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Towards thermal imaging based condition monitoring in offshore wind turbines

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This paper illustrates the potential of thermal imaging as a new sensor for condition monitoring in offshore wind turbines by monitoring fully covered and sealed rolling element bearings using a thermal camera. This potential is confirmed by the presented results, illustrating the suitability of thermal imaging to detect different lubrication levels as well as an outer raceway fault both with and without unbalance.

Introduction

The significance of renewable energy has increased and will keep increasing over the coming decades as the European Union has set a 20% renewable energy target for 2020. With this goal in mind, the European Wind Energy Association (EWEA) proposed three possible growth scenarios for wind energy towards 2020. The three scenarios project an increase in installed wind turbine capacity of 41%, 64%, or 85% respectively compared to 2013 [1]. Offshore wind energy will play a major role as it profits from better wind conditions at sea than onshore. As, according to the EWEA, offshore wind is generally 8 m/s higher at European coastal waters compared to those onshore [2], offshore wind farms can easily outpace onshore farms in terms of installed capacity. However, exploitation of offshore wind farms is significantly more expensive than onshore wind farms as a result of the high construction costs, including foundation and cables, in order to withstand rough weather conditions. Furthermore, maintenance of offshore wind farms is more expensive and complex as logistics at sea are time intensive and costly, and access to the wind farms depends on the weather conditions. Offshore wind farms are sometimes not accessible for days or weeks, even when repairs are necessary. Therefore, in order to operate offshore wind turbines in an economic viable perspective, a reliable operation needs to be assured such that downtime and maintenance costs remain low and energy generation guaranteed [3]. Unplanned, short-term maintenance on high sea is twice as expensive as planned interventions. Moreover, replacing broken components can take months [4]. Therefore, early and reliable fault detection is necessary to avoid more expensive consequential damage, or even a complete failure leading to a long loss of production [5].

Condition Monitoring of the Drive Train

Figure 1 schematically presents the main components of a gearbox-based wind turbine drive train. Faults in this drive train are the main cause for downtime in offshore wind farms [6]. More specifically, because of their tribological nature, wind turbine drive train components such as gears and bearings are affected by friction and wear [7].

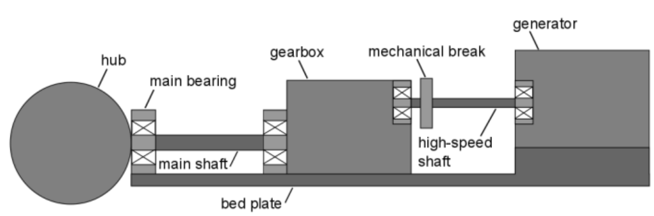

Figure 1: Scheme of a wind turbine drive train with gearbox

Additionally, bearings must deal with cyclic and transient loading as well as with alignment issues [8], making bearing faults one of the major issues regarding reliability of wind turbine drive trains.

Condition monitoring aims to detect degradation in an early stage, by continuously monitoring and interpreting well-chosen parameters. Combined with the knowledge of the expected evolution of the degradation and the remaining lifetime of components, intelligent planning and maintenance decisions can be made resulting in high performance. Additionally, condition monitoring can potentially even replace certain expensive and risky inspections by specialist staff.

Present condition monitoring techniques for industrial machinery includes vibration analysis, acoustic emissions and lubricant analysis. All present techniques show shortcomings for real-time measurements and data processing [9]. In particular, vibrations and acoustic emissions propagate through the structure which makes fault localization difficult. Different types of errors can result in similar vibration behavior, complicating fault classification. Other techniques such as lubricant analysis require onshore sample analysis in order to identify the faulty component, which itself is already costly in terms of time and financing. Furthermore, it requires the system to stop so that samples can be taken.

Besides noise and vibrations, faults will also cause specific temperature changes [10]. Contrary to vibrations, this elevated temperature is a local phenomenon and offers potential for thermal imaging to monitor drive-train components. Thermal imaging is a non-contact and non-intrusive technique, enabling condition monitoring without disrupting operation. Furthermore, thermal imaging allows spatial visualization of a monitored area and its heat propagation.

Thermal imaging is already commonly used on test rigs and in real environments such as pipelines, underground reservoirs and electric components. Huda et al. [11] and Jadin et al. [12] use machine learning algorithms applied on thermal images to detect faulty electrical components. Moreover, thermal imaging can also be used for weld monitoring, corrosion detection, and gas/air flow monitoring.

Using Thermal Imaging on Rotating Machinery

Despite its proven potential, thermal imaging has not yet received wide application for condition monitoring of rotating machinery, but receives increasing attention in research and industry. Younus [13], Widodo [14] and Lim [15] use thermal imaging to distinguish between misalignment, mass unbalance, bearing fault and normal operational conditions for rotating machinery, illustrating the potential of thermal imaging. However, previous work trains models on samples extracted from the same test run, risking overfitting and thus a memorized machine learning model instead of a generalized one, this way not being able to classify unseen data from other test runs correctly.

This paper analyses the potential of thermal imaging for monitoring rolling element bearings. The different tests of faults and conditions are done using a set of different bearings. After introducing the test setup, a methodology for analysing the thermal data is presented and applied on both healthy and faulty bearings. Afterwards, the results and major conclusions are presented.

Experimental Setup

The presented test setup (see Figure 2) is used for monitoring completely covered and sealed FAG 22205-E1-K spherical roller bearings. These bearings consist of cylindrical rollers which manage high axial forces oscillating in both directions as well as radial forces. They are specifically designed to handle heavy loads similar to those in wind turbines. The close osculation between rollers and raceways supports uniform stress distribution, as it is usually the case in industrial applications such as in wind turbine drive trains.

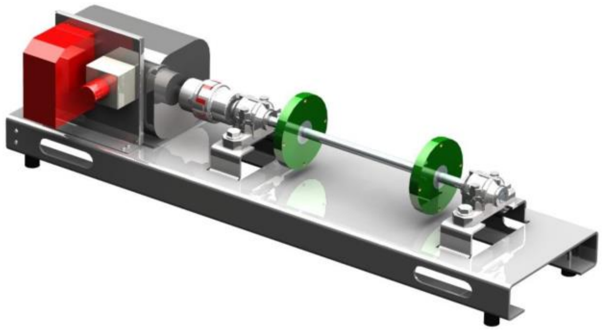

Figure 2: Test setup

In this particular setup, the bearings are mounted in a FAG SNV052-F-L plummer block housing. The used shaft has a diameter of 20 mm and is made of solid Cf53 with h6 tolerance rate.

Beside intact bearings, bearings with manually added pitting faults on the outer raceway have been monitored, as well as mildly inadequately lubricated and extremely inadequately lubricated bearings. All four conditions are also tested during mass imbalance, created by adding a 13 gram bolt to the disk located next to the monitored bearing housing at a radius of 5.4 cm, this way resulting in eight conditions. For every one of the eight conditions, five bearings are tested. Each test was run for one hour at a rotational speed of 1,500 rotations per minute, which is a standard rotational speed for high-speed components in European wind turbine drive trains. For monitoring the setup, the A655sc, an uncooled long-wave infrared (LWIR) camera by FLIR, has been used at a frame rate of 6.25 frames per second. Additionally, two thermocouples, located next to the setup, have been used to monitor the ambient temperature to provide reference temperatures for the data processing. Only the last 10 minutes of each hour (i.e. when the steady state is reached) are exported to AVI files for further processing and analysis. To reduce the size of the video files, lossless compression is applied using the H264 standard. The resulting videos consist of monochrome frames where the gray values correspond to temperatures in the range of [10°C 60°C]. Figure 3 presents an example of a frame, showing the shaft entering the bearing housing through the rubber seal as well as the two thermocouples at the left back and right front side.

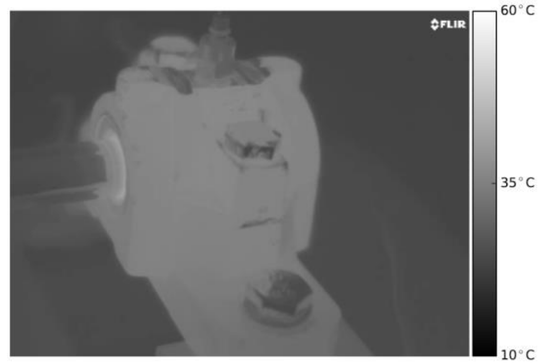

Figure 3: One frame of an IR video of a healthy bearing

Methodology

A fault detection system automatically has to distinguish between conditions without human intervention for result interpretation. The automatic detection of a specific condition is regarded as a combination of a binary classification problem (pipeline 1) and a multi-class classification problem (pipeline 2). Hence, every 10-minute IR video has to be classified according to a certain machine condition, i.e. balance or imbalanced, and according to a suitable bearing condition, i.e. healthy, outer raceway fault, mildly inadequately or extremely inadequately lubricated. By using two pipelines, multiple labels are eventually assigned to a sample. For this research, a random decision forest (RDF) classifier is chosen for both pipelines as it has several advantages such as ease of use, human-interpretable decision rules of the individual decision trees and feature importance scores [16].

Results

The first pipeline distinguishes between imbalance and balance, whereas the second pipeline distinguishes between healthy, outer raceway fault, mildly inadequately lubricated and extremely inadequately lubricated bearings. Classifying between balance and imbalance is a trivial task, as thermal imaging clearly indicates imbalance. As a result, the mean accuracy achieved by the RDF classifier during the leave-one-out cross-validation is 100% (+/- 0%). Classifying the different bearing conditions is a more difficult task, resulting in an accuracy score of 87.5% (+/- 1.12%). Although the two pipelines work independently from one-another and have their own conditions to distinguish, in the end they need to be combined to get the most accurate fault diagnosis and distinguish between all eight possible combinations. As pipeline one has an accuracy of a 100% and pipeline two 87.5%, the eventual system is able to distinguish between the 8 conditions with an overall accuracy of 87.5%. For more details on feature selection for data mining on IR imaging, the reader is referred to [17].

Conclusion

Fully covered and sealed rolling element bearings, similar to those in large size industrial applications and in wind turbines, have been monitored by a thermal camera. Whereas vibrations propagate through the drive train and fault localization requires high expertise, temperature increase is a more local phenomenon, supporting thermal imaging, a non-contact and non-intrusive technique, to enable condition monitoring without disrupting operation.

The presented results confirm the potential of thermal imaging as a new sensor for condition monitoring in offshore wind turbines and illustrate that by the use of IR imaging different levels of lubrication, with and without imbalance, or even an outer raceway fault can be detected. The different faults are classified by combining two random decision forest classifiers, resulting in 87.5% accuracy using leave-one-out cross-validation, illustrating that thermal cameras are a promising sensor for condition monitoring of wind turbine drive trains.

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