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A hybrid framework combining data-driven and model-based methods for system remaining useful life prediction

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ABSTRACT

Remaining useful life prediction is one of the key requirements in prognostics and health management. While a system or component exhibits degradation during its life cycle, there are various methods to predict its future performance and assess the time frame until it does no longer perform its desired functionality. The proposed data-driven and model-based hybrid/fusion prognostics framework interfaces a classical Bayesian model-based prognostics approach, namely particle filter, with two data-driven methods in purpose of improving the prediction accuracy. The first data-driven method establishes the measurement model (inferring the measurements from the internal system state) to account for situations where the internal system state is not accessible through direct measurements. The second data-driven method extrapolates the measurements beyond the range of actually available measurements to feed them back to the model-based method which further updates the particles and their weights during the long-term prediction phase. By leveraging the strengths of the data-driven and model-based methods, the proposed fusion prognostics framework can bridge the gap between data-driven prognostics and model-based prognostics when both abundant historical data and knowledge of the physical degradation process are available. The proposed framework was successfully applied on lithium-ion battery remaining useful life prediction and achieved a significantly better accuracy compared to the classical particle filter approach.

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1. Introduction

Prognostics technology covers many aspects such as yielding advanced warning of impending failures and estimating remaining useful life (RUL), etc., which ultimately result in increased availability, reliability and safety as well as reduced maintenance and logistics cost. As defined in ISO13381-1 [1], prognostics is 'an estimation of time to failure and risk for one or more existing and future failure modes.' RUL was defined as 'the length from the current time to the end of the useful life' in [2]. RUL prediction has been applied to many systems such as military and aerospace systems, manufacturing equipment, and structure, power systems and electronics. In general, there exist two main types of RUL prediction methods, namely date-driven methods and model-based methods.

Data-driven methods rely only on previously observed data to predict the projection of systems' state or match similar patterns in the history to infer RUL. Data-driven methods include but are not limited to statistical methods, reliability functions, and artificial intelligence methods. Statistical methods such as Hidden Markov Models (HMM) have been applied for prognostics as proposed in [3] for bearing RUL prediction. Statistical methods can further utilize time-series regression techniques such as auto-regressive moving average as mentioned in [4] for lithium-ion battery RUL prediction. Reliability functions such as Weibull distributions have also been used for data-driven prognostics. Guo et al. [5] presented a three-parameter Weibull failure rate function for wind turbine reliability assessment. Artificial intelligent methods such as neural networks were presented by Li et al. [6] using an enhanced fuzzy-filtered neural network method for material fatigue prognostics. Yu [7] proposed a self-organizing maps method for machine health assessment. Data-driven methods derive models only from historical data and are applicable when data is abundant. Similar methods can be applied to different systems without understanding the complex system physics. The output generated from real monitoring data tends to give more precise information than expert

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experience or maintenance feedback. However, most results of data-driven methods are not easy to explain or relate to any physical meaning. In prognostics applications, there are also challenges in determining thresholds, defining data to describe normal behavior, and solving overfitting issues, etc.

Model-based or physics-based methods are approaches that involve the knowledge of a system's failure mechanisms (e.g. crack growth) to build a mathematical description of the system's degradation process in order to estimate the RUL. The mathematical models quantitatively characterize a system's behavior using the first principles, e.g. Zhao et al. [8] presented a prognostics method for remaining useful life prediction for gears. The method was based on a first-principle degradation model (Paris' law) whose parameters were updated within a Bayesian framework. When available and sufficiently complete, behavioral models tend to significantly outperform other types of models [9]. Additionally, changes in model outputs as described by the residuals tend to have a direct (or easily translatable) physical meaning [10]. However, model-based methods may not be applicable to complex systems due to the lack of understanding of all failure modes and behaviors under a range of operating conditions. Model parameter identification also requires extensive experiments. In addition, a model-based method is often built case by case. Hence, it is not generally applicable to a different system without significant amount of effort.

There is no universally the best prognostics method since each method has its advantages and disadvantages and sometimes case specific. It is intuitive to use a fusion approach via combining data-driven methods and model-based methods to leverage their strengths and improve the RUL prediction performance. There are generally four types of fusion approaches reported in the literature, which are listed as follows:

- Use a data-driven method to infer a measurement model and a model-based method to predict RUL (e.g. [11]): This method makes it possible to use a mathematically sound model-based approach to predict system state, especially when the system state itself is not directly measurable or can not be measured accurately. The data-driven model builds a mapping from the measurement to the system state, which ideally requires the life cycle data to establish an exhaustive mapping. This is costly for some applications, while it is also reasonable to build the mapping using data collected when incipient fault is detected.
- Use a data-driven method to replace a system model in a model-based RUL prediction method (e.g. [12]): Building a system model or fault growth model is prohibitive for a complex system, because it may involve detailed finite element analysis. Using a data-driven method to replace the system model provides an alternative to reduce modeling effort. However, data exhaustiveness cannot always be met to build such a model. For example, data in multiple temperature conditions for battery life prediction requires a significant amount of effort to collect.
- Use a data-driven method to predict future measurements which are used within a model-based method (e.g. [13]): This method overcomes the hurdle of measurement availability during long-term prediction which assumes the system parameters to be constant in the future. The trade-off is that only accurate measurement prediction can help correct the system model. Otherwise, the prediction accuracy may not be ensured.
- Combine a data-driven method and a model-based method for prediction by "averaging" their results (e.g. [14]): This method shares similar advantages and disadvantages with the data-driven methods and the model-based methods as mentioned earlier. The benefit is potentially rewarding, while it requires more engineering effort and it is not trivial to design the "averaging" mechanism.

It was found out that a lot of research has been concentrated on the fusion approach of combining data-driven methods and model-based methods. The above mentioned methods have been proposed to fuse the two types of models with different interfaces. These fusion methods addressed the fusion mechanism from different aspects with a single interface (e.g. use a data-driven model to replace the system degradation model as an interface to a model-based method which eventually predicts the RUL). However, it is not clear how to fuse different types of models with multiple interfaces to improve the prediction accuracy, especially when data becomes abundant. The proposed fusion prognostics framework uses data-driven methods both to predict future measurements and to infer the measurement model within a model-based method for RUL prediction. The content was organized as follows: Section 2 described the proposed data-driven method and model-based method fusion framework in detail. Section 3 firstly described the goal of a battery RUL prediction case study and the dataset that was used. Secondly, the prediction results of a traditional model-based method and the proposed fusion approach were analyzed. Finally, a conclusion and discussion of further improvements were given in Section 4.

2. The proposed data-driven and model-based methods fusion prognostics framework

The proposed fusion prognostics framework estimated remaining useful life by combining the data-driven methods and model-based methods. The model-based method described the system degradation in the form of an analytical system equation (degradation model). The degradation model should accurately describe the general progression of degradation, however, there might always be deviations from this model in real applications. Data-driven prediction methods that incorporate historical data from both comparable systems and the very system under test can contribute to the prediction in a way that improves the prediction accuracy and lowers the uncertainty boundaries. The detailed interface between the data-driven methods and the model-based method was shown in Fig. 1 followed by a detailed descriptions of each method.

The novelty of the proposed method is to introduce two data-driven methods into the classical model-based particle filter framework to improve prediction accuracy. The novelty can be summarized as follows:

- Introduce a data-driven method to estimate the measurement model;
- Introduce a data-driven method to predicted future measurement in long term prediction.

The proposed hybrid prognostics framework generalizes the Bayesian state estimation by introducing two data-driven methods within a model-based method, which is particle filter in this case. The internal system state X_k (e.g. degradation) of a complex system is usually not directly accessible to the measurements Y_k from sensors. Hence, inference needs to be made from measurements to indirectly estimate the internal system state, which is predicted by a model-based method. While the classical Bayesian state estimation relies on an analytical measurement model $Y_k = h(X_k) + \nu_k$, there are numerous cases where such analytical representation

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