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A belief function theory based approach to combining different representation of uncertainty in prognostics

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ABSTRACT

In this work, we consider two prognostic approaches for the prediction of the Remaining Useful Life (RUL) of degrading equipment. The first approach is based on Gaussian Process Regression (GPR) and provides the probability distribution of the equipment RUL; the second approach adopts a Similarity-Based Regression (SBR) method for the RUL prediction and belief function theory for modeling the uncertainty on the prediction. The performance of the two approaches is comparable and we propose a method for combining their outcomes in an ensemble. The least commitment principle is adopted to transform the RUL probability density function supplied by the GPR method into a belief density function. Then, the Dempster's rule is used to aggregate the belief assignments provided by the GPR and the SBR approaches. The ensemble method is applied to the problem of predicting the RUL of filters used to clean the sea water entering the condenser of the boiling water reactor (BWR) in a Swedish nuclear power plant. The results by the ensemble method are shown to be more satisfactory than that provided by the individual GPR and SBR approaches from the point of view of the representation of the uncertainty in the RUL prediction.

1. Introduction

For industry, unforeseen equipment failures are extremely costly in terms of repair costs and lost revenues. To anticipate failures, predictive maintenance approaches are being developed, based on the assessment of the actual equipment degradation condition and on the prediction of its evolution for setting the optimal time for maintenance [22,23,44,48,49]. The underlying concept is that of failure prognostics, i.e., predicting the Remaining Useful Life (RUL) of the equipment, defined as the amount of time it will continue to perform its function according to the design specifications.

In this work we tackle the problem of predicting the RUL of filters placed upstream the condenser of the boiling water reactor (BWR) of a Swedish nuclear power plant. The filters main function is to clean the sea water entering the secondary side of the cooling system. During operations, particles, seaweed, and mussels from the cooling water can cumulate in the filter medium, causing a clogging process. Thus, to assure correct and efficient operations, which require stopping these wastes before entering the condenser, prompt and effective cleaning of the filter is desirable. In this respect, predictive maintenance can allow to increase the component reliability, keeping maintenance costs reasonably low.

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We consider a case in which few sequences of observations taken during the clogging process experienced by filters of the same plant in the past are available (training trajectories). Each observation contains the values of three parameters (pressure drop, flow across the filter and sea water temperature), which provide indirect indications about the degradation (clogging) state of the filters. Since the clogging process under investigation is affected by large uncertainties, mainly due to the variable conditions of the sea water, the challenge is to associate a confidence interval to the RUL prediction. This uncertainty assessment, which describes the expected mismatch between the real and predicted equipment failure times, can be used by the maintenance planner to confidently plan maintenance actions, according to the desired risk tolerance [3,19,36,38,39]. Thus, a proper characterization and representation of the uncertainties affecting the RUL prediction is of paramount importance in prognostics.

Given the unavailability of an explicit model of the degradation process, we resort to data-driven methods for RUL predictions. Among data-driven methods one can distinguish between (i) degradation-based approaches, modeling the future equipment degradation evolution and (ii) direct RUL prediction approaches, directly predicting the RUL [45].

Degradation-based approaches (i) are based on statistical models that *learn* the equipment degradation evolution from time series of the observed degradation states [16,44,47]; the predicted degradation state is, then, compared with failure criteria, such as the value of degradation beyond which the equipment fails performing its function (failure threshold). Examples of modeling techniques used in degradation-based approaches are Auto-Regressive models [10,16], multivariate adaptive regression splines [18], Artificial Neural Networks [23,24], Relevance Vector Machines [26] and Gaussian Processes [4,31].

Direct RUL predictions approaches (ii), instead, typically resort to artificial intelligence techniques that directly map the relation between the observable parameters and the equipment RUL, without the need of predicting the equipment degradation state evolution and fixing a failure threshold [27,34,50]. Examples of techniques used in direct RUL prediction approaches are the Bayesian approach [25] and similarity measures [3,50].

Degradation-based prognostics provides more informative and transparent outcomes than direct RUL prediction prognostics, since it supplies a prediction not only of the current equipment RUL, but also of the entire degradation trajectory that the equipment will follow. This can be very useful, since it allows checking the prediction consistency considering expert intuition or information on-line acquired during the equipment degradation. However, degradation-based prognostics, differently from direct RUL prediction prognostics, requires identifying a degradation indicator and fixing a failure threshold, which could not be easy in practice and may introduce further uncertainty and sources of errors.

Since in practice, it is often hard to choose between degradation-based and direct RUL prediction prognostics, in this work we consider the possibility of aggregating the predictions of a degradation-based and a direct RUL prediction method. This choice is also motivated from the observation that the aggregation of the outcomes of multiple models built using different pieces of information and different modeling approaches has been proven to make the prediction more accurate and robust [29].

In this context, the main contribution of the present work is to propose a technique for aggregating the outcomes provided by different prognostic approaches taking into account the prediction uncertainty.

With respect to the degradation-based approaches (type (i)), we have adopted Gaussian Process Regression (GPR) [4,31] to fit the degradation probability distribution function (pdf) to the degradation trajectories of training. The uncertainty in the future evolution of the degradation states is explicitly modeled by GPR and the predictions about the future degradation state distribution is provided in the form of a Gaussian pdf [4,24]. Finally, by comparing the predicted distribution of the future degradation states with a failure threshold, we estimate the probability distribution of the equipment RUL and the desired prediction intervals. The choice of GPR is motivated by the fact that other regression methods such as ANNs, which in recent research works have been shown to provide accurate predictions of the degradation state [43,15], typically do not provide an explicit and direct quantification of the uncertainty of the predicted degradation states, as do methods like Relevance Vector Machine (RVM) [40] or Gaussian Process Regression (GPR) [20,31]. Since the RVM method is actually a special case of a Gaussian Process (GP) [31], GPR has been used in this work.

With respect to the direct RUL prediction approaches (type (ii)), we have adopted an approach based on the combined use of Similarity-Based Regression (SBR) [50] and Belief Function Theory (BFT) (also called Dempster–Shafer or evidence theory [14,33,35]). Similarity-based regression methods are able to provide reliable RUL predictions even in a case, such as the one here addressed, in which very few training degradation trajectories are available [3]. Notice that other direct RUL prediction approaches, such as the Bayesian approach proposed in [25], typically require the availability of a larger number of training trajectories in order to provide reliable RUL predictions. Our estimate of the prediction uncertainty is, then, based on the use of Belief Function Theory (BFT). This choice is motivated by the large amount of uncertainty to which the model predictions are expected to be subject, given the randomness of the degradation process and the large imprecision of the employed empirical models trained using only the few available degradation trajectories. Indeed, according to the considerations in [5,17,41], it has been argued that the representation of the RUL uncertainty using probability distributions could be critical and uncertainty representation is best accounted for by belief function theory. The result of the application of the method is a Basic Belief Assignment (BBA) that quantifies one's belief about the value of the test trajectory RUL, given the evidence provided by the reference trajectories. The identification of prediction intervals relies on the definition of the total belief assigned by the predicted BBA to an interval, which is interpreted as a lower bound for the probability that the test equipment RUL belongs to such interval. With respect to the aggregation of the predictions of the two approaches, the problem is complicated by the necessity of taking into account the prediction uncertainty representations provided by the two methods.