Hybrid Prognostics for Predictive Maintenance

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Prognostics are essential to fully benefit from predictive maintenance. Because purely physics-based and data-driven prognostic models both have their benefits and limitations, a hybrid approach is proposed to combine their strengths and alleviate their limitations. Bayesian filtering is the main algorithm applied in this research. It is used to update physics-based degradation models with real-time degradation measurements. Special attention in this research is given to assets in varying usage conditions. The algorithm is successfully applied to a case study on simulated crack propagation and to a case study on atmospheric corrosion based on real data. It was shown that the algorithm yields perfect prognostics when the degradation process and loads could be described well. If they only could be described to a limited extent the results were still acceptable, but more prone to varying usage conditions. Although good performance was shown in the case studies, a challenge remains to apply the algorithm when no direct degradation measurements are available.

Introduction

Predictive maintenance reduces unexpected down-time, prevents replacement of healthy components, and enables efficient and effective maintenance logistics [1]. Although the term *predictive maintenance* also encompasses anomaly detection and diagnostic algorithms, those algorithms are not sufficient to achieve optimal maintenance planning. For example, logistic issues such as spare part deliveries, maintenance clustering and workplace availability require a forecast. Furthermore, prognostics may give insight in the way usage can be altered to extend lifetime of components.

Prognostic approaches can be classified as physics-based, data-driven or hybrid [2]. Physics-based approaches use physics-of-failure to predict the remaining useful life (RUL). This enables accurate prognostics based on expected future usage. However, in practical applications it is extremely complex to obtain a representative degradation model and relevant loads. Data-driven approaches use historical failure data to predict the RUL. They relieve the requirement of complex physics-based models but require sufficient representative historical failure data to train the models.

These data are often unavailable, especially when historical usage is not representative for future usage of an asset. As purely physics-based or data-driven approaches are not ideal, hybrid approa-ches help to alleviate limitations and use the benefits of both physics-based and data-driven approaches.

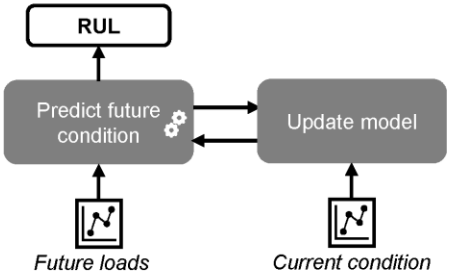

Figure 1: A simplified representation of the prognostic approach using a Bayesian filter.

Methods and Approach

The hybrid approach used in this research is based on Bayesian filtering. A simplified representation of the algorithm is shown in Figure 1. The algorithm predicts the RUL with a physics-based degradation model and updates the model with real-time condition measurements of the degradation process. This approach does not require large historical data sets and makes predictions independent of historical usage. Real-time updating improves accuracy of the degradation model or compensates for missing physics in the model when the physics can only be described to a limited extent. Bayesian filters used in this research are the Unscented Kalman Filter [3] and the Particle Filter [4].

The application of these types of filters is not new in the (theoretical) field of prognostics and the number of adaptations to the basic algorithms is large [5]. Still, practical applications are lacking, and therefore the focus of this research project is on the application of Bayesian filtering in practical applications with varying usage conditions. During the research, a three-step approach is taken, increasing in complexity:

1. Application to *simulated* data with *direct* condition measurements (Unscented Kalman Filtering for crack propagation [6]).
2. Application to *real* data with *direct* condition measurements (Particle Filtering for corrosion prognostics [7]).
3. Application to *real* data with *indirect* condition measurements (future work).

Results of the first two steps are given in the following section.

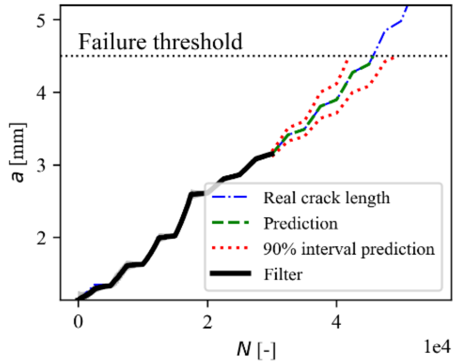

Figure 2: Unscented Kalman Filter for crack propagation [6].

Results

In the first case study [6], a crack propagation problem was simulated by the Paris-Erdogan equation. Crack lengths were assumed to be measured and four scenarios regarding availability of load measurements are compared. An example of a prediction of future crack growth for the scenario where loads are assumed to be measured and future loads are assumed to be known is shown in Figure 2. This figure shows that the prediction (green line) converges very well to the actual crack growth process (blue line), yielding very accurate prognostics. When loads were assumed not to be measured, the filter adapted to its current operating conditions such that prognostics could only be performed when loading profiles remain (quite) constant.

In the second case study [7], mass loss measurements of an atmospheric corrosion process from experiments performed by *NIMS* [8] were used to create a continuous corrosion process. Because the physics of corrosion are extremely complex, it is practically impossible to generate an accurate physics-based model [9]. Therefore, a simplified corrosion model that uses only temperature as input parameter is used to predict atmospheric corrosion, and a particle filter compensates

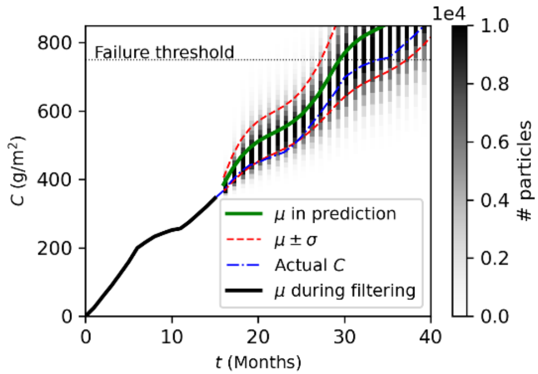

Figure 3: Particle Filter on atmospheric corrosion [7].

for the missing physics. An example of a prediction for future mass loss is shown in Figure 3, which shows that the particle filter learned the clear seasonal effect on the corrosion process and can predict future corrosion quite accurately.

Conclusion and Future Work

Bayesian filtering has shown to be a valuable tool for prognostics because of its ability to either optimize the degradation models, or compensate for missing physics of the degradation models. However, in the discussed cases direct condition measurements were available and relevant loads could be estimated. In many practical applications only indirect condition measurements are available, such as vibrations, acoustic emission or temperatures. This complicates prognostics because the link between data and a degradation model is unclear, and failure thresholds are hard to define. The main focus of future work is on the link between indirect and direct condition measurements.

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