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Statistical gear health analysis which is robust to fluctuating loads and operating speeds

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ABSTRACT

Condition-based maintenance is concerned with the collection and interpretation of data to support maintenance decisions. The non-intrusive nature of vibration data enables the monitoring of enclosed systems such as gearboxes. It remains a significant challenge to analyze vibration data that are generated under fluctuating operating conditions. This is especially true for situations where relatively little prior knowledge regarding the specific gearbox is available. It is therefore investigated how an adaptive time series model, which is based on Bayesian model selection, may be used to remove the non-fault related components in the structural response of a gear assembly to obtain a residual signal which is robust to fluctuating operating conditions. A statistical framework is subsequently proposed which may be used to interpret the structure of the residual signal in order to facilitate an intuitive understanding of the condition of the gear system. The proposed methodology is investigated on both simulated and experimental data from a single stage gearbox.

1. Introduction

Condition-based maintenance (CBM) is concerned with the collection and interpretation of data to support maintenance decisions. Vibration analysis is especially applicable to the monitoring of enclosed systems, such as gearboxes, due to its non-intrusive nature [1]. A significant challenge remains with the monitoring of gears under fluctuating operating conditions [2]. Fluctuating loads tend to cause amplitude modulation of the vibration signal, while fluctuating rotational speeds induce frequency modulation [2]. Baydar and Ball [3] indicate that not only do the amplitudes and sideband content of frequency components change under varying load conditions, but some non-fault related components may also appear or disappear completely. It may subsequently become difficult to differentiate between load-dependent and fault-dependent characteristics in the time or spectral domains [1].

The inability of spectral domain analysis to interpret non-stationary waveforms may to some extent be overcome by using time-frequency transforms (including the short-time Fourier transform, Wigner–Ville, and Choi–Williams distributions [3,4]) or time-scale transforms (including Wavelets and Wavelet packet analysis [5–7]) to extract features which could be used to detect gear damage in the presence of fluctuating loading conditions. However manual interpretation of these transforms tends to be difficult and requires the expertise of highly trained and experienced personnel.

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Automatic pattern recognition algorithms, such as Neural networks [5–7], Support vector machines [8], and Fuzzy logic systems [9], avoid the need for manual interpretation of the data. However due their dependence on expensive training data – which need to be representative of various fault and operating conditions for the specific machine – it is often not possible to implement these supervised learning techniques in practice [10].

Various order domain techniques exist which attempt to remove the effects of non-stationary speeds on the vibration signal. Computed order tracking resamples a signal to fixed increments of the shaft position, rendering it possible to analyse the order domain spectrum [11]. Order domain averaging computes an average of the resampled signal over a number of revolutions in attempt to reduce noise and non-synchronous effects from sources other than the shaft of interest [2]. Other order tracking techniques, such as Vold–Kalman filters or Gabor order tracking, assume sinusoidal waveforms to extract order information from the time domain [11]. While these techniques often prove very valuable, they continue to suffer from certain limitations. Computed order tracking for instance is sensitive to jittery shaft speeds, while Vold–Kalmal filters require correct filter bandwidth selection [11].

Residual signal analysis is a technique which attempts to isolate or extract the diagnostic information from the vibration waveform. A residual signal is obtained by removing the non-fault related vibration components from the signal so that only those parts of the signal which are indicative of true faults remain. A number of different approaches of obtaining residual signals have been investigated in literature. Stewart [12] computes a residual signal by eliminating the gear meshing harmonics and its adjacent sidebands from the signal average spectrum before converting the signal back to the angle domain. He also defines a non-dimensional parameter (FM4) which has been found to be especially sensitive to general faults. Lin et al. [13] investigate a residual signal based on the work by [14], where a family of Morlet Wavelets is composed based on an assumed gear motion model. These wavelets are used as a comb filter to decompose the signal into the gear motion and residual signals. The residuals are shown to be sensitive to propagating gear faults. Wang and Wong [15] propose using a autoregressive (AR) model of the signal of the gear in interest to represent its healthy state. A residual signal is subsequently obtained as the difference between a future observed signal and the one step ahead prediction made by an autoregressive filter. The residual signal is shown to be an effective tool in the detection and diagnosis of gear faults.

This paper investigates two novel ideas. The first is to use an adaptive time series model (based on Bayesian model selection) to obtain a sensitive residual signal which is more robust to fluctuating operating conditions. The second idea is that the structure of the residual signal may also contain valuable diagnostic information. The proposed method will be seen to have some analogy to performing a synchronous averaging of the residual signal. This paper presents a statistical framework which interprets the structure of the residual signal with the aim of offering an intuitive interpretation of the condition of a gearbox which is robust to fluctuating operating loads or speeds.

The remainder of the paper is structured as follows: Section 2 investigates the nature of the gear casing waveform, and discusses how the adaptive time series model is used to generate a residual signal. The statistical framework which is subsequently used to interpret the residual signal is considered in detail. Section 3 investigates the proposed methodology on data which are simulated by means of a dynamic gear model. The final section discusses an experimental case study where the methodology is applied to a gearbox which is run to destruction over an accelerated life cycle.

2. The gear casing waveform

If it is assumed that a gear fault is present, such as a cracked or broken gear tooth, then it might be expected that the measured vibration waveform from the gear system will be distorted for the duration (or shortly after) that the faulty tooth has been in mesh. Let the measured gear casing waveform y_m at time instant m be described as a combination of the healthy waveform x_m, fault induced distortion f_m and some white measurement noise n_m. It is often most convenient to measure the vibration signal on the casing of the gear, but the analysis presented here is not restricted to this definition. It is thus assumed that the measured signal may be expressed as follow:

$$y_m = x_m + f_m + n_m \tag{1}$$

2.1. Modeling the healthy waveform

It is desirable to model the healthy waveform x_m, so that this component may be subtracted from the observed signal y_m in attempt to isolate the fault induced signal distortion f_m. It will now be discussed how the healthy waveform may be modeled by means of an adaptive time series which is based on Bayesian model selection.

Consider the AR process which predicts the one step ahead datum point $\hat{y}_m^{\rightarrow}$ from the p number of past observations $\{y_{m-i}; i=1\ldots p\}$:

$$\hat{y}_m^{\rightarrow} = \sum_{i=1}^{p} w_i y_{m-i} \tag{2}$$

The past observations may also be denoted in vector notation so that $\mathbf{y}^{\rightarrow}$ is a column vector of length p. The superscript $\{\rightarrow\}$ denotes that this vector will be used to make one step ahead predictions, in contrast to $\{\leftarrow\}$ which will later be used to denote one step back. The filter coefficients of the all-pole filter $\{w_i; i=1\ldots p\}$, contained in the column vector $\mathbf{w}$, are