Chapter 19
A Particle Filtering Based Approach for Gear Prognostics

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ABSTRACT

In this chapter, a particle filtering based gear prognostics method using a one-dimensional health index for spiral bevel gear subject to pitting failure mode is presented. The presented method effectively addresses the issues in applying particle filtering to mechanical component remaining useful life (RUL) prognostics by integrating a couple of new components into particle filtering: (1) data mining based techniques to effectively define the degradation state transition and measurement functions using a one-dimensional health index obtained by a whitening transform; and (2) an unbiased l-step ahead RUL estimator updated with measurement errors. The presented prognostics method is validated using data from a spiral bevel gear case study.

INTRODUCTION

Recently, applications of particle filtering to prognostics have been reported in the literature, for example, remaining useful life (RUL) predication of a mechanical component subject to fatigue crack growth (Zio and Peloni, 2011), on-line failure prognosis of UH-60 planetary carrier plate subject to axial crack growth (Orchard and Vachtsevanos, 2011), degradation prediction of thermal processing unit in semiconductor manufacturing (Butler and Ringwood, 2010), and prediction of lithium-ion battery capacity depletion (Saba *et al*., 2009). The reported application results have shown that particle filtering represents a potentially powerful prognostics tool due to its capability in handling non-linear dynamic systems and

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non-Gaussian noises using efficient sequential importance sampling to approximate the future state probability distributions. Particle filtering was developed as an effective on-line state estimation tool (see Doucet *et al*., 2000; Arulampalam *et al*., 2002). In order to apply particle filtering to RUL prediction of a mechanical component such as gears, a few practical implementation problems have to be solved: (1) define a state transition function $\mathbf{f}_k$ that represents the degradation evolution in time of the component; (2) select the most sensitive health monitoring measures or condition indicators (CIs) and define a measurement function $\mathbf{h}_k$ that represents the relationship between the degradation state of the component and the CIs; (3) define an effective *l*-step ahead RUL estimator. In solving the first problem, research on using particle filtering for mechanical component RUL prognostics has used Paris' law to define the state transition function $\mathbf{f}_k$ (Zio and Peloni, 2011; Orchard and Vachtsevanos, 2011). As an empirical model, Paris' law can be effective for defining a state transition function that represents a degradation state subject to fatigue crack growth. For other type of failure modes such as pitting and corrosion, effective alternatives for defining the state transition function should be explored. Regarding the second problem, on the surface, it doesn't seem to be a problem to use multiple CIs to define a measurement function for particle filtering as it allows information from multiple measurement sources to be fused in a logical manner (Zio and Peloni, 2011). In particle filtering, measurements are collected and used to update the prior state distribution via Bayes rule so as to obtain the required posterior state distribution. Subsequently, various kinds of uncertainties arise from different sources that are correlated. In most real applications, no single CI is sensitive to every failure mode of a component. This suggests that defining the measurement function $\mathbf{h}_k$ will have some form of de-correlated sensor fusion. In order to apply particle filtering to estimate the RUL, an *l*-step ahead estimator has to be defined. Both biased and unbiased *l*-step ahead estimators have been reported by Zio and Peloni (2011) and Orchard and Vachtsevanos (2011). However, as pointed out by Zio and Peloni (2011), one issue related to these estimators is that state estimation and prediction must be accompanied by a measure of the associated error.

In this chapter, a particle filtering based gear prognostics using one-dimensional health index method for spiral bevel gear subject to pitting failure mode is presented. In particular, in presenting the method, the three particle filtering prognostics implementation related issues will be addressed: (1) define the state transition function using data mining approach; (2) use an one-dimensional health index (HI) obtained by a whitening transform to define the measurement function; (3) an *l*-step ahead RUL estimator incorporated with a measure of the associated error. The presented method is validated using fatigue testing data from a spiral bevel gear case study performed in the NASA Glenn Spiral Bevel Gear Test Facility.

THE APPROACH

The general framework of the particle filtering based gear prognostics method for spiral bevel gear subject to pitting failure mode is shown in Figure 1.

As shown in Figure 1, to predict the RUL of the spiral bevel gear subject to pitting failure mode, the oil debris mass (ODM) is used to represent the degradation state of the gear. Therefore, the state transition function $\mathbf{f}_k$ is defined by an ODM ARIMA model established using data mining based approach. The one-dimensional HI obtained by the applying a Cholesky decomposition based whitening transform and statistical generation models is used to define the measurement function $\mathbf{h}_k$ by double exponential smooth-

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