, the hybrid approach is more accurate than pure data-driven or physics model based approaches for crack growth rate prediction. Jouin et al. [16] applied sequential importance sampling particle filtering to update the available non-exact and nonlinear degradation models of proton exchange membrane fuel cells.

Hybrid approaches provide a relevant framework for scaling up from component to system-level prognostics, especially for nonlinear systems, where estimating system behavior given stochastic models of multiple degrading components is difficult. Several techniques, such as least squares estimation (LSE) [17], extended Kalman filters (EKF) [18], and PF schemes [19] have been developed for state and parameter estimation in nonlinear systems. Saha et al. [20] presented a comparative study of the performance of the auto regressive integrated moving average (ARIMA), relevance vector machine, EKF, and PF schemes for degradation rate estimation and RUL prediction for lithium-ion batteries. They concluded that the PF scheme had comparatively better performance and the highest robustness values for different types of uncertainties.

A number of factors, such as model and future input uncertainty affect RUL prediction [21], making it important to capture these uncertainties using credibility bounds for decision-making and mission planning. If the number of stochastic variables is finite, we can use a sampling approach to explore the behavior space and compute RUL distributions. However, the computational complexity of this approach increases significantly as the number of degrading components in the system increase. Daigle et al. [22] used an unscented transform (UT) to estimate RUL distributions. UT sampling is computationally efficient but does not work well for computing the tail of a RUL PDF.

Alternative approaches use analytic methods, such as FOSM [23] and FORM [24] to compute system RUL. FOSM and FORM are computationally efficient and provide repeatable solutions for online prognostic monitoring. However, previous work [25] shows that like UT, FOSM fails to estimate the tails of the system RUL PDF accurately.

3. System-level prognostics: an example

System-level prognostics applies to systems with two or more degrading components, and interactions between the degrading components makes system-level RUL prediction complex. A systematic approach to system-level prognostics combines degradation models for individual system components and information about how components interact to define the system behavior. System behavior is a complex function of individual component behaviors, thus system behavior prediction is a complex function of the component degradation models. We develop a simple example to illustrate the complexities in computing the PDF of a system's RUL.

Consider three capacitors configured in parallel as shown in Fig. 1a. Assume that the degradation function for each capacitor is given by:

$$C_i(n+1) = (1-\alpha_i)C_i(n), \quad i \in \{1, 2, 3\}, \tag{1}$$

where $C_i(n)$ is the capacitance of capacitor i at time point n, and $0 < \alpha_i < 1$ represents capacitor i's degradation rate. How do we combine the individual degradation rates to determine degradation in performance of the capacitor bank, and then use this information to compute the system end of life (EOL) and the RUL functions? We can define EOL as the first defined failure of a component in the system (e.g., a capacitance parameter falls below 90% of its nominal value). This is likely to be inaccurate, because the system performance may degrade at a faster (or sometimes slower) rate than the individual components.

Assume that the system state and the degradation parameters are estimated at time $n=0$, as shown in Table 1. C_{i_0} represents the initial distribution of the capacitance value for capacitor i, α_i is the degradation rate of capacitor i, Δt is the measurement sampling time and r is the pre-defined threshold that specifies the lower bound on system performance. In this example, this is specified as the ratio of the equivalent capacitance of the system, $C_{eq} = C_1(n) + C_2(n) + C_3(n)$, to the nominal equivalent capacitance, N_{eq1}. In fact, $\frac{C_{eq}(n)}{N_{eq1}} < r$ is the system EOL threshold. Fig. 2 shows the

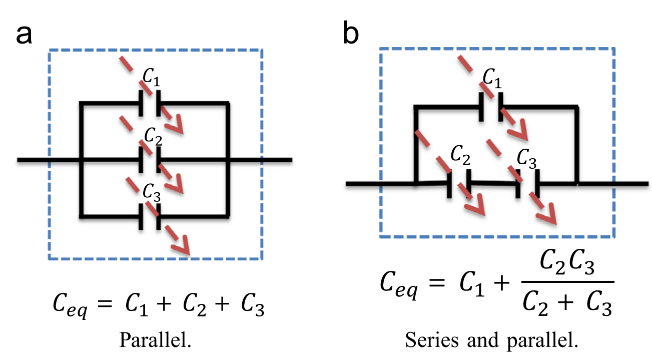

Fig. 1. Capacitors configurations. (a) Parallel. (b) Series and parallel.

Table 1
Degrading system parameters.

Parameter	Value
C_{1_0}	$N(0.0021, 0.0001)$
C_{2_0}	$N(0.0022, 0.0001)$
C_{3_0}	$N(0.0020, 0.0001)$
α_1	0.0000075
α_2	0.000005
α_3	0.000005
Δt	0.1 (h)
r	0.9