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Analysis of Fault Diagnostic Technique in Wind Turbine Using Machine Leaning Models

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Abstract

Wind energy stands out as a key player in the renewable energy landscape, thanks to its cost-effective and low-carbon electricity generation methods. However, the reliability of wind turbines hinges on effective maintenance strategies. When turbines experience unscheduled downtime, it not only drives up Operation & Maintenance (O&M) costs but also impacts the overall reliability and availability of wind energy production. A major culprit behind these unexpected outages is the premature failure of rotating components. To tackle this issue, condition monitoring serves as a vital tool, continuously tracking turbine dynamics and identifying faults at their early stages. This proactive approach allows for the prediction of potential failures, enabling timely maintenance to prevent serious damage. In this research, we propose a fault diagnostic technique that utilizes adaptive time-space processing through vibration signal analysis, combined with a machine learning model. This method aims to classify common tribological faults in wind turbine drivetrains, such as scuffing, polishing, fretting corrosion, overheating, and assembly damage.

Keywords: Fault Diagnostic, Machine Leaning, Wind Turbine.

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Introduction

Rapid growth in world energy demand poses challenges in environmental sustainability. British Petroleum energy outlook predicted that in India's (the sixth-largest economy in world) energy demand is set to increase by 4.2 % a year by 2035 British Petroleum, (2017). The rapid growth in economy triggers the acute need for large scale, clean and green energy production in India Global wind report, (2015). Reliance only on fossil fuels is inadequate to meet such huge demand. Renewable sources play a vital role in clean, green energy production. Harnessing renewable electricity depends on reliable cost-effective technologies. Significant enhancement of system integration requires for reliable renewable energy generation. Wind power is the prime contributor in renewable and sustainable energy sector. In recent years, wind energy production rate increases gradually (Tuerxun et al., 2021). Poor maintenance practice will lead longer downtime and worst cases cause catastrophic accidents. Predictive maintenance basically predicts the component faults well in advance to avoid severe failures. Predictive maintenance is a multidisciplinary condition-based maintenance strategy that collects the machine condition dynamics, assess the collected data and predicts the trends that may cause catastrophic failures in future. Particularly in rotating machines, it employs Condition Monitoring System (CMS) that periodically monitors the machine dynamics such as vibration, acoustics, temperature, pressure, oil debris, corrosion etc. Trend Monitoring and Condition checking are two main functions in condition monitoring. Trend monitoring scheme continuously collects the data from the running machine and predicts the significant changes in trends as indicative of incipient faults. In condition checking method break point measurements are taken periodically from the running machine to compare the measurement values to the machines that are in good conditions (Saufi et al., 2019). CMS is an important tool that reduces the unscheduled downtime of wind turbines and ensure the drivetrain components are at acceptable mechanical conditions. Mechanical component deterioration speeds up with degree of severity. Early detection of wind turbine component deterioration is too important in safety aspects so as to avoid catastrophic accidents.

Need of the Study

Vibration Based CM systems used in other traditional rotating machinery limited to directly applied to the wind turbine monitoring because of its non-stationary operating conditions since the wind speed and direction dynamically varies during vibration measurement. Constant speed and constant load machines vibration has stationary statistical properties that makes fault diagnostics is simple and economic in computational point of view. The motivational factors to carry over this research is listed as follows in wind turbines, various environmental factors can lead to fluctuations in loads, which in turn affect vibration tests (Yang et al., 2016). The resulting vibration spectra often show broad blurs at higher frequencies, making the peaks appear wider than usual and reducing amplitude levels, which can significantly impact fault diagnosis. The aerodynamic effects, combined with aeroelastic vibrations at the rotor blades, transmit through to the rotor shafts and other components. The interconnectedness of these components can create vibration signatures even when everything seems to be functioning well. For instance, in wind turbines, when wind speeds exceed the rated speed, pitch control is adjusted to manage the aerodynamic forces, which in turn affects the vibration signatures. Variable speed wind turbines introduce additional complexity due to their nonlinear operations. A typical geared wind turbine drivetrain design features one or two planetary gear stages, and a standard planetary gear for a 2MW rating includes 20 bearings and 9 gear trains. To obtain accurate vibration measurements, sensors should be positioned as close as possible to the gear or bearing of interest (Stetco et al., 2019). However, due to the intricate design and geometry, measuring vibrations in the planetary gear stage can be quite challenging. The way sensors are mounted can significantly influence the vibration readings of the planetary gear, so this needs careful attention. Low-speed rotor shafts in wind turbine drives present a critical challenge for vibration monitoring. At low speeds, the vibration amplitude is minimal and often diminishes, making it more susceptible to environmental noise. Additionally, multiple and varying transmission paths can dampen the vibration signals in planetary epicyclic gears. Nonlinear load distribution in these gears can even cause sideband modulations in the vibration spectra, even under normal operating conditions.

System Implementation

This research focused on developing an adaptive automatic fault diagnostic framework for the condition-based maintenance of the wind turbine drivetrains. The primary goal of this thesis is to create a vibration-based fault diagnostic algorithm. This algorithm aims to identify both local and distributed faults in key components of the wind drivetrain, including the main bearings, gearbox, and main shafts, especially during nonstationary operating conditions (Helbing & Ritter, 2018). In vibration-based condition monitoring systems, the vibration measurement data sample rate is in the order of 40-50kHz. Online condition monitoring is a non-interrupt process that collects the high-volume

data with high speed. In traditional condition monitoring systems, the personal expertise requires to evaluate and analyse this high dimensionality data that to carried over periodically. Machine learning models efficient in massive data analytics. The research focused on optimum knowledge-based fault diagnostic modelling. Knowledge Based Fault Diagnostics (KB-FD) method employs machine learning that acquires knowledge from the condition indicators and process the new measurement with the acquired knowledge to predict the machinery condition levels.

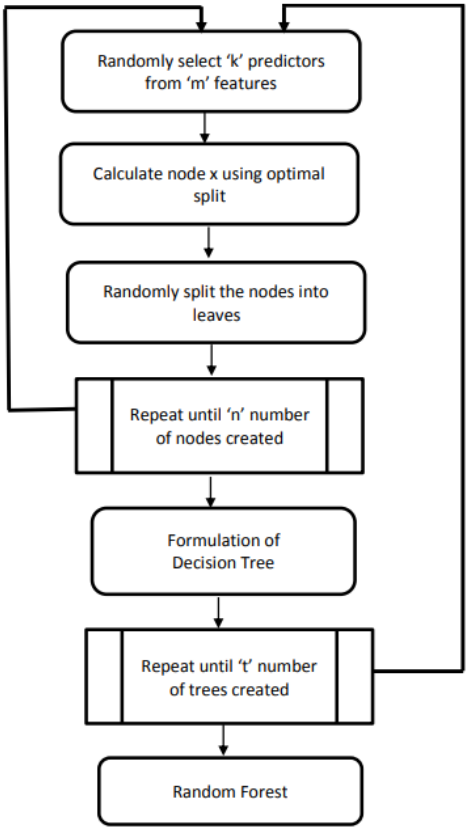

Fig. 1: Schematic Diagram

The process of acquiring knowledge is called as training the machine learning model. In vibration monitoring the reliability of the fault diagnostics depends on the condition indicators that featured the changes in machinery condition and indicate the possibility of deterioration (Leahy et al., 2016). Knowledge based fault diagnostic machine learning models training accuracy depends on the condition indicator features extraction. Feature extraction in turn depends on signal pre-processing that transforms the raw vibration data into the information centric format. With this back ground, the objective of the fault diagnostic system is to develop a predictive model that sensitive to the limitations of data uncertainties and produce robustness to the fault diagnostics by exploiting machine learning capabilities. The research objective of the present thesis aims to develop a fault diagnostic predictive model for wind turbine drivetrain in non-stationary operating conditions.

Simulation Results

The multivariate time series multi-dimensional visualization indicated in the Figure 2. The feature distributionin 14000 observations illustrated. Predictor variables represented as the parallel axes and the multivariant vibration time series represented as the polylines intersects the axes. The plot shown is generated with 16-dimensional space (16 predictors selected based on the feature importance) (Ng & Lim, 2022). Instances are indicated as the poly lines drawn from the predictor vertical axes. It observed from the plot; the similar incidences are grouped based on the combination of transparency and the overlapping regions. The similar group incidences are known as braids; well defined braids of different classes indicate the well-defined separability between the classes.

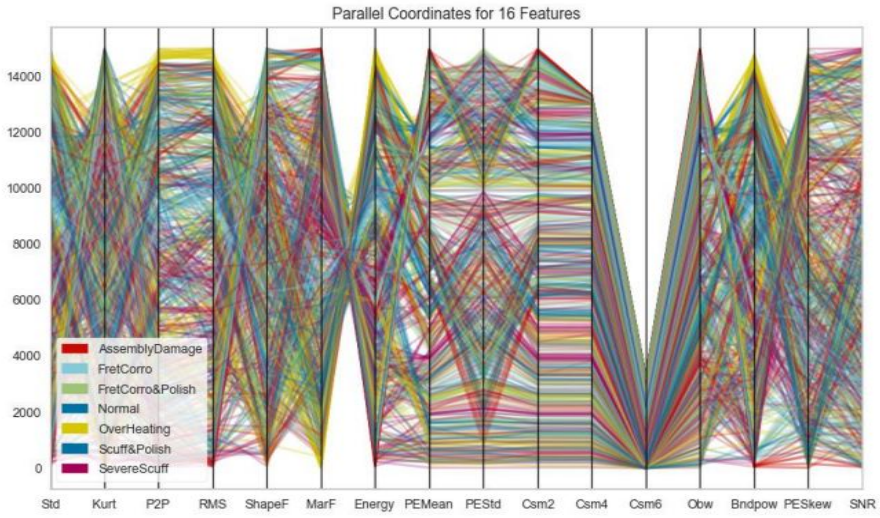

Fig. 2: Parallel Coordinate Plot to Visualize the Multivariate High Dimensional Data

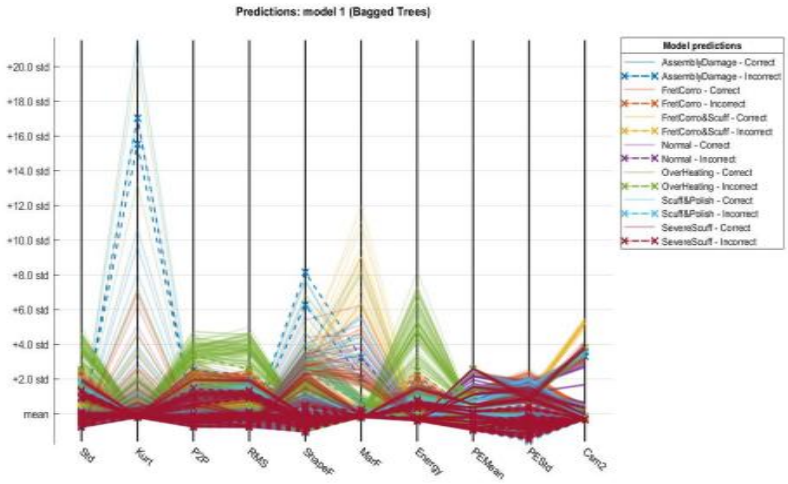

Fig. 3: Parallel Coordinate Plot

Multi-class classification performance evaluated by the parallel coordinates plots as illustrated in the Figure 3. The training accuracy and the misclassified instances shown in the Figure 2.

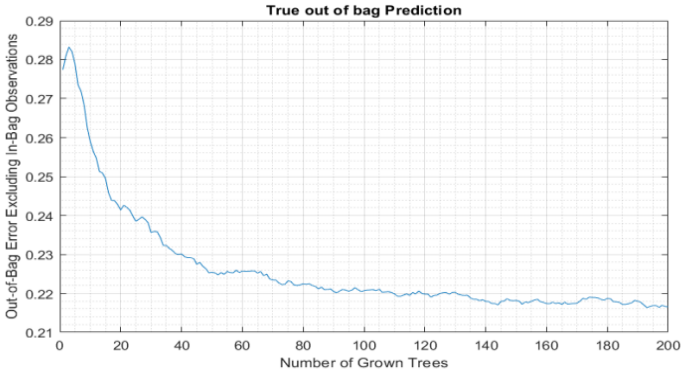

Fig. 4: True Out of Bag of Prediction

Only 10 predictors are shown as the parallel axes which can be controllable and accessible predictors. These 10 predictors set is known as the hyper subset that drops the false negatives in the hyper subspace (Sun et al., 2021). It observed from the parallel coordinate plot, the classifier shows the skill to classify the unique labels and it struggles to classify the multilabel classes such as fretting corrosion and scuffing and scuffing and polishing.

Conclusion

Multivariate signal processing is used to combine measurements from multiple sensors. The vibrations captured from different channels and components are broken down into common oscillatory modes that align in a synchronized manner. By projecting these multichannel vibrations into the Time-Frequency domain, we can analyse the non-stationary blind vibration signatures, while a dyadic filter structure helps to separate the individual components. To further refine the analysis, we look at the correlation between channels from various sensors, which allows us to break down multi-mode components into single intrinsic modes across a distributed spectrum. This approach utilizes the Noise Assisted Multivariate Empirical Mode Decomposition (NAMEMD) technique for separating blind vibration sources. Additionally, we create a hybrid feature space that incorporates condition indicators across the time, frequency, and time-frequency domains. Finally, we develop a predictive model for classifying multiple fault types and assess the performance of the classifier.

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