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Significance, interpretation, and quantification of uncertainty in prognostics and remaining useful life prediction

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ABSTRACT

This paper analyzes the significance, interpretation, and quantification of uncertainty in prognostics, with an emphasis on predicting the remaining useful life of engineering systems and components. Prognostics deals with predicting the future behavior of engineering systems, and is affected by various sources of uncertainty. In order to facilitate meaningful prognostics-based decision-making, it is important to analyze how these sources of uncertainty affect prognostics, and thereby, compute the overall uncertainty in the remaining useful life prediction. This paper investigates the classical (frequentist) and subjective (Bayesian) interpretations of uncertainty and their implications on prognostics, and argues that the Bayesian interpretation of uncertainty is more suitable for condition-based prognostics and health monitoring. It is also demonstrated that uncertainty quantification in remaining useful life prediction needs to be approached as an uncertainty propagation problem. Several uncertainty propagation methods are discussed in this context, and the practical challenges involved in such uncertainty quantification are outlined.

1. Introduction

1.1. Prognostics and remaining useful life prediction

Advanced engineering systems are being used for time-critical, safety-critical, and cost-critical missions, and the performance of such engineering systems needs to be monitored through the use of an onboard health management system. An accurate health management system directly aids in diagnosis and prognosis, and eventually facilitates decision-making regarding the operations of such engineering systems. Diagnosis consists of fault detection, isolation, and estimation, while prognosis deals with predicting possible failures and the remaining useful life of these systems.

The prediction of remaining useful life (RUL) is one of the most important functional aspects of prognostics and health management. The RUL prediction is not only necessary to verify whether the mission goal(s) can be accomplished but also important to aid online decision-making activities such as fault mitigation and mission replanning. Sun et al. [1] discuss the benefits of prognostics and explain how the calculation of RUL is important for technical health determination and life extension [2]. Since the prediction of RUL is critical to operations and decision-making, it is imperative that the RUL be estimated accurately. Degradation signals [3,4] and deterioration models [5] have been used in combination with statistical

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methods for estimating remaining useful life. Researchers have investigated both model-based approaches [6] and data-driven approaches [7,8] for prognostics [9] and RUL prediction [10]. A wide variety of advanced computational techniques such as support vector machines [11], artificial neural networks [12] and dynamic Bayesian networks [13] have been used for estimating the remaining useful life of engineering systems. These methods have been applied to a variety of applications including mechanical bearings [14], gears [15], lithium-ion batteries [16], mobile robots [17], helicopter gear plates [18], and unmanned aerial vehicles [19].

1.2. Uncertainty in prognostics

Since prognostics deals with predicting the future behavior of engineering systems, there are several sources of uncertainty that influence such future prediction, and therefore, it is not meaningful to perform prognosis without estimating the associated uncertainty. As a result, uncertainty plays a significant role in estimating the remaining useful life of engineering systems, and therefore, researchers have been developing different types of approaches for quantifying the uncertainty associated with prognostics.

Existing methods for quantifying uncertainty in prognostics and remaining useful life prediction can be broadly classified as being applicable to two different types of situations: testing-based prognostics and condition-based prognostics. Methods for *testing-based* prognostics are based on rigorous testing *before* and/or *after* operating an engineering system (offline), whereas methods for *condition-based* prognostics are based on monitoring the performance of the engineering system *during* operation (online).

There are several research papers that discuss uncertainty quantification in crack growth analysis [20,21], structural damage prognosis [22,23], electronics [24], and mechanical bearings [25], primarily in the context of testing-based approaches. Such approaches may be applicable to smaller components when it may be affordable to run several such components to failure, and it may not be practically feasible to extend this approach to large scale systems. Further, the prediction of remaining useful life is more significant in an online health monitoring context where the performance of a system under operation needs to be monitored and its remaining useful life calculated. Engel et al. [26] discuss several issues involved in the prediction of remaining useful life in online prognostics and health monitoring. Though some of the initial studies on remaining useful life prediction lacked uncertainty measures [27], researchers have recently started investigating the impact of uncertainty on estimating the remaining useful life. For example, there have been several efforts to quantify the uncertainty in remaining useful life of batteries [28] and pneumatic valves [29] in the context of online health monitoring. Different types of sampling techniques [6] and analytical methods [16] have been proposed to predict the uncertainty in the remaining useful life.

However, a review of the aforementioned papers reveals that there exist several challenges in applying uncertainty quantification methods for online health monitoring purposes. For example, several papers claim to account for uncertainty in prognostics using Bayesian filtering techniques like Kalman filtering [30] and particle filtering [31]. Such a claim is not technically accurate because filtering can be used only to estimate the health state of the system based on data. The key in prognostics is to predict future deterioration based on the estimated health state and filtering cannot be used for future prediction. Therefore, it is necessary to resort to other statistical approaches that can compute the uncertainty in the future prediction and the remaining useful life [32].

Another important and related issue is that, while the importance of uncertainty quantification in prognostics has been understood, there have been few efforts to understand and appropriately interpret such uncertainty. Celaya et al. [33] discussed the interpretation of RUL in the context of Kalman filtering-based prognostics techniques, and explained that it is not appropriate to arbitrarily force the variance of RUL to be small. It is necessary to further investigate the aspects of interpretation and quantification of uncertainty, in order to completely understand and quantify the impact and effect of uncertainty on prognostics and remaining useful life prediction.

1.3. Goals and contributions of this paper

The present paper delves deeper into the philosophical aspects of uncertainty in prognostics and focuses on four important questions in order to understand and quantify uncertainty in prognostics.

1. What causes uncertainty in prognostics?
2. How to interpret uncertainty in prognostics?
3. How to facilitate effective treatment of uncertainty in prognostics?
4. How to accurately quantify uncertainty in prognostics?

The answers to the above questions are sought from multiple points of view, and different fundamental concepts relating to uncertainty in prognostics are explained in detail. In order to facilitate better understanding of these fundamental concepts, a conceptual example is presented in Section 2, and used as an illustrating guide, throughout this paper. The answers to the above questions, in turn, lead to the following contributions of this paper.