Vibration-based Condition Monitoring in Wind Turbine Gearbox Using Convolutional Neural Network

Abdelrahman Amin¹, Amin Bibo², Meghashyam Panyam² and Phanindra Tallapragada³

Abstract— A significantly increased production of wind energy offers a path to achieve the goals of green energy policies in the United States and other countries. However failures in wind turbines and specifically their gear boxes are higher due to their operation in unpredictable wind conditions that result in downtime and losses. Improved and early detection of faults in wind turbines will greatly increase their reliability and commercial feasibility. Faults in the rotating components in the gear box can leave their signature in the vibrations that can be measured by accelerometers. This paper presents a machine learning framework and results in vibration based condition monitoring of wind turbines. Time series acceleration data from several bearings in the wind turbine drive train are used to calculate the bivariate cyclic spectral coherence and spectral kurtosis that produce two dimensional images. These images are used to train convolutional neural networks that then identify faults, including those of small magnitude or in early stages, in test data with a high accuracy. Benchmark test cases inspired by an NREL study are tested and successfully detected.

I. INTRODUCTION

Wind energy is currently playing a crucial role in renewable energy production and is rapidly growing in the world. In 2014, 28% of the electricity generation in the U.S. state of Iowa was from wind energy [1]. By 2030, wind power is expected to provide 20% of the US electricity demand [2]. However operation and maintenance costs of wind energy can be high. Compared with other types of turbines, failures in wind turbines are often higher due to their operation in harsher environment with fluctuating wind speed. Statistically, the gearbox is considered the component with the highest contribution to wind turbines’ downtime, about 20%, which significantly increase operation and maintenance costs [3]. Damages mainly occur in bearings and gears due to several reasons, such as manufacturing and installation faults, design and material flaws, misalignment, torque loads, wear and fatigue. Gear failures include tooth cracks, abrasion, corrosion, fracture, pitting and scuffing [3]. An example of a gear scuffing error is shown in Fig. 1. According to [2], if a defective $5,000 bearing is not identified and replaced on time, consequent damages of the entire gearbox can easily happen that would cost up to $250,000 including cranes, replacement and downtime losses. Therefore, having smarter fault diagnosis and online condition monitoring systems for wind turbines is crucial for their increased reliable operation in the field and commercial feasibility.

Fig. 1: NREL Test Gearbox HSS Gear Scuffing Damage [4]

Online condition monitoring of a wind turbine aims to identify changes in parameters to diagnose the potential future failures in system components while wind turbines are operating in the field with vibration based condition monitoring playing an important role. A wind turbine gear box and drive train consists of multiple rotating shafts, sun-planetary gears and bearings. Faults in the gears and bearings manifest themselves in the vibrations, measured through accelerometers, at specific frequencies related to the rotating and gear mesh frequencies. Therefore online condition monitoring based on vibrations is the most commonly used approach [3].

Using the vibration signals, several algorithms and signal processing techniques, such as frequency analysis, time synchronous averaging and envelope analysis are conducted to derive useful information [4]. Each of these methods has its limitations in their application for example being restricted to the case where the shaft rotating speed is constant or non torque loads are absent or wind speed and direction are constant. More advanced methods of analyzing vibration data such as cyclic spectral correlation [5] or kurtograms [6] have been used to identify single specific fault signatures, that have failed to diagnose faults on.

This paper addresses the gap in vibration based condition monitoring by extending the methods of kurtograms and cyclic spectral coherence with applying machine learning (convolutional neural networks) to identify fault signatures as well as the extent of faults. The proposed framework automates the process of fault diagnosis obviating the need for an expert to inspect vibration data of components for specific fault signatures. In simulations the proposed framework has been able to identify and diagnose the extent of faults in gears under realistic conditions of wind: turbulent wind conditions with varying speeds and non torque load...
on the wind turbine. The proposed framework was applied on one of the benchmark fault detection problems described in a study initiated by the National Renewable Energy Lab (NREL) in which sixteen research groups participated. The specific problem of identifying the fault on the low speed shaft (LSS) of a gearbox of a 16 KW wind turbine was not successfully achieved by any of the research groups in the study [4]. Subsequently Mauricio et.al. in [7] used the cyclic spectral coherence analysis to successfully detect this LSS fault. However the NREL dataset was based on a laboratory test case with the high speed shaft speed being constant. In contrast the present paper performs fault detection with turbulent wind scenarios, non torque loads and time varying shaft speeds using simulation data of a SIMPACK wind turbine model developed by NREL [8].

A SIMPACK multi-body model of a 5 megawatt (MW) wind turbine has been used to run full wind turbine simulations with different wind conditions. Figure 2 shows the flow chart of this simulation-based study presented in this work. Time series accelerometer data acquired from the simulations is preprocessed using synchronous resampling and converted to bivariate maps of cyclic spectral coherence and spectral kurtosis. These images are used to train convolutional neural networks to identify gear pitch faults. The paper is structured as follows: section II introduces the SIMPACK multi-body model and the simulated wind loading cases and types of simulated gear faults; Section III describes signal preprocessing methods; Section IV discusses the challenges of fault detection for the simulation scenarios and the motivation behind using convolutional neural network (CNN) in this study; Section V presents CNN fault diagnosis results.

Fig. 2: An overview of the fault identification framework - Wind turbine loads are applied on the nacelle and time series accelerometer data is acquired. Synchronous sampling is conducted on acquired acceleration signals before generating kurtogram and cyclostationary maps (images) which are then passed to a CNN for fault diagnosis.

II. MODEL DESCRIPTION AND SIMULATED WIND CONDITIONS

The SIMPACK multi-body model shown in fig. 3 is an onshore 5 MW three blade up-wind turbine model. The nacelle, mounted at the top of the tower, encloses the drivetrain components. The drivetrain consists of an input main shaft, a three stage planetary gearbox and a high speed coupling which is connected to the generator, a main-frame, a housing and a yaw bearing. The low speed shaft connects the rotor hub to the gearbox while the high speed shaft drives the electrical generator. The gearbox model consists of a flexible main shaft and flexible housing with 3 activated dynamic modes. Eight accelerometers, numbered in fig. 4, are placed in the drivetrain simulated model to measure accelerations at different locations on the gearbox.

All gears, in this SIMPACK model, employ a high-fidelity gear force element to better simulate the gear tooth contact and account for the forces and moments created in the gear mesh. The gearbox final gear ratio is 97.83. Tables I-III show the gear element details, the calculated rotating and gear mesh frequencies (GMF) of the gearbox with a rated input speed of 12 rpm.

<table>
<thead>
<tr>
<th>Gearbox Stage</th>
<th>Gear Element</th>
<th>No. of Teeth</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st Planetary Stage</td>
<td>Ring Gear</td>
<td>93</td>
</tr>
<tr>
<td></td>
<td>Planet Gear</td>
<td>34</td>
</tr>
<tr>
<td></td>
<td>Sun Gear</td>
<td>23</td>
</tr>
<tr>
<td>2nd Planetary Stage</td>
<td>Ring Gear</td>
<td>97</td>
</tr>
<tr>
<td></td>
<td>Planet Gear</td>
<td>37</td>
</tr>
<tr>
<td></td>
<td>Sun Gear</td>
<td>20</td>
</tr>
<tr>
<td>High Speed Parallel Stage</td>
<td>HSS Gear</td>
<td>63</td>
</tr>
<tr>
<td></td>
<td>HSS Pinion</td>
<td>19</td>
</tr>
</tbody>
</table>

TABLE I: Gearbox Elements Details

Fig. 3: Full onshore wind turbine model, hub and nacelle. Screenshot images from the SIMPACK model are taken by the author.

Fig. 4: Sensor & fault placements. Sensors’ locations: LSS 1st and 2nd bearings, IMS 1st and 2nd bearings, HSS gear 1st and 2nd bearings, HSS pinion 1st and 2nd bearings. 2 fault locations: LSS planet gear and HSS driver gear.
Full wind turbine simulations are carried out under 6 different wind conditions and speeds in which the gearbox was always healthy. The 6 simulated cases are as follows: 3 turbulent, 2 laminar and 1 extreme operating gust. Following this wind loads, speeds and torques of each case are extracted to be applied at the abstracted nacelle only model to replicate the loads supplied by the wind turbine blades. Figure 5 presents an example of the extracted hub loads and their FFT plots for one of the three turbulent wind load scenarios termed here as ‘Turbulent 18’, with an average wind speed of 18 m/s. The high dynamic forces and moments in fig. 5, have a frequency spectrum mostly in the low frequency range.

A tooth pitch error is created in the model to replicate the existence of a localized fault on gears. The first simulated fault is created on one of the planet gears on the low-speed planetary stage (LSS). The second fault is located at the driver high speed shaft (HSS) gear as shown in fig. 4. The magnitude of the each simulated fault varies between 100, 50 and 20 microns to reflect variations in the severity level. The fault is introduced on only one tooth of the respective gear wheels.

From the simulation dataset, vibration signals from sensors 1-4 are chosen to classify and detect the fault located on the LSS. The last four sensors, 5-8, are the ones chosen to classify the HSS fault.

III. SIGNAL PRE-PROCESSING & IMAGE GENERATION

A. Signal Resampling

In rotating machinery, vibration responses are emitted at multiples, orders, of the shaft rotating speed. Equation 1 is showing this relationship between the order $O$ and the shaft rotation frequency $f$ in Hz.

$$f = \frac{O \times \text{RPM}}{60}$$

FFT analysis is efficient if the shaft rotating speed is constant. However, if the speed varies with time, orders in the frequency domain will be smeared into several frequency bins. Based on the frequency analysis resolution, the frequency of interest could be washed away in this case. Figure 6 shows an example of an input speed curve for a turbulent 18 wind scenario. Since this input speed of the main shaft is variable, synchronous resampling is performed in which a Fourier transform is done on a fixed number of revolutions regardless of speed. Thus, data is acquired at an equal increment of the shaft rotational position instead of time [9]. As a pre-processing step in our analysis, the cumulative rotational angle of the low speed shaft planetary carrier (LSS-PLC) is taken as a reference to do the resampling. Calculated orders are presented in column 4 of Table II & III. The resampling frequency is 500 Hz.

![Fig. 6: Variable Input Shaft RPM.](image)

<table>
<thead>
<tr>
<th>Rotating Frequencies</th>
<th>RPM</th>
<th>HZ</th>
<th>Orders</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input = LSS Carrier</td>
<td>12</td>
<td>0.2</td>
<td>1.00</td>
</tr>
<tr>
<td>LSS Sun = IMS Carrier</td>
<td>60.52</td>
<td>1.01</td>
<td>5.04</td>
</tr>
<tr>
<td>IMS Sun = HSS Input</td>
<td>354.05</td>
<td>5.90</td>
<td>29.50</td>
</tr>
<tr>
<td>HSS Output</td>
<td>1173.96</td>
<td>19.57</td>
<td>97.83</td>
</tr>
<tr>
<td>LSS Planets</td>
<td>32.82</td>
<td>0.547</td>
<td>2.74</td>
</tr>
<tr>
<td>IMS Planets</td>
<td>158.67</td>
<td>2.64</td>
<td>13.22</td>
</tr>
</tbody>
</table>

**TABLE II: Rotating Frequencies with 12 RPM Input**

<table>
<thead>
<tr>
<th>Gear Mesh Frequencies</th>
<th>RPM</th>
<th>HZ</th>
<th>Orders</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st Planetary Stage</td>
<td>1116</td>
<td>18.60</td>
<td>93</td>
</tr>
<tr>
<td>2nd Planetary Stage</td>
<td>5870.61</td>
<td>97.84</td>
<td>489.22</td>
</tr>
<tr>
<td>HSS Stage</td>
<td>22305.29</td>
<td>371.75</td>
<td>1858.8</td>
</tr>
</tbody>
</table>

**TABLE III: Gear Mesh Frequencies with 12 RPM Input**

B. Cyclic spectral coherence and Kurtograms

Raw vibration signals from wind turbines often have amplitude modulation, side bands and harmonics induced by gear meshing and ball pass frequencies. Gear meshing frequencies can strongly mask any other frequency component due to faults. The raw vibration signal therefore has to be preprocessed in order to identify fault signature frequencies. Several methods like peak envelope criterion [10], cepstrum editing [11], spectral kurtosis [12] and cyclostataionarity [10], [13] have been used in the preprocessing steps. This paper adopts the method of cyclostationarity and spectral kurtosis due to their recent successful application in fault

![image](image)
A signal is said to be of cyclostationary of order \( n \) when its \( n \)th order statistics are periodic. A first order cyclostationary signal, \( x(t) \) is one whose mean is periodic; a second order cyclostationary signal \( x(t) \) is one whose autocorrelation \( R_{xx} \) function is periodic,

\[
R_{xx}(t, \tau) = \mathbb{E}[x(t - \tau/2)x(t + \tau/2)] = R_{xx}[t + T, \tau]. \tag{2}
\]

Since the autocorrelation function \( R_{xx} \) is a function of two variables a two dimensional fourier transform is performed to give the spectral correlation

\[
S_{xx}(\alpha, f) = \lim_{W \to \infty} \frac{1}{W} \int_{-W/2}^{W/2} R_{xx}(t, \tau)e^{-j2\pi(f\tau + \alpha t)}dt \tag{3}
\]

where \( f \) is the carrier frequency, the dual of the time lag \( \tau \) and \( \alpha \) the dual of \( t \) represents the modulation frequency also called the cyclic frequency, [5], [14]. The cyclic spectral coherence \( \gamma_{xx}(\alpha, f) \) defined as the normalized cyclic spectral correlation with values in the range of \([0, 1]\)

\[
\gamma_{xx}(\alpha, f) = \frac{S_{xx}(\alpha, f)}{S_{xx}(0, f)S_{xx}(0, f - \alpha)} \tag{4}
\]

A bivariable map, based on \( S_{xx}(\alpha, f) \) and \( \gamma_{xx}(\alpha, f) \) is generated with cyclic frequency \( \alpha \) on the x-axis and spectral frequency content \( f \) on the y-axis. This frequency-frequency map is robust in generating enhanced demodulated spectrum and extracting any hidden periodicity.

An alternative preprocessing approach has also been adopted, that of the Kurtograms, proposed in [6] as an effective method to identify defect impacts in vibration signals and their locations in the frequency domain. Its algorithm is based on spectral kurtosis (SK) which is an envelope analysis statistical method that is computed from the short-time Fourier transform (STFT) in [12]. SK indicates the non-stationary transients parts of the signal as a function of frequency. The kurtosis computation of a signal \( x(t) \) is the normalized fourth order spectrum:

\[
K_{x}(t) = \frac{\langle |H(t, f)|^4 \rangle}{\langle |H(t, f)|^2 \rangle^2} - 2 \tag{5}
\]

where \( \langle \cdot \rangle \) is for the time averaging operator, \( H(t, f) \) is calculated by STFT and represents the time/ frequency envelope of the signal. Then, multiple decomposition layers with organized frequency kurtosis values generates the Kurtogram 2D color diagram. Frequency is represented on the x-axis and frequency resolution is on the y-axis while the SK values are shown in the color scale [6].

Figure 7 (a) & (b) shows examples of cyclic spectral coherence maps of 100 microns for both the LSS and HSS faults; respectively with turbulent 18 applied loads. The map axes in the two plots are normalized with the same scale to cover the whole range of the cyclic frequencies of both faults. Since the re-sampled vibration signals are used in these variable speed cases, the LSS fault signature is at \( 2.74/2\pi = 0.44 \) cycle/rad. However, the HSS fault signature is at \( 29.5/2\pi = 4.7 \) cycle/rad. Coherence map images that are passed to the CNN are generated without any labels, numbers or colorbars for all fault types under different simulated wind load conditions.

From fig. 7, the HSS fault signature is very obvious on the cyclostationary plot on the right; on the contrary, it is not easy to trace the LSS fault signature. The reason is that HSS fault signature lies at the high frequency range. In addition, the mechanical transmissibility from the planetary gear components, where LSS fault is, is usually low. The locations of sensor 1 and 2 are not directly close to the simulated LSS fault on the planet gears. Also, the LSS fault occurs at a very low frequency with a very low amplitude. Therefore, it is masked by the level of noise.

IV. MOTIVATION FOR USING CNNS

Without applying actual wind loads at the hub, the use of cyclostationary analysis is effective in detecting LSS fault signatures. Visual inspection of the maps in fig. 8 clearly identifies the fault at the cyclic frequency of 0.54 Hz, the LSS-PLT rotating frequency in Table II. With a smaller fault magnitude, 20 microns, the signature is still there on the color map but weaker in magnitude. In this scenario, a constant input speed of 12 rpm is applied at the input shaft. An external ramp-up to a constant rated torque of 42500 Nm is applied at the generator. The simulation integration time

![Cyclic Spectral Coherence](image_url)
was 200 seconds with a sampling frequency of 2000 Hz. The extracted vibration/acceleration signal was from the last 100 seconds at the steady-state phase.

After applying the wind loads at the hub, the impact signature of the 20 microns fault becomes even weaker and more complicated to detect. Turbulent 18 applied wind loads are used as an example. Figure 9 shows cyclic spectral coherence maps for the 20 microns LSS fault and a healthy gearbox when wind loads are included. There is an insignificant difference between the two maps without having high intensity spot at 0.54 Hz for the 20 microns fault. The reason is that both frequencies of the applied wind loads and LSS fault signature occur in the low frequency domain. Therefore, an earlier detection of the LSS fault using only cyclostationary analysis becomes more challenging; especially with the inclusion of a variable input speed due to variations of the wind speed. As a result, the use of CNN in this case is promoted to extract the needed features and patterns for an accurate detection and classification.

V. FAULT DETECTION AND DIAGNOSIS USING CNNs

A convolutional neural network (CNN) is often used in image recognition for damage classification [15], [16]. A CNN unlike an artificial neural network (ANN) is capable of identifying spatially local correlation features in an image. The performance of CNN depends on the convolution operation for feature extraction and pattern recognition. CNN architecture usually consists of 3 types of layers. The first one is the convolutional layer which is composed of multiple 2D filters with weight parameters. Feature maps are the output of these filters’ convolution with the input data. Each convolution layer is followed by a pooling, sub-sampling, layer to reduce the dimension of the convolution features and boosts robustness of the acquired features. A classifier is the last type which is a fully-connected layer that is trained for damage detection based on the calculation of the dot product of the input vector, weight and the sigmoid function.

In our study, two CNN models are designed and trained for damage classification and detection depending on the type of the input images, Cyclic Spectral Coherence and Kurtogram maps. A total of 180 images are passed to each CNN model. 126 images, 70%, are for training and validation while the remaining 54 images, 30%, are used for testing. Both CNN models have the same architecture that contains four convolution layers and four pooling layers: 20 $3 \times 3$ kernels, 90 $3 \times 3$, 120 $3 \times 3$ kernels, 150 $3 \times 3$ kernels in the first, second, third and the fourth convolution layer; respectively. The four pooling layers have a size of $2 \times 2$. Two pixels symmetric padding is added in each layer to ensure including image borders in the processing and to avoid missing information too early in the network. The selection of CNN hyper parameters is problem dependent and obtained by trial and error iteration. The CNNs were implemented on MATLAB using the Deep Learning Toolbox.

1) Cyclostationary-based CNN: For the first CNN model type, Cyclostationary-based, training batch size is set as 50. The training of CNN is done through 102 iterations, 51 epochs, to guarantee convergence and accuracy. The learning rate of neural network is 0.0008 to ensure fine tuning for accuracy improvement. An early stopping criteria is implemented causing the training simulation to stop automatically if the validation accuracy does not improve within 20 epochs. The confusion matrix in fig. 10 shows the best results obtained using this model with an accuracy of 87%. All HSS faults are detected and correctly classified based on the fault magnitude. No missed detection or false positives are obtained. The model is accurate in detecting the location of the fault either on the LSS or HSS. However, every error in the classification is actually an error in classifying the magnitude of the fault and not the identification of the location of the fault. For example, out of the 7 tested images of LSS 20 microns fault, 4 were correctly classified. The remaining 3 images were wrongly classified as LSS 50 microns fault giving an accuracy level of 57%.

2) Kurtogram-based CNN: For the second CNN model type, Kurtogram-based, training batch size is set as 100. The training of CNN is done through 208 iterations, 208 epochs, to guarantee convergence and accuracy. The learning rate of neural network is 0.001 to ensure fine tuning for accuracy improvement. An early stopping criteria is implemented causing the training simulation to stop automatically if the validation accuracy does not improve within 20 epochs. The confusion matrix in fig. 11 shows the results obtained using this model with an accuracy of 81.5%. Like the Cyclostationary-based CNN model, all HSS faults are detected and classified based on the fault magnitude. No missed detection of faults or false
A combined vibration analysis and deep learning method for detection and classification of faults located on the wind turbine gearbox has been addressed in this work. A simulation-based analysis is performed to evaluate the effectiveness of this proposed method in detecting faults located on the low speed shaft and diagnosing the magnitude of the faults. Different actual wind loading scenarios have been simulated to extract wind loads to be applied at the abstracted nacelle model. Unlike the round-robin study dataset, these transient loads add more complexity since forces from the wind that could impact the vibration excitement are now included. In addition, speed variation coming from the wind is also incorporated into the simulations. The fault diagnosis under these realistic conditions in the modeling and simulation are more challenging than those in the NREL round robin study [4]. Faults with different amplitude and locations are simulated to test the validity and sensitivity of this method. Both Cyclostationary-based CNN and Kurtogram-based CNN gave classification accuracy levels greater than 80%. Both models are able to accurately classify the fault location, even if they do not correctly classify the magnitude of the faults. The work in this paper sets a pathway to applying machine learning in vibration based fault detection and diagnosis in wind turbines in continuous and real time condition monitoring framework.

VI. CONCLUSION

A combined vibration analysis and deep learning method for detection and classification of faults located on the wind turbine gearbox has been addressed in this work. A simulation-based analysis is performed to evaluate the effectiveness of this proposed method in detecting faults located on the low speed shaft and diagnosing the magnitude of the faults. Different actual wind loading scenarios have been simulated to extract wind loads to be applied at the abstracted nacelle model. Unlike the round-robin study dataset, these transient loads add more complexity since forces from the wind that could impact the vibration excitement are now included. In addition, speed variation coming from the wind is also incorporated into the simulations. The fault diagnosis under these realistic conditions in the modeling and simulation are more challenging than those in the NREL round robin study [4]. Faults with different amplitude and locations are simulated to test the validity and sensitivity of this method. Both Cyclostationary-based CNN and Kurtogram-based CNN gave classification accuracy levels greater than 80%. Both models are able to accurately classify the fault location, even if they do not correctly classify the magnitude of the faults. The work in this paper sets a pathway to applying machine learning in vibration based fault detection and diagnosis in wind turbines in continuous and real time condition monitoring framework.

REFERENCES