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Detecting Wind Turbine Blade Damage Using Supervised Machine Learning Algorithms

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1 ABSTRACT

Wind energy continues to see growth, solid performance, and attractive prices in the U.S. Improved plant performance over the last decades has been driven by larger turbines mounted on taller towers and featuring longer blades, which adds significant challenges to blade inspection and maintenance. Automated inspection process will reduce the downtime caused by sudden breakdowns and improve safety considerations for maintenance personnel. Developing a technology enabling condition-based monitoring would significantly reduce operation and maintenance costs. In this study the monitoring and analysis of wind tower vibration is proposed to detect structural damage of the blades. This method allows for monitoring of the operating wind turbine blades by instrumenting the tower with accelerometers and displacement meters. Tower vibrations data in form of eight signals measured in two blade health conditions were obtained using free and open-source software OpenFAST provided by the National Renewable Energy Laboratory (NREL). Utilizing different signal processing techniques, such as Fast Fourier Transform (FFT), Discrete Wavelet Transform (DWT), Scattering Wavelet Transform (SWT), and Statistical Feature Extraction (SFE) enables the comprehensive analysis of signals in different domains including time, frequency, and time-frequency. To classify the tower vibration signals obtained from simulation of healthy and faulty conditions of the blades Support Vector Machine (SVM) and Gradient Boosting Machine (GBM) classifiers are developed and employed.

2 INTRODUCTION

With the increasing concern of environmental protection and energy demand wind power has been developed rapidly all over the world (Arshad et al., 2019). Providing 10.1 % of electricity in the United States wind became the largest source of renewable electricity generation in the country. The growing capacity of wind turbines and continuously decreasing cost of wind-generated electricity made wind one of the most affordable sources of renewable energy. Despite this progress, the reduction in Operating and Maintenance (O&M) costs that account for up to 30% of energy costs for onshore and even higher for offshore wind farms and improved reliability remain top priorities in wind turbine maintenance (Kusiak et al., 2011).

Blade and tower damages are the most common types of structural damage in wind turbines (Chiang et al., 2008). The wind turbine blade (WTB) damage had the highest number of reported failures among all other components in the US in 2012 (Figure 1).

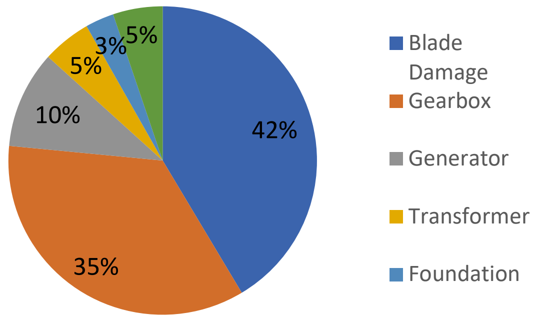

Figure 1 - Most frequently reported component damage (based on number of 2012 US reported claims) (GCube Insurance Services Inc., 2012).

Inspection and maintenance of the blades is difficult and expensive considering the height of the turbine and its location (usually remote), create a physical risk to the inspector (fatal accidents have been reported), require special lifting and handling equipment, such as cranes. Therefore, blade damage is the most expensive type of damage to repair and also has the greatest repair time (Shohag et al., 2017). Additionally, rotating mass unbalance due to even minor blade damage can cause serious secondary damage to the whole wind turbine system if prompt repair action is not taken and this can result in the collapse of the whole tower. Early detection of blade failures provides engineers with more time to offer cost-effective solution and can prevent catastrophic failure, which typically results in blade replacement and significantly decreases the turbine availability. Therefore, structural health monitoring (SHM) and damage detection of wind turbine blades has become a major research focus.

The process of SHM involves system monitoring through periodically sampled dynamic response measurements collected from sensors, the extraction and analysis of the damage-sensitive information from these measurements to identify the current condition of the structural health (Chiang et al., 2008).

There are numerous inspection techniques utilized when the blades are stationary. Periodic visual inspection, acoustic emission (Arora et al., 2014), wave propagation and vibration-based methods are widely used to evaluate the structural health of turbine blades. Visual inspection has serious limitations such as safety concerns, subjectivity, and inability to capture internal defects. Other approaches require the installation of a significant number of sensors, that are costly, difficult to instrument, and challenging to maintain. Additionally, the application of contact-type measurement sensors is very limited for rotating machinery due to the potential damage of contact sensors or their attachments (Inalpolat et al., 2020). The challenge is to develop a new technique to detect damage of the wind turbine blades in operation. This study proposes monitoring of the tower vibrations, considered to be a fault indicator to detect structural damage of the blades. This method will allow the monitoring of the wind turbine in-operation and decrease the labor and installation costs by avoiding the installation of many sensors and huge wiring. Additionally, it will decrease the number of data to be processed and stored.

This work proposes a data-driven approach based on signal processing, data mining and machine learning methods. Using this approach can make SHM of the blades more affordable and less time-consuming. Gathered SHM information can be used for condition-based maintenance to minimize inspection time, prevent fatal failures and unnecessary replacements, making wind energy even more affordable and attractive.

3 METHODOLOGY

The purpose of this study is to develop a tower vibration-based damage detection method by employing machine learning algorithms to determine whether a turbine blade in operation requires maintenance. The proposed method involves the following stages: data simulation, data processing and decision making (classification). The conceptual workflow is shown in the diagram (Figure 2).

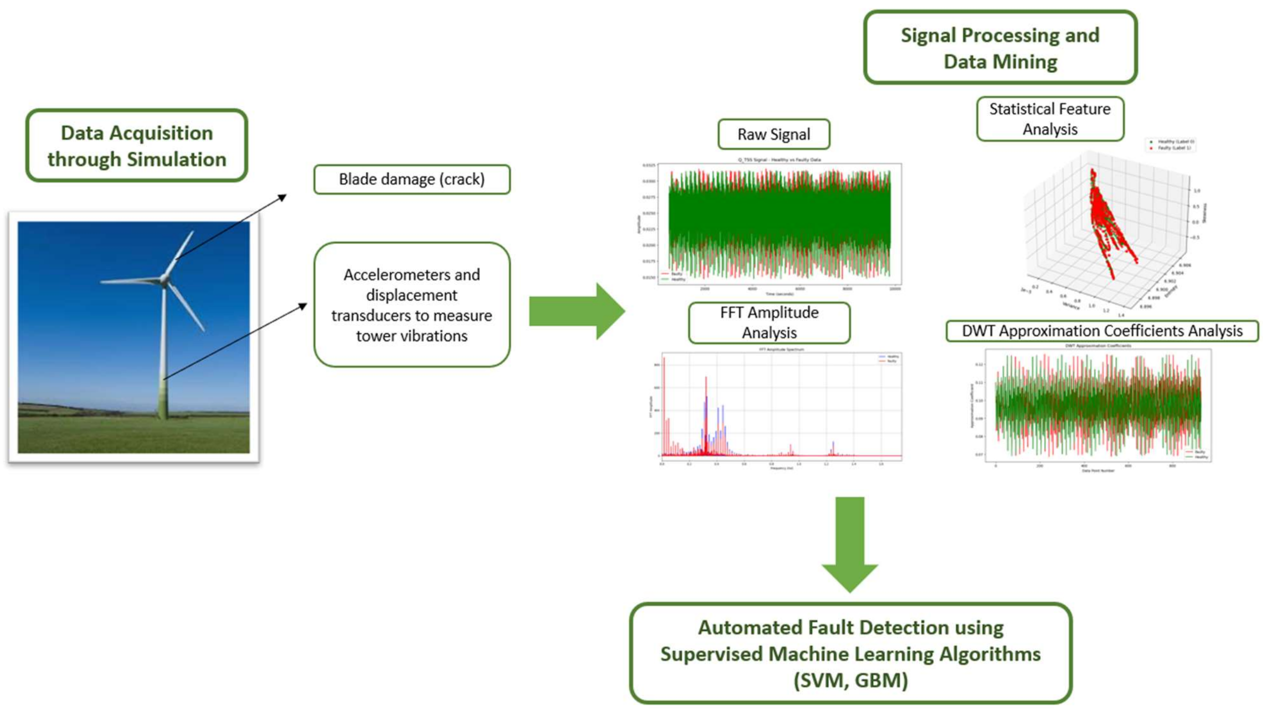

Figure 2 – Analysis workflow

3.1 Examined Structural Damage

Most common types of damages in wind turbine blades are splitting and fracture, cracks, and the de-bonding of the adhesive layer and joint with fatigue damage (Ciang et al., 2008). This study focuses on investigating early crack detection. Crack does not prevent the wind turbine from functioning, but the surface defects grow and develop and can lead to structural damage of the blade. The development of crack can be modeled by reducing local structural stiffness (Kim et al., 2014). The region between the root section and two-thirds of the blade length is the area where cracks most probably can occur (Rizk et al., 2020). This region is shown in Figure 3.

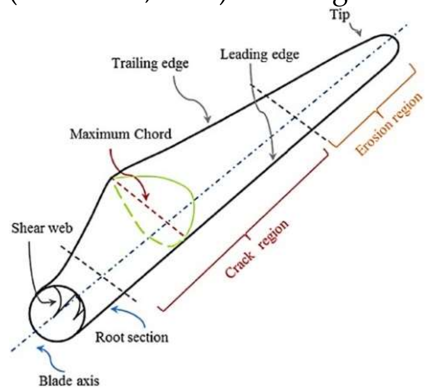

Figure 3 – Crack region

In this study the damaged condition is implemented by reducing the structural stiffness by 30% at a specific point (0.5561 of the blade length from blade root).
Wind turbine blades affected by cracks can be easily repaired to prevent structural breakdowns. This is done by filling the cracks with special resins, fillers, or gels, which effectively seal the cracks, prolong the blade's lifespan, and prevent further damage.

3.2 Data Simulation

The present study relies on the simulation data obtained using free and open-source software OpenFAST provided by the National Renewable Energy Laboratory (NREL). FAST joins aerodynamics models, hydrodynamics models for offshore structures, control and electrical system (servo) dynamics models, and structural (elastic) dynamics models to enable coupled nonlinear aero-hydro-servo-elastic simulation in the time domain. OpenFAST is based on advanced engineering models—derived from fundamental laws, but with appropriate simplifications and assumptions and enables the analysis of a range of wind turbine configurations. OpenFAST has modularization framework shown in Figure 4, where various mathematical models are implemented in distinct modules and interconnected to solve for the global, coupled, dynamic response of a system.

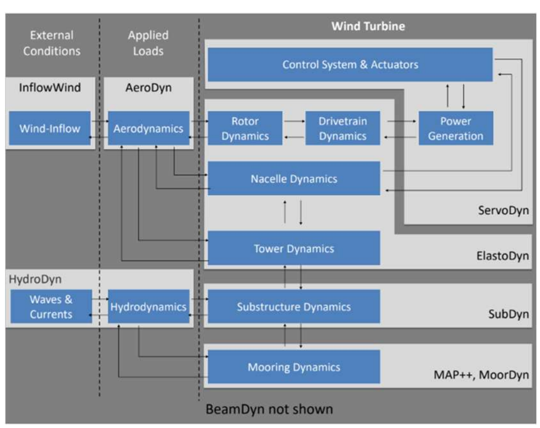

Figure 4 – OpenFAST modularization framework

Tower vibration data were simulated for a representative utility-scale multimegawatt turbine now known as the “NREL 5-MW baseline wind turbine”, which is a fictitious but representative multi-MW wind turbine. This wind turbine is a conventional three-bladed upwind variable-speed variable blade-pitch-to-feather-controlled turbine. The specifications of NREL 5-MW can be found on the NREL official website (https://www.nrel.gov/docs/fy09osti/38060.pdf).

The average wind speed and turbulence intensity used in the simulation are 8 m/sec, and 10% respectively. Because of the turbulence effect the wind speed varies in all directions, causing the excitations of the blade and tower in all directions. The accelerations and displacements of the first two fore-aft (FA) and side-to-side (SS) modes of tower vibrations are obtained from the virtual sensors. The corresponding modes of the wind tower are displayed in Figure 5.

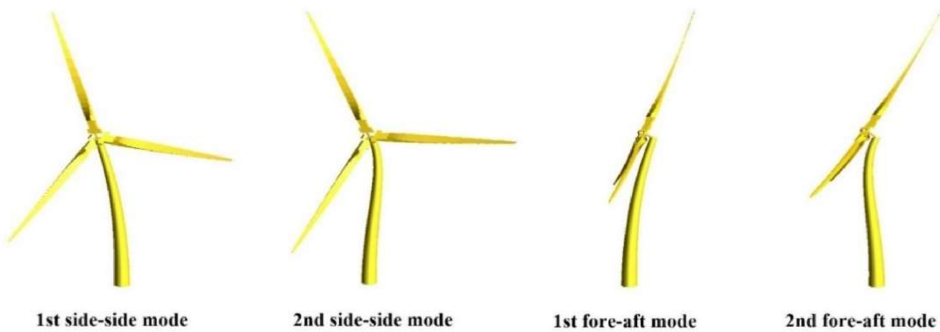

Figure 5 – Eigenmodes of the wind turbine tower

The vibration signals of the wind turbine tower were captured during operation in two different states: healthy, and faulty. 930 samples of healthy vibration signals in form of acceleration and displacement were measured under healthy operation condition of the wind turbine blade. The cracks on the blades were modeled by reducing the local structural stiffness of the blade material, and 930 faulty signals were measured. A correlation between blade stiffness and tower vibrations is inferred in this work and will be used for blade health status. The length of each signal is 10 seconds, and the sampling rate is 100 Hz.

A total of eight time-domain tower vibration signals in form of displacement (1^{st} and 2^{nd} FA mode, 1^{st} and 2^{nd} SS mode) and acceleration (1^{st} and 2^{nd} FA mode, 1^{st} and 2^{nd} SS mode) were obtained through simulation (Figure 6).

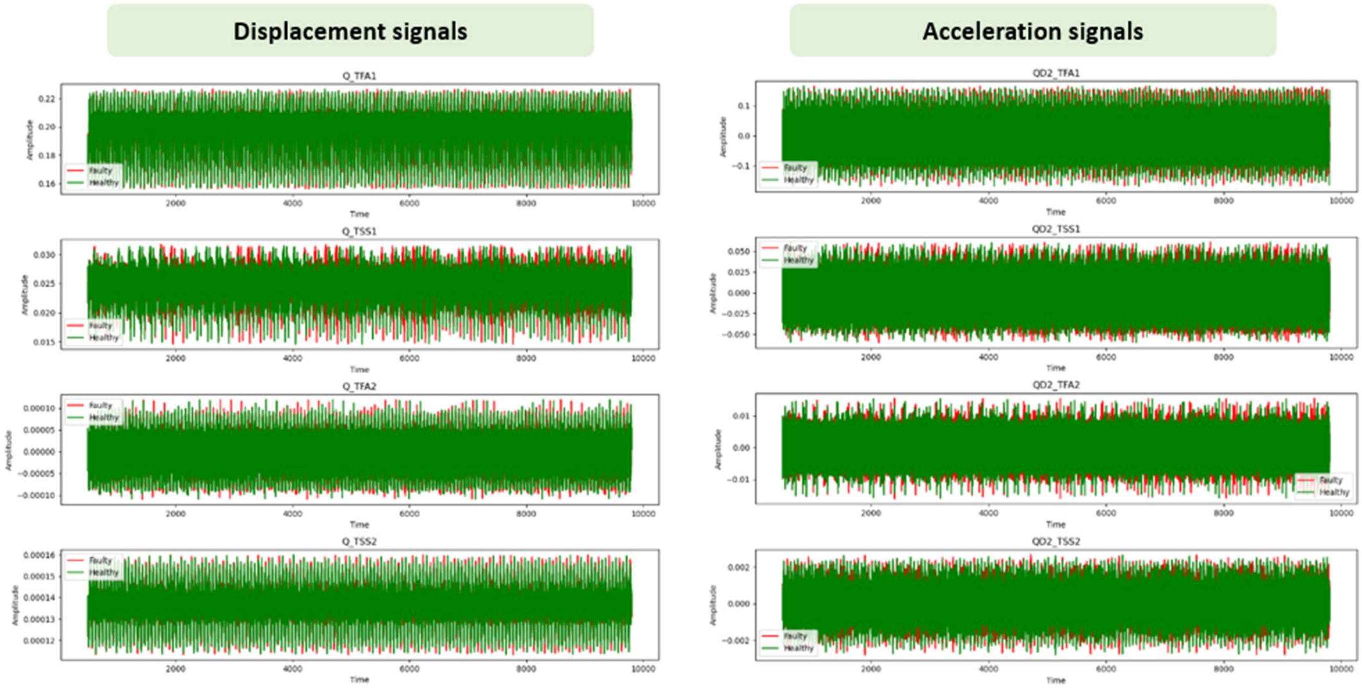

Figure 6 – Tower vibration signals

A comparison between tower vibrations signals for healthy and faulty blade conditions indicates that these two conditions are mostly distinguishable in displacement of the 1st SS mode signal (Q_TSS1). Hence, this signal is selected for further analysis in this study.

3.3 Signal Processing and Data Mining

Vibration signals contain many noises and useless data, making it challenging to extract useful and clean information about the structural condition. The valuable information about the structural condition is hidden and cannot be distinguished easily. Also, there are many vibration sources in a wind turbine, such as the main bearing and gearbox. It is crucial to only focus on the blade and tower vibrations, as blade damage detection is the focus of this work. Therefore, signal processing and data mining are essential steps in vibration monitoring. This work includes a range of signal processing techniques in time, frequency, and time–frequency domains.

In this study four different input vectors were constructed and fed to the predictive models: Statistical Features (SF), containing multi-domain feature set, Fast Fourier Transform Amplitudes (FFTA), Discrete Wavelet Transform Approximations (DWTA), Scattering Wavelet Transform Representations (SWTR). Each of these input vectors contains information indicative of the WTB health condition.

Transforming vibration signals to the frequency domain using FFT is one of the most common approaches in fault diagnosis applications. It makes some patterns not visible in the time domain apparent and gives a better understanding of vibrational behavior by providing clear information about dominant frequencies. FFT is defined by the following equation:

$$X(f) = \int_{-\infty}^{+\infty} x(t)e^{-i\omega t}dt, \qquad \omega = 2\pi f, \tag{1}$$

where t is time, f is frequency, X(f) is Fourier transform of time domain signal.

The FFT amplitudes of wind tower vibration signal are extracted utilizing the **np.fft.fft()** function in Python. This function computes the one-dimensional Discrete Fourier Transform (DFT) with the efficient Fast Fourier Transform (FFT) algorithm, generating a high-dimensional feature vector. To reduce the dimensionality of this vector, the Principal Component Analysis (PCA) was applied. Subsequently, the first 10 principal components (PCs), explaining 99.65% of the variability in the data, were employed as the input vector for the classifiers. These top 10 PCs can be used in classification models without losing much of the information in the data, while significantly reducing its dimensionality.

FFT are well-suited for the analysis of stationary signals, where frequency content is relatively constant over time. Due to the presence of turbulence and varying stochastic wind speeds, wind turbine tower vibration signals are non-stationary. In such cases, multi-resolution methods such as Discrete Wavelet Transforms (DWT), providing a time-frequency representation of the signal are more effective for the study of non-stationary signals. DWT is defined by the equation:

$$DWT_{\psi}^{x} = \Psi_{\psi}^{x}(j,k) = \frac{1}{\sqrt{2^{j}}} \int_{-\infty}^{+\infty} x(t)\psi(\frac{t - 2^{j}k}{2^{j}})dt \tag{2}$$

where i and j are counters, s=2^{j} is scale, $\tau = 2^{j}k$ – translation, and ψ is a mother wavelet.

DWT with a four level Daubechies-1 (db1) wavelet function was applied to the tower vibration signal. This transformation was performed using the **'PyWavelets'** library in Python. The approximation coefficients of the fourth level were extracted and used as the input vector for the classifier.

Scattering Wavelet Transform (SWT) operates equivalent to deep convolutional network. It is formed by a cascade of wavelets, modulus nonlinearities, and lowpass filters. It generates representations that are time-shift invariant, robust to noise, and stable against time-warping deformations. This method demonstrated its effectiveness in many classification tasks. SWT representations of a vibration signal were computed using **'kymatio'** library in Python and utilized for classification in this study.

Statistical feature extraction focuses on retrieving the information relevant to the blade condition. A total of 28 features, including eighteen time-domain, four frequency-domain and six time-frequency domain features extracted from the original vibration signal. The full list of these features is provided in Table 1.

Table 1 – Statistical features

Time Domain Features	**Frequency Domain Features**	**Time-Frequency Domain Features**
Mean	Mean Frequency	IMF1 Mean
Root Mean Square	Root Mean Square Frequency	IMF1 Root Mean Square

Root	Frequency Center	IMF2 Mean
Variance	Root Variance Frequency	IMF2 Root Mean Square
Standard Deviation		IMF3 Mean
Skewness		IMF3 Root Mean Square
Kurtosis		
Entropy		
4th Central Moment		
FM4		
Median		
Root Sum of Squares		
Shape Factor		
Crest Factor		
Impulse Factor		
Clearance Factor		
Skewness Factor		
Kurtosis Factor		

The Empirical Mode Decomposition (EMD) energy method is utilized to mine for time-frequency domain features in this study. By this method, the original vibration signal is decomposed into a finite stationary Intrinsic Mode Functions (IMFs). Based on EMD algorithm, original vibration signal can be decomposed into a set of IMFs (Wang et al., 2015):

$$x(t) = \sum_{j=1}^{n} c_j(t) + r_n(t) \tag{3}$$

where $c_j(t)$ is the j-th IMF of the signal x(t), and $r_n(t)$ is the final residue. The means and root mean squares of the first 3 IMFs are selected as time-frequency domain features.

To reduce the number of candidate input variables while preserving the relevant information and discarding the redundant one, two feature selection techniques were applied – Random Forest (RF) Feature Importance and Fisher's Score. The corresponding RF Feature Importances and Fisher's scores in descending order are provided in Figure 7.

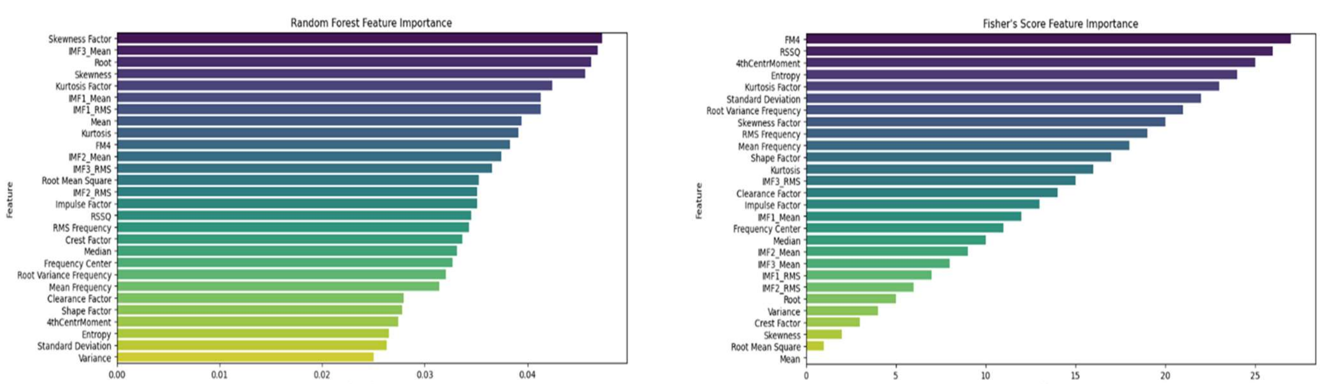

Figure 7 – RF Feature Importance and Fisher's score plot

Using the smaller subset of the features lowers the complexity of the model, makes it easier to understand, reduces the computation time and helps avoid overfitting by enhancing generalization, and often improves the performance of the model.

Figure 8 shows the flow chart of the proposed fault diagnosis approach using multi-domain statistical features.

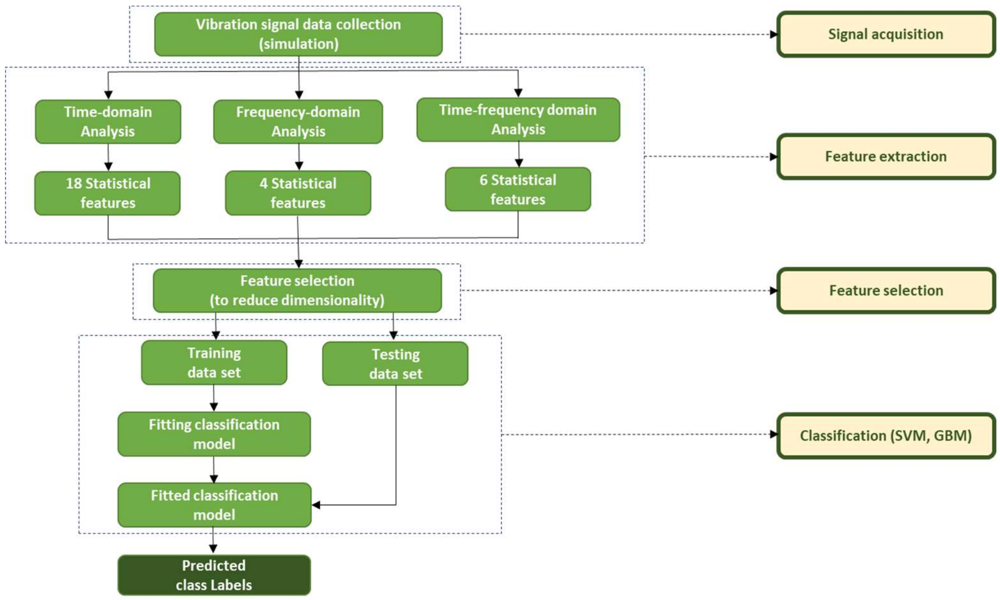

Figure 8 – Flow chart of the proposed approach (using multi-domain statistical features)

3.4 Classification

In this study, four different feature vectors containing information about blade health condition were utilized as input vectors for predictive modeling. Support Vector Machine (SVM) and Gradient Boosting Machine (GBM) are two classification algorithms that were developed and employed to detect the presence of the blade damage (crack) by monitoring tower vibration signal.

SVM is commonly used for classification problems. It is a supervised machine learning algorithm that classifies data by finding the optimal hyperplane, that maximizes the distance between different classes in a multidimensional space. SVM has the ability to produce linear as well as non-linear boundaries by using kernel functions to transform the feature space. In this study, various types of SVM kernels, including 'poly', 'rbf', and 'sigmoid' were explored when searching for optimal hyperparameters.

GBM is a machine learning ensemble technique that combines the predictions of multiple weak learners, typically decision trees, sequentially. GBM is known for its prediction speed and accuracy even when working with large and complex datasets.

Certain preprocessing steps, such as feature scaling and mean normalization, were taken before applying machine learning (ML) algorithms. These transformations of the data help the algorithm to converge to an optimal solution faster and are very useful for algorithms that are sensitive to the scale of the input features, such as SVM. The next step was to randomly split the data into training (75%) and testing (25%) sets to evaluate the models' performance on unseen data and to determine how well the algorithm can generalize.

The hyperparameter tuning was performed using the 5-fold cross-validation technique, utilizing the **GridSearchCV()** function from the '**sklearn**' library in Python. The code loops through all combinations of the parameters within a parameter grid and selects the model with the highest classification accuracy. Using optimal parameters improves predictive power of the model. Performing cross-validation for both classification models was computationally very intensive. Utilizing optimal hyperparameters resulted in a significant accuracy improvement compared to the default settings.

Assessment of model performance is very important in practice, since it defines the choice of machine learning algorithm or model and gives us a measure of the quality of the chosen model. Classification accuracy, providing the percentage of correctly classified samples is the most straightforward evaluation of the classification models. Since the data set of vibration signals used in this analysis is balanced, classification accuracy will be the primary evaluation metric. A confusion matrix provides more detailed comparison between true and predicted class. This matrix is often used to calculate other metrics, such as accuracy, precision, recall, F1-score. Both false alarms (model predicts 1 when the actual value is 0) and missed damage detection or false dismissal (model predicts 0 when the actual value is 1) are costly in the case of WTB health diagnostics. Thus, it is important to maintain a balance between minimizing false alarms and efficiently detecting faulty conditions. Precision is the proportion of true positives among all predicted positives. A high precision is very important to minimize false alarms. Recall is the proportion of true positives among all actual positives. A high recall indicates that the model is effective at detecting faulty signals. F1 Score is the harmonic mean of precision and recall. The ROC (receiver operating characteristic) curve is the plot of the true positive rate (TPR) against the false positive rate (FPR) at each threshold setting. The AUC is the area under the ROC curve, it measures the ability of a classifier to distinguish between classes. Finally, classification accuracies obtained through 5-fold cross-validation are provided for a robust evaluation of the models' performances. These cross-validated accuracy values are more reliable and provide more realistic models' performances.

4 RESULTS AND DISCUSSION

In this section, the results of the proposed fault diagnosis method for WTB based on the monitoring of wind tower vibrations are presented. The data set utilized in this study was obtained through simulation. The results are provided for two classifiers, employing four different input vectors: multi-domain SF, FFTA, DWTA, and SWTR. In this section the focus will be on the 1st SS mode signal (Q_TSS1) due to the better separability between blade healthy/faulty conditions in the plots.

4.1 Multi-Domain SF

Among the 28 extracted multi-domain features one of the most important ones according to RF Feature Importance technique are Skewness Factor, IMF3_mean, Root, Skewness, and Kurtosis Factor. Similarly, FM4, RSSQ, 4^{th} Central Moment, Entropy, and Kurtosis Factor were highlighted as significant features according to Fisher's Score technique. The plots in Figure 9 demonstrate that these features allow for a good separability between healthy and faulty signals.

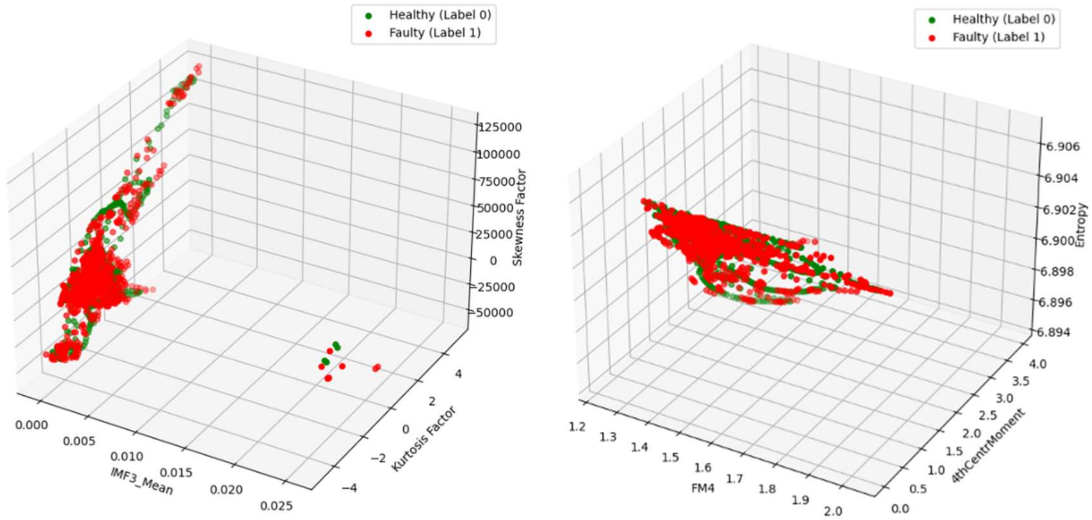

Figure 9 – Statistical features of healthy and faulty signals

The classification results provided in Table 2 were obtained for 2 classifiers (GBM and SVM) across 3 different scenarios:

- Employing the full set of features (28).
- Employing a reduced subset (the top 15 variables in the list, sorted descending order) of features, selected by RF Feature Importance technique.
- Utilizing a reduced subset (the top 15 variables in the list, sorted descending order) of features selected by Fisher's Score technique.

Table 2 – Classification results based on multi-domain SF

Classifier	**GBM**			**SVM**		
Performance Metric	**Full**	**Reduced (RF)**	**Reduced (Fisher's Score)**	**Full**	**Reduced (RF)**	**Reduced (Fisher's Score)**
Testing Accuracy	0.7462	0.7333	0.757	0.8043	0.7591	**0.8495**
Precision	0.7284	0.7315	0.7489	0.8213	0.7545	0.8632
Recall	0.7545	0.7054	0.7455	0.7589	0.7411	0.817
F1-score	0.7412	0.7182	0.7472	0.7889	0.7477	0.8394
AUC	0.81	0.81	0.84	0.81	0.78	0.91

SVM yielded a slightly higher testing accuracy of 80.43% when employing the full set of features. Both classifiers benefitted from employing a reduced subset of the top 15 features selected by Fisher's score, indicating that this simpler model is able to better generalize to new/unseen data than more complex model utilizing all 28 features. SVM achieved the highest testing accuracy of 84.95% when employing this reduced subset of features (the ROC curve and confusion matrix of this SVM model are provided in Figure 10).

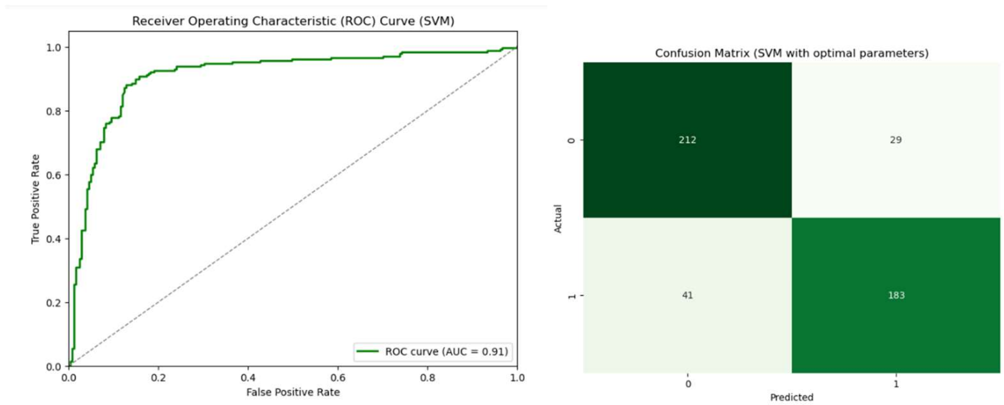

Figure 10 – ROC curve and confusion matrix for SVM with the highest testing accuracy (utilizing reduced subset of multi-domain statistical features as input data)

4.2 FFT Amplitudes

FFT provides frequency information about the signal by converting it into individual spectral components. As shown in Figure 11, the frequency spectrum of wind tower vibrations ranges from 0 Hz to 1.5 Hz, indicating that wind turbine systems are low-frequency structures.

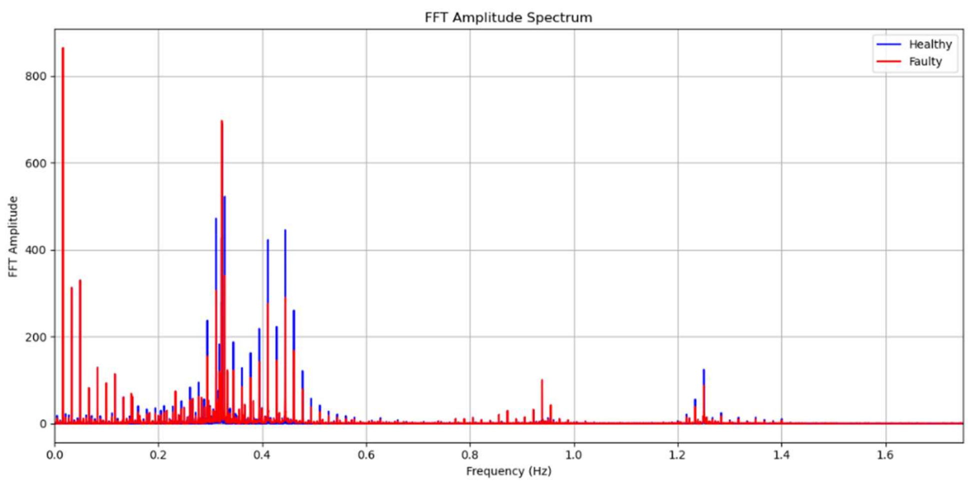

Figure 11 – FFT amplitude spectrum of wind tower vibration displacement

Results derived from utilizing the top 10 PCs computed from FFT amplitudes of the wind tower vibration signal as the wind turbine blade damage indicator are provided in Table 3.

Table 3 – Classification results based on FFT Amplitudes

Classifier	GBM	SVM
Performance Metric		
Testing Accuracy	**0.8323**	0.7656
Precision	0.8544	0.7833
Recall	0.7857	0.7098
F1-score	0.8186	0.7447
AUC	0.91	0.77

GBM achieved a testing accuracy of 83.23% when utilizing the first 10 principal components computed from the FFT amplitudes of the vibration signal (the ROC curve and confusion matrix of this GBM model are provided in Figure 12).

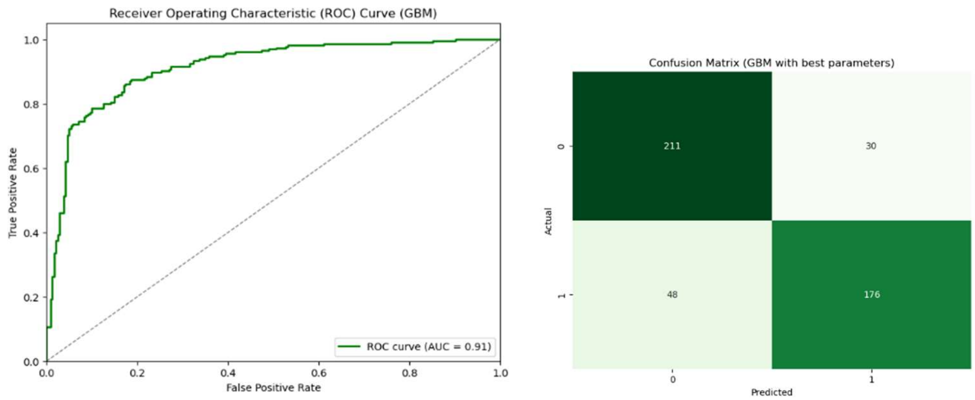

Figure 12 – ROC curve and confusion matrix for GBM with the highest testing accuracy (utilizing top 10 PCs computed from the FFT amplitudes as input data)

4.3 DWT Approximation Coefficients

Different wavelet families including Daubechies (db), Symlets (sym), and Morlet (morl) and different wavelet decomposition levels were investigated to find the most suitable parameters for wavelet decomposition of a vibration signal. According to the experimental results, the optimal selection of the mother wavelet function is "db1" from Daubechies family, and the most suitable decomposition level is four. Only approximation coefficients at level 4 were fed to the classifiers. Classification results when utilizing DWT approximation coefficients as input data are provided in Table 4.

Table 4 – Classification results based on DWT Approximation Coefficients

Classifier / Performance Metric	GBM	SVM
Testing Accuracy	0.9113	**0.9946**
Precision	0.9227	1.0
Recall	0.8978	0.9892
F1-score	0.91	0.9946
AUC	0.96	1.0

SVM achieved an outstanding testing accuracy of 99.46%. Figure 13 displays the confusion matrix and ROC curve for SVM.

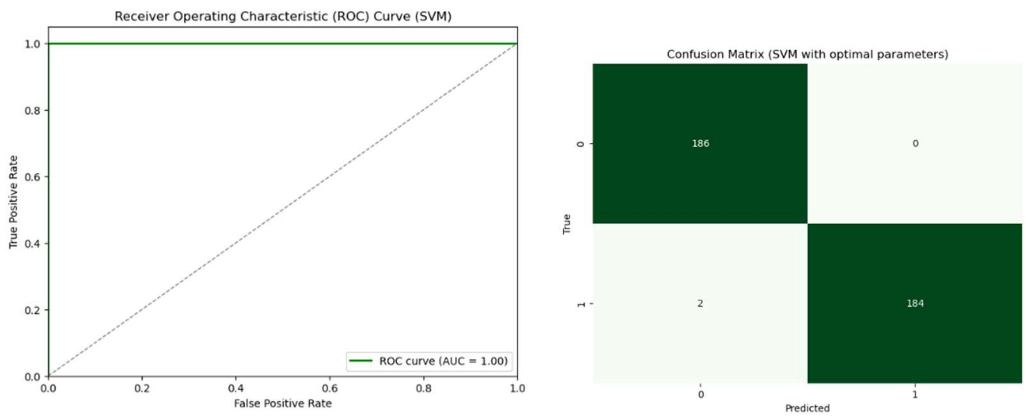

Figure 13 – ROC curve and confusion matrix for SVM with the highest testing accuracy (utilizing DWT approximation coefficients as input data)

4.4 SWT Representations

Scattering Wavelet Transforms were applied to the vibration signal with a maximum scale equal to 16. Subsequently, only the last scale representation was utilized as the input data for the classifier. This decision was made because the representations at lower scales contain more noise and irrelevant variation in the data. Classification results when utilizing last scale SWT representation as input data are provided in Table 5.

Table 5 – Classification results based on SWT Representation

Classifier	GBM	SVM
Performance Metric		
Testing Accuracy	0.7097	**0.9054**
Precision	0.6961	0.9286
Recall	0.7054	0.8705
F1-score	0.7007	0.8986
AUC	0.76	0.95

A high accuracy of 90.54% was demonstrated by SVM classifier. Figure 14 displays the confusion matrix and ROC curve for SVM.

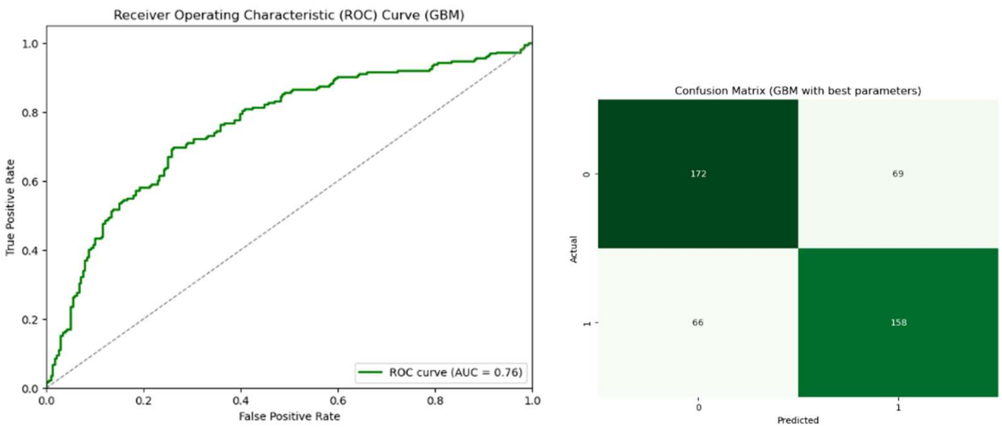

Figure 14 – ROC curve and confusion matrix for SVM with the highest testing accuracy (utilizing SWT representation as input data)

Table 6 summarizes the classification accuracies of both classifiers obtained through 5-fold cross-validation from utilizing four different input vectors for the classifiers.

Table 6 – Classification results obtained through cross-validation.

Classifier	GBM	SVM
Input data		
Multi-domain statistical features (reduced subset selected by Fisher's score)	81.99%	90.22%
FFT Amplitudes (first 10 PCs)	90.48%	78.71%
DWT approximation coefficients (4^{th} level approximation coefficients)	93.44%	**99.84%**
SWT representation (the last scale representation)	78.6%	96.67%

The highest accuracy is achieved when employing DWT approximation coefficients as a faulty signal indicator. The classifier is able to identify the presence of the blade crack employing DWT approximation coefficients of the vibration signal with a remarkable accuracy of about 99%. This result highlights the effectiveness of applying a multi-resolution signal processing technique. It provides a time-frequency representation of the signal and proves that DWT is well-suited for analyzing non-stationary transient signals, such as wind tower vibration.

5 CONCLUSIONS AND FUTURE STUDIES

In this study, a comprehensive analysis of wind tower vibration signal was performed to understand the blade damage detection ability of two supervised machine learning algorithms, support vector machine and gradient boosting machine. Four different input vectors, containing the information about blade health condition, namely multi-domain statistical features, FFT amplitudes, DWT approximation coefficients and SWT representations were fed to the classifiers. The results suggest a high potential for detecting wind blade damage (cracks) by utilizing wind tower vibration signal, specifically displacement of the first side-to-side (SS) mode of tower vibrations. Both classifiers were able to classify signals into classes with high accuracies. SVM with 'poly' kernel achieved a remarkable accuracy of over 99% when employing DWT approximation coefficients. The obtained results indicated that Fisher's score can be used to determine reduced feature subset when analyzing multi-domain statistical features. It was found that processing vibration signal in time-frequency domain by performing Discrete Wavelet Transforms resulted in the most effective signal analysis and was best for detecting blade damages, providing the highest classification accuracy.

As a potential future studies, other common types of blade damages, such as trailing edge cracking, lightning damage, delamination may be explored. Utilizing other machine learning algorithms such as convolutional neural networks may be a good extension of this work. Also, additional features could be explored and introduced in the machine learning algorithms. Finally, algorithms could be extended to provide not only the identification of damage presence, but also the location and type of damage.

CITATIONS

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