Extended Abstract

Wind power is a renewable energy source that is experiencing a rapid growth worldwide. It employs wind turbines that are continuously increasing in size and capacity [1]. The turbines have an average service life of 20 years, which is ample time to experience a premature fault. Rolling element bearings in the gearbox subsystem represent the predominant source of these premature faults [2]. Operation and maintenance of rolling element bearings demands efficient condition monitoring methods that support a wide range of requirements depending on the operational and environmental conditions of the wind turbine. Typical condition monitoring methods use information supplied by experts, for example, about kinematical properties of the bearings for detection of operational abnormalities. This information is provided by the manufacturers, but it can be compromised during installation or maintenance if components are replaced and do not match documented specifications. As a result, condition monitoring methods that incorporate solutions enabling verification and extraction of the kinematical properties with analytics for the prediction and detection of faults are beneficial to improve diagnostics reliability.

However, the analysis of signals originating from bearings and the surrounding components is a challenging problem due to the high variability and complexity of the systems. The performance of a wind turbine evolves over time due to wear, which implies a concept drift challenge, and due to changing operational/environmental conditions. In addition, the large variety of fault signatures and mechanisms makes it difficult to derive generally useful and accurate models that enable early detection of faults. These challenges are further complicated by limited availability of field data, which is highly unbalanced, while the generation of labeled data is difficult and expensive [3]. This motivates the investigation of unsupervised learning methods, like sparse coding with dictionary learning, which enable automatic modeling and characterization of repeating signal structures that are naturally generated by rotating equipment. These methods are used for feature learning and detection of deviations from the normal state of operation of a rotating machine while avoiding some of the above challenges given the automated online adaptation of the signal model.

In this work, we investigate an unsupervised learning approach for feature learning and anomaly detection, which can operate online without pre-training with labeled data. We use sparse coding with dictionary learning to represent vibration signals as a linear superposition of noise and atomic waveforms of arbitrary shape, amplitude and position. Our interest lies in distance measures that can be used to track changes of these atomic waveforms and the activation rates of the waveforms, which possess a cyclic nature in rotating environments, similar to the bearing kinematical properties. However, the relationship between distance measures and activation rates to changes of kinematical properties is not explicit. This motivates our investigation of the possibility to detect abnormal changes and extract bearing kinematical properties from sparse representations.

Former work [4], [5] that describes the use of sparse coding for the detection of anomalies in rolling element bearing signals has used data from test rigs. They trained dictionaries for different bearing conditions, which are merged and used for fault classification. Here, we apply sparse coding with dictionary learning to vibration signals recorded from sensors installed on the gearboxes of six turbines at a wind farm in northern Sweden. The method developed in this work is based on a model by Smith and Lewicki [6], [7], which is inspired in the work of Olshausen and Field [8], [9]. We analyze the vibration signals using our implementations of the local sparse coding algorithm [10] and Smith and Lewicki’s dictionary learning algorithm [7]. The learned dictionaries are propagated over a few years of monitoring data when faults are known to occur in two of the six turbines. We compare two dictionaries at different points in time, for example, comparing the present dictionary with a baseline dictionary. We find time periods of abnormal adaptation starting six months before bearing replacement and one year before gearbox replacement in Turbine 5. In addition, we identify an electrical failure in Turbine 2. The experiment is repeated using two sparse coding algorithms to investigate if the algorithm selection affects the signature of abnormal conditions, and we find that both algorithms indicate the presence of anomalies.

The results of this work show that dictionary distance based indicators are useful for condition monitoring of wind turbines. In addition, sparse coding provides the possibility for self-learning of kinematic frequencies of a bearing, which can be interesting for further development of automated anomaly detection methods. Dictionary learning provides a possibility for online analysis of vibration signals by identification of features, indicators and kinematical properties in these noise-like signals. However, further testing that draws from a larger population of turbines with documented faults is still required.
Figure 1. Median absolute deviation (MAD) of the distance between a propagated dictionary and a baseline dictionary versus time in the case of (a) matching pursuit (MP) and (b) orthogonal matching pursuit (OMP) algorithms for the six turbines. The MAD describes the absolute deviation of the dictionary distance given by Eq. (1) with respect to the population median distance. The label A points to a time period with a possible electrical fault in the data acquisition system of Turbine 2. The label B indicates when the output shaft bearing was replaced in Turbine 5, and label C indicates the subsequent gearbox replacement.

REFERENCES