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A novelty detection diagnostic methodology for gearboxes operating under fluctuating operating conditions using probabilistic techniques

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ABSTRACT

In this paper, a fault diagnostic methodology is developed which is able to detect, locate and trend gear faults under fluctuating operating conditions when only vibration data from a single transducer, measured on a healthy gearbox are available. A two-phase feature extraction and modelling process is proposed to infer the operating condition and based on the operating condition, to detect changes in the machine condition. Information from optimised machine and operating condition hidden Markov models are statistically combined to generate a discrepancy signal which is post-processed to infer the condition of the gearbox. The discrepancy signal is processed and combined with statistical methods for automatic fault detection and localisation and to perform fault trending over time. The proposed methodology is validated on experimental data and a tacholess order tracking methodology is used to enhance the cost-effectiveness of the diagnostic methodology.

1. Introduction

Condition-based maintenance uses the current condition of the machine as basis for maintenance decisions and can be a cost-effective and more efficient alternative to run-to-failure and time-based maintenance procedures [1]. Rotating machines, such as gearboxes, frequently operate under fluctuating operating conditions due to its varying operating environment (e.g. ground properties for bucket wheel excavators [2], wind speed for wind turbines [3,4], etc.). The fluctuating operating conditions lead to amplitude and frequency modulation [5], phase distortion when performing computed order tracking [6,7] and varying signal-to-noise ratios [8] which complicate the condition monitoring process.

In recent years, machine learning techniques gained popularity in the engineering community due to its ability to solve difficult inference tasks such as problems found in the condition monitoring field [9–14]. Machine learning-based diagnostic methodologies, using supervised learning approaches, assume that historical fault data, of all relevant damage modes, are readily available for model optimisation. However, this assumption is rarely realised in industrial applications, which makes optimising the relevant models difficult. Novelty detection approaches in the machine diagnostic field, are attractive alternatives to supervised learning approaches, because the assumption is made that data from a healthy machine are abundant. A model of the healthy machine data is used to determine whether new data are from a healthy machine or not. Fernandez-

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Francos et al. [15] performed novelty detection for bearing diagnostics using a one-class support vector machine. Heyns et al. [16] used a statistical approach to average linear prediction models for gear fault detection under fluctuating operating conditions.

Discrepancy analysis is a novelty detection approach that uses a discrepancy measure to quantify the deviation of newly acquired data from the behaviour of data of a healthy machine. Heyns et al. [17] generated a discrepancy signal from the envelope of the residual signal obtained from a forward prediction made by a neural network. Heyns et al. [18] used a Gaussian mixture model to model the behaviour of a gearbox in a healthy condition. The negative log-likelihood, also known as the error function [19], was used to generate a discrepancy signal. Heyns et al. [20] developed a methodology using smart features and machine learning techniques for gearboxes operating under fluctuating operating conditions. A two-phase feature extraction approach was proposed using the concept of smart features, which was used to determine the instantaneous operating conditions and machine condition. Hidden Markov models (HMMs) and Gaussian mixture models modelled the operating and the machine condition features respectively, with its information combined using hard classification rules to generate a discrepancy signal. Heyns et al. [18] proposed synchronous averaging, and Schmidt et al. [21] proposed additional discrepancy signal processing techniques which can be used to detect, locate and trend gear damage over the machine's operational lifetime.

In this paper, a fault diagnostic methodology is proposed for gearboxes operating under fluctuating conditions with its process diagram presented in Fig. 1. It is assumed that only vibration data, measured from a single transducer on a healthy gearbox, are available for optimising the respective models. Operating and machine condition information are extracted separately from the order tracked vibration signal and modelled using separate HMMs. Information from the operating condition HMM is used to optimise a machine condition HMM for each operating condition state. The operating and machine condition information are statistically combined to automatically detect the relevance of each machine condition model, which is subsequently used to generate the discrepancy signal. The discrepancy signal is processed to detect, locate and trend damage automatically. The discrepancy generation process holds the advantage that the machine condition can be inferred in the presence of distinct operating condition states such as idling, full load and for transient states within a measurement. Another major advantage of this approach is that it does not require historical fault data and it is more flexible and simpler to implement than physics-based models with the condition being easily inferred from the processed discrepancy signal.

In this article, $x(t)$ denotes a continuous function, $x[t]$ indicates a scalar at instant t, $\boldsymbol{x}_t$ indicates a vector or multidimensional feature at instant t and $\boldsymbol{X} = [\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_N]$ indicates a multidimensional dataset over the N samples in the considered time period.

2. Proposed methodology

The key steps of the proposed methodology, with its process diagram in Fig. 1, are motivated and discussed in this section.

2.1. Order tracked vibration signal

The vibration signal, measured from a transducer on a rotating machine, is best represented in the angle domain due to the characteristics of rotating machines [22]. The signal is transformed from the time to the angle domain for example by

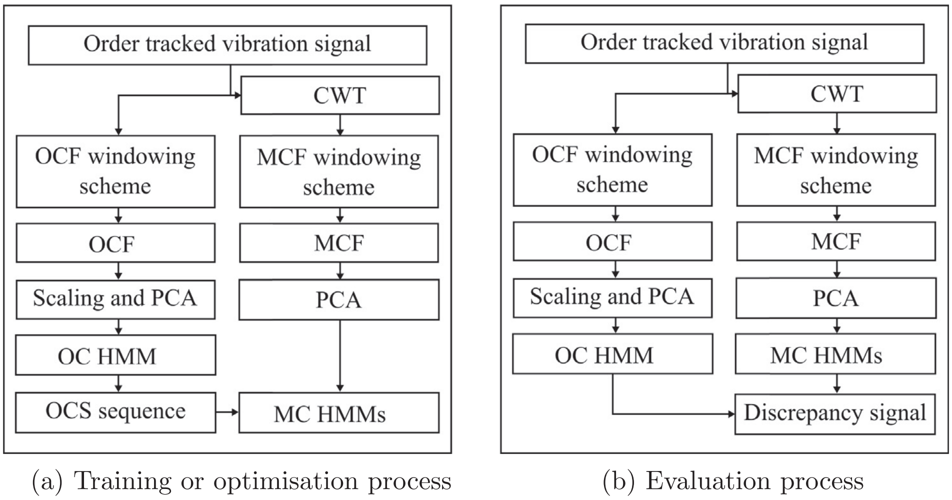

Fig. 1. The optimisation and evaluating processes that are used in the proposed methodology. The following abbreviations are used: Operating condition (OC); Machine condition (MC); Operating condition feature (OCF); Machine condition feature (MCF); Principal component analysis (PCA); Continuous wavelet transform (CWT); Operating condition state (OCS); Hidden Markov Model (HMM).