EFFECT OF SAMPLING FREQUENCY AND SAMPLE LENGTH ON FAULT DIAGNOSIS OF WIND TURBINE BLADE

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ABSTRACT

The purpose of this research is to determine the effect of sampling frequency and sample length on fault diagnosis of the wind turbine blade in order to optimise the cost as high sampling frequency leads to high cost. This study uses machine-learning approach followed by feature extraction and feature selection with J48 decision tree algorithm. In this take a look at, statistical features had been extracted from vibration signals with various sampling frequency and corresponding sample duration. With extracted features, function choice and category turned into achieved. With the help of J48 decision tree algorithm the optimal sampling size is obtained at sampling frequency of 4000Hz, which gives the classifier accuracy as 72.66%. The obtained results can be used with low cost accelerometer i. e. MEMS based accelerometer.

Keywords: Sampling frequency, sample length, machine learning, fault diagnosis, wind turbine

1. INTRODUCTION

The machine learning approach is an analytical method of doing condition monitoring. It involves obtaining signals from the component and then processing it to get statistical features. These statistical features are then used to distinguish the faults using various algorithms. The statistical features extracted from the signals are different for different sampling frequencies and sample lengths. This is because as the sample length of the signal changes the entropy and information gain associated with the signals also change. According to Nyquist sampling theory, frequency for any rotating element should be at least twice its operating frequency. The purpose of this study is to find out if it is possible to achieve appreciable results at a smaller sampling frequency and sample length which will reduce the computation time and fault diagnosis cost

Developing a model that can assist in predicting various faults occurring in wind turbine blades when it is in operating mode is important to conduct fault diagnosis with the help of machine learning approach. By recording vibration signals, the results can be obtained that state the classification accuracy equal to 85.33% for wind turbine at sampling frequency of 12,000Hz and sample length 10,000 (Joshuva, *et al.,* 2016). When fault diagnosis of wind turbine was performed for sample length of 1024 and sampling frequency 1600Hz different results were achieved (Wenyi, *et al.,* 2012). Various structural health monitoring methods for large wind turbine blades exist (Schubel, *et al.,* 2012). Understanding and learning the history, and recent stable releases to the WEKA workbench educates us about various classifiers that can be used (Mark Hall, *et al.,* 2009). For different components like centrifugal pump, when fault diagnosis was performed at a constant speed of 2880 rpm, best results were obtained at 24,000Hz sampling frequency and sample length of 1024. The classification accuracy obtained was 99.52% (V. Muralidharan, *et al.,* 2010). When fault diagnosis of wind turbine on the basis of Morlet wavelet transformation and Winger-Ville distribution was performed, results were obtained with the experimental parameters as 1600Hz sampling frequency and 256 sampling points (B. Tang, *et al.,* 2010).

From all of the above literature it can be seen that higher is the sampling frequency and sample length, the classification accuracy and fault identification is improved. In the following sections we shall discuss the possibilities of getting desired results at lower sampling frequencies and sample lengths too.

2. EXPERIMENTAL STUDIES

A test rig resting on a stationary stand is taken for the study as shown in Fig. 2. The detailed explanation is described in following subsections.

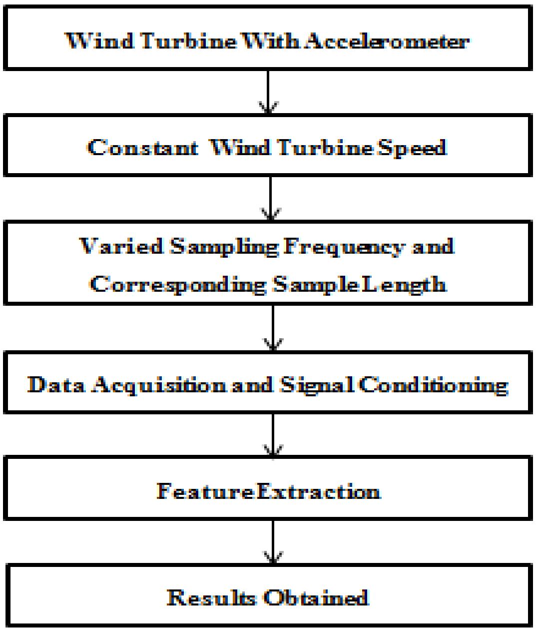

Fig. 1 Methodology

In the present study, three-blade variable horizontal axis wind turbine (HAWT) turned into used with constant rated speed at 850rpm. At first, the breeze turbine was considered in great condition (free from abandons, new setup) and the signals were recorded utilizing the piezoelectric accelerometer which is mounted on turbine blade hub using an adhesive. These signals were recorded with the following detail:

Fig. 2 Experimental Setup

1. Varying sampling frequency and corresponding sample length: The turbine speed kept constant at 850 rpm i.e. 14.1667rps. Therefore the sample length should be nearly 0.08 for 1 second of rotation. Hence, the required sample length is calculated as,

Sample Length = Frequency*0.08 (1 rotation time)

Frequency varied from 1000Hz, 1500Hz…, 2000Hz, and 25000Hz

2. Number of samples: For each state of the wind turbine blade least of hundred samples were procured and put away.

The following faults were simulated on different blades, and signals were recorded for each fault each one in turn while every other part was kept up in exact condition.

2.1 *Blade bend (BB):* High-speed wind causes a bend in the blade and even complex forces too. The blade was made to bend, flap side, with 10 degrees angle

2.2 *Blade crack (BC):* While in the operating condition, if any foreign object causes crack on blade.

2.3 *Blade erosion (BE):* This is because of the wearing endlessly of the upper layer of the sharp edge by the rapid breeze.

2.4 *Hub-blade loose contact:* This fault for the most part emerges on wind turbine edge due to over runtime.

2.5 *Pitch angle twist (PAT):* The fast breeze causes worry in edge and consequences in pitch angle twist. To attain this fault, with reference to the ordinary blade state, edge pitch was turned around 120 degrees.

3. STATISTICAL ANALYSIS FOR FEATURE EXTRACTION: The time domain sampled signals cannot be given directly as input to a classifier, as the number of samples should be constant. It varies with speed. Before classifying the faults, features must be extracted. A total of thirteen informative statistical parameter, namely sum, mean, median, mode, minimum, maximum, standard error, range, skewness, standard deviation, kurtosis and sample variance were figured to help as highlights in the component extraction process. The qualities are taken from measurable component extraction and the element determination process is done. The values are taken from statistical feature extraction and the feature selection process is carried out.

4. CLASSIFICATION WITH J48 DECISION TREE ALGORITHM: The arrangement of highlights accessible at hands frames the contribution to the calculation and the yield got is the decision tree. The branches of the tree address to every conceivable estimation of the function node from which they begin. The J48 algorithm give best results because it uses entropy reduction and information gain. Fig. 3 shows decision tree obtained with J-48 algorithm for sampling frequency at 4000Hz.

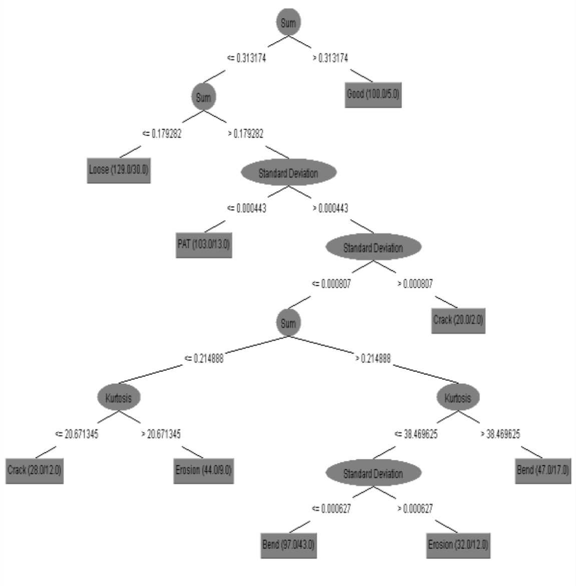

Fig. 3 Decision tree-J48 algorithm

5. RESULTS AND DISCUSSION

According to the Nyquist sampling theorem, the sampling frequency ought to be as a minimum two times the very best frequency contained in the signals. High sampling rate leads to high cost. So, to cut the cost, we can use optimal sample size i.e. lowest sample size which gives the results closer to actual sample size.

For fixing the sample size sampling frequency and corresponding sample length was taken into account. The vibration signals were recorded and 600 samples were taken from great condition and other faulty states of wind turbine blade. Out of which one hundred specimens belong to precise situation blade. For the faults that were simulated, 100 samples were gathered for every condition. The statistical features extracted act as input to the algorithm and the classified data is taken as the required yield of the algorithm.

The decision tree used for study is C4.5 based binary tree creation of J48 algorithm. Twelve statistical highlights were removed from the vibration flags and highlight determination was done with J48 decision tree algorithm keeping confidence factor as 0.35 and a minimum number of objects as 3. Then the features were grouped into several combinations according to their accuracy. Initially inputs were taken and processed through J48 algorithm and maximum accuracy of 72.66% was achieved at 4000Hz. Fig. 4 shows effect of sampling frequency on classifier accuracy. Confusion matrix represents classification accuracy and its interpretation is given as below. Table-3 shows the confusion matrix for J48 algorithm.

- Diagonal elements of confusion matrix signify rightly categorized instances for each defective condition.
- Element from first line, first segment signifies rightly categorized data points in BEND class by the classifier. Second element from first line signifies data points of BEND class wrongly categorized as belonging to CRACK class and so on.

Fig. 4 shows effect of sampling frequency on classifier accuracy obtained by using J-48decision tree algorithm. The results are discussed in following sections.

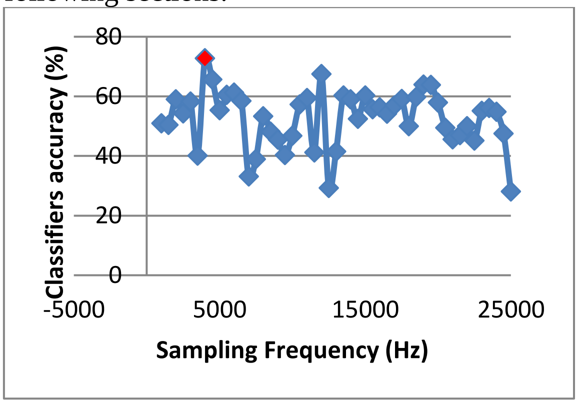

Fig. 4 Effect of sampling frequency on classifier accuracy

Table 1 Confusion matrix

	BEND	CRACK	EROSION	GOOD	LOOSE	PAT
BEND	**59**	15	18	3	0	5
CRACK	19	**46**	19	0	8	8
EROSION	25	19	**48**	0	7	1
GOOD	4	0	0	**96**	0	0
LOOSE	0	6	3	0	**90**	1
PAT	4	5	1	2	0	**88**

6. CONCLUSION

By studying confusion matrix and detailed accuracy by class it is confirmed that the tested model is gives best result for various sample sizes. The present model uses ten folds cross-validation and the J48 algorithm classifier results were compared for different sample sizes and correctly classified instances were found as 72.66% for 4000Hz which can be used for low-cost fault diagnosis. Hence it is practically possible to go through with minimum sample size for fault detection of wind turbine blade.

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