

Aging modeling and state-of-health determination for lithium-ion batteries used in embedded applications

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Summary: In this presentation, an approach for failure prognostics by online estimation of the residual life before the system performance requirement is no longer met will be proposed. To do it, we must anticipate the onset of failures of a system for a specific mission. The proposed approach is based on physics-based models. Model-based prognosis was conducted in two phases: the first used the data available on this system to estimate unmeasured states and relevant parameters which are able to characterize system performance, given that the degradations may remain partially or totally hidden. To carry out this phase, we used an observer. In the second phase, to estimate online the duration before the system performance requirement is no longer met, the historical states and parameters obtained in the first phase were exploited. Thus, assuming unknown the models describing the parameter dynamics, we used time series prediction methods. To illustrate the proposed failure prognosis approach, a Li-ion battery was used.

Keywords: Prognosis, RUL. Observer, ANFIS, SVR, Li-ion battery.

Description of your Keynote Presentation

The proposed approach is based on the Model-based prognosis architecture for purposes of practical use presented in [1-2]. The model must be able to represent the behavior of the system. The approach consists of two phases (Figure 1).

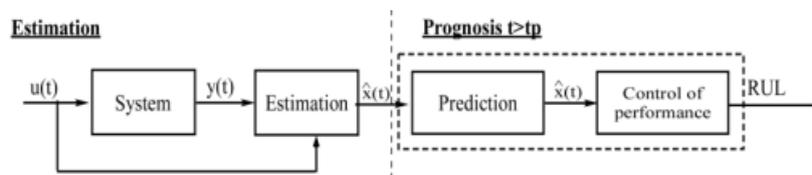


Figure 1. Model-based prognosis architecture [1-2].

In the estimation part, System gets input $u(t)$ and produces output $y(t)$ and the Estimation module estimates the states and parameters, given system inputs and outputs. The Prognosis phase consists in determining when the desired performance will no longer be met over for a specified mission. Thus, the estimation of the RUL is obtained by comparing the performance estimated by model simulation with the desired performance.

Results

We adopt a Li-Ion Battery as a simulation-based case study. The model of the Li-Ion battery used (figure 2) was presented in [3].

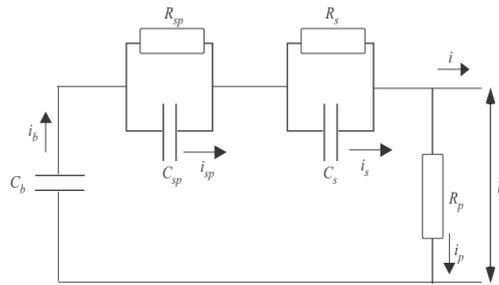


Figure 2. Variables considered in the prognosis phase.

In figure 3 (a, c), the estimated Remaining Useful Life (cycle) is shown in red, the evolution of the real RUL in blue. In figure 5 (b, d), the RUL probability distributions obtained around the real value in hour showing by the red line is presented.

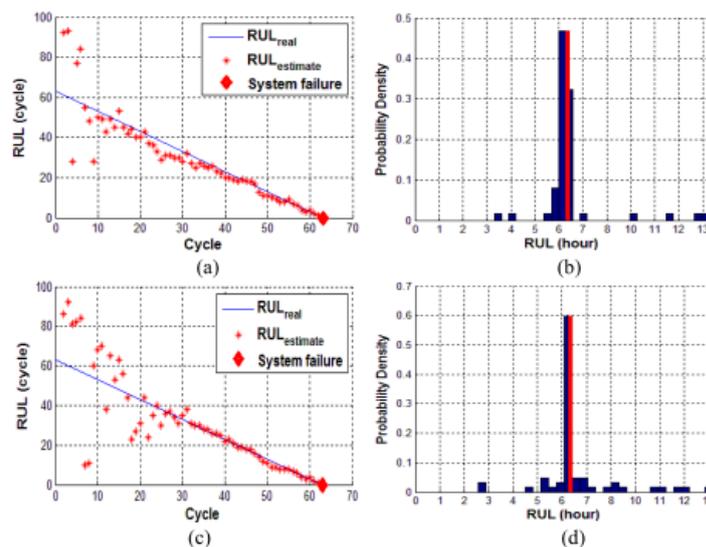


Figure 3. Results for estimation: (a, b) SVR, (c, d) ANFIS.

Final remarks

The aim of the approach was to estimate the RUL without a priori knowledge of the degradation mechanism. The approach is based on the behavioral model. Its implementation requires knowledge of future operating conditions and of the dynamics of the system parameters (degradation causing a deviation of the system parameters). Initially, an observer was used to estimate the states and the unmeasured parameters capable of characterizing the system performance. History of these estimates was then used to determine the parameter dynamics.

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[3] B. Bole, M. Daigle and G. Gorospe. Online prediction of battery discharge and estimation of parasitic loads for an electric aircraft. In *Proceedings of Annual Conference of the Prognostics and Health Management Society*. 2014.