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Wind Turbine Blade Fault Diagnosis Using Vibration Signals through Decision Tree Algorithm

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Abstract

Objectives: The main objective of this research is to develop a model which can able to predict the various blade faults occurs in the wind turbine blade while the turbine in operating condition using vibration signals. **Method**: This study is considered as a machine learning problem which consist of three phases, namely feature extraction, feature selection and feature classification. In this research, statistical features are extracted from vibration signals, feature selection are carried out using J48 algorithm and different parameters of J48 algorithm were optimized to build a better classifier. **Findings:** In this study, the J48 algorithm was used and the classification accuracy was found to be 85.33% for multiclass problem. This is a novel approach of finding the different problem occurs in wind turbine blade at once. **Improvements**: This algorithm is applicable for real-time analysis and further the condition monitoring can be made as a portable device with less computation time.

Keywords: Fault Diagnosis, J48 Algorithm, Statistical Feature, Structural Health Monitoring, Vibration Signal, Wind Turbine Blade

1. Introduction

Today, power creating wind turbines utilize demonstrated and tried innovation, and give a protected and maintainable energy supply[1]. Numerous nations have impressive wind assets, which are still unutilized. The wind turbine framework[2] is utilized to separate the wind energy from accessible wind. The blades of a wind turbine rotor are the most important part seen as the most essential section of the wind turbine framework. Thus the blade designer ought to intentionally consider the fatigue life of the blades in their layout and ought to test the full-size structure[3]. Due to numerous failures in the wind turbine blade, the efficiency of wind energy is getting affected. To resolve this, fault diagnosis using machine learning approach is incorporated on wind turbine.

A work on problem recognition in wind turbines by means of support vector machines (SVM) and radial basis function (RBF) was utilized as Kernel function[4]. A work on adaptive control of a wind turbine using data mining technique and swarm intelligence utilizing SCADA data[5]. A pitch angle twist on blade was initiated and classified the fault using particle-swarm-fuzzy algorithm. Wind turbine blade condition monitoring based on vibration signals and empirically decomposed feature using ANSYS[6].

A work on wind turbine pitch fault diagnosis using a-priori information based adaptive-neuro-fuzzy inference system (ANFIS) utilizing SCADA data and attained 88.30% accuracy in ANFIS[7]. A study on optimization of small wind turbines airfoil profiles with emphasis on firm enactment under extremely unsteady wind circumstances using Mesh Adaptive Direct Search (MADS) optimization algorithm and obtained 39% accuracy[8].

A reasonable study on power coefficient assessment for wind turbine by soft computing methodologies[9]. In this study they used support vector regression (radial basis function), support vector regression (polynomial), ANFIS (adaptive neuro-fuzzy inference system), NN (neural network) algorithms for comparison. Correlation Coefficient of algorithms where found to be SVR (RBF)-0.997, SVR (Polynomial)-0.504, ANFIS-0.978, NN-0.922.

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A work on integrating SHM with contingency control using nonlinear high fidelity simulation for wind turbines and achieved 90% accuracy[10]. A study on SHM acoustic source localization for wind turbine blades using wireless sensor networks and obtained an error rate of 7.98%[11].

Many works where carried out using simulation work and very limited in exploratory investigation. Machine learning methodology was less considered for wind turbine blade condition investigation and very restricted faults were considered. This study makes an attempt to determine different blade defects utilizing machine learning approach (statistical feature and decision tree algorithm). Vibration signals are taken from the blade using uni-axial accelerometer. Figure 1 shows the methodology of the work done. In this study for wind turbine blade fault diagnosis,

- Faults like pitch angle twist, blade bend, erosion, hub-blade loose connection and crack are considered.
- Vibration signals are taken for the blade using data acquisition.
- Statistical analysis is used for feature extraction.
- J48 algorithm is used for feature selection.
- Feature classification is carried out using J48 algorithm where the various parameters are compared.

2. Experimental Studies

The main aim of this study is to classify whether the blades are in good condition or in defective circumstance. If it is defective, then the objective is to isolate the condition of fault. The experimental setup and experimental procedure are described in below subsections.

2.1. Experimental Setup

The experiment was carried out on a 50W, 12V variable wind turbine (MX-POWER, model: FP-50W-12V). The wind turbine technical parameters are given in Table 1. The wind turbine was mounted on a fixed steel stand. The wind speed ranges from 5m/s to 15 m/s where the turbine is placed for conducting the experiment and open circuit wind tunnel was used as the wind source in this study. The piezoelectric accelerometer (DYTRAN 3055B1) was mounted on the nacelle near to the wind turbine hub to record the vibration signals using the adhesive mounting technique. The accelerometer was directly connected to the data acquisition unit (NI USB-4432), where the analog signals were converted into digital signals and it was stored in computer memory. These signals were used to study the classification of the faults. Figure 2 shows the wind turbine setup.

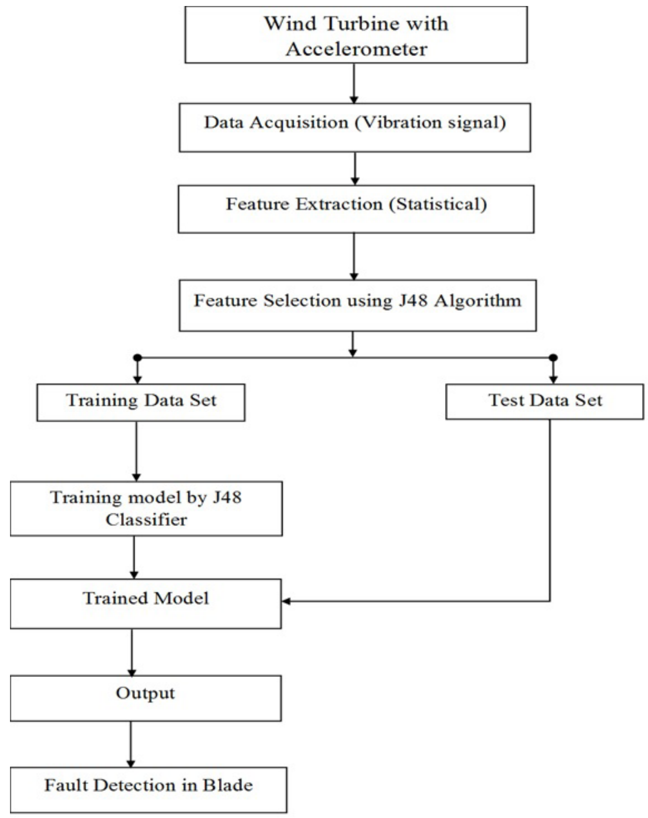

Figure 1. Methodology

Table 1. Technical parameters of wind turbine

Model	FP-50W-12V
Rated Power	50W
Rated Voltage	12V
Rated Current	8A
Rated Rotating Rate	850r/m
Max Power	150W
Start-up Wind Speed	2.5m/s
Cut-in Wind Speed	3.5m/s
Cut-out Wind Speed	15m/s

Security Wind Speed	40m/s
Rated Wind Speed	12.5m/s
Engine	Three-phase permanent magnet generator
Rotor Diameter	1050mm
Blade Material	Carbon fiber reinforced plastics

Figure 2. Experimental 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 as good condition (free from defects, new setup) and the signals were recorded using the accelerometer. These signals were recorded with the following specification:

1. Sample length: 10000 (Ten thousand data points).
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. A 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.

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.

2.2.1 Blade bend (BB):

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

2.2.2 Blade crack (BC-2):

This occurs due to foreign object damage on blade while it is in operating condition. On blade, 15mm crack was made.

2.2.3 Blade erosion (BE):

This fault is due to the erosion of the top layer of the blade by high-speed wind. The smooth surface of the blade was eroded using emery sheet (320Cw) to provide an erosion effect on the blade.

2.2.4 Hub-blade loose contact:

This fault generally occurs on wind turbine blade due to over runtime. The connection between the hub and blade bolt was made loose to obtain this fault.

2.2.5 Blade pitch angle twist (PAT):

This fault occurs due to the stress on blade caused by the high-speed wind. This makes the pitch get twisted and creates 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 shows the time domain signals which were taken from different conditions of wind turbine blade. They show the vibration signal plot (time vs amplitude of the vibration) for good condition blade, blade bend, blade erosion, hub-blade loose connection, blade crack and pitch angle twist respectively.

3. Statistical Analysis

The vibration signatures were obtained for healthy (good) and other faulty conditions of the blade. If the time domain sampled signals are given directly as inputs to a classifier, then the number of samples should be constant. The number of samples obtained which are the function of rotation of the blade speed. Hence it varies with speed. If the number of digitized data points in a signal is too large, then the work of classifiers may not handle it efficiently. Therefore, a few features must be extracted before the classification process. Descriptive statistical param-

BG - Blade good condition

BC-2 – Blade crack

BPT – Blade pitch twist

BE – Blade erosion

BB – Blade bend (Front View)

Blade bend (Top View)

Figure 3. Different blade fault conditions (Considered)

eters[12] such as sum, mean, median, mode, minimum, maximum, standard error, range, skewness, standard deviation, kurtosis and sample variance were computed to aid as features in the feature extraction process. Once the statistical feature extraction is complete, the values are taken and the feature selection process is carried out. The statistical features serve as the input to the feature selection process. With the selected feature the further classification is carried out.

4. J48 Tree Algorithm

A decision tree is a tree based statistics procedure used to express the classification rules. A standard tree induced with J48 algorithm comprises of various branches, one root, various nodes and leaves. One branch is a series of nodes from root to a leaf; and every node includes one feature. The result of a characteristic feature in a tree gives the information about the significance of the related condition of the blade. The approach of framing the decision tree[13] and exploiting the same for feature selection is described below:

- The set of features available at nearby the input to the algorithm; the output is the decision tree.
- The decision tree has leaf hubs, which express class names, and different hubs connected with the classes being characterized.

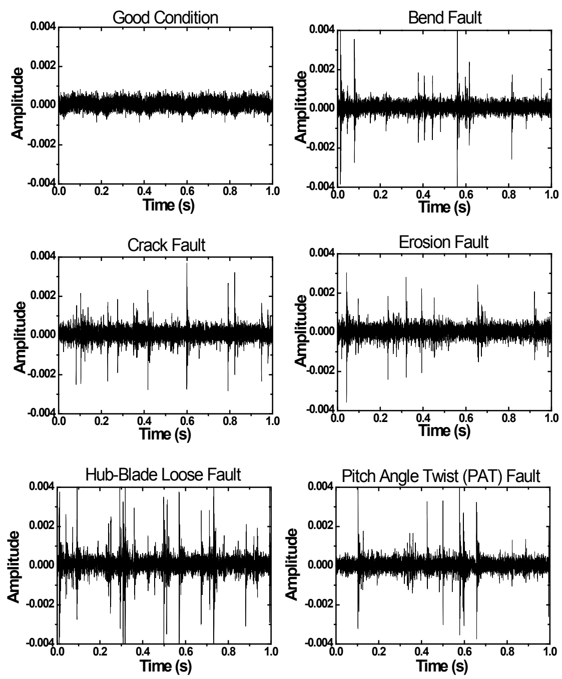

Figure 4. Time-Domain Signal plot

- The branches of the tree express to every conceivable estimation of the feature node from which they start.
- The decision tree can be utilized to arrange feature vectors by beginning at the root of the tree and traveling through it until a leaf node, which gives an order of the instance.
- At every decision hub in the decision tree, one can choose the most helpful feature for order utilizing proper estimation criteria. The rule used to recognize the best element conjures the ideas of entropy reduction and information gain. Figure 5 shows the tree representation of J48 algorithm.

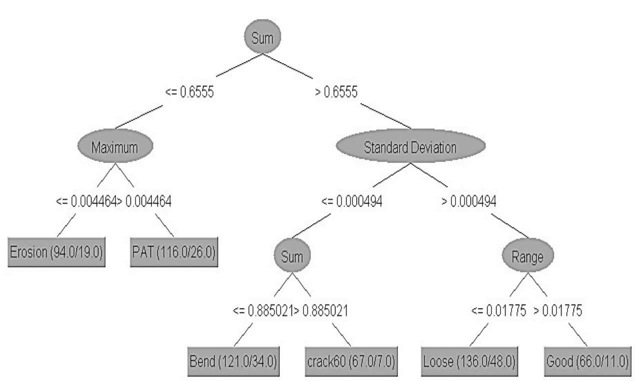

Figure 5. J48 Tree Classification

4.1. Information Gain and Entropy Reduction

Information gain is the expected reduction in entropy caused by portioning the samples according to the features. Entropy is a measure of similarity of the set of instances. Information gain measures by what means a given attribute isolates the training samples as indicated by their classification arrangement[14]. The measure is used to select among the candidate features at every step while developing the tree. Information gain (*S, A*) of a feature *A* relative to a collection of samples *S*, is defined as:

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

where *Values (A)* is the set of all conceivable values for feature *A*, and S_v is the subclass of *S* for which feature *A* has value *v* (i.e., $S_v = \{s\epsilon\ S|A(s)| = v\}$). Note the principal term in the comparison for Gain is only the entropy of the first gathering *S* and the second term is the normal estimation of the entropy after *S* is distributed utilizing feature A. The normal entropy represented by the second term is the immediate sum of the entropies of every subset S_v, weighed by the division of tests $|Sv|/|S|$ that fit in to S_v. Gain (*S, A*) is therefore the predictable reduction in entropy caused by deliberate the value of feature *A*. Entropy is given by

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

where *c* is the number of classes and P_i is the proportion of *S* belonging to class *i*.

5. Results and Discussion

The vibration signals were recorded for good condition blade and other faulty states of wind turbine blade. 600 samples were gathered; out of which 100 samples were from good condition blade. For different issues such as, blade crack, hub-blade loose connection, erosion, pitch angle twist, blade bend, 100 samples from every condition were gathered. The statistical features were considered as features and serve as input to the algorithm. The corresponding condition of the classified data will be the required output of the algorithm.

Totally 12 statistical features were extracted from the vibration signals. All features may not be important for the classification purpose. More number of irrelevant features actually may reduce the performance of the classification algorithm. Also, they increases the computational resources required. One cannot predict which are the parameters will be helpful for the purpose of classification using machine learning algorithms. So, examiners have to extract all descriptive statistical features and then select the good ones.

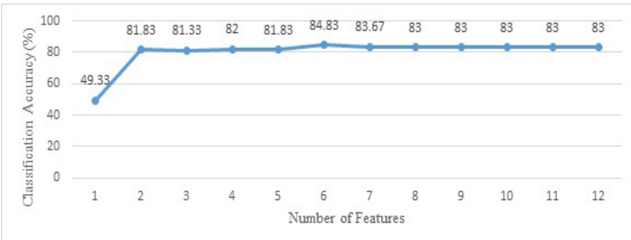

Figure 6. Classification accuracy for number of features

Here, decision tree was used for feature selection. The statistical features provide the initialization of the process. Then feature selection is carried out by J48 decision tree algorithm which is shown in Figure 5. In this feature selection with respect to Figure 5, the feature that take place in first will be the root node and the same will be the superior feature for classification. The other features in the tree are present in the order of significance. In this study, from Figure 6, six features (sum, standard deviation, kurtosis, mode, skewness, range) have the maximum accuracy of 84.83% and hence the number of features are fixed as six.

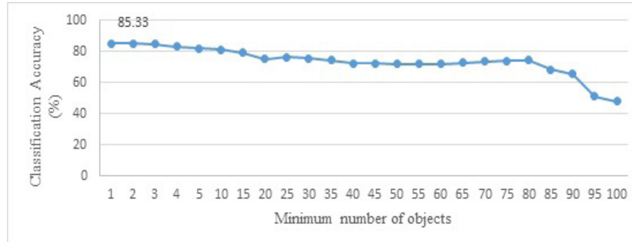

Figure 7. Minimum Number of Objects Vs Classification Accuracy

The number of objects which required for creating a class was varied from 1 to 100. When M=2, the algorithm gives the best accuracy of 85.33% which shown in Figure 7. At the point when the number of data focuses is less, then the algorithm tends to over fit the data. When it is more, then the algorithm has a tendency to simplify the built model. Hence, it is better to select least number of object to frame a class. The confidence factor is varied from 0.1 to 1.0 and found that the maximum accuracy of 85.33% for C=0.3 which shows in figure 8. Hence, in this study M=2 and C=0.3 is fixed and the classifier performance is verified using 10-fold cross validation[15]. In this confusion matrix, the diagonal element represents the correctly classified instance and the others are misclassi-

Table 2. Confusion matrix of J48 decision tree algorithm

Blade conditions	Good	Bend	Crack	Loose	Pitch twist	Erosion
Good	80	0	1	18	1	0
Bend	0	88	8	0	0	4
Crack	0	12	83	5	0	0
Loose	14	0	5	80	1	0
Pitch twist	0	0	0	0	95	5
Erosion	0	5	0	0	9	86

Table 3. Classwise accuracy of J48 tree classifier

Class	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC area
Good	0.8	0.028	0.851	0.8	0.825	0.937
Bend	0.88	0.034	0.838	0.88	0.859	0.95
Crack	0.83	0.028	0.856	0.83	0.843	0.936
Loose	0.80	0.046	0.777	0.80	0.788	0.913
Pitch twist	0.95	0.022	0.896	0.95	0.922	0.99
Erosion	0.86	0.018	0.905	0.86	0.882	0.967

fied. Table 2 represents the confusion matrix of the J48 decision tree classifier.

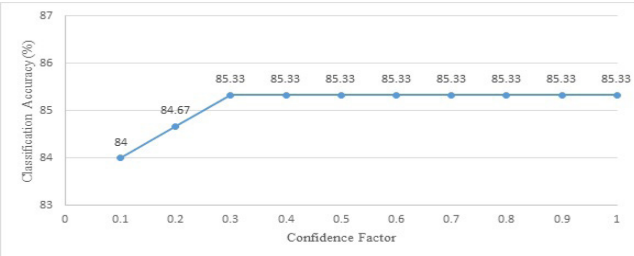

Figure 8. Confidence Factor Vs Classification Accuracy

From this classifier, the kappa statistic was found to be 0.824 with the mean absolute error to be 0.0566. The root mean square error value is about 0.2089. The detailed classwise accuracy of nested dichotomy is shown in Table 3. TP and FP are very much important in the classification accuracy. 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 classification. In the J48 decision tree algorithm, it has the TP near to 1 and FP close to 0 then we can predict that the classifier we build for the particular problem is very much effective for the fault diagnosis problem.

6. Conclusion

This paper displays an algorithm based clarification of vibration signals for the evaluation of the wind turbine blade condition. From the acquired vibration data, a model was set up using data modelling technique. A J48 tree classifier was used to learn and classify the different conditions of the blade. The model is tested under 10-fold cross validation and correctly classified instances was found to be 85.33%. The error rate is relatively less and may be considered for the blade fault diagnosis. Hence J48 algorithm can be practically used for the condition monitoring of wind turbine blade to reduce the downtime and to 7

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