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Remaining useful life estimation in aeronautics: Combining data-driven and Kalman filtering

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A B S T R A C T

Data-driven prognostics can be described in two sequential steps: a training stage, in which, the data-driven model is constructed based on observations; and a prediction stage, in which, the model is used to compute the end of life and remaining useful life of systems. Often, these predictions are noisy and difficult to integrate. A technique well known for its integrative and robustness abilities is the Kalman filter. In this paper we study the applicability of the Kalman filter to filter the estimates of remaining useful life. Using field data from an aircraft bleed valve we conduct a number of real case experiments investigating the performance of the Kalman filter on five data-driven prognostics approaches: generalized linear models, neural networks, k-nearest neighbors, random forests and support vector machines. The results suggest that Kalman-based models are better in precision and convergence. It was also found that the Kalman filtering technique can improve the accuracy and the bias of the original regression models near the equipment end of life. Here, the approach with the best overall improvement was the nearest neighbors, which suggests that Kalman filters may work the best for instance-based methods.

1. Introduction

In maintenance, data driven prognostics approaches are used when it is not possible to model an engineering system by applying domain knowledge about the system's damage behavior or when the complexity of the problem is too high. These approaches consist of empirical techniques that compute, on an individual basis, prognosis information on the remaining useful life (RUL) of the equipment. Here, the general prognostic problem can be divided into two sequential stages: i) a training stage, in which, a model is fit to past observations, and an ii) estimation stage in which, using the model, the end of life or the residual life of the system is determined based on new observations [1].

After the estimation stage, data-driven point predictions may tend to show noise and irregularities which can significantly influence the models' final accuracy [2,3]. State observers, or filters are commonly used in prognostics to improve the accuracy and robustness of health degradation measurements, such as temperature or vibration signals [4]. A not so explored possibility is to use these same techniques to filter RUL predictions [2]. A suitable solution to this kind of problem is the Kalman filter (KF), a recursive solution that estimates the internal state of the prognostics linear system from a series of noisy measurements [5].

In this paper, we develop a data-driven prognostics architecture that follows a Kalman-based approach to RUL estimation. Using a bleed valve of a commercial aircraft as our case study, we conduct a number of real case experiments investigating the performance trade offs of our proposed architecture. Performance is measured using established prognostics metrics [6]. Concretely, we aim to show that the performance of data-driven prognostics models can be significantly enhanced by Kalman-based RUL filtering. The novelty of our work is that we compare the application of the Kalman filter to a number of different regression techniques, namely generalized linear modeling, neural networks, nearest neighbors, regressive support vector machines and random forests. In summary, the main contributions of this work are the following:

- We show that the effectiveness of applying the Kalman filter as a post-processing solution depends both on the method and time when the filter is applied.
- The late stage of the equipment life is shown to be the most important phase to apply the Kalman filter solution. This is also the most

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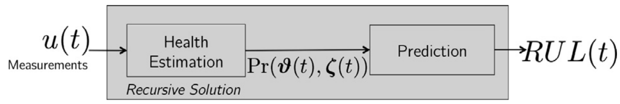

Fig. 1. Model-based prognostics architecture. Model-based prognostics usually proceed in two stages: a joint state-parameter stage, in which, the health of a system or component is determined based on the observations; and a prediction problem, in which, the state parameter distribution is simulated forward in time to compute the remaining useful life. The first stage is usually implemented using a recursive solution, i.e, a filter. The choice of filter depends on the assumptions made about the system, and the desired performance.

important phase for prognostics which reinforces the importance of our findings.

- We compare different data-driven solutions when combined with the Kalman filter solution. The nearest neighbor's model is shown to be the most responsive model. As the quantity and quality of the prognostics may tend to increase (as more quality data becomes available), the nearest neighbor's models will theoretically produce better estimates.

As a result, we hope to contribute to create a greater awareness of the importance of using these kind of models and filter techniques for prognostics. The remaining of the paper is organized as follows. Section 2 reviews related work. Section 3 formally introduces and describes the data-driven prognostics architecture. Section 4 introduces the case study while Section 5 discusses the used methodology. Section 6 provides results from a number of real case experiments. Section 7 concludes the paper and outlines future work.

2. Background and related work

In this section we review model-based prognostics and their use of recursive algorithms such as the Kalman filter. We also provide an overview of what has been done in Kalman-based data-driven prognostics.

2.1. Model-based state-space methods

Model-based prognostics uses domain knowledge of the system and its degradation behavior to develop a physics-based model [7]. Different approaches have been proposed to solve the problem of model-based prognostics [8]. In this section we discuss state-space methods, or in other words, models where the input, output and state variables are related by first-order differential equations [9].

Fig. 1 presents the model-based state-space approach. As shown, in this kind of approach, damage estimation reduces to joint state-parameter estimation, that is, to the computation of the probability density function (PDF) $\Pr(\boldsymbol{\vartheta}(t), \boldsymbol{\zeta}(t))$ where $t \in \mathbb{R}$ is the discrete time variable, $\boldsymbol{\vartheta}(t) \in \mathbb{R}^{n_\vartheta}$ is the state vector, and $\boldsymbol{\zeta}(t) \in \mathbb{R}^{n_\zeta}$ is the parameter vector. Here, the state vector $\boldsymbol{\vartheta}(t)$ usually consists of m physical variables, such as a temperature or vibration

$$\boldsymbol{\vartheta}(t) = \begin{pmatrix} \vartheta_1(t) \\ \vartheta_2(t) \\ \dots \\ \vartheta_m(t) \end{pmatrix} \tag{1}$$

In model-based systems, domain knowledge is in the form of a set of constraint functions $\{C_i\}_{i=1}^{c}$ [4] that map each probability density function (PDF) in the joint state-parameter space $(\boldsymbol{\vartheta}(t), \boldsymbol{\zeta}(t))$ to the Boolean domain $\mathbb{B} \triangleq [0, 1]$

$$C_i : \mathbb{R}^{n_\vartheta} \times \mathbb{R}^{n_\zeta} \to \mathbb{B} \tag{2}$$

where $C_i(\boldsymbol{\vartheta}(t), \boldsymbol{\zeta}(t)) = 1$ if the constraint is satisfied and $C_i(\boldsymbol{\vartheta}(t), \boldsymbol{\zeta}(t)) = 0$ otherwise. The restrictions determine when the system is within the region of acceptable behavior. These constraints may be combined into a single threshold function T_{EOL}, where

$$\mathrm{T}_{EOL}(\boldsymbol{\vartheta}(t), \boldsymbol{\zeta}(t)) = \begin{cases} 1, & 0 \in C_i(\boldsymbol{\vartheta}(t), \boldsymbol{\zeta}(t)) \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

Using the previous function, EOL can be formally defined as

$$EOL(t) \triangleq \inf\{t \in \mathbb{R} : t_i \geq t \wedge T_{EOL}(\boldsymbol{\vartheta}(t_i), \boldsymbol{\zeta}(t_i)) = 1\} \tag{4}$$

and RUL as

$$RUL(t) \triangleq EOL(t) - t \tag{5}$$

To solve the joint state-parameter estimation, recursive techniques like the Kalman filter, extended Kalman filter, and particle filter are among the most used algorithms [10]. In such methods, damage progression is described as a discrete state-space system

$$\boldsymbol{\vartheta}(t+1) = \mathrm{g}(t, \boldsymbol{\vartheta}(t), \boldsymbol{\zeta}(t), \boldsymbol{u}(t), \boldsymbol{v}(t)) \tag{6}$$

$$\boldsymbol{\varphi}(t) = \mathrm{h}(t, \boldsymbol{\vartheta}(t), \boldsymbol{\zeta}(t), \boldsymbol{u}(t), \boldsymbol{n}(t)) \tag{7}$$

where $\boldsymbol{\vartheta}(t) \in \mathbb{R}^{n_\vartheta}$ is the state vector, $\boldsymbol{\zeta}(t) \in \mathbb{R}^{n_\zeta}$ is the parameter vector, $\boldsymbol{u}(t) \in \mathbb{R}^{n_u}$ is the input (measurement) vector, $\boldsymbol{v}(t) \in \mathbb{R}^{n_v}$ is the process noise vector, g is the state update equation, $\boldsymbol{\varphi}(t) \in \mathbb{R}^{n_\varphi}$ is the output vector, $\boldsymbol{n}(t) \in \mathbb{R}^{n_n}$ is the measurement noise vector, and h is the output equation.

Eqs (6) and (7) represent the most general form of a nonlinear joint state-space model. Different filters have distinct assumptions about the functional forms of g and h, or how the noise terms relate to the states and parameters.

Regarding the contributions to the field of model-based state-space prognostics we cite the work of Daigle et al. [4] that compares the Daum filter, the unscented Kalman filter, and the particle filter on a centrifugal pump simulation experiment. Overall, from these three non-linear filters, the authors find the unscented filter the easier to tune, and the one with the best accuracy and precision. Seemingly, in [11] the authors find that the unscented Kalman filter model can successfully capture damage degradation during the aging process while predicting the equipment's remaining useful life with satisfactory accuracy.

Interestingly, the choice of the most suitable filter solution appears to depend on the industrial application. For instance, Simon [12] compares the application of diverse Kalman filters namely, the linearized, extended and unscented filters in the evaluation of aircraft engine health. The author finds the extended filter to show the best compromise between accuracy and computational resources. The authors conclude that engine dynamics, even though nonlinear, may not exhibit a nonlinearity that justifies the extra computational expense of an unscented Kalman filter [12].

There is also the work of Lim and Mba [13] who use a switching Kalman filter on a case study of gearbox bearings from a Republic of Singapore Air Force AH64D helicopter. In the proposed approach, multiple degradation models are used, with the most suitable method being inferred from condition monitoring data by Bayesian estimation. Using this approach the authors circumscribe the problem of having a single dynamical model which may not adequately represent the equipment's different degradation processes.

2.2. Data-driven models

In data-driven prognostics the prediction of end of life and the remaining useful life of a technical system is addressed by assuming the existence of a function f such that

$$\boldsymbol{y}(t) = f(t, \boldsymbol{x}(t), \boldsymbol{\theta}(t)) \tag{8}$$