Ensemble of Bootstrapped Models for Remaining Useful Life Prediction and Uncertainty Treatment

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Abstract

The safety of industrial equipment can be enhanced, and the costs of operation and maintenance reduced, by means of prognostic and health management systems which enable detecting, diagnosing, predicting and proactively managing the equipment degradation toward failure [1-2]. Compared to fault detection and diagnosis techniques, which have been extensively investigated in the last decades, prognostics is a relatively new research field which is still in the development phase, although it is a fundamental task for an effective condition–based maintenance strategy [3]. The main goal of prognostics is to predict the Remaining Useful Life (RUL) of degrading equipment by projecting the current system condition in time using a predictive model in the absence of future measurements. This necessarily entails large propagated uncertainty that needs to be analyzed to assign a probability density function (pdf) around the RUL prediction, and calculate confidence bounds for the estimation of important system reliability measure such as the probability of failure [4].

In this context, we consider a situation where sequences of observations of the evolution to failure of a set of similar equipments operating under similar conditions are available to train a data-driven prognostic model that receives in input an observation related to the current degradation of the equipment and returns in output an estimate of its RUL. We analyze the main sources of uncertainty affecting this prediction and decompose the variance of the RUL prediction error into three terms representing the randomness in the future degradation of the equipment, the modeling error, and the uncertainty on the input observation [5]. Next, to supply a measure of confidence in the RUL prediction, we estimate the variance of the RUL prediction error by resorting to the bootstrap method for building an ensemble of diverse prognostic models [6]. The ensemble approach allows estimating the model uncertainty by considering the variability in the predictions of the diverse models of the ensemble. On the other hand, the estimate of the uncertainty due to the stochasticity of the degradation process and the input noise requires investigating the relation between the input and the error of the prognostic model based on its performance on a validation dataset [5-6].

The ability of this approach in providing measures of confidence for the RUL predictions is evaluated in the context of a simulated case study of interest in the power generation industry and concerning turbine blades affected by developing creeps [7-8].

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