

A Comparative Study of Bayes Classifiers for Blade Fault Diagnosis in Wind Turbines through Vibration Signals

A. Joshuva¹ and V. Sugumaran²

Abstract Renewable energy sources are considered much in energy fields because of the contemporary energy calamities. Among the important alternatives being considered, wind energy is a durable competitor because of its dependability due to the development of the innovations, comparative cost effectiveness and great framework. To yield wind energy more proficiently, the structure of wind turbines has turned out to be substantially bigger, creating conservation and renovation works troublesome. Due to various ecological conditions, wind turbine blades are subjected to vibration and it leads to failure. If the failure is not diagnosed early, it will lead to catastrophic damage to the framework. In order to increase safety observations, to reduce down time, to bring down the recurrence of unexpected breakdowns and related enormous maintenance, logistic expenditures and to contribute steady power generation, the wind turbine blade must be monitored now and then to assure that they are in good condition. In this paper, a three bladed wind turbine was preferred and using vibration source, the condition of a wind turbine blade is examined. The faults like blade crack, erosion, hub-blade loose connection, pitch angle twist and blade bend faults were considered and these faults are classified using Bayes Net (BN), Discriminative Multinomial Naïve Bayes (DMNB), Naïve Bayes (NB), Simple Naïve Bayes (SNB), and Updateable Naïve Bayes (UNB) classifiers. These classifiers are compared and better classifier is suggested for condition monitoring of wind turbine blades.

Keywords: Condition Monitoring; Fault diagnosis; wind turbine blade; machine learning; statistical features; vibration signals.

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1 Introduction

The blades of present day wind turbines are very complex, innovative structure, and their expenditure makes a massive share of the entire wind turbine cost. While working, the blades are dynamically stacked and exposed to different climatic conditions, predominantly off-shore wind turbines. Due to severe vibration, the blade leads to damage. “If the damage to the blades grows to a critical level, it might leads to catastrophic consequences. This can be predicted initially using condition monitoring techniques which automatically detect the fault which caused on the blade [Liu *et al.*, (2015)]. The condition monitoring technique is highly effective in damage prediction. It can able to predict the fault caused in blade while the turbine is in operating condition using vibration signals. This technique can be improved much effectively by using machine learning approach where the defects are categorized with respect to the faults which occurred on blade. These can prevent the loss of structural integrity and can reduce the downtime of the turbine which leads to more wind energy generation by the wind turbine [Chehouri *et al.*, (2015)].

Many studies had been carried out on the condition analysis of wind turbine blade, to name a few, Jeffries *et al.*, (1998) had conducted an experiment with bicoherence of electrical power for condition monitoring of wind turbine blades using vibration data. This study was carried out by creating flap wise bending to the blade and simulated using MATLAB. This study considered only the blade bend as a parameter. Godwin and Peter (2013) have done classification and detection of wind turbine pitch faults through SCADA data analysis and RIPPER algorithm. This algorithm yielded about 87.05% of classification accuracy in pitch angle fault where other faults were not considered which occurs on wind turbine.

Andrew Kusiak and Anoop Verma (2011) carried out a work on data-driven approach for monitoring blade pitch faults in wind turbines using SCADA data. This study considered two blade pitch faults namely, blade angle asymmetry and blade angle implausibility and determine the associations between them. The study was carried out using bagging, artificial neural network (ANN), pruning rule-based classification tree (PART), K-nearest neighbor (K-NN) and genetic programming (GP) algorithms. The accuracy was obtained to be of GP-74.7%, Bagging-72.5%, PART-75.5%, ANN-76.2%, K-NN-73.5%. This study considered only pitch fault and other faults was not considered.

Abouhnik and Albarbar (2012) have carried out a work on wind turbine blades condition assessment based on vibration measurements and the level of an empirically decomposed feature intensity level (EDFIL). The crack was simulated and the location prediction of the crack fault was considered in this study. The main drawback in this study is it did not considered other fault parameters apart from crack. A study on integrating structural

health management with contingency control for wind turbines using nonlinear high fidelity simulation was carried out by Frost *et al.*, (2013). This study is about the structural health of blade, the speed of the turbine and decision making using prognostic information and achieved 90% accuracy in their work. Apart from bend fault, other faults were not considered.

Liu *et al.*, (2015) carried out a study on the influence of alternating loads on nonlinear vibration characteristics of cracked blade in rotor system using FEM analysis. The experiment is for different alternating loads for the identification of the crack fault and other faults not taken into consideration. A vibration induced aerodynamic loads on large horizontal axis wind turbine blades was done by Xiong Liu *et al.*, (2016). Aerodynamic load analysis of a 5MW wind turbine was performed and the impact of blade vibration on the lifetime aerodynamic fatigue loads was analysed in this study.

Numerical investigation on aerodynamic performance of a novel vertical axis wind turbine with adaptive blades was studied by Wang *et al.*, (2016). This study makes a novel Darrieus vertical axis wind turbine design whose blade can be deformed into a desired geometry and they achieved a better aerodynamic performance. In this study, performance was analysed for vertical axis wind turbine (Darrieus) blade. Vučina *et al.*, (2016) has done a numerical models for robust shape optimization of wind turbine blades using 3D geometric modeller. A computational framework for the shape optimization of wind turbine blades is developed for variable operating conditions specified by local wind speed distributions. This study considered the blade design using simulation process and didn't focused on the faults which affects the performance of the wind turbine.

Numerous works were carried out using simulation analysis; however, only a very few in the experimental analysis for wind turbine blade condition monitoring. Machine learning technique was considered for wind turbine blade fault diagnosis; however, the usage was limited in the literature. A very limited set of defects were considered for analysis. This is especially true in the case of fault diagnosis of wind turbine blade. Hence, there is a strong need to design a fault diagnosis system which can handle multiple faults in wind turbine blades using machine learning approach [Joshuva and Sugumaran (2016)]. This study makes a novel attempt to find different blade faults applying machine learning approach and statistical analysis. Figure 1 shows the methodology of the work done.”

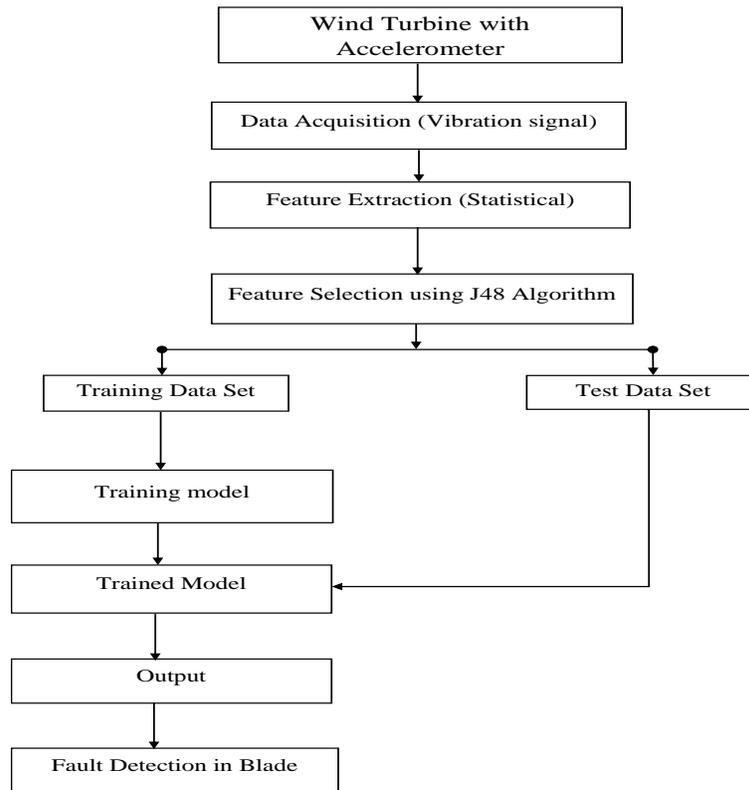


Figure 1: Methodology

The rest of the paper is organized as follows. Section 2 presents the experimental setup and experimental procedure. In section 3, feature extraction is explained, followed by feature selection in section 4. The classifiers used in this study are explained in section 5. The classification accuracy of the models was discussed and the suggestion of the better model is proposed in section 6. Conclusions are presented in the final section (section 7).

2 Experimental Studies

The main aim of this study is to classify whether the blades are in good condition or in a defective state. If it is defective, then the objective is to identify the type of fault. The experimental setup and experimental procedure are described in the following subsections [Joshuva and Sugumaran (2017)].

2.1 Experimental Setup

The experiment was carried out on a 50W, 12V variable speed wind turbine (MX-POWER, model: FP-50W-12V). The technical parameters of a wind turbine are given in Table 1.

Table 1: Technical parameters of wind turbine

Model	FP-50W-12V
Rated Power	50W
Rated Voltage	12V
Rated Current	8A
Rated Rotating Rate	850 rpm
Max Power	150W
Start-up Wind Velocity	2.5 m/s
Cut-in Wind Velocity	3.5 m/s
Cut-out Wind Velocity	15 m/s
Security Wind Velocity	40 m/s
Rated Wind Velocity	12.5 m/s
Engine	Three-phase permanent magnet generator
Rotor Diameter	1050mm
Blade Material	Carbon fiber reinforced plastics

The wind turbine was mounted on a fixed steel stand in-front of the open circuit wind tunnel outlet. The wind tunnel speed ranges from 5m/s to 15 m/s and act as a wind source to start the wind turbine. The wind speed was varied continuously in order to simulate the environmental wind condition. Experimental setup is shown in Figure 2. Piezoelectric type accelerometer was used as transducer for acquiring vibration signals. It has high-frequency sensitivity for detecting faults. Hence accelerometers are widely used in condition monitoring. In this case, a uniaxial accelerometer of 500g range, 100 mV/g sensitivity, and resonant frequency around 40 Hz was used. The piezoelectric accelerometer (DYTRAN 3055B1) was mounted on the nacelle near to the wind turbine hub to record the vibration signals using an adhesive mounting technique. It was connected to the DAQ system through a cable. The data acquisition system (DAQ) used

was NI USB 4432 model. The card has five analog input channels with a sampling rate of 102.4 kilo samples per second with 24-bit resolution. The accelerometer is coupled to a signal conditioning unit which consists of an inbuilt charge amplifier and an analogue-to-digital converter (ADC). From the ADC, the vibration signal was taken. These vibration signals were used to extract features through feature extraction technique. One end of the cable is plugged to the accelerometer and the other end to the AIO port of DAQ system. NI – LabVIEW was used to interface the transducer signal and the system (PC).

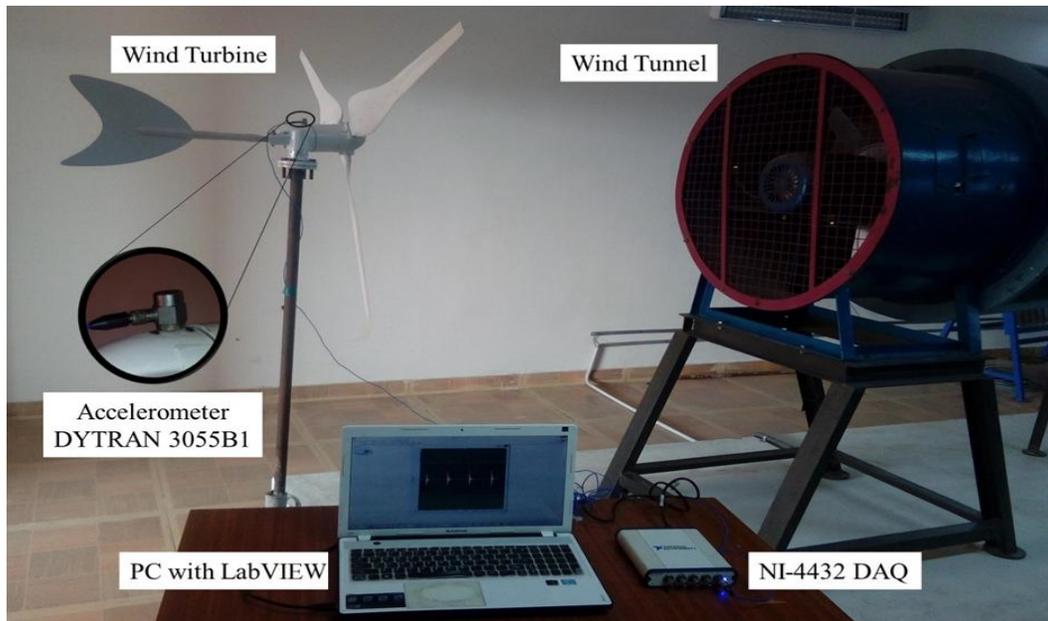


Figure 2. Wind turbine setup

2.2 *Experimental procedure*

In the present study, three-blade variable horizontal axis wind turbine (HAWT) was used. Initially, the wind turbine was considered to be in good condition (free from defects, new setup) and the signals were recorded using an accelerometer. These signals were recorded with the following specifications:

1. Sample length: The sample length was chosen long enough to ensure data consistency; and also the following points were considered. Statistical measures are more meaningful, when the number of samples is sufficiently large. On the other hand, as the number of samples increases the computation time increases. To strike a balance, sample length of 10000 was chosen.

- 2. Sampling Frequency: The sampling frequency should be at least twice the highest frequency contained in the signal as per Nyquist sampling theorem. By using this theorem sampling frequency was calculated as 12 kHz (12000Hz).
- 3. Number of samples: Minimum of 100 (hundred) samples were taken for each condition of the wind turbine blade and the vibration signals were stored in data files.

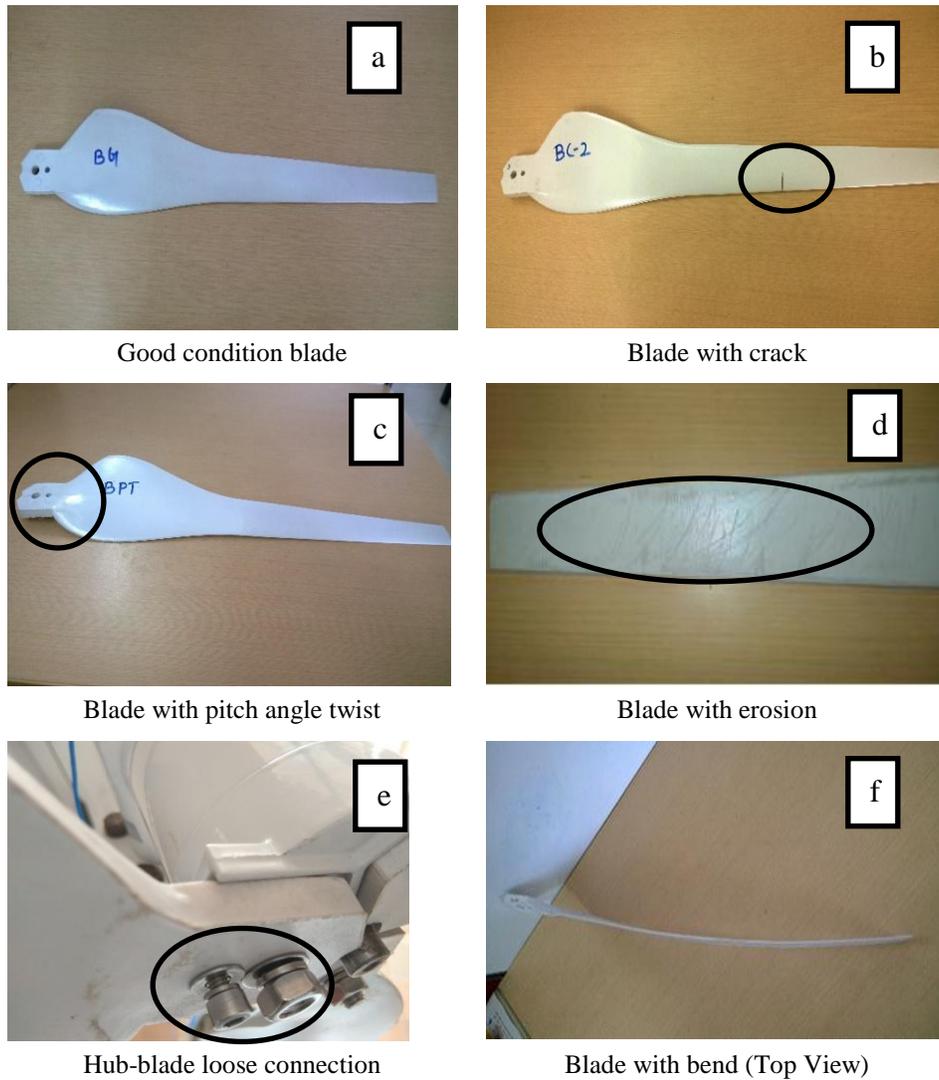


Figure 3: Different blade fault conditions (Considered)

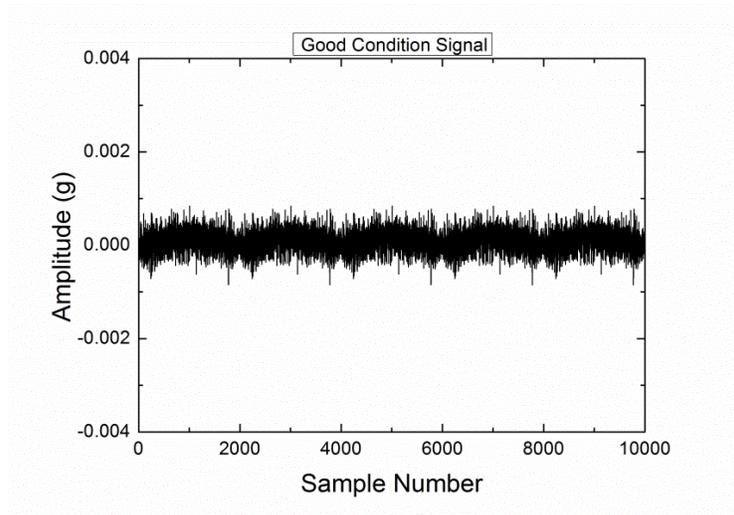


Figure 4.1: Good condition signal plot

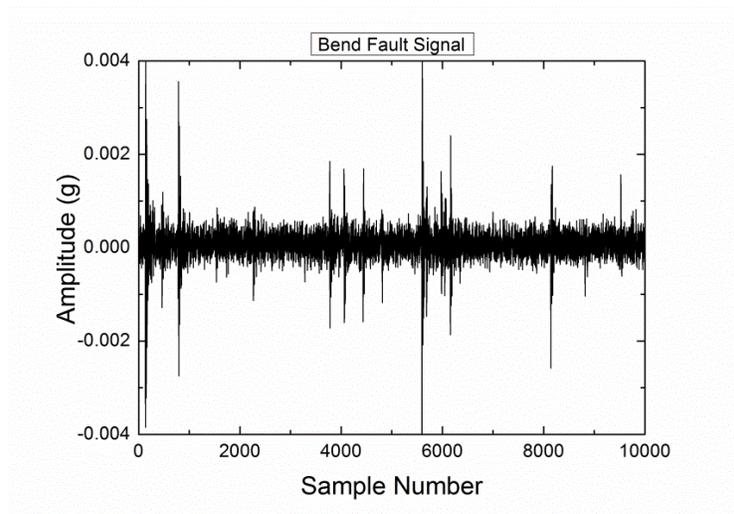


Figure 4.2: Bend fault condition signal plot

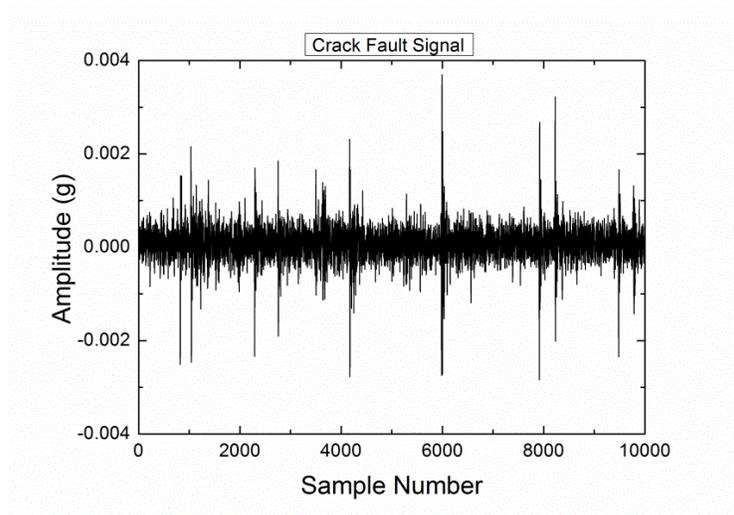


Figure 4.3: Crack fault condition signal plot

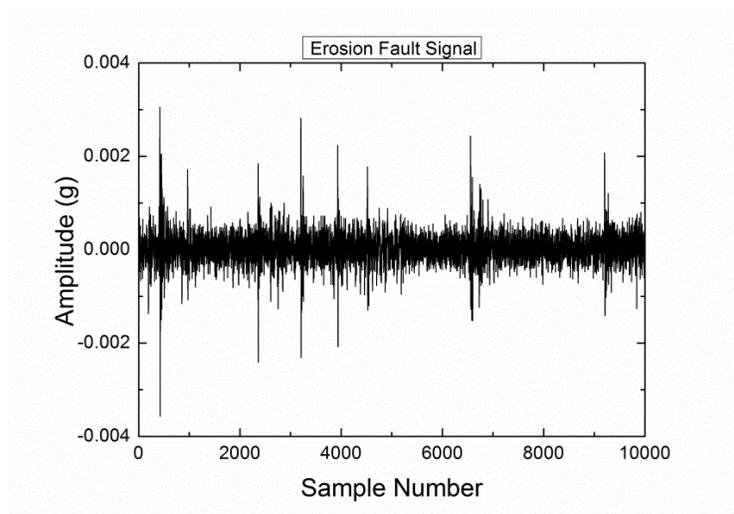


Figure 4.4: Erosion fault condition signal plot

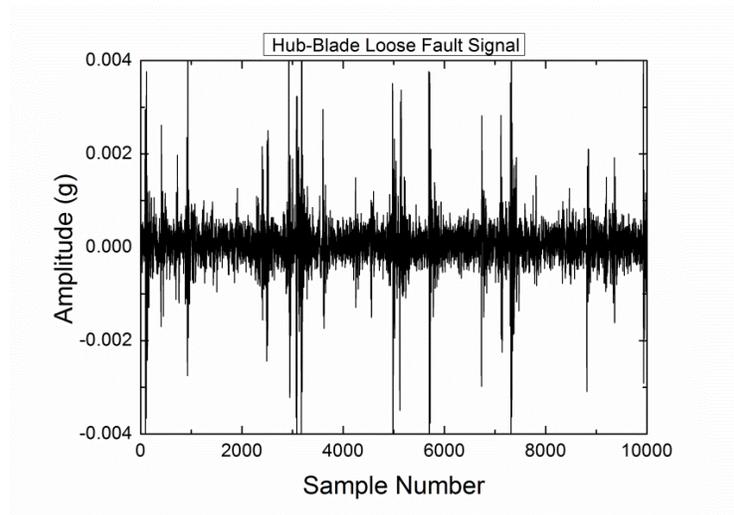


Figure 4.5: Hub-blade loose fault condition signal plot

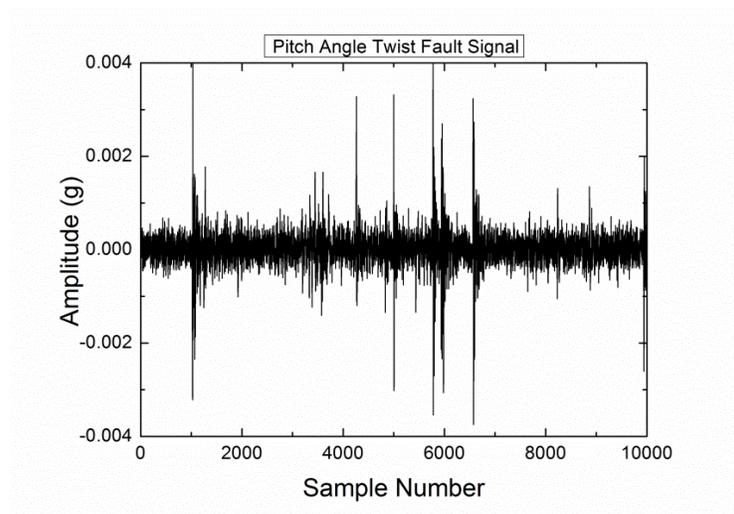


Figure 4.6: Pitch angle twist fault condition signal plot

The following faults were simulated one at a time while all other components remain in good condition and the corresponding vibration signals were acquired. Figure 3 shows the different blade fault conditions which are simulated on the blade.

- a) Blade bend: This fault occurs due to the high-speed wind and complex forces caused by the wind. The blade was made to flap wise bend with 10^0 angles.

- b) Blade crack: This occurs due to foreign object damage on blade while it is in operating condition. On blade, 15mm crack was made.
- c) Blade erosion: This fault is due to the erosion of the top layer of the blade by the high-speed wind. The smooth surface of the blade was eroded using emery sheet (320Cw) to provide an erosion effect on the blade.
- d) Hub-blade loose contact: This fault generally occurs on a wind turbine blade due to an excessive runtime or usage time. The bolt connecting the hub and blade was made loose to obtain this fault.
- e) Blade pitch angle twist: This fault occurs due to the stress on the blade caused by high-speed wind. This makes the pitch get twisted, creating a heavy vibration to the framework. To attain this fault, blade pitch was twisted about 12^0 with respect to the normal blade condition.”

Figure 4.1 to Figure 4.6 shows the time domain signals which were taken from different conditions of the wind turbine blade. They show the vibration signal plot (amplitude vs time of the vibration) for good condition blade, blade bend, blade erosion, hub-blade loose connection, blade crack and pitch angle twist respectively [Joshuva and Sugumaran (2017)].

3 Statistical analysis for feature extraction

The vibration signals were obtained for good and other faulty conditions of the blades. If the time domain sampled signals are given directly as inputs to a classifier, then the number of samples should be constant. “The numbers of samples obtained are the function of rotation of the blade speed. Hence, it cannot be used directly as the input to the classifier. However, a few features must be extracted before the classification process. Descriptive statistical parameters [Amarnath *et al.*, (2013)] such as sum, mean, median, mode, minimum, maximum, range, skewness, kurtosis, standard error, standard deviation and sample variance were computed to serve as features in the feature extraction process. Statistical analysis allows researchers to quantify a huge range of phenomena, allowing them to study topics as diverse as fault classification from an objective perspective. It has the tendency to produce excessively simple answers to complex questions. The statistical methods are classified with different parameters which provide the best analysis for the problem and we can able to predict how much the error or deviation has occurred for the particular problem.

- Sum: It is the sum of all feature values for each sample.
- Skewness: Skewness illustrates the degree of irregularity of a distribution around its mean. The following formula was used for calculation of skewness.

$$\text{Skewness} = \frac{n}{(n-1)(n-2)} \sum \left(\frac{x_i - \bar{x}}{s_d} \right)^3 \quad (1)$$

- Kurtosis: Kurtosis point toward the flatness or the spikiness of the signal. Its value is very low for normal condition of the blade and high for the faulty condition of the blade due to the spiky nature of the signal and ‘s’ is the sample standard deviation

$$\text{Kurtosis} = \left\{ \frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum \left(\frac{x_i - \bar{x}}{s_d} \right)^4 \right\} - \frac{3(n-1)^2}{(n-2)(n-3)} \quad (2)$$

- Standard error: Standard error is a measure of the amount of error in the prediction of y for an individual x in the regression, where x and y are the sample means and ‘n’ is the sample size.

$$\text{Standard Error (y)} = \sqrt{\frac{1}{n-2} \left[\sum (y - \bar{y})^2 - \frac{\sum [(x - \bar{x})(y - \bar{y})]^2}{\sum (x - \bar{x})^2} \right]} \quad (3)$$

- Standard deviation: This is a measure of the actual energy or power content of the vibration signal. The following formula was used for calculation of standard deviation.

$$\text{Standard Deviation } (\sigma) = \sqrt{\frac{n \sum x^2 - (\sum x)^2}{n(n-1)}} \quad (4)$$

- Sample variance: It is the variance of the signal points and the following formula was used for calculation of sample variance.

$$\text{Sample Variance} = \frac{n \sum x^2 - (\sum x)^2}{n(n-1)} \quad (5)$$

- Mean: The arithmetic average of a set of values or distribution.
- Median: Middle value sorting out the greater and lesser splits of a data set.
- Mode: Most frequent value available in the data set.
- Minimum value: It refers to the least signal point value in a given signal.
- Maximum value: It refers to the extreme signal point value in a given signal.
- Range: Difference in extreme and least signal point values for a given signal.

When the statistical feature extraction was completed, the features were taken and the feature selection method was carried out. The statistical features form the input to the feature selection method. With the selected features, the further classification was carried out respectively [Joshuva and Sugumaran (2016)].”

4 J48 decision tree algorithm for feature selection

J48 decision tree algorithm is adapted from the C4.5 algorithm in WEKA [Sugumaran *et al.*, (2007)]. It consists of a number of branches, one root, a number of nodes, and a number of leaves. One branch is a chain of nodes from the root to a leaf, and each node involves one attribute. The occurrence of an attribute in a tree provides information about the importance of the associated attribute. A decision tree is a tree based knowledge representation methodology used to represent classification rules. J48 decision tree algorithm is a widely used one to construct decision trees. The procedure of forming the decision tree and exploiting the same for feature selection is characterized by the following:

1. The set of features available at hand forms the input to the algorithm; the output is the decision tree.
2. The decision tree has leaf nodes, which represent class labels, and other nodes associated with the classes being classified.
3. The branches of the tree represent each possible value of the feature node from which they originate.
4. The decision tree can be used to classify feature vectors by starting at the root of the tree and moving through it until a leaf node, which provides a classification of the instance, is identified.
5. At each decision node in the decision tree, one can select the most useful feature for classification using appropriate estimation criteria. The criterion used to identify the best feature invokes the concepts of entropy reduction and information gain.

Information gain measures how well a given attribute separates the training examples according to their target classification. The measure is used to select the candidate features at each step while growing the tree. Information gain is the expected reduction in entropy caused by partitioning the samples according to this feature.

Information gain (S, A) of a feature A relative to a collection of examples S , is defined as:

$$Gain(S, A) = Entropy(S) - \sum_{v \in Value(A)} \frac{|S_v|}{|S|} Entropy(S_v) \quad (6)$$

where $Value(A)$ is the set of all possible values for attribute A , and S_v is the subset of S for which feature A has value v . Note the first term in the equation for gain is just the entropy of the original collection S and the second term is the expected value of the entropy after S is partitioned using feature A . The expected entropy described by the second term is simply the sum of the entropies of each subset S_v , weighted by the fraction of samples $|S_v|/|S|$ that belong to S_v . $Gain(S, A)$ is, therefore, the expected reduction in

entropy caused by knowing the value of feature A. Entropy is a measure of homogeneity of the set of examples and it is given by

$$Entropy(S) = \sum_{i=1}^c -P_i \log_2 P_i \quad (7)$$

where, c is the number of classes, P_i is the proportion of S belonging to class 'i'.

The J48 decision tree algorithm has been applied to the problem of feature selection. The input to the algorithm is the set of statistical features described above and output of the decision tree shown in Figure 5. It is clearly shown that the top node is the best node for classification [Joshuva and Sugumaran (2016)]. The other features in the nodes of decision tree perform in descending order of significance. It is to be mentioned here that only features that contribute to the classification appear in the decision tree and other features do not contribute much. The features which have the less discriminating capability can be consciously discarded by deciding on the threshold. This concept is made use for selecting good features. The algorithm identifies the good features for the purpose of classification of the given training data set, and thus reduces the domain knowledge required to select good features for pattern classification problem. Referring from Figure 5, one can identify the most dominating feature to represent the blade conditions are the sum, range, standard deviation, and kurtosis.

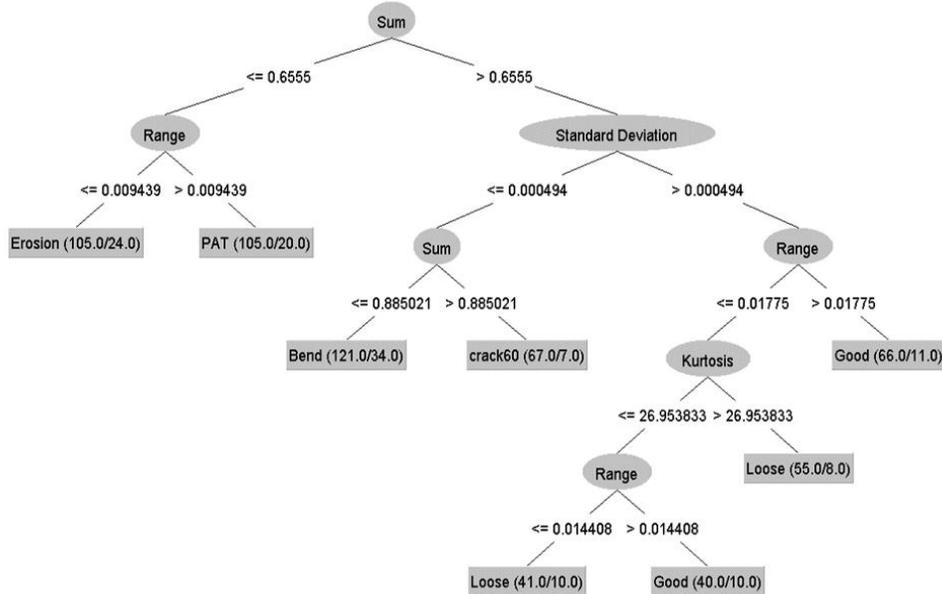


Figure 5: J48 Tree classification for feature selection

5 Feature classification

After the feature selection, the fault classification was carried out using Naïve Bayes (NB), Discriminative Multinomial Naïve Bayes (DMNB), Simple Naïve Bayes (SNB), Updateable Naïve Bayes (UNB) and Bayes Net (BN), classifiers. “The Naïve Bayes classifier [Muralidharan *et al.*, (2012)] is an classification algorithm based on Bayes rule, that assumes the features X_1, \dots, X_n are all uncertainly independent of each other, given Y . The value of this statement is that it theatrically simplifies the illustration of $P(X/Y)$, and the problem of approximating it from the training data. Consider, for example, the case where $X = (X_1, X_2)$. In this circumstance

$$P(X/Y) = P(X_1X_2/Y) = P(X_1/X_2, Y) = P(X_2/Y) = P(X_1/Y)P(X_2/Y) \quad (8)$$

More commonly, when X contains n features which are tentatively independent of one another given Y

$$P(X_1, \dots, X_n|Y) = \prod_{i=1}^n P(X_i|Y) \quad (9)$$

When Y and the X_i are Boolean variables, only 2^n parameters are required to explain $P(X_i = X_{ik}/Y = y_j)$ or the required i, j, k . This is a theatrical reduction compared to the $2(2n - 1)$ parameters required to describe $P(X/Y)$ if no conditional independence hypothesis is made. Assuming in overall that Y is any discrete valued variable, and the features X_1, \dots, X_n are any discrete or real valued features. The objective is to train a classifier that will yield the likelihood distribution over probable values of Y , for each new example X that needs to be classified. The expression for the likelihood that Y will take on its k^{th} conceivable value, according to Bayes rule, is

$$P(Y = y_k|X_1, \dots, X_n) = \frac{P(Y=y_k)P(X_1, \dots, X_n|Y=y_k)}{\sum_j P(Y=y_j)P(X_1, \dots, X_n|Y=y_j)} \quad (10)$$

Where the sum is taken over all conceivable values y_j of Y . Now, assuming the X_i are conditionally independent given Y , one can use the equation to rewrite this as

$$P(Y = y_k|X_1, \dots, X_n) = \frac{P(Y=y_k) \prod_i P(X_i|Y=y_k)}{\sum_j P(Y=y_j) \prod_i P(X_i|Y=y_j)} \quad (11)$$

This is the major equation for the Naïve Bayes classifier. Given a new illustration $X_{new} = (X_1, \dots, X_n)$, this equation shows how to compute the probability that Y will take on any given value, given the witnessed feature values of X_{new} and given the distributions $P(Y)$ and $P(X_i/Y)$ and estimated from the training data. If most probable value of Y is to be found, then the Naïve Bayes classification rule is given by:

$$y \leftarrow \arg \max_{y_k} \frac{P(Y=y_k)P \prod_i P(X_i|Y=y_k)}{\sum_j P(Y=y_j)P \prod_i P(X_i|Y=y_k)} \quad (12)$$

Which make simpler to the following (because the denominator does not depend on y_k).

$$y \leftarrow \arg \max_{y_k} P(Y = y_k)P \prod_i P(X_i|Y = y_k) \quad (13)$$

5.1 Bayes net

Bayesian network [Sakthivel *et al.*, (2011)] consists of a set of variables, $V = \{A_1, A_2, \dots, A_N\}$ and a group of directed edge, E , between variables, which form a directed acyclic graph (DAG) $G = (V, E)$ where a combined distribution of variables is denoted by the product of conditional distributions of each variable given its parents. Each node, $A_i \in V$ denotes a random variable and a directed edge from A_i to A_j , $(A_i, A_j) \in V$ denotes the conditional dependency between A_i and A_j . In a Bayesian networks, each variable is independent on its non-descendants, given a value of its parents in G . This independence encoded in G reduces the number of parameters which is essential to illustrate a joint distribution, so that following distribution can be efficiently contingent. In a Bayesian network over $V = \{A_1, A_2, \dots, A_N\}$, the joint distribution $P(V)$ is the product of all conditional distributions stated in the Bayesian network such as

$$P(A_1, A_2, \dots, A_N) = \prod_{i=1}^N P\left(\frac{A_i}{Pa_i}\right) \quad (14)$$

Where $P(A_i/Pa_i)$ is the conditional distribution of A_i , given Pa_i which represents the parent set of A_i . A conditional distribution for each variable has a parametric form that can be learned by the maximum probability estimation.”

6 Results and discussion

The vibration signals were noted for good condition and faulty blade conditions using DAQ. “Totally 600 samples were collected; out of which 100 samples were from good condition blade. For different faults such as like blade bend, erosion, blade crack, hub-blade loose connection, pitch angle twist, 100 samples from every condition were noted. J48 decision tree algorithm was used to select the best contributing statistical features from twelve features which can have a say in discriminating fault conditions specifically sum, mean, median, mode, minimum, maximum, range, skewness, kurtosis, standard error, standard deviation and sample variance [Joshuva and Sugumaran (2016)].

From Figure 5, the selected features (sum, range, standard deviation, and kurtosis) are given as the input to the classifier to determine the classification accuracy with respect to

faults created on the wind turbine blade. The classification accuracy of different classifiers is shown in Table 2. The accuracy was obtained for the Bayes Net (BN), Discriminative Multinomial Naïve Bayes (DMNB), Naïve Bayes (NB), Simple Naïve Bayes (SNB), and Updateable Naïve Bayes (UNB).

These results are compared for forecasting the better classifier which suits for the problem. From Figure 6, the Bayes Net (BN) provides the maximum classification accuracy of 85.67% when compared to other classifiers. In the Bayes Net classifier, the simple estimator is chosen with alpha value 0.5 and simulated annealing was assigned to the classifier. Simple Estimator is used for estimating the conditional probability tables of a Bayes network once the structure has been learned.

Table 2: Classification accuracy of the classifiers

Classifier	Classification Accuracy (%)
Bayes Net (BN)	85.67
Discriminative Multinomial Naïve Bayes (DMNB)	78.17
Naïve Bayes (NB)	84.83
Simple Naïve Bayes (SNB)	85.17
Updateable Naïve Bayes (UNB)	84.83

This Bayes Network learning algorithm uses the general purpose search method of simulated annealing to find a well scoring network structure. The confusion matrix of the Bayes Net is shown in Table 3. In confusion matrix, the diagonal element represents the correctly classified instance and the others are misclassified [Joshuva *et al.*, (2016)].

From Bayes Net, the kappa statistics was found to be 0.828. It is used to measures the arrangement of likelihood with the true class. The mean absolute error was found to be 0.0716. It is a measure used to measure how close forecasts or prediction are to the ultimate result. The root mean square error was found to be 0.1891. It is a quadratic scoring rule which processes the average size of the error. The detailed class-wise accuracy is shown in Table 4. From confusion matrix (Table 3), the good signal shows 23 faulty signals are classified as loose condition [Joshuva and Sugumaran (2016)]. This does not have much impact when compare to the loose condition being classified as good signals (13 signals). From 600 samples, 514 samples are correctly classified (85.67%) and remaining 86 are misclassified (14.33%). The time taken to build the model is about 0.56 seconds; hence, this can use in real time for the condition monitoring of the wind turbine [Joshuva and Sugumaran (2017)] .

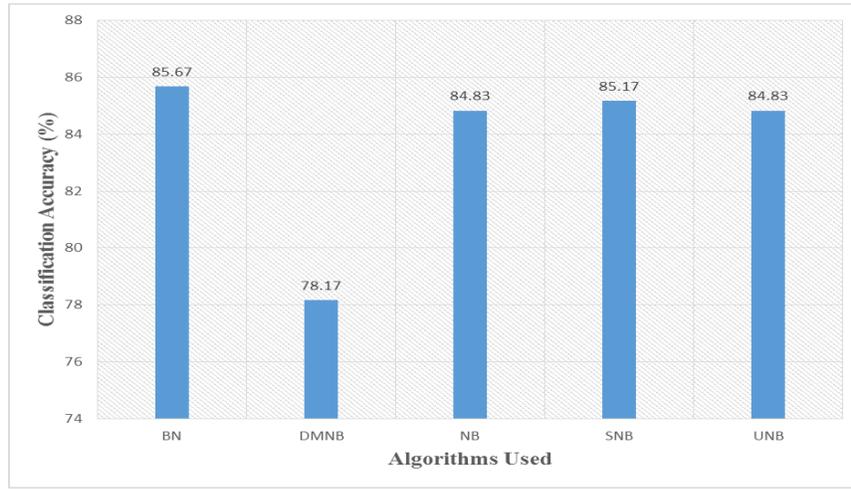


Figure 6: Overall classification accuracy of the classifiers

Table 3: Confusion matrix for Bayes Net

Blade conditions	Good	Bend	Crack	Loose	Pitch twist	Erosion
Good	75	1	1	23	0	0
Bend	1	93	2	0	0	4
Crack	0	8	85	6	1	0
Loose	13	1	6	80	0	0
Pitch twist	0	0	0	0	95	5
Erosion	0	4	1	0	9	86

Table 4: Class-wise accuracy of Bayes Net

Class	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC area
Good	0.75	0.028	0.843	0.75	0.794	0.971
Bend	0.93	0.028	0.869	0.93	0.899	0.991
Crack	0.85	0.02	0.895	0.85	0.872	0.989
Loose	0.80	0.058	0.734	0.80	0.766	0.953
Pitch twist	0.95	0.02	0.905	0.95	0.927	0.991
Erosion	0.86	0.018	0.905	0.86	0.882	0.987

TP is also called as sensitivity which used to predict the ratio of positives which are correctly classified as faults. FP is commonly described as a false alarm in which the result that shows a given fault condition has been achieved when it really has not been

achieved. The true positive (TP) rate should be close to 1 and the false positive (FP) rate should be close to 0 to propose the classifier is a better classifier for the problem classification. In the Bayes Net, it shows that the TP near to 1 and FP close to 0, then one can predict that the classifier we build for the particular problem is very much effective for the fault diagnosis problem [Joshuva and Sugumaran (2017)].

Precision is the ratio of correctly classified instances for those instances that have been classified as positive. The recall is merely equal to sensitivity in which the information retrieval is the fraction of the faults that are relevant to the query that are successfully retrieved. F-measure is defined as the equivalent resistance formed by sensitivity and precision positioned in parallel phase. ROC is a graphical representation that demonstrates the performance of a classifier as its discrimination threshold is varied. The classifier error chart is shown in Figure 7. Here the squared dots represent the misclassification and the 'x' denotes the correct classification.

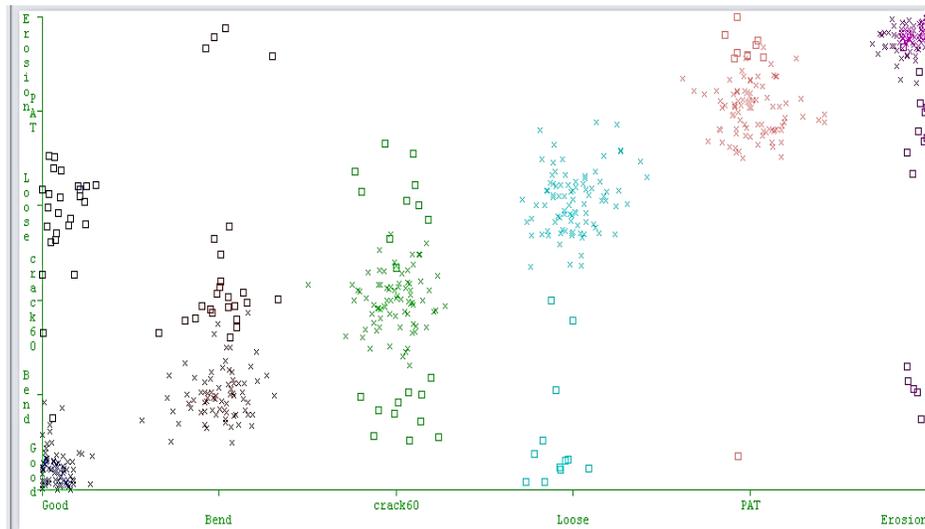


Figure 7: Classifier errors (classification vs misclassification)

7 Conclusions

The wind turbine is very important in using wind energy. “This paper displayed an algorithm based classification of vibration signals for the evaluation of the wind turbine blade conditions. From the acquired vibration data, five models were developed using data modelling techniques. Bayes Net (BN), Discriminative Multinomial Naïve Bayes (DMNB), Naïve Bayes (NB), Simple Naïve Bayes (SNB), and Updateable Naïve Bayes (UNB) classifiers were used to learn and classify the different fault conditions of the

blade. The model was tested in 10-fold cross validation. All the classifiers were compared with respect to their types and maximum correctly classified instances were found to be 85.67% for Bayes Net (BN) classifier. The error rate is relatively less and may be considered for the blade fault diagnosis. Hence, the Bayes Net can be practically used for the condition monitoring of wind turbine blade to reduce the downtime and to maximize the usage of wind energy. The methodology and algorithm suggested in this paper can be potentially used for any kind of wind turbine blade to diagnosis the blade fault with minimal modification.”

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