ANALYSIS OF WIND TURBINE GEARBOX SENSOR DATA

Aaron Rababaah, University of Maryland Eastern Shore, USA, (arrababaah@umes.edu)
Brian C. Miller, University of Maryland Eastern Shore, USA, (bcmiller@umes.edu)
Avinash Dudi, University of Maryland Eastern Shore, USA, (adudi@umes.edu)

ABSTRACT

We present an intelligent failure detection system based on signal data analysis in offshore wind turbines. The Main purpose of this research is to build an intelligent system which can detect structural failures in off-shore wind turbines. An approach involving Euclidean Distance and Correlation coefficient on transformed frequency domain signal are used to study the similarity between signals. Another approach involving Fourier Transforms is applied to study the differences between the peaks of frequencies and identifying a pattern. In this paper Artificial Neural Network classifier is used for detecting failures in off-shore wind turbines. Data collected, healthy and damaged gear boxes, from NREL is used for this experiment. A system embedded with a trained Artificial Neural Network works as an intelligent system to classify the incoming signal. Based on two different training approaches randomized and non-randomized cases of 100% true positive detection are achieved on gear box data. Future work is to extend this detection method other structural components of the wind turbine.

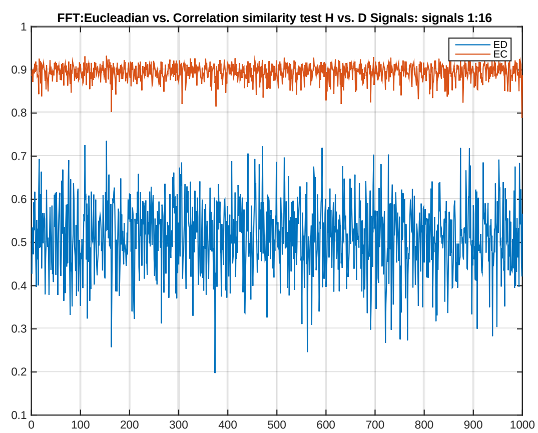
***Keywords**: NREL Gearbox Data, Artificial Neural Networks, Fourier Transform, Randomized sampling.*

INTRODUCTION

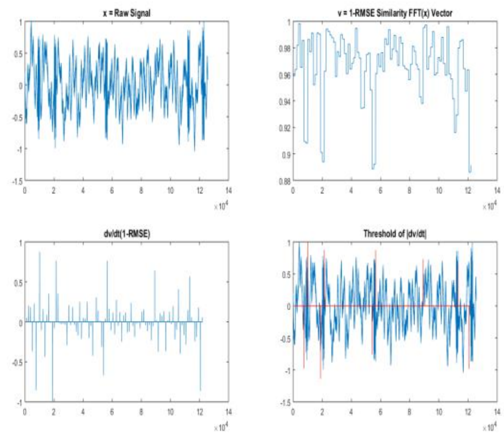
With demand for energy raising every day and climate change in mind a reliable renewable energy resource is what in need of hour. Wind energy provides that alternative with only small share of its huge potential utilized on both Off and On shore there is a lot of untapped potential which can be harnessed. With the advantages of no noise pollution, ecofriendly and much more consistent strong winds, offshore wind farms are perfect alternative for onshore wind farms. One of the most significant hurdle in developing offshore wind farms is operation and maintenance costs. Since these are installed miles away from shore, economics, logistics of maintenance and operation are way higher than onshore projects. Considering gearbox failures are leading reasons for higher maintenance in offshore wind energy farms, we decided to study gearbox data by comparing healthy and damaged sensor data. National Renewable Energy Laboratories (NREL) installed one healthy and one damaged gear box of 750 KW capacity from two decommissioned wind turbines in their lab and acquired data by installing sensors at different locations. Data is collected at 40 KHz sampling per channel using National Instruments PXI-4472B DAQ module and 8 sensors are industrial accelerometers with model numbers IMI 626B02 and IMI 622B01. Dynamometer test is conducted on damaged gear box and sent into the field for data collection. It experienced many faults of greater than 90C bearing temperature and two significant oil loss events. Unit is shipped back to NREL labs where sensor data was collected and sent to engineering company for detailed failure analysis. Significant damages are observed in signal signature when plotted and a corresponding sensor location can be identified with the help of provided documentation. For more information on gear box, failures, sensors and its placement please refer to [1] and [3]. In this paper we analyze signal data using different characterization techniques (FFT, DCT) [2] to find most accurate method to detect failures. We are using Artificial Neural Networks with Multi Layered Perceptron for classifying the signals. This technique utilizes supervised learning where pre-classified data set is fed to machine for training. Our method provides a comprehensive status of the turbine. During a fault condition, it is possible to know where the fault occurs 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 shut it down to prevent further damage to components. Our approach maximizes the economic utility of the wind turbine. Wang *et al* [4] approach is a gross assessment of the health of the turbine. The turbine is either in a good state or a faulty state. In Wang's model, is not possible to determine where a fault occurs. Upon entering a fault condition, the operator must shut down the turbine. The advantage of our system over other approaches is that it helps in determining the location of particular defects in the gearbox system rather than classifying the entire gearbox as defective. This allows an engineer to make an educated decision as to whether or not to shutdown the turbine or run it in a reduced capacity based on the classification of the fault.

THEORETICAL BACKGROUND AND TECHNICAL APPROACH

The information obtained from NREL is 2,400,000 data points length for each sensor. With 40 KHz sensor and collecting time of 10 minutes results in exactly the same amount of data. Each data set of a sensor is then transformed into 2400x1000 matrix for processing. The original data is transformed into a column vector matrix of 2400 rows and 1000 columns. In order to detect better peaks and descends, signal in the time domain is trasnformed into the frequency domain. Two transformation approaches are considered, Fast Fourier Transform (FFT) and Discrete Cosine Transform (DCT), where DCT results in only real values and FFT results in values with complex numbers. In this paper we chose to transform the signal into the frequency domain using FFT. There is an option to choose between DCT and FFT, or use the data directly in the time domain. An initial analysis is performed on some of the random column vectors by choosing a random index number from both the healthy and damaged data set of each corresponding sensor. Euclidean distance and correlation coefficient which signifies the similarity in statistical point of view between two data points are used in this initial process and they confirmed the discerning gap. One such example is shown below in figure (1).



Figure(1): Euclidean and Correlation



Figure(2): RMSE-1 and Derivative on random signal

A non-intelligent approach of detecting anomalies in a signal is designed based on RMSE-1 (Root mean square error). Whereever there is a steep change in the signal the difference is magnified using RMSE and a derviative at this location gives us a point of failure in signal. For testing this process a random signal is generated. Taking a fourier transformed healthy signal and randomly selecting a frequency by random number generator function and changing it by the product of another random number and difference between the original value and damaged signal value at the corresponding location. The difference between the original value and damaged signal keeps the value in practical range, above healthy value but below the maximum, thereby validating the signal. RMSE is applied on the randomly generated signal and healthy signal and the differences are derived for first order to get the slope, and a threshold is chosen for classification on trial basis. Since the number of index changes in the healthy signal to generate random signal are known, the accuracy is calculated by dividing the number of detected failures by the number of changes made. For this method, accuracy was around 60% true positives with a false positive rate of 20%. Refer to figure (2) for the associated plots.

EXPERIMENTAL WORK AND RESULTS ANALYSIS

Based on the method implemented to train the Artificial Neural Network classifier, experiments are conducted on the Healthy and Damaged gearbox signal data. Two training methods are implemented in this phase, in the first phase, the experiment data required for training the ANN is fed into the system in a in Non-Randomized manner. After the transformed signal is segmented into one thousand column vectors of which the first eight hundred (eighty percentage in all cases) is used for training and the remaining twenty percent is used as testing (validation). In the second experiment the training data set is randomly selected. For randomization, the indices of the column vectors are shuffled and the first eighty percent of data is used as training and rest for testing (validation). Tables 1 and 2 show the aggregated results of one hundred tests performed on each sensor data from the Randomized and Non-Randomized experiments respectively. A significant improvement in the accuracy values of True Positive (TP) detection and reduction in False Positive (FP) is observed for Randomized training when compared with the Non-Randomized training on same signal data. Four cases of one hundred percent accuracy results are observed in the random experiment when compared to one such case in the non-randomized experiment. One such case is shown below.

Sensor	TP Mean	TP Std. Dev	FP Mean	FP Std. Dev
AN3	0.999	0.009	0.150	0.094
AN4	1.000	0.000	0.073	0.077
AN5	1.000	0.000	0.074	0.083
AN6	0.997	0.015	0.065	0.080
AN7	0.995	0.026	0.336	0.115
AN8	0.997	0.015	0.077	0.084
AN9	1.000	0.000	0.083	0.084
AN10	0.998	0.020	0.087	0.086
Speed	1.000	0.000	0.082	0.081

Table: 1 Randomized experiment results

Sensor	TP Mean	TP Std. Dev	FP Mean	FP Std. Dev
AN3	0.999	0.008	0.437	0.123
AN4	0.999	0.008	0.065	0.097
AN5	0.999	0.008	0.086	0.073
AN6	0.996	0.020	0.082	0.088
AN7	0.999	0.008	0.246	0.123
AN8	0.998	0.014	0.084	0.075
AN9	0.997	0.017	0.072	0.083
AN10	0.999	0.006	0.069	0.090
Speed	1.000	0.000	0.081	0.078

Table: 2 Non- Randomized (Systematic) experiment results

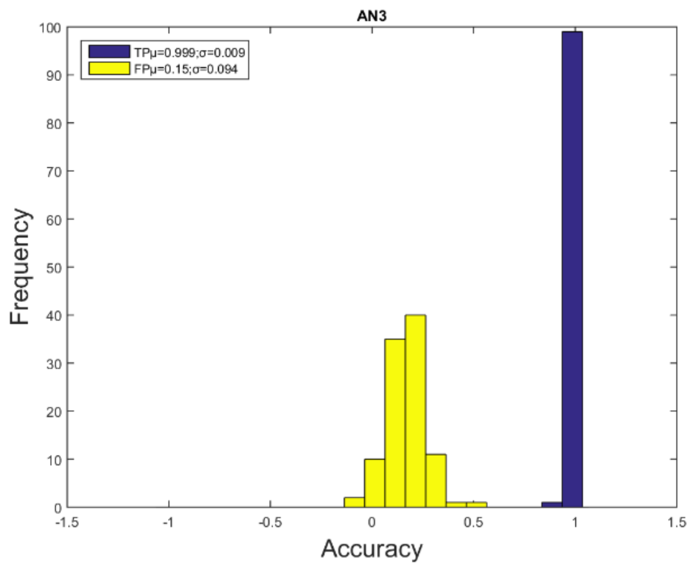


Figure (a): Accuracy results for AN3 random.

Figures (a) and (b) show the accuracy results for one hundred tests performed on AN3 sensor signal through randomized and non-randomized training approaches respectively. A three hundred percent reduction in mean false positive detection accuracy is observed in randomized training when compared to non-randomized. The legend text in both graphs contain the mean and standard deviation values for one hundred test results conducted on the associated sensor signal. This signifies that randomized training improves detection accuracies overall which is a desirable result. The mean false positive accuracies are 11.4% and 13.6% for all the sensors from randomized and non-randomized experiment respectively and a 15% reduction is observed.

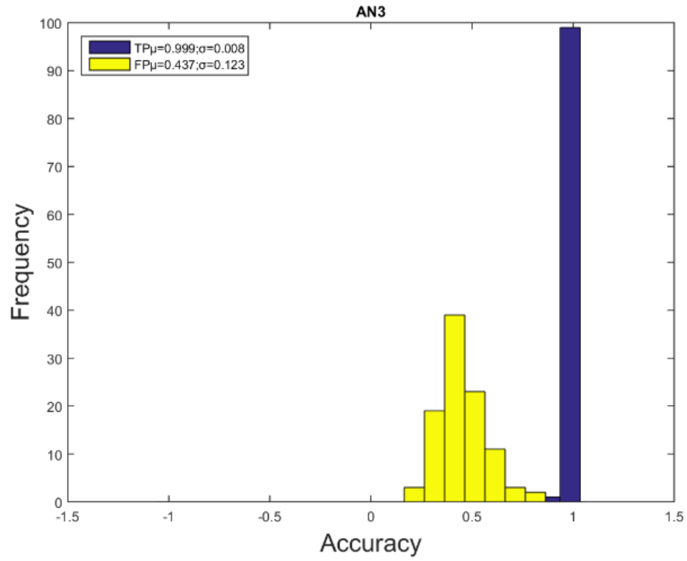


Figure (b): Accuracy results for AN3 non-random.

CONCLUSION AND FUTURE WORK

Even though one hundred percent accuracy for true positive detection is achieved, the false positive results are in the range of 11% and is not technically viable. Our focus regarding future work is to reduce the false positives and the target would be to bring it down to 5 % or less and develop efficient methods to do this. Our next step is to change the parameters in the training process and then feed the training process with much more data and explore different ways to improve the results. With this convincing result, our aim 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.

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