Planetary Gear Faults Detection in Wind Turbine Gearbox Based on a Ten Years Historical Data From Three Wind Farms

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Abstract: Gear faults contribute to a significant portion of failures in wind turbine system. As such, condition monitoring and fault detection of these components assist in maintenance scheduling; hence, preventing catastrophic failures of the gearbox. This paper introduces a new hybrid fault detection approach to detect gear faults in wind turbines. to accomplish this task, vibration signals are collected and used to extract various time-domain features. Next, a Dynamic Principle Component Analysis (DPCA) is adaptively employed to identify failure dynamics by reducing the time-domain feature dimension. Following that, a Support Vector Machine (SVM) is implemented to detect and isolate gear faults. Experimental test studies with ten-year historical data of three wind farms in Canada are conducted. Test results indicate that the proposed hybrid approach performs superior compared to DPCA using Multilayer Perceptron (MLP) Neural Networks (NNs).

Keywords: Wind turbine gearboxes, fault detection, feature extraction, dynamic principle component analysis, support vector machine.

1. INTRODUCTION

Condition-Based Maintenance (CBM), and monitoring have been recognized as indispensable means to enhance the availability and reliability of Wind Turbines (Gao et al. (2016)). Fault Detection and Diagnosis (FDD) is an essential step in CBM, which can be applied to isolate incipient faults. The FDD information is then managed to set a maintenance schedule (Kordestani et al. (2019)).

The drive-train of Wind Turbines (WT) retains a gearbox, which is connected to a generator (McFadden and Basu (2016)). Gearboxes are prone to faults due to the fact that they are exposed to heavy loads and harsh environmental conditions. Gearbox faults lead to a downtime of 18 days on average, which translates into 20% of the wind turbines downtime (Lu et al. (2017)). Gear faults consist of surface wear, cracks, or tooth breakage, etc. They can be caused by varying loads, fatigue, and issues due to installation problems. Gear faults often reduce wind turbine performance and may lead to sudden failure of WT.

Gear fault diagnosis has been widely investigated in the literature (Jiang et al. (2018); Guo et al. (2019); Wang et al. (2019); Jiang et al. (2017)). Most gear FDD techniques are based on signal processing techniques using acoustic emission transducers, vibration sensors, or electrical measurements such as current (Loutas et al. (2009); Xue and Howard (2018)).

Sharma and Parey (2017) developed a new gear detection method approach based on signal processing methods using acoustic emission and vibration signals. Different measures, including envelope-detected acceleration and vibration acceleration, were computed as vibration signals. For acoustic signals, sound pressure and intensity were calculated. Afterward, A kurtosis feature under a fluctuating speed was used with the acoustic signal to distinguish gear faults such as detecting a missing tooth in gears. Test results indicated that the proposed methods were adequate under various loading conditions and fluctuation speeds. A model-based gear fault detection method was presented by Park et al. (2016) using transmission error. A parametric model of a planetary gear was formed to measure the transmission error. Following that, damage features were extracted by the transmission error. Then, the damage

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features were used to monitor the health condition of the gears. However, simulation test results revealed that the transmission error was dependent on torque magnitude, which would cause some difficulty in adjusting the fault criteria.

A current-based fault diagnosis was developed by Lu et al. (2012) to recognize gear defects in WTs. Here, the stator current of the generator was appropriated to obtain characteristic frequencies. These frequencies were non-stationary. Therefore, a signal re-sampling method was executed to convert these signals to stationary values at varying speed conditions. A gear fault could then be detected using statistical analysis of the stationary signals. Simulation test results indicated that a gear fault could effectively be detected using the frequency spectra of the stator current. Cheng et al. (2017) applied an intelligent fault diagnosis method for drivetrain gearboxes. For this purpose, the rotor current of a Doubly-Fed Induction Generator (DFIG) was estimated. Then, its frequency was extracted. Afterward, a Hilbert transform was engaged to compute the signal's envelope. Following that, the envelop was converted to a stationary signal using an angular re-sampling method. Later, gear features were extracted based on the power spectral density function. In the end, deep learning was applied to the features to classify gear faults. Test results indicate a high performance of the proposed fault detection method.

Vibration-based fault detection methods are favored for identifying gear defects in comparison with acoustic emission methods due to the availability of cost-efficient devices for measurements and monitoring (Park et al. (2016)). A vibration-based gear fault detection was developed by Si et al. (2017). An Empirical Mode Decomposition (EMD) was applied to decompose vibration signals and evoke Intrinsic Mode Function (IMF) to obtain various frequencies. Later, the IMF components were interpreted to distinguish the faults in the planetary gears. Test results proved the feasibility of the proposed EMD in fault diagnosis. Reference Zheng and Zheng (1704) presented a data-driven method using an EMD method and K Nearest Neighbors (KNN) classifier to disclose gear faults. First, the EMD was executed to estimate the frequency spectrum from vibration signals. Then, a peak magnitude of the frequency spectrum was deduced to feed KNN classifier. Test results confirmed the high performance of the method in pinion gear fault detection.

A fault detection method via Minimum Entropy Deconvolution (MED) and frequency band analysis was designed by He et al. (2017) to detect gearbox faults. The main idea is to employ modulation sidebands in mesh frequency for fault detection by filtering the signal using the MED filter and then boosting the value through the spectrum analysis. Test data from a two-stage wind turbine was practiced to verify the proposed fault detection. The results confirmed that the enhanced MED filter could effectively distinguish gear faults. Reference Zhang and Hu (2019) introduced a gear fault detection using Continuous Vibration Separation(CVS) and MED. The CVS was retained to reduce various disturbances such as noise or modulation effect of gear movements. Then, the MED was executed to recognize gear faults. Test results indicated that the suggested method could effectively detect sun gear faults. A vibration-based fault gear detection was developed by McDonald et al. (2012). The goal was to identify gear tooth faults form acceleration data. For this purpose, a Maximum Correlated Kurtosis Deconvolution (MCKD) was utilized to improve Kurtosis performance for fault detection. Test results with experimental data indicated a higher performance in comparison with the MED method.

A combination of various methods has also been investigated for gear failure detection. Reference Park et al. (2019) introduced a new fault detection method to distinguish planetary gear fault in varying speed conditions. For this aim, a Short-Time Fourier Transform (STFT) was used to capture a time-varying response of vibration signals. Later, an averaging method was conducted over time to improve sensitivity to faults. After this, a Gaussian process (GP) regression was executed on the signal to estimate the means of STFT coefficients. Finally, an energy residual was calculated by subtracting STFT coefficients from the means. This energy residual was appropriated for monitoring purposes and gear fault detection. Simulation results proved that this method was cost-efficient as it did not need extra pieces of equipment like angular measuring devices. An integrated fault detection method was introduced by Zhao et al. (2018) to distinguish gear faults. First, Generalized Demodulation Transform (GDT) was employed to convert non-stationary signals to stationary values. Then, a Vold-Kalman generalized demodulation method was used to extract a time-frequency ridge. Besides, instantaneous dominant meshing multiple trend was deduced from the raw signal to estimate phase functions of the fault. Finally, a Fast Fourier Transform (FFT) was executed to filter the signal. It was noted that rotational speed measurements and angular re-sampling were not required in this method, making it cost-efficient.

In this paper, a new integrated vibration-based method is proposed to detect faults in gearboxes. The primary assumptions for this work are as follows:

- Vibration signals are measured by Integrated Circuit-Piezoelectric (ICP) accelerometer sensors.
- Real-time data is recorded in the nacelle of wind turbines by M-system device.
- The real-time data is monitored and is further processed in the Turbine Condition Monitoring (TCM) site server, which is located in the wind farm station.

The objective of this work is to develop a new fault detection method to better identify gear faults. For this aim, various time-domain features are extracted. Afterward, a Dynamic Principle Component Analysis (DPCA) is employed on the extracted feature to reduce the data dimension. Finally, a Support Vector Machine (SVM) is implemented to detect gear faults. The main contributions of this work are:

- Various time-domain features are examined to extract failure dynamics from vibration signals.
- Applying the dynamic PCA helps to capture nonlinear dynamics of a fault and therefore enhances the detectability of the proposed method.
- Ten-year real historical data from three wind farms in Canada is investigated to evaluate the proposed fault detection method. Furthermore, the performance of

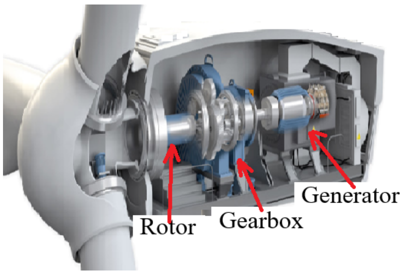

Fig. 1. A wind turbine drive-train components

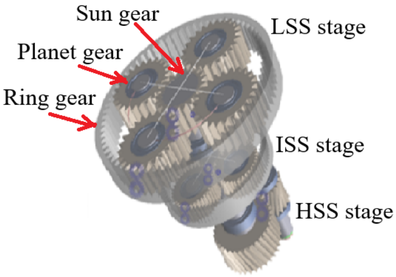

Fig. 2. The internal components of a gearbox.

the proposed method is compared to Multilayer perceptron (MLP) neural network, and indicates a better performance of the proposed gear failure detection method.

The rest of this research work is organized as follows: Section 2 describes wind turbine gearbox systems. The proposed fault detection method is explained in Section 3. Section 4 illustrates the design implementation and experimental test results. A summary of conclusions and some future directions are provided in Section 5.

2. WIND TURBINE GEARBOX

Gearboxes are retained in wind turbines to convert a low speed of a rotor to a high speed of generator (Teng et al. (2014)). Figure 1 illustrates a wind turbine drivetrain, which consists of a rotor, a gearbox, and a generator. This energy conversion is conducted in three stages known as Low-Speed Shaft (LSS), Intermediate-Speed Shaft (ISS), and High-Speed Shaft (HSS). Figure 2 depicts the internal components of a gearbox.

It is noted from Figure 2 that a planetary gearbox is comprised of a ring gear, planet gear, and sun gear. The planetary gearbox operates in varying heavy load conditions with low speed. These conditions may lead to damage to the gearbox (Xiao and Huan (2017)). Gearbox faults often include a significant portion of failures in wind turbines, which account for a long downtime in wind farms (Lu et al. (2012)). Thus, condition monitoring of gearbox is often demanding to detect incipient gear faults in the gearbox and prevent further damage to wind turbines.

3. PROPOSED FAULT DETECTION APPROACH

This section demonstrates the theory of the proposed fault detection approach. The block diagram showing

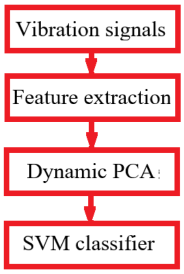

Fig. 3. Various steps in the proposed fault detection approach

Table 1. Statistical time-domain features for vibration signal X with a length of N ($X = [x_1, ..., x_i, ..., x_N]$)

Features	Formula
Mean	$A_1 = \frac{1}{N}\Sigma_{i=1}^{N} x_i$
Root Mean Square	$A_2 = \sqrt{\frac{1}{N}\Sigma_{i=1}^{N} x_i^2}$
Standard Deviation	$A_3 = \sqrt{\frac{1}{N-1}\Sigma_{i=1}^{N}(x_i - A_1)^2}$
Variance	$A_4 = \frac{\frac{1}{N}\Sigma_{i=1}^{N}(x_i-A_1)^3}{[\frac{1}{N}\Sigma_{i=1}^{N}(x_i-A_1)^2]^{\frac{3}{2}}}$
Peak to peak	$A_5 = \max(x) - \min(x)$
Skewness	$A_6 = E[(\frac{x-A_1}{A_2})^3]$
Kurtosis	$A_7 = E[(\frac{x-A_1}{A_2})^4]$
Peak factor	$A_8 = \frac{x_{peak}}{A_3}$
Kurtosis factor	$A_9 = \frac{\Sigma_{i=1}^{N} x_i^4}{N \times A_3}$
Waveform factor	$A_{10} = \frac{A_3}{\frac{1}{N-1}\Sigma_{i=1}^{N}\lvert x_i\rvert}$
Margin factor	$A_{11} = \frac{x_{peak}}{(\frac{1}{N}\Sigma_{i=1}^{N}\lvert x_i\rvert)^2}$
Impulse factor	$A_{12} = \frac{x_{peak}}{\frac{1}{N-1}\Sigma_{i=1}^{N}\lvert x_i\rvert}$

various stages of the proposed fault detection approach are illustrated in Figure 3.

The proposed fault detection method utilizes vibration signals and performs feature extraction, dynamic PCA, and SVM classifier tasks. In the following, each block is briefly discussed.

3.1 Feature extraction

Vibration signals are often employed for condition monitoring of rotating machinery systems (Sharma and Parey (2016)). Time-domain statistical features are devised to extract fault characteristics from vibration signals (Soualhi et al. (2019)). In this research work, comprehensive statistical features which are collected in Table 1 are implemented for condition monitoring purposes. In a case of gear fault, abnormal deviations occur in vibration signals, which may alert some statistical features. These can be employed to detect the faulty condition.

3.2 Dynamic PCA

After feature extraction, a mechanism must be used to engage the features with the classifier. It is noted that all the features cannot be applied to the classifier as they increase computational complexity or may reduce fault detection accuracy. In this research work, a DPCA is used to capture failure dynamics using extracted features. The following two-step procedure is executed to obtain the DPCA.

Step 1: define $X_s \in \mathbb{R}^{N \times sm}$ as follows.

$$X_s = \begin{bmatrix} x_1^T & x_2^T & \cdots & x_s^T \\ x_2^T & x_3^T & \cdots & x_{s+1}^T \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ x_N^T & x_{N+1}^T & \cdots & x_{N+s-1}^T \end{bmatrix}$$

It is noted that $x_i \in \mathbb{R}^m, i = 1, ..., N+s-1$, is a vector of m features, scaled to zero mean and unit variance. A time interval s is considered to be a small integer.

Step 2: Decomposition of correlation matrix.

$$R \approx \frac{1}{N-1}(X_s^T)(X_s) = P \Lambda P^T \tag{1}$$

where

$$\Lambda = \begin{bmatrix} \Lambda_{pc} & 0 \\ 0 & \Lambda_{res} \end{bmatrix} \tag{2}$$

$$\Lambda_{pc} = diag(\sigma_1^2, ..., \sigma_{l_K}^2) \in \mathbb{R}^{l_K \times l_K} \tag{3}$$

$$\Lambda_{res} = diag(\sigma_{l_K+1}^2, ..., \sigma_{sm}^2) \in \mathbb{R}^{(sm-l_K)\times(sm-l_K)} \tag{4}$$

$$P = [\, P_{pc} \ P_{res} \,] \tag{5}$$

$$P_{pc} \in \mathbb{R}^{sm \times l_K} \tag{6}$$

$$P_{res} \in \mathbb{R}^{sm \times (sm-l_K)} \tag{7}$$

Note that $\sigma_1, \sigma_2, ..., \sigma_{l_K}$ ($\sigma_1 \geq ... \geq \sigma_{l_K}$) are the l_K largest (principal) singular values and $\sigma_{l_K} \geq \sigma_{l_K+1} \geq ... \geq \sigma_{sm}$.

3.3 SVM classifier

The SVM method is a well-known classifier, which is widely used for pattern recognition and data mining (Kordestani et al. (2018)). The SVM classifier invokes an optimization technique to attain a hyperplane or surface to maximize the distance between two classes. Figure 4 displays the optimization problem for two classes of A and B.

Assume $\{(x_1, y_1), (x_2, y_2), \cdots, (x_m, y_m)\}$ that $x_i \in R^n$ represent inputs, and $y_i \in \{-1, 1\}$ are class labels. In the following, the classification problem is formulated:

$$\begin{aligned} &min \frac{1}{2} w^T w + c \sum_{i=1}^{m} \xi_i \\ &y_i(w\phi(x_i) + b) \geq 1 - \xi_i; \forall i = 1, \cdots, m; \xi_i \geq 0 \end{aligned} \tag{8}$$

where Vector w denotes a normal distance to the surface or hyperplane. Parameter $c \geq 0$ indicates a penalty term.

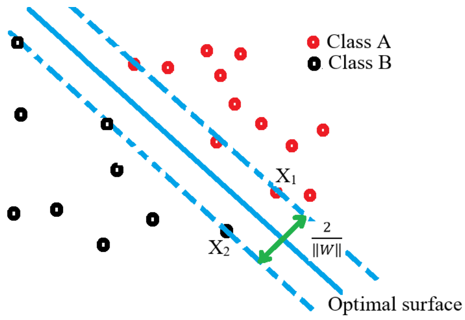

Fig. 4. The optimization problem for two classes of A and B.

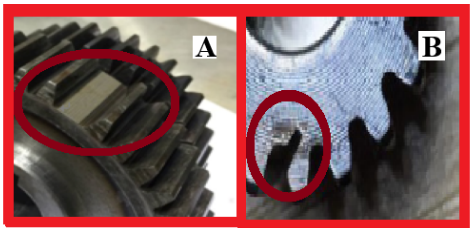

Fig. 5. A) a gear tooth fault, and B) gear crack fault

Variables ξ_i represents a positive slack. Function $\phi(0)$ implies a mapping. Lagrange method is often used to solve (8) and determine the surface or hyperplane as follows:

$$f(x) = sgn(\sum_{i=1}^{m} y_i \alpha_i K(x_i, x_j) + b) \tag{9}$$

where $K(x_i, x_j) = \phi(x_i)\phi(x_j)$ denotes a kernel. Function $f(x)$ is the surface formula. It should be noted that various kernels such as linear, and Radial Basis Function (RBF) can be fitted to obtain the surface.

4. SIMULATION STUDIES AND EXPERIMENTAL TEST RESULTS

In this section, design implementation and test results are discussed. First, data collection and test scenarios are illustrated. Afterward, design implementation is discussed. Following that, experimental test results are explained.

4.1 Failure scenarios

A ten-year data from three wind farms in Canada is investigated. Two of the wind farms are located in Southwestern Ontario, and the third one is located in the Prince Edward Island (PEI) Province.

Vibration data of 136 wind turbine in healthy and faulty conditions are analyzed during this period, and their faults are detected. Figures 5 shows A) a gear tooth fault and B) gear crack fault.

4.2 Design implementation

Real-time Vibration signals accessible from the TCM site server is utilized to conduct fault detection task. Then, time-domain features in Table 1 are extracted and are to

Table 2. The characteristic and design criteria of the proposed fault detection.

Characteristics	Description or values
Number of features	12
Number of PCs	3
Performance of PCs	91.24%
Kernel of SVM	linear, Gaussian, RBF
Number of Input of MLP	3
Number of Hidden layer	7
Number of Output of MLP	1
Inputs nodes type	Buffer
Hidden-layer type	Log-sigmoid
Output Node type	Linear function
Training method	Back propagation
Training Error of MLP	0.095
Test Error of MLP	0.124
Maximum epochs	182

be used as inputs of dynamic PCA. Afterward, the DPCA is recursively updated using Eqs. (1) and (2), and Principle Components (PCs) are recursively obtained from Eq (6). Sequentially, the SVM problem is optimized using Eq. (8), and the optimal surface is computed based on Eq. (9).

Remark 1: It must be noted that the DPCA reaches 84.47%, 91.24% and 95.38% accuracy, withholding two, three and four PCs, respectively. Although adding extra PCs will enhance the accuracy of the proposed method, here, only three PCs are kept, and the remaining are discarded to avoid computational complexity of the proposed fault detection method.

4.3 Experimental test results

Various kernels ($K(x_i, x_j)$) such as linear, Gaussian and RBF are appropriated in the structure of the SVM classifier. Furthermore, a comparison with Multi-Layer Perceptron (MLP) neural network (NN) is made to evaluate the performance of the proposed fault detection. Table 2 explains the design criteria of the proposed fault detection.

The MLP NN holds three buffers in the inputs, seven log-sigmoid functions in the hidden layer, and one linear function in the output. For the case of healthy data, the MLP output is set to zero in the training phase, and the output adjusts to one in faulty conditions. A backpropagation algorithm is implemented to train the network. After 182 epochs, the network is trained, and Mean Squared Error (MSE) for training and testing are 0.095 and 0.124, respectively.

In the test phase, any value between -0.5 and $+0.5$ is considered as healthy result, and a value between $+0.5$ and $+1.5$ is recognized as a faulty. Further, 70% of the dataset is applied for training, and the rest is employed for testing.

Table 3 presents the performance of the gear fault detection algorithms.

It is noted from Table 3 that the proposed method with RBF kernel distinguishes 92% of gear fault, and only 8% is wrongly detected (False alarm rate). The lowest detection results belong to the linear kernel that identified 78% of gear faults. A combination of DPCA and MLP network holds a performance of 82%, which is better than DPC+SVM using a linear kernel.

Table 3. The confusion matrix of the fault detection

Methods	Detected	False-alarm
DPC+SVM-RBF kernel	92%	8%
DPC+SVM-Gaussian kernel	86%	14%
DPC+SVM-linear kernel	78%	22%
DPC+MLP	82%	18%

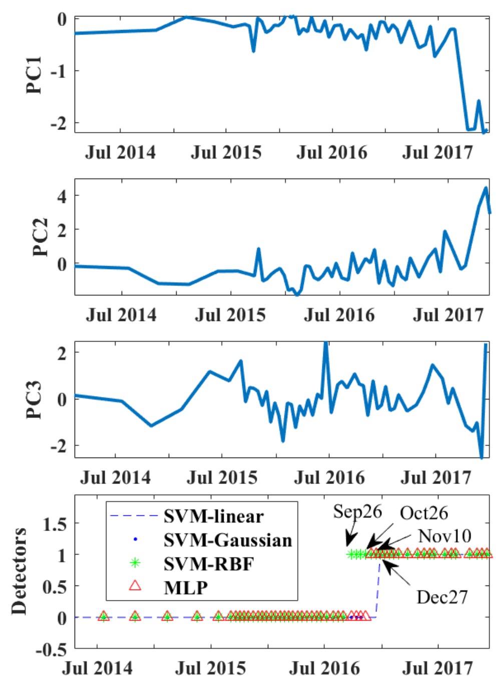

Fig. 6. The PCs and output of various fault detectors.

To show the performance of the detector, time-domain responses of various detectors are investigated. A ring gear fault occurred in T-16 in Enbridge wind farm. Figures 6 illustrates the PCs and output of various fault detectors. It is noted from Figure 6 that the proposed method with the RBF kernel could detect the fault on Sep 26, 2016, which was the fastest detection time in comparison with MLP and the other detectors.

5. CONCLUSIONS AND FUTURE WORK DIRECTIONS

This paper presented a new fault detection approach for wind turbine gearbox. Gear faults form a high percentage of failures in wind farms, and often lead to significant costly downtime. To reduce the maintenance cost, a new fault detection was proposed in this paper. First, time-domain statistical features were extracted from vibration signals. Then, a dynamic PCA was recursively applied to capture the failure dynamics. Following that, SVM classifier was implemented to detect the gear fault. A ten-year experimental data from three wind farms in Canada was investigated to verify the proposed fault detection method. Test results indicate that the proposed fault detection method with the RBF kernel is more accurate when compared to other kernel and also the MLP network. Finally, some future directions to explore are as follows:

(1) Investigating other technologies such as image-processing to diagnose the failure types.
(2) Preforming the remaining useful life (ROL) estimation to predict the useful lifetime of the system.

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