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ScienceDirect

Procedia CIRP 38 (2015) 177 – 182

www.elsevier.com/locate/procedia

A Simple State-Based Prognostic Model for Filter Clogging

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Abstract

In today's maintenance planning, fuel filters are replaced or cleaned on a regular basis. Monitoring and implementation of prognostics on filtration system have the potential to avoid costs and increase safety. Prognostics is a fundamental technology within Integrated Vehicle Health Management (IVHM). Prognostic models can be categorised into three major categories: 1) Physics-based models 2) Data-driven models 3) Experience-based models. One of the challenges in the progression of the clogging filter failure is the inability to observe the natural clogging filter failure due to time constraint. This paper presents a simple solution to collect data for a clogging filter failure. Also, it represents a simple state-based prognostic with duration information (SSPD) method that aims to detect and forecast clogging of filter in a laboratory based fuel rig system. The progression of the clogging filter failure is created unnaturally. The degradation level is divided into several groups. Each group is defined as a state in the failure progression of clogging filter. Then, the data is collected to create the clogging filter progression states unnaturally. The SSPD method consists of three steps: clustering, clustering evaluation, and remaining useful life (RUL) estimation. Prognosis results show that the SSPD method is able to predicate the RUL of the clogging filter accurately.

Keywords: Prognostics, Remaining Useful Life, Data Collection, Filter Clogging.

1. Introduction

Prognostics is an inherent part of Condition-based maintenance (CBM). Prognostics is the ability to predict the health status of a given component/system, for a predefined time in the future or forecast the failure's time, and its remaining useful life (RUL).

Large amounts of literature focusing on prognostic techniques have been published by researchers [1-12]. Prognostic approaches can be classified into experience-based models, data-driven models, and physics-based models, as shown in Figure 1. Experience-based models correlate knowledge and engineering experience with the observed monitoring data to infer RUL from historical measurements [1]. Data-driven models rely only on learning systems behaviour directly from collected raw monitoring data to predict the projection of a system's state or to match similar patterns in the history to infer RUL. Data-driven models include but are not limited to statistical models, reliability functions, and artificial intelligence models [2]. Physics-based models quantitatively characterize the progression of failures using physical laws to estimate the RUL [3]. More recently, hybrid prognostics approaches have been presented, attempting to leverage the advantages of combining different prognostics techniques in the aforementioned different classifications for better capability of managing uncertainty related to system complexity and data availability to achieve more accurate RUL. However, hybrid prognostics models can have higher computational cost which leads to more difficulties in some applications. Hybrid prognostics models can be mainly categorised into experience-based model & data-driven model [4], experience-based model & physics-based model [5], data-driven model & data-driven model [6], data-driven model & physics-based model [7], and experience-based model & data-driven model & physics-based model [8]. Moreover, hybrid modelling can be performed in two approaches, namely: series approach and parallel approach [9]. The main challenges of hybrid prognostic approaches are choosing the right category which depends on available data and information, and choosing the appropriate fusion mechanism for developing the hybrid model.

Filtration phenomenon is an interest for several engineering processes including automotive, chemical, nuclear reactor, and process engineering applications. Besides, several

doi:10.1016/j.procir.2015.08.094

industrial applications such as food, petroleum, pharmaceuticals, metal production, and minerals embrace filtration process [13]. The aim of the filtration systems is to keep the rest of the system running smoothly; moreover, they play a vital role in maintaining the process operating. Modern commercial vehicles and automobiles have numerous types of filters including fuel, lubricant, and intake air [14].

Sharing an important role with pumps, fuel filters filtrate dirt and other contaminants in the fuel system such as sulphates, polymers, paint chips, dust, and rust particulate which are released from a fuel tank due to moisture or other numerous types of dirt have been uplifted via supply tanker [15, 16]. Consequences like engine and pump performance degradation due to increased abrasion and inefficient burning in the engine are the main motivators for fuel filtration leading to a purified fuel. However, filtering the fuel associates with some complications (e.g. clogging of filter) as well. System flow rate and engine performance declines once a fuel filter is clogged where it does not function well in its desired operation ranges. [16] reports that filter clogging indication due to fuel contamination may result in an aircraft having to return to the ground for further fuel filter inspection or replacement. In today's maintenance planning, fuel filters are replaced or cleansed on a regular basis. [16] reports that Boeing 777 fuel filter inspections are performed at every 2000 flight hours. Monitoring and implementation of prognostics on filtration system have the potential to avoid costs and increase safety.

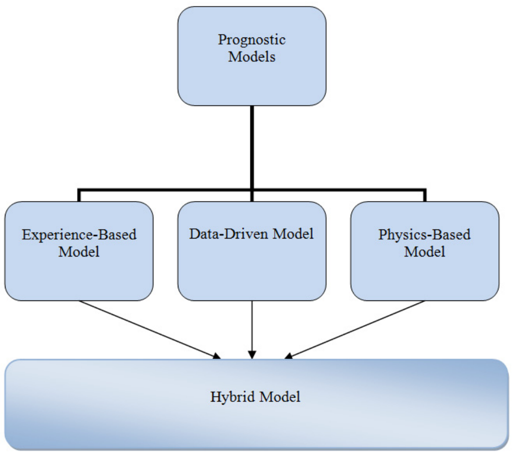

Figure 1. Classification of prognostics models

Clogging process of different types of filtration mechanisms has been studied in the literature. [17] presented a particle level filtration case study; stating that the general clogging process can be considered as a function of: ratio of particle to mesh pore size, solid fraction, and the number of grains arriving at each mesh hole during one test. [18] developed a mathematical model for dynamic behaviour of filtering process for ceramic foam filters. The model is capable of estimation of the filtration efficiency, accumulation of particle mass in the filter, and the pressure drop throughout the filter. [19] presented a diagnostic and prognostic solution for water recycling system for next generation spacecraft. They simulated several failure scenarios including clogging of membranes and filters. [20-21] developed a similarity-based and Gaussian process regression (GPR) prognostic approach to estimate the remaining useful life (RUL) of sea water filters. [22] presented a nuclear research reactor air filter pressure drop modelling scheme which utilises gamma processes.

The failure mechanism of system components are often caused due to a degradation process. Therefore, degradation data of system components can sometimes provide more information for assessing the reliability and estimating the RUL of system components. In some cases, actual degradation can be observed with time. An example of this would be a crack growing with time on a component. As the crack grows to a certain width, the component will fail. On the other hand, some actual degradation process cannot be observed, but measuring the component's performance is sufficient to be an indicator for component's degradation. Moreover, for some components, the degradation rates at nominal operations are considerably low that no meaningful and sufficient information can be extracted from the degradation data. Thus there is a need to use accelerating methods to increase the degradation rate to collect useful data for prognosis. The implementation of accelerated degradation testing is an appropriate choice to overcome obstacles of developing prognostics techniques in engineering, such as insufficient data, time and cost constraints. For accelerated degradation testing, by using more severe testing conditions to accelerate performance degradation process than that experienced in normal condition, more performance information would be collected in a shorter time.

Organization of the paper is as follows. Section two represents a simple state-based prognostic method. Section three discusses thoroughly the fuel system experimental scenario and the obtained results. Section four concludes the article and future research direction is pointed out.

2. Simple State-Based Prognostics with Duration Information (SBPD)

This section summarises the main steps of SBPD approach in (see [23] for more details), which implemented to predict the RUL. The implementation of SBPD approach has three stages, as shown in Figure 2: the first stage is clustering the health state of the system. k-means clustering technique is used in this work for its simplicity and effectiveness. The k-means clustering method aims to group the samples of the dataset into clusters by optimizing the dispersion between the samples of the datasets and the centre of the identified cluster [24].

In the second stage, the number of clusters will be evaluated because the real number of clusters are not known. In this work, Calinski-Harabasz (CH) index is chosen for its robustness. Calinski-Harabasz (CH) index gives the optimal number of clusters and health states in our problem. CH index is calculated using the formula in Eq. (1) [23]