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Mechanical System Fault Detection using Intelligent Digital Signal Processing

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***Abstract*-This paper presents an intelligent method for failure detection based on digital signal analysis in offshore wind turbines. The primary goal of this research is to build an intelligent method which can detect mechanical failure in offshore wind turbines. The proposed method is a multi-stage process including signal acquisition, pre-processing, model training, testing, defect pattern detection and result verification. Two primary stages were investigated for design choice: signal characterization which includes feature selection and extraction, and defect classification. For the characterization stage, two techniques were investigated: discrete cosine transform (DCT) and fast Fourier transform (FFT). A pre-examination of the similarity measure among the resulting vectors of the two techniques was conducted and results indicate that a Euclidian-based similarity measure was superior to a correlation-based similarity measure of the signal vectors by a significant factor. FFT was chosen over DCT because FFT naturally relates to the frequency domain of a signal and signifies a direct interpretation of the primary harmonics of the original signal. For the classification stage, two implementations of the process were executed and compared: one implementation did not utilize an intelligent agent and the other utilized a neural network model to classify signal vectors into healthy and damaged classes. The difference between the two implementations was very significant: the intelligent agent demonstrated a very reliable classification accuracy > 90% while the other demonstrated an accuracy of only 53%.**

Keywords- Wind Turbine Health Monitoring; NREL Gearbox Data; Artificial Neural Networks; Fourier Transform; Randomized Sampling

I. INTRODUCTION

Green sustainable energy is one of the most sought-after goals of humanity, and wind energy is among these important renewable energy sources [1]. With demand for renewable energy rising every day and with climate change in mind, a reliable renewable energy resource is therefore of high priority. Wind energy provides that alternative. With only a small share of its huge potential utilized by offshore and onshore energy applications, wind energy provides significant untapped potential which can be harnessed. With the advantages of no noise pollution, ecofriendliness and much more consistent strong winds, offshore wind farms are perfect alternatives to onshore wind farms.

II. RELATED WORKS

A number of related works were explored. Crowther [2] studied load measurement and fatigue using blade strain sensors and real time sensing/processing which focused on gears and bearings, continuous updated life prediction and probability of failure oil, grease and filter analysis (lubrication monitoring). Supervisory control and data acquisition (SCADA) statistical analysis was conducted on several parameters including temperature, power and pitch motor currents, and vibration signals analysis (simulation was used to estimate the resonance frequency of gears). Sample data for one week was visualized, processed and presented. Simulated data was also used to demonstrate the significance of pitch-error in gear fatigue. A case was demonstrated in which the system was able to flag a spalling in bearings and preventive maintenance was performed before the problem escalated. Customized signal processing can provide significant benefits, and a traditional signal processing method work well for many failures. Smarsly, et al., [3] used data acquisition units (DAUs) and a database backup redundant array of inexpensive disks (RAID) to remotely access an on-site server. They used sensors including tower temperature, wind speed, acceleration and displacement. The study addressed the need for structural health monitoring (SHM) reliability as well as the use of software agent-based monitoring of the different units of the SHM system to detect possible software malfunctions. Case studies and scenarios for SHM reliability were presented. Examples of collected sensory data retrieved remotely were also presented. The authors recommended that SHM reliability must be further addressed. Adams, et al., [4] studied SHM and focused on individual wind turbines at the component level. The authors argued that if the loading and health of individual wind turbines can be quantified, the maintenance, operation and control of each turbine can be tailored to maximize uptime by increasing the mean time between inspections and other factors which influence uptime. The authors proposed a four-step method: operational evaluation to understand how the loading envelope affects the wind turbine unit

(WTU) responses, data acquisition and filtering, feature extraction and a statistical model for discrimination. Hahn, et al., [5], discussed many available condition monitoring systems and compared different types of sensors used in the systems. The authors also compared different analytical techniques used by different sensor manufacturing companies to analyze the collected data. The paper concluded that vibration monitoring is currently favoured in commercially available systems using standard time and frequency domain techniques for analysis. Carroll, et al., [6] compared five sets of drive trains and gearboxes available on the market and tested them under controlled conditions to observe their performances. The tests were conducted on with offshore and onshore wind data and failure rates. Results were tabulated according to the installation site and concluded that direct drive permanent magnet synchronous generators with fully rated converters demonstrate the best availability at 93.35%. Hart, et al., [7] presented a direct-drive option that can deliver the lowest energy costs. The authors argued that permanent magnet generators have a limited track record in the wind industry (particularly in offshore scenarios) indicating that a generator replacement scenario conducted once during the turbine's lifetime is unreasonable. Zhao, et al., [8] proposed a pattern recognition algorithm to model baseline behaviour and measure deviation of current behaviour; a self-organizing map (SOM) and minimum quantization error (MQE) method were selected to assess degradation. For feature extraction, the root mean square (RMS), kurtosis and crest factor are time domain features used for testing. The authors reported that when using wavelet transform for feature extraction, the selection of the mother wavelet function is crucial to obtain the optimal decomposition results.

III. THE PROPOSED SYSTEM

The proposed system is illustrated by the model shown in Fig. 1. The model consists of five primary components: the sensor network attached to (or embedded in) the structure of the wind turbine, the server that manages the data collection and database maintenance, the intelligent anomaly detection and classification software, the client (operator) that interacts with the server, resources and maintenance plans to issue necessary corrective and preventive actions, and the resources available to the entire system to be used upon request by the client. These components are discussed as follows.

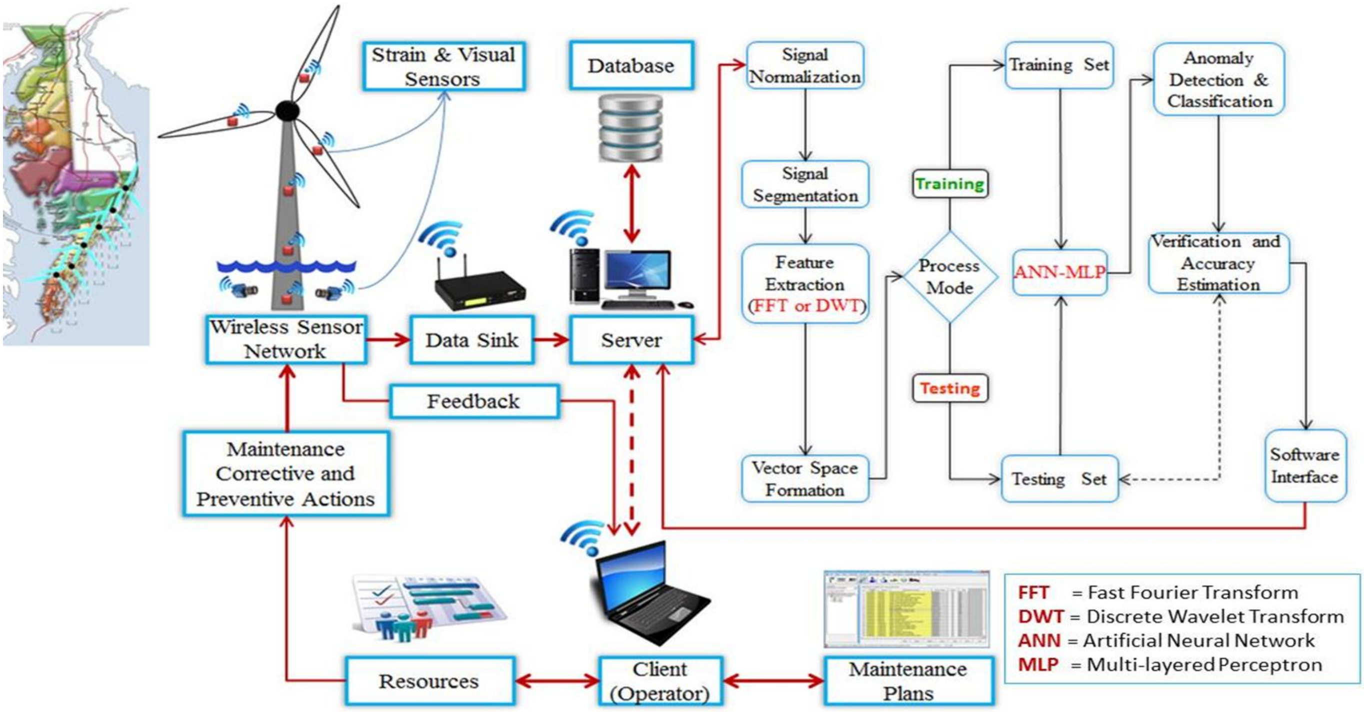


Fig. 1 Intelligent health monitoring system for offshore wind power turbines

Wireless sensor network: A network of sensors deployed on the structure of the turbine to monitor the current structural health of the wind turbine. The modalities of the sensors include vibration, stress, strain and visual. The sensors collect data periodically which is wirelessly transmitted to a data sink which temporarily buffers all data collected from all sensors and then wirelessly transmits them to the server which, in turn, permanently archives the streams of collected sensor readings in a database to be used in the analysis phase of the intelligent software system.

Server: A computer node that coordinates and maintains all sensor readings in a database. This database can be remotely queried by the client operator. The database is used by the intelligent software system for data analysis required for further decision making and actions based on the anomaly detections.

Client operator: A computer node that enables an operator to remotely access the server and database in real time and query the current and archived status of the sensor readings. Furthermore, the client can manage the operation of the intelligent system and collect results and issue reports to schedule maintenance plans for the wind turbine structure. The client operator has access to the available resources of the system and can task them to enact the recommended maintenance plans.

Intelligent software system: A software system which integrates two techniques to achieve reliable anomaly pattern detection and classification: digital signal processing (DSP) and artificial neural networks (ANN). For the DSP, the fast Fourier transform (FFT) and the discrete wavelet transform (DWT) are used to filter and characterize the sensor signals. For the ANN, the multi-layered perceptron (MLP) is used as a classification network for the characterized signals of the sensors.

One of the most significant hurdles to the development of offshore wind farms is the cost of operation and maintenance. Since the turbines are installed miles away from the shoreline, the economics and logistics of maintenance and operation are much more complicated than those of onshore projects. In this paper, signal data were analyzed using two different characterization techniques: FFT and DCT. Link et al., [9] to determine the most accurate method of failure detection. Artificial neural networks with multi-layered perceptron were used to classify the signals. This technique utilizes supervised learning whereby a pre-classified dataset is fed into the machine for training. This method provides a comprehensive status of the turbine. During a fault condition, it is possible to know where the fault occurred and in many cases, ascertain the severity of the fault. An engineer can make an educated decision whether to continue running the turbine at a reduced capacity until repairs can be scheduled, or to shut the turbine down to prevent further damage to components. The proposed approach maximizes the economic utility of the wind turbine. Wang, et al., [10] proposed a gross assessment of the health of the turbine, in which the turbine was determined to be in a good state or a faulty state. According to Wang's model, it was not possible to determine where a fault occurred. Upon entering a fault condition, the operator must shut down the turbine. The advantage of the proposed system over other approaches is that it helps determine the location of particular defects in the gearbox system rather than simply classifying the entire gearbox as defective. This allows an engineer to make an educated decision as to whether or not to shut down the turbine or run it at reduced capacity based on the classification of the fault.

IV. THEORY AND TECHNICAL APPROACH

The technical approach and theories related to the different techniques used in the proposed model are presented and discussed to provide the background for this work. Reference will be made to Fig. 1, which depicts the concept of the model.

A. Fast Fourier Transform (FFT) and Multi-Layer Perceptron (MLP)

The theoretical formulations for FFT and MLP are described as follows.

1) Fast Fourier Transform (FFT) [11]

Fourier transform is a mathematical model based on Fourier series analysis, as developed by 18th century mathematician, Joseph Fourier. The Fourier series revolutionized function transforms, in which an extremely complex function can be transformed into a summation of a much simpler set of preemptive functions such as sines and cosines. Let $a_0, a_1, a_n, \ldots \quad and \quad b_0, b_1, b_n, \ldots$ be real or complex numbers, referred to as the Fourier coefficients, so that:

$$f(x) = \frac{a_0}{2} + \sum_{n-1}^{\infty} [a_n \cos(nx) + b_n \sin(nx)] \tag{1}$$

$$a_n = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) \cos(nx) dx, \quad b_n = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) \sin(nx) dx \tag{2}$$

Solving for a_n and b_n and substituting them into Eq. (1), the function f(x) is expressed as a linear combination of the n^{th} terms of sinusoidal functions, in which n determines the accuracy of the Fourier series expansion. An example of a Fourier series expansion of a sawtooth signal:

$f(x) = \left\{ \begin{matrix} cx, & x \in [-\pi, \pi] \\ f(x \pm 2\pi), & elsewhere \end{matrix} \right\}$ is shown in Fig. 2.

Applying Eq. (1) to the signal f(x), the n^{th}-term Fourier expansion is expressed as:

$$f(x) = 2 + \sum_{n=1}^{\infty} \frac{(-1)^{n+1}}{n} \sin(nx), \quad -\infty < x < \infty \cdot$$

The resulting signal of the 1st through the 16th-term Fourier series expansion is depicted in Fig. 2. The effect of the number of terms in the Fourier expansion can be observed in Fig. 2 by varying n and recovering the signal. With (n=1), the resulting signal is simply a sine wave, but as n increases the recovered signal becomes a very close approximation to the original one, as shown in the last image when (n=16) in Fig. 2.

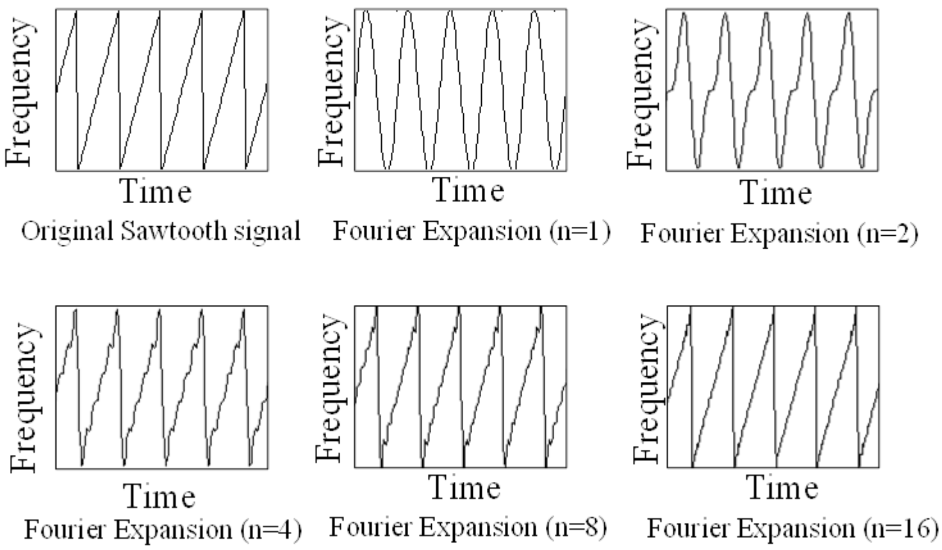


Fig. 2 Example of Fourier series expansion for a sawtooth signal

The use of Fourier series expansion allows us to represent complex signals in a simple fashion as a linear combination of primitive functions, typically sinusoidals. This property of a Fourier series leads us to a very useful transform: the fast Fourier transform (FFT). FFT is a mathematical transform model that converts the input function in the time domain into its equivalent function in the frequency domain. Discrete Fourier transform (DFT) addresses time-discrete signals. Let x[t] denote a discrete set of real or complex numbers; the discrete-time Fourier transform of signal x[t] is given as:

$$X(f) = \sum_{n=-\infty}^{\infty} T \cdot x(nT) \cdot e^{-j2\pi f n T} \tag{3}$$

where,

T = sampling period

n = number of samples per period

f = sampling frequency = 1/T.

2) Multi-Layer Perceptron (MLP) [11]

The basic functional unit in the network architecture of MLP is the perceptron (Fig. 3), which computes the weighted sums of the components of the input vector and subtracts a threshold value (θ). The result is then passed to an activation function which can be hard-limiting or sigmoid. The sigmoid function is essential to the learning process as it has the property of being differentiable, which is very important for derivative-based optimization techniques such as the gradient descent. The basic functionality of a perceptron involves being a discriminant function in a pattern recognition problem, where it performs a nonlinear transformation from the input space into the output space. Additionally, it is used as a binary logic unit that is capable of implementing many logic functions including AND, OR, and NOT. The capabilities of a single perceptron is limited to problems that are linearly separable, i.e., the boundaries of the different classes can be separated by a linear function as depicted in Fig. 4.

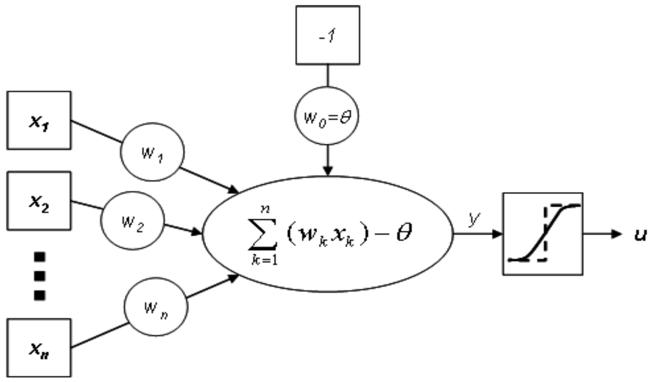


Fig. 3 The perceptron, the functional unit in artificial neural networks

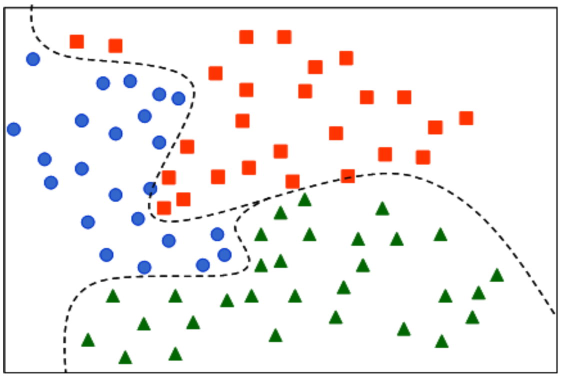


Fig. 4 Input feature spaces that demonstrate linearly inseparable vector space

The power and the capabilities of the perceptron are greatly extended by multi-layered architecture with the back propagation learning algorithm. This architecture is illustrated in Fig. 5.

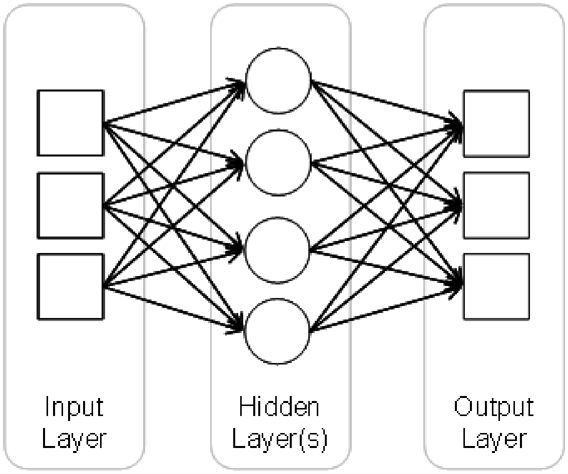


Fig. 5 Typical architecture of a multi-layer perceptron

The structure of the MLP (Fig. 5) consists of three parts: an input layer, hidden layers, and the output layer. The input layer is the first layer of perceptrons that receives the input vector. Hidden layers are located between the input and the output layer; the output of the input layer is fed into the first hidden layer, the output of the first layer is fed into the next hidden layer, etc. The number of hidden layers necessary varies based on the complexity of the application. Often the nodes (perceptrons) of the adjacent layers are fully connected. The multiple nodes in the output layer typically correspond to multiple classes for multi-class pattern recognition problems. The most common approach used in the learning process is the gradient descent algorithm, in which a gradient search technique is used to determine the network weights that minimize a criterion function. The criterion function to be minimized is the sum-of-square-error, and the convergence of the algorithm depends on the threshold error.

B. Data Acquisition

Considering that gearbox failures are the leading cause of necessary higher maintenance in offshore wind energy farms, it was decided to study gearbox data by comparing healthy and damaged sensor data. The National Renewable Energy Laboratories (NREL) installed one healthy and one damaged gear box of 750 KW capacity from two decommissioned wind turbines in their laboratory and acquired data by installing sensors at different locations. Data was collected at 40 KHz sampling per channel using a National Instruments PXI-4472B DAQ module and eight industrial accelerometer sensors with model numbers IMI 626B02 and IMI 622B01. A dynamometer test was conducted on a damaged gear box and sent into the field for data collection. Many faults occurred at bearing temperatures greater than 90C in addition to two significant oil loss events. The unit was shipped back to the NREL laboratory where sensor data was collected and sent to an engineering company for detailed failure analysis. Significant damages were observed in the signal signature when plotted, and a corresponding sensor location was identified with provided documentation. For more information on the gear boxes, failures, sensors and their placements, please refer to Sustainable energy (2016, March 26) and Smarsly. According to the NREL [12], the data acquisition was conducted by a 40KHz sampling per channel using National Instruments PXI-4472B DAQ module, 8 industrial accelerometer sensors with model numbers IMI 626B02 and IMI 622B01, 1 RPM sensor, a sensor to measure the high-speed shaft and sensors rated for 0.2Hz-6KHz(626B02) and 0.2Hz-10KHz(626B01). The data was conveniently stored in MatLab format. Two datasets, one for the healthy gearbox and the other for the damaged gearbox, were utilized. Each set consisted of ten one-minute samples from every sensor. All the data was acquired under the conditions depicted in Table 1, below.

TABLE 1 NREL DATA ACQUISITION CONDITIONS

Main Shaft Speed (rpm)	Nominal HSS Speed (rpm)	Electric Power (% of rated)	Duration (min)
22.09	1800	50%	10

The data collection process involved several sensors installed at different locations on the NREL lab settings. Table 2 describes the specifications and locations of the different sensors used in data acquisition.

TABLE 2 SENSOR SPECIFICATIONS USED IN NREL DATA ACQUISITION PROCESS

Sensor Label/Signal	Description	Sensor Model	Units in Data File
AN3	Ring gear 6 o'clock	IMI 626B02	m/s^2
AN4	Ring gear 12 o'clock	IMI 626B02	m/s^2
AN5	LS-SH radial	IMI 622B01	m/s^2
AN6	IMS-SH radial	IMI 622B01	m/s^2
AN7	HS-SH radial	IMI 622B01	m/s^2

AN8	HS-SH upwind bearing radial	IMI 622B01	m/s^2
AN9	HS-SH downwind bearing radial	IMI 622B01	m/s^2
AN10	Carrier downwind radial	IMI 622B02	m/s^2
Speed	HS-SH		rpm

C. Data Pre-Processing

The data obtained from NREL consists of 2,400,000 data points in length for each sensor. With a 40 KHz sensor and a collecting time of 10 minutes resulted in exactly the same amount of data for each sensor. Each sensor dataset was then transformed into a 2400x1000 matrix for processing. The original data was transformed into a column vector matrix of 2400 rows and 1000 columns. In order to better detect peaks and troughs, signals in the time domain were transformed into the frequency domain. Two transformation approaches were considered: fast Fourier transform (FFT) and discrete cosine transform (DCT). DCT resulted in only real values, while FFT resulted in values with complex numbers. In this paper, the sensor signals were transformed into the frequency domain using FFT. The FFT approach was chosen over the DCT since the FFT naturally relates to the frequency domain of a signal and signifies direct interpretation of the primary harmonics of the original signal. Samples of the resulting raw FFT signals are presented in Fig. 6.

As a typical signal processing step after raw signal characterization, the resulting FFT signatures must be normalized with respect to amplitude as well as to the frequency range, which limits the size of the final signal. Furthermore, for signal filtration, a Gaussian Zero-Phase filter is used to low-pass filter the resulting FFT signals in order to eliminate high-frequency noise. The filter was adopted as described by Kuscu, et al., [13]. Fig. 7 depicts the corresponding normalized FFT signals according to the criteria described previously. This normalization process is crucial to the sound functionality of any classifier to be trained based on these samples, since it guarantees systematic references of amplitudes and frequencies so that the classifier is not confused with the training dataset.

The next step in pre-processing is to determine the similarity measure among the generated FFT signals. This step reveals how the sample space is distributed according to a similarity measure. An initial analysis was performed on some of the random column vectors by choosing a random index number from both the healthy and damaged dataset of each corresponding sensor. Euclidean distance and correlation coefficients were used to investigate effective characterization of the input signals by FFT, as shown in Fig. 8. Furthermore, the results of the analysis in Fig. 8 are validated in Fig. 9 by plotting the same data in a histogram which clearly shows the significant difference between the two techniques. Fig. 9 presents a statistical perspective on the effectiveness of the Euclidean-based histogram (blue) as compared to Correlation-based histogram (red). The two histograms clearly indicate that the Euclidean-based method is superior as a measurement model of feature vector similarity in which the spread and variance is favorable, and which produces more separable classes in a vector space. In the case of the Correlation-based method, the histogram shows low variance compared to the Euclidian-based method, which is ineffective for the clustering and classification processes.

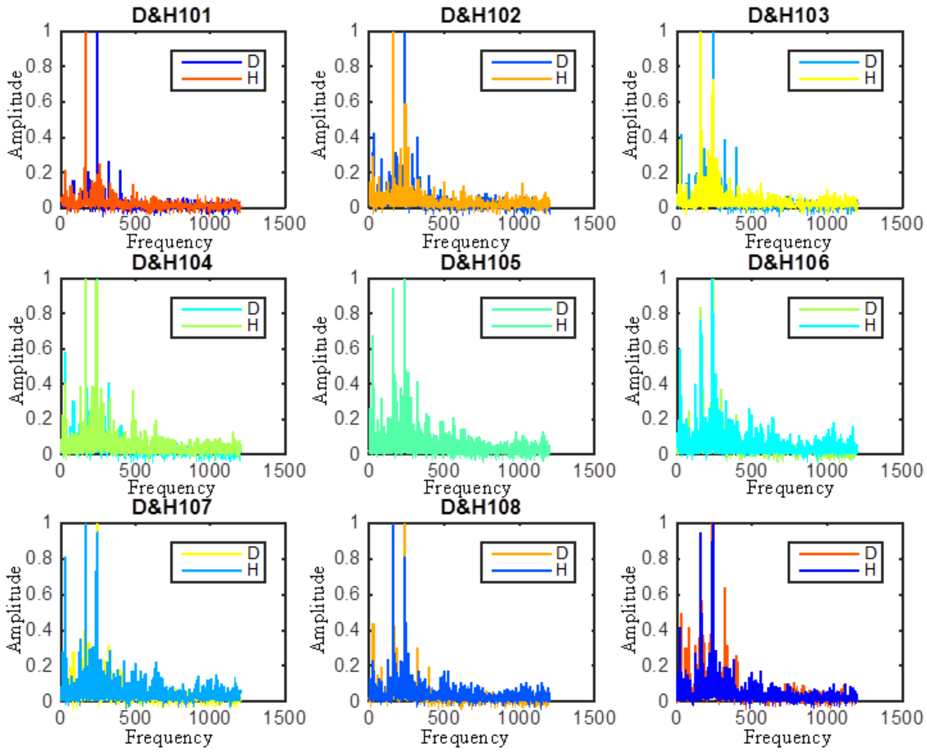


Fig. 6 Samples of the resulting raw FFT signals

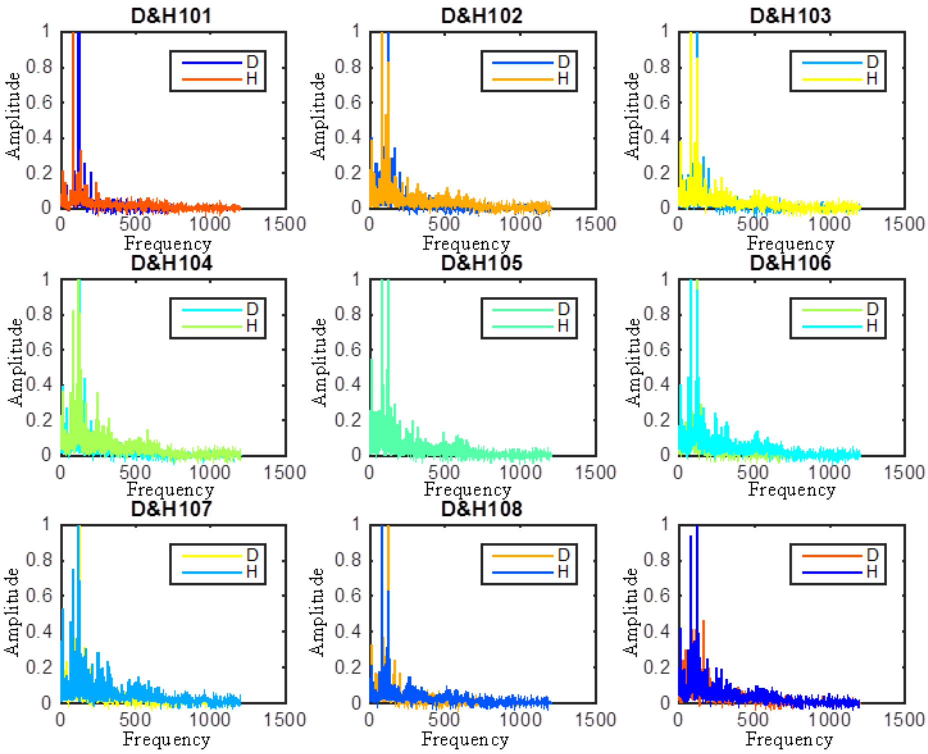


Fig. 7 Normalized FFT signals with respect to amplitude and frequency range

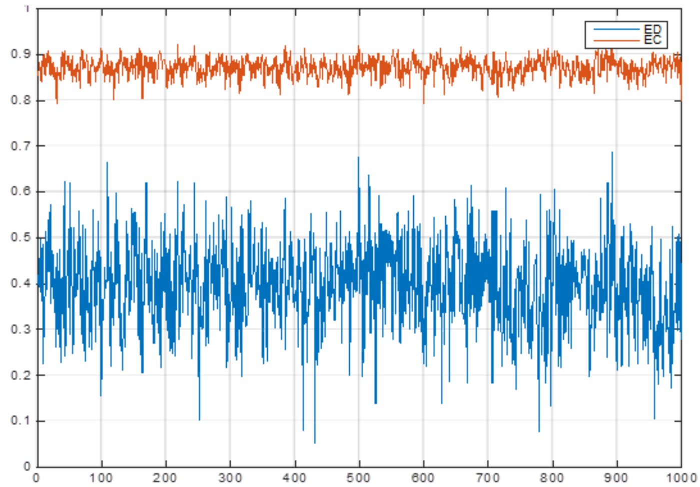


Fig. 8 Euclidian-based vs. correlation-based signal similarity measure comparison

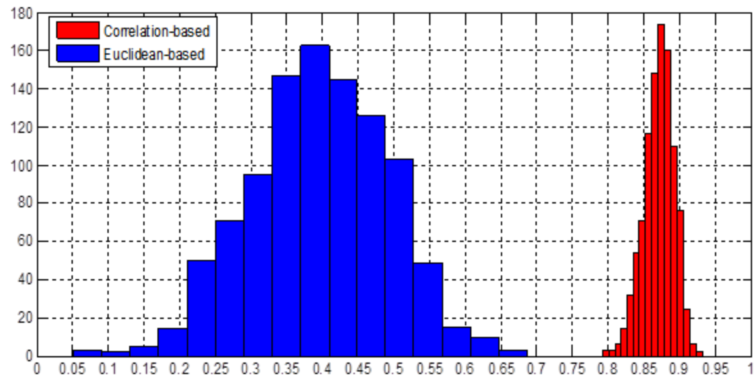


Fig. 9 Different data plotting perspective of Fig. 4 using histograms

D. Visual Comparison of Healthy Data vs. Damaged Data

To obtain a visual perspective of the effects of mechanical damage in the system on the collected sensor signal data, a 3D plot was generated for all the processed FFT signals from both the healthy and damaged data, as demonstrated in Fig. 10. As shown in Fig. 10, the damaged gearbox sensor data demonstrates increased noise, additional peaks, and the attenuation or strengthening of existing peaks present in the healthy state.

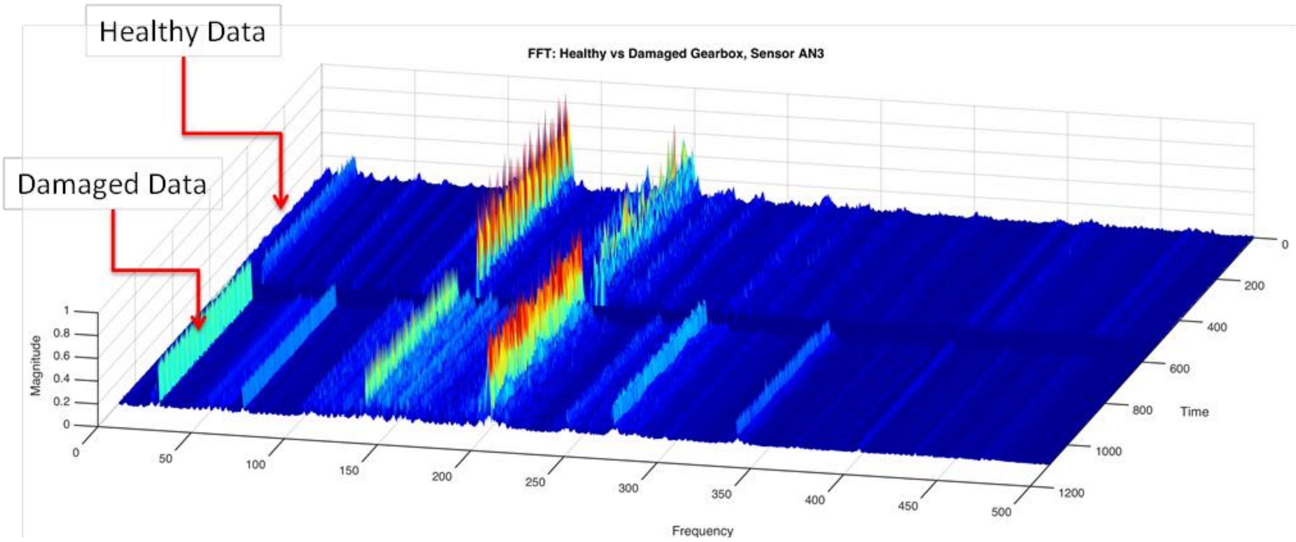


Fig. 10 Plotting healthy FFT data against damaged data

E. Anomaly Detection

To prove that the use of a neural network model can improve the detection rate, test were performed twice: once without the neural network model and the second with the neural network model. The basic algorithm is described as follows:

1) Input signal s = x(t)
2) Segment s for n sub signals, each of which is 1 second length $s_i = \{s[i]\}$, $i=k_l, k_l+1, \ldots, k_u$.
3) For each s_i, Calculate $S_i = FFT(s_i)$
4) Compute Euclidean distance for each consecutive $\{S_i, S_i+1\}$pair:

$$e = \sqrt{\sum_{k=1}^{n}(s_i - s_{i+1})^2}$$

5) Compute first derivative of e' = $\frac{de}{ds}$
6) Threshold e' based on a heuristic level:

$$e_t^{'} = \begin{cases} 1, & e^{'} > T \\ 0, & \leq T \end{cases}.$$

7) The final signal will indicate the locations of the detected anomalies in the input signal.

The algorithm is illustrated in Fig. 11 as it was applied to a sample input signal. The summary of this testing method using a simulated healthy signal with embedded simulated damaged segments (basic method) are:

True Positive (TP) = 53.33% and False Positive (FP) = 33.33%.

The second test was conducted using a neural network model, as shown in Fig. 12. The parameters of the ANN were as follows: 1) Type: A multi-layer Perceptron model was used as available in the standard MatLab Toolboxes. 2) Number of layers: three layers were used (input, hidden and output layer). A total of 16 neurons in the hidden layer were used after several experiments were conducted with layers consisting of few neurons and gradually increasing this number until the gained accuracy was insignificant. 4) Network connectivity was fully connected. 5) Training/testing: 1000 signal vectors were used in training/testing states. Heuristically, 80% of the data vectors were used for training and 20% were used for testing. The training of the ANN model and its parameters were used to train an intelligent classifier. Furthermore, sample testing results after using a trained ANN model is shown in Fig. 13. As shown in Fig. 13, the input signal (blue) was segmented into blocks and FFT features were computed and fed into the trained ANN model, which successfully detected all failures in the signal as automatically indicated by a red pulse function. The summary of this testing method using a real healthy signal with embedded real damaged segments (ANN Classifier): True Positive (TP) = 100%, False Positive (FP) = 9%.

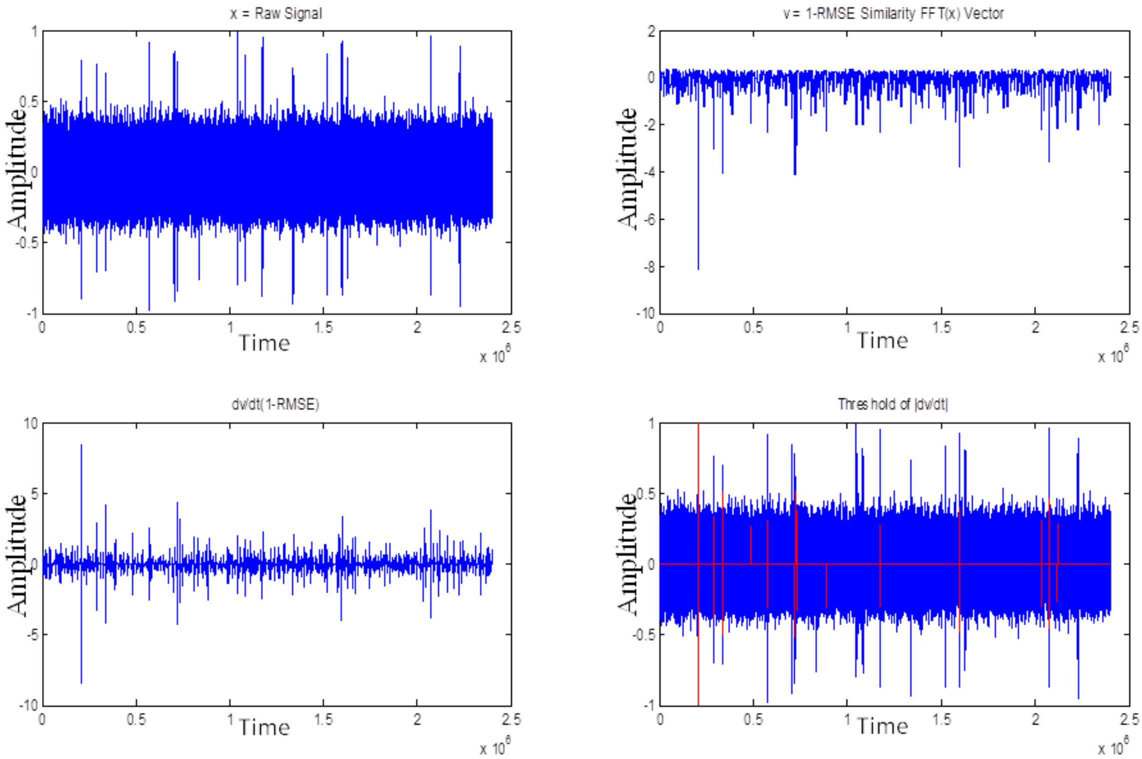


Fig. 11 Signal anomaly detection algorithm applied to a sample input signal

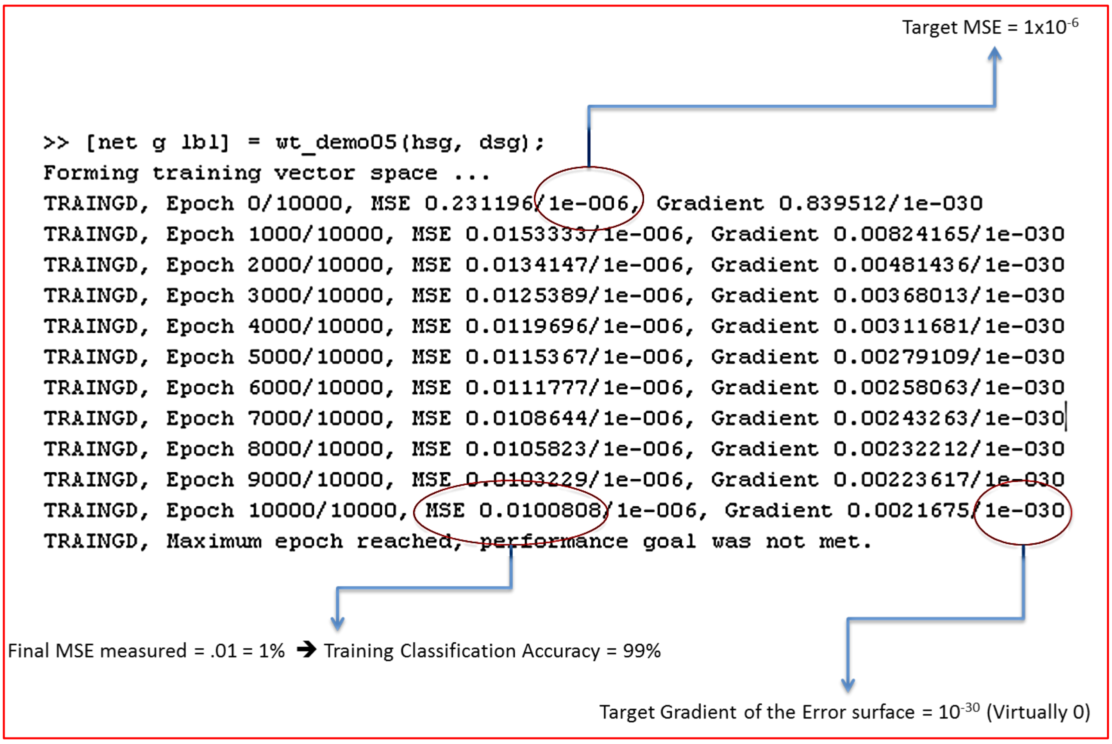


Fig. 12 Training artificial neural network model as a classifier

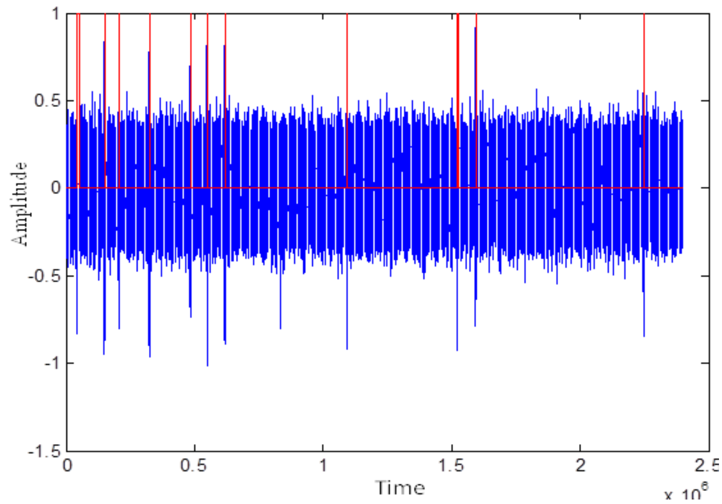


Fig. 13 Sample testing results after use of a trained ANN model

Finally, when the two testing methods (intelligence and basic) were applied to all signal space and studied, the true positive (TP) and false positive (FP) rates were determined, and the following observations were drawn based on the data presented in Figs. 14 and 15. As shown in Figs. 14 and 15, the intelligent method is superior to the basic method as follows: True Positive (TP) detection rates were 99.8% for the intelligent method vs. 71.3% for the basic method. As for the False Positive (FP) detection rates, they were equal to 18.3% for the intelligent method vs. 43.4% for the basic method. Both statistical measures strongly support the superiority of the intelligent method over the basic method.

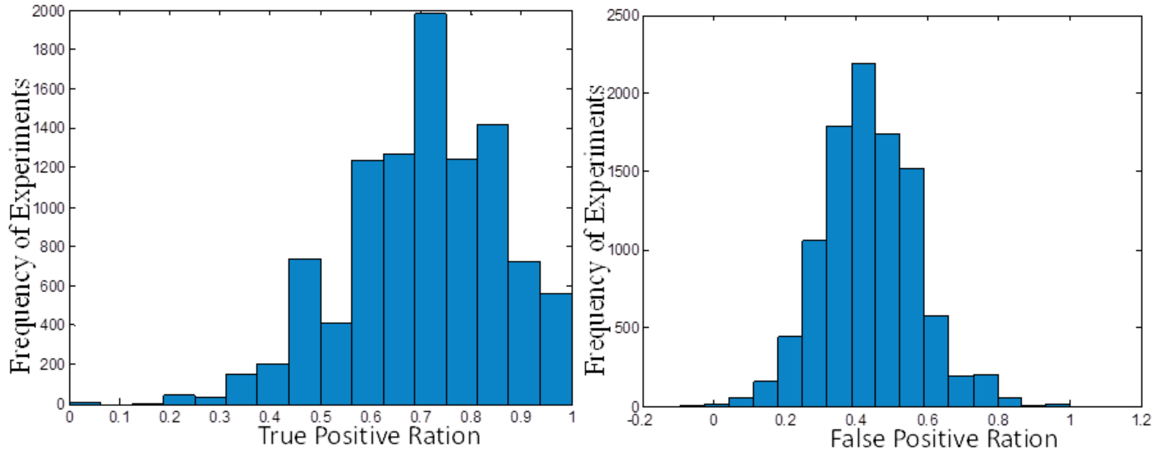
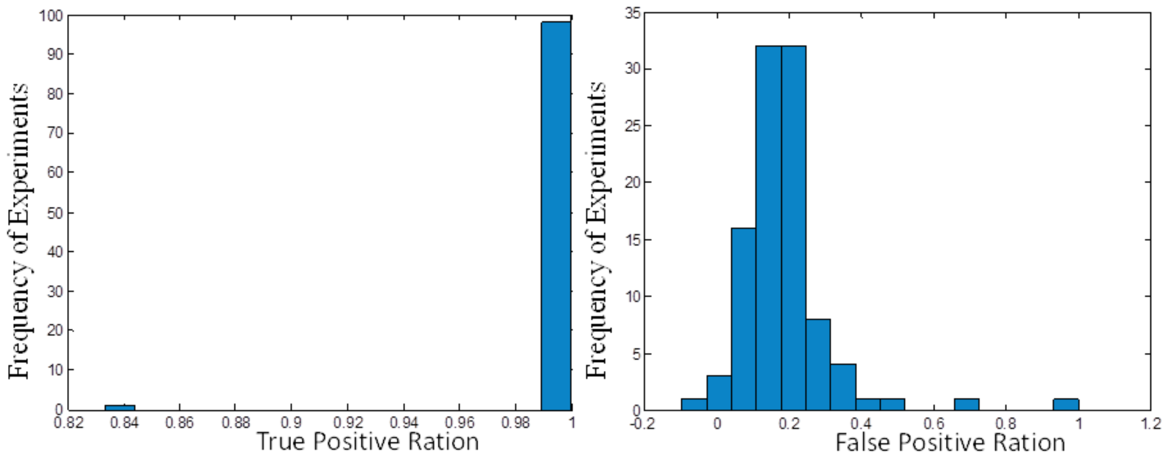


Fig. 14 (a) True positive (TP) results; (b) false positive (FP) results of basic method



(a) (b)

Fig. 15 (a) True positive (TP) results; (b) false positive (FP) results of intelligent method

V. RESULTS

In summary, the test results of both the basic and intelligent methods have been presented, as listed in Table 3.

TABLE 3 RESULTS OF THE BASIC AND INTELLIGENT METHODS

Method	Accuracy Measure	μ	σ
Basic	True Positive - TP	0.7133	0.1529
Intelligent	True Positive - TP	0.9983	0.0167
Basic	False Positive - FP	0.4342	0.1325
Intelligent	False Positive - FP	0.1825	0.1275

It is clear that the intelligent method is superior to the basic method, as verified by the TP and FP measures of accuracy and precision.

VI. CONCLUSION

This paper presented an intelligent method for failure detection in offshore wind turbines based on digital signal analysis. The proposed method used a multi-stage process to acquire, pre-process, train the model, test, detect the defect pattern and verify results from sensor signals. Signal characterization and defect classification were investigated for design choice. For the characterization stage, two techniques were investigated: discrete cosine transform (DCT) and fast Fourier transform (FFT). A pre-examination of the similarity measure among the resulting vectors of the two techniques demonstrated that a Euclidian-based similarity measure was superior to a correlation-based similarity measure by a significant factor. FFT was chosen over DCT because FFT naturally relates to the frequency domain of a signal and signifies a direct interpretation of the primary harmonics of the original signal. For the classification stage, two implementations of the process were executed and compared: one method did not utilize an intelligent agent while the other utilized a neural network model to classify signal vectors into healthy and damaged classes. The difference between the two implementations was highly significant as the intelligent agent demonstrated a very reliable classification accuracy > 90% while the other demonstrated an accuracy of 53%. Although one high-percent accuracy measure for true positive detection was achieved, the false positive results fell in the range of 11% and are not technically viable. The focus of future work will be to reduce the false positive rate to 5% or less and develop efficient methods according to which this may be achieved. The next step will be to change the parameters in the training process and then feed it with much more data to explore various methods of result improvement. With the convincing result of the present investigation, the next step will be to implement similar experiments on other structural components of wind turbines such as the nacelle vibration sensors and strain gauges, the yaw system and turbine blades.

VII. FUTURE WORK

Future work of interest include conducting a significant number of experiments with the current configuration of the ANN classifier and measure TP/FP rates for each trial, as well as analyzing the probability distribution function (PDF) of TP and FP through their respective histograms and computing their means and standard deviations. Heuristically, if TP > 90%, FP < 5%, results are satisfactory and presentable; otherwise, there are a number of optimization techniques that may be investigated including ANN parameter configuration; adjusting the number of hidden layers, the number of neurons per layer, the learning coefficient, or momentum factor; randomizing the training/testing sets; applying the same ANN to other sensor signals. Finally, this study targeted one single wind turbine, whereas in real world deployments, wind farms may include numerous turbines in each farm. Therefore, it is of high interest that a simulation of at least one wind farm that contains 50-100 turbines be performed and an investigation of the upscaling of the proposed method to handle such a typical wind farm. Additionally, the ways in which data may be collected, processed, and interfaced with the final human consumer and integrated with the other system components must be explored.

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* MOWER = Maryland Offshore Wind Energy Research

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