Wind Turbines Fault Diagnosis Using Ensemble Classifiers

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Abstract. Fault diagnosis in machines that work under a wide range of speeds and loads is currently an active area of research. Wind turbines are one of the most recent examples of these machines in industry. Conventional vibration analysis applied to machines throughout their operation is of limited utility when the speed variation is too high. This work proposes an alternative methodology for fault diagnosis in machines: the combination of angular resampling techniques for vibration signal processing and the use of data mining techniques for the classification of the operational state of wind turbines. The methodology has been validated over a test-bed with a large variation of speeds and loads which simulates, on a smaller scale, the real conditions of wind turbines. Over this test-bed two of the most common typologies of faults in wind turbines have been generated: imbalance and misalignment. Several data mining techniques have been used to analyze the dataset obtained by order analysis, having previously processed signals with angular resampling technique. Specifically, the methods used are ensemble classifiers built with *Bagging*, *Adaboost*, *Geneneral Boosting Projection* and *Rotation Forest*; the best results having been achieved with *Adaboost* using C4.5 decision trees as base classifiers.

Keywords: fault diagnosis, wind turbines, ensemble classifiers, angular resampling.

1 Introduction

Vibration analysis has been studied and applied to rotating machinery for decades. It is widely accepted as one of the main fault diagnosis techniques in machine maintenance [11]. As the signal analysis technology has advanced and new sensors have been developed, fault diagnosis and maintenance of machines working under more severe conditions have become a new target area for experts. Examples of machines that work under variable conditions of load and speed are wind turbines, excavators and helicopters [2]; [4]; [5]; [3]. Gear transmission plays a crucial role in the reliability of these machines.

One of the first research in the field of transmission damage diagnosis focused on vibration signals analysis [6]. At first, the statistical features of the signal in the time

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domain were the main element of study [18]. However, the field quickly spread to include spectral analysis, time-frequency analysis and, finally, models based on artificial intelligence. All of these approaches are still valid and current. As new techniques of signal processing arise, they are applied to the problem of damage detection in chain drives and should be adapted to the needs and specific characteristics of each mechanical system.

The main purpose of this work is to study fault diagnosis in wind turbines. To do so, the test-bed shown in Figure 1 is used to approximate real conditions and the typical faults of a real wind turbine.

Many studies have applied several signal analysis methods that are suited to conditions of fluctuating loads. Among these, we may quote works by Stander, Heyns, Zhan and Barlelmus [21]; [24]; [3]. However, no studies have yet been completed on such wide working ranges as those of a wind turbine, in terms of real wind regimes that therefore have a very wide range of speed and load operating conditions. The development of intelligent devices, both for monitoring and for diagnosis of this type of industrial equipment that operates under highly variable loads and speeds is, therefore, a highly topical field of research. Vibration monitoring systems require signal processing procedures to compensate for fluctuations in axis speeds and amplitude modulation, due to the variable wind-resistance loads [20]; [19].

Although exhaustive research into the analysis of the signals obtained from several types of sensors and particularly accelerometers has been completed to date, the standard technique used for fault diagnosis is the identification of critical variables by an expert and the development of a regression model that forecasts the failure [24]. The aim of this work is to develop an alternative classification system with greater reliability using ensemble classifiers.

There are several works in which ensemble classifiers have been used for fault detection. In Hu [12] *Adaboost* is used to combine *Support Vector Machines* (a type of base classifier) for fault diagnosis in rotating machinery. This method is also used in Donat [8] for the fault detection of engines in gas turbines. In Alonso [1] , failure identification in continuous processes is managed by an ensemble classifier building method -*Stacking*- that combines nearest-neighbours base classifiers (*k-Neighbours Classifier, kNN*). Furthermore, *Adaboost* and *Bagging* of neural networks in El-Gamal [9] are used for fault diagnosis in analogue circuits.

2 Description of the Test-Bed and Measurement Procedure

The experiments conducted on the test-bed are meant to simulate the behaviour of wind turbines. This test-bed is used to simulate different defects under variable loads and speeds. The right side of the test-bed (Figure 1) is composed of an engine, a parallel gearbox and a planetary gearbox. Both gearboxes resemble a commercial wind turbine in terms of their configuration and gear ratios (1:61).

To simulate the variable load in the drive train of a wind turbine, due to randomness of the wind, an electric brake has been added to the right side of the bench.

For the measurement of vibration signals four accelerometers distributed in the axial and radial position in the gearboxes situated on the right side of the test-bed were used.

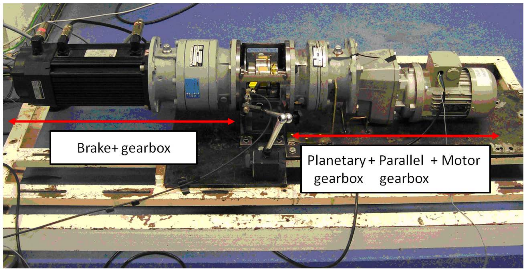

Fig. 1. Test-Bed

Preliminary processing of the vibration signals need to be performed, due to the speed and load variations caused by the operating conditions of wind turbines, in order to extract the information on its spectral analysis. The technique of angular sampling, a methodology that may be found in [22], appears suitable to solve this problem.

The faults simulated on the test-bed were imbalance and misalignment, starting with small values and increasing at each measurement to simulate a progressive fault (Table 1). This table illustrates the value of the weight in grams and its equivalent in percentages with regard to the total of the weight of the rotor of the bench, and the thickness used for producing the misalignment, as well as the resulting value.

Table 1. Types of faults and magnitudes induced in the test-bed

Imbalance			**Misalignment**		
	gr	%		mm	°
Imbalance A	5.79	0.077	Misalignment A	0.75	1.53
Imbalance B	9.13	0.12	Misalignment B	0.75	1.53
Imbalance C	19.5	0.26			
Imbalance D	28.8	0.38			

To guarantee the speed and load conditions, several profiles were generated to cover a wide range of speeds from 1000 to 1800 rpm at random, and from 0 to 100 % of the load. An example of this profile is shown below in the Figure 2.

These profiles were generated to cover a whole day of measurement (24 hours), with constant 100 second intervals of speed and load. The speed measurements were generated from 1000 rpm, which is the approximate speed at which a wind turbine begins to produce energy. Data acquisition was taken at intervals of 72 seconds from each of the four accelerometers with a sampling frequency of 25600 Hz. The speed signal was captured at 6400 Hz.

The set of tests done are reported in [23].

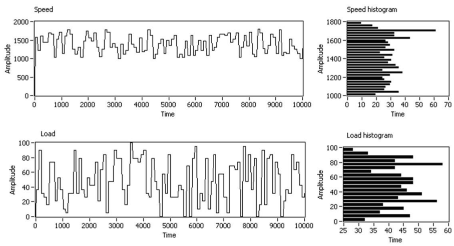

Fig. 2. Speed and load profile

3 Variables Analyzed

As explained in the previous section, several working faults in the turbine are analyzed. For that reason, a discrete output variable was defined, referred to as the fault type, and several input variables.

The type of fault matches the two previously explained ones; misalignment and imbalance, for which there are three possible numerical values in the first case (0, 0.75 and 2) and five in the second one (0, 5.79, 9.13, 19.5 and 28.8). We will refer to these degrees of misalignment as DA1, DA2 and DA3, and to imbalance as DB1, DB2, DB3 DB4, DB5.

There are therefore fifteen possible values for each type of faults, shown below in Table 2:

Table 2. Fault Classes

	DB1	**DB2**	**DB3**	**DB4**	**DB5**
DA1	0 (C0)	1 (C1)	2 (C2)	3 (C3)	4 (C4)
DA2	5 (C5)	6	7	8	9
DA3	10 (C6)	11	12	13	14 (C7)

In the previous table, class 0 matches the case in which there is no fault (no misalignment nor imbalance), and the 14 remaining classes match several types of faults that could theoretically occur, but in the experimental trials only 8 classes took place. These fault classes will be referred to as C0, C1, C2, C3, C4, C5, C6 and C7.

The variables in this problem are, on the one hand, 3 magnitudes which describe the operational state of the machine in the terms of torque, speed and electric input current and, on the other, several magnitudes measured with 5 sensors, 1 current sensor and 4 accelerometers, 2 by each of the two gearboxes, distributed along two perpendicular axis.

The current sensor provides 4 measurements of electric current, and the accelerometers provide the data for a vibration analysis along the axis, by using three aspects of the vibration spectrum. On the one hand, 5 measurements which summarize their distribution (average, RMS, skewness, kurtosis and interquartile range); on the other,

Table 3. Input variables

Operation State		
Variable	**Number of measurments**	**Units**
Torque	1	% of maximum torque
Speed	1	Hz
Input current	1	Amperes
Current Sensors		
Variable	**Number of measurments**	**Units**
Electrical current in the axis	4	Amperes
Vibration analysis		
Variable	**Number of measurments**	**Units**
Harmonics	272	mm/s^2
Bands	245	mm/s^2
Average	4	mm/s^2
RMS	4	mm/s^2
Skewness	4	dimensionless
Kurtosis	4	dimensionless
Interquartile Range	4	mm/s^2

a harmonic analysis (natural frequency of system vibrations and multiples thereof, 80 measurements in total); and finally, dividing the vibration spectrum into bands of fixed position (unrelated to the natural frequency of the system), with another 77 measurements. Each accelerometer provides a total of 162 measurements, although the total number of considered variables in the vibration analysis is 537, as some measurements with redundant information have been removed.

The final number of variables for the problem is 544, adding to the 537 from the vibration analysis, the measurements from the current sensor, the torque, the speed and the electric current. In the next table, a summary of the previously explained variables is completed, although it is possible to search for a more detailed information in [23].

During the day of the experimentation, 6551 different conditions in the considered variables were registered. The data set under study therefore has a size of 6551 instances with 544 attributes, such that it can be considered a high dimensional problem.

The distribution of the instances among the classes is as shown in Table 4:

Table 4. Distribution of the instances among the classes

C0	887 (13.54 %)
C1	847 (12.93 %)
C2	856 (13.07 %)
C3	838 (12.79 %)
C4	864 (13.19 %)
C5	872 (13.31 %)
C6	835 (12.75 %)
C7	552 (8.43 %)

4 Fault Analysis by Ensemble Classifiers

Forecasting several faults that may occur in turbine operation is included in data mining classification problems. In this article, the use of techniques to combine several individual classifiers is proposed, to obtain an ensemble classifier. These techniques have developed over the last decade and their output has been proven in several situations.

An ensemble classifier is a classification technique by which the forecasted class is obtained from the individual forecasts of a series of base classifiers. There are several ways of combining the various forecasts, the most usual one is to select the most voted class. The global accuracy of the ensemble classifier depends on the diversity of the classifiers and their individual accuracy, as an ensemble classifier should be capable outperforming any individual classifier [7]; [14].

There are several ways of forcing diversity between base classifiers [13]; [17], having taken four of these techniques in this study, *Bagging* and *Adaboost* on the one hand, are the most commonly used, and *Rotation Forest* and *General Boosting Projection (GBPC)* on the other, which are more novel techniques that have been shown to be very competitive [16]; [10].

The algorithm *Rotation Forest* algorithm is based on Principal Component Analysis (PCA) extraction procedures that achieve better accuracy in the ensemble classifier, by acting at the same time on the individual accuracy of each base classifier and on its diversity [16]. Thus, a random division of the data is made, in groups of attributes (3 in this work), and subsequently a PCA analysis is completed over part of the samples of each group, also random, storing the projection matrix that is used and combined later on to project all the samples of each group.

The *GBPC (General Boosting Projection)* is based on the use of supervised projections to improve global accuracy, due to the individual improvement of each base classifier as well as its diversity [10]. It is an iterative process in which the first base classifier receives the data set without any modification followed by a projection over the misclassified instances by the previous classifier. By doing so, we seek to obtain better results in the next classifier, in cases where the previous classifiers failed. The Non-parametric Discriminant Analysis (NDA) version proposed by [15] was used as the supervised projection method.

5 Results

Three methodologies for the classification were tested: C4.5 decision trees, k-Nearest Neighbour (*kNN*) and Naive Bayes. These three base techniques were chosen as they are the three most commonly used in data mining.

These methods have been tested individually as well as with ensemble classifiers using the techniques of *Bagging*, *Adaboost*, *GBPC* and *Rotation Forest*, taking in all cases 100 base classifiers, and performing a 5×2 cross validation (all the methods are compared using the same sets for training and testing).

Two ways to measure the accuracy of each classifier have been taken:

- Success rate in a 5×2 cross validation, indicating the standard deviation of the iterations.
- Confusion matrix, in which the class forecasted by the classifier is compared against the class of the instance to which actually belongs.

5.1 Success Rate

The following table illustrates the success rate of both the individual and the different ensemble classifiers, which includes the standard deviation with regard to the 5 repetitions of the cross validation between parentheses.

In all cases, we can see that decision trees are more suitable as base classifiers, however we should highlight the notable increase of the *GBPC* with regard to the efficiency of the classification with the *kNN* as base classifier.

Table 5. Average success and standard deviation for the different classifiers

	C4.5 trees	**kNN**	**Naive Bayes**
Classifier individually	92.60 (0.51)	66.12 (0.44)	70.29 (2.68)
Bagging	95.33 (0.23)	66.01 (0.41)	70.73 (1.59)
Adaboost	96.24 (0.12)	67.57 (0.59)	78.96 (0.71)
GBPC (NDA)	90.70 (5.61)	87.45 (1.26)	70.29 (2.68)
Rotation forest	95.84 (0.14)	66.19 (0.54)	71.92 (2.25)

The low performance of the kNN classifier could be caused by the well-known problem of the "curse of dimensionality" (analyzing high-dimensional spaces). In the following sections we compare the two methods in which better results are reached, *Adaboost* with decision trees versus *Rotation Forest* with decision trees.

5.2 Confusion Matrix

The next step is to compare the results of *Adaboost* and *Rotation Forest* with 100 C4.5 trees as base classifiers, by using the average confusion matrix of the 5×2 ccross validation (the confusion matrix average of those provided by each of the 10 classifiers obtained in the cross validation has been calculated, and the values have been rescaled with regard to the total).

Regarding to the operation control, the most critical cases are those registered in the first column in both tables, as they match with those in which the ensemble classifier estimates that there are not a fault operation. By analyzing the data of this column, we can see that the undetected percentage of errors is 0.23 % in the case of *Adaboost*, and 0.68 % in the case of *Rotation Forest*.

Using the *t* test to compare the ensemble classifiers *Adaboost* and *Rotation forest* with a level of significance of 1 %, we may conclude from the statistical evidence that the first algorithm outperforms the second one with regard to the way it models the data.

Table 6. Confusion matrix for *Adaboost* (top) / *Rotation Forest* (bottom) of C4.5 trees

	C0	C1	C2	C3	C4	C5	C6	C7
C0	13.40	0.00	0.14	0.00	0.00	0.00	0.00	0.00
C1	0.00	11.53	0.03	1.18	0.19	0.00	0.00	0.00
C2	0.01	0.00	12.87	0.19	0.00	0.00	0.00	0.00
C3	0.02	0.56	0.27	11.23	0.71	0.00	0.00	0.00
C4	0.01	0.04	0.00	0.41	12.73	0.00	0.00	0.00
C5	0.00	0.00	0.00	0.00	0.00	13.31	0.00	0.00
C6	0.00	0.00	0.00	0.00	0.00	0.00	12.75	0.00
C7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	8.42

	C0	C1	C2	C3	C4	C5	C6	C7
C0	13.39	0.00	0.15	0.00	0.00	0.00	0.00	0.00
C1	0.00	11.80	0.03	0.90	0.20	0.00	0.00	0.00
C2	0.03	0.00	12.88	0.15	0.00	0.00	0.00	0.00
C3	0.02	0.78	0.48	10.72	0.79	0.00	0.00	0.00
C4	0.04	0.09	0.02	0.46	12.58	0.00	0.00	0.00
C5	0.00	0.00	0.00	0.00	0.00	13.31	0.00	0.00
C6	0.00	0.00	0.00	0.00	0.00	0.02	12.73	0.00
C7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	8.43

6 Conclusions

This study has proposed a fault diagnosis system for machines with high variation in the speed and load conditions, such as wind turbines. These devices have undergone significant growth over the last five years and require immediate industrial solutions to their tele-maintenance problems. The failure diagnosis system explained in this work consists of several measurement sensors, especially accelerometers, signal analysis equipment based on resampling angular techniques to process the data from these sensors, and a module that implements different data mining techniques for the classification of the operational state of wind turbines. Several methods of combining base classifiers have been applied to identify seven different levels of two typical faults in wind turbines: misalignment and imbalance. *Adaboost* using J48 decision trees as base classifiers achieved high accuracy (correct forecasts in 96.24 % of cases) when analyzing a wide real dataset measured on a test-bed that simulate real conditions of wind turbines operation (65551 instances with 544 attributes). Future research will be focused in the improvement of the industrial application through the testing of the proposed fault diagnosis system on a more extensive dataset that includes more fault cases and has been recorded under real industrial conditions, because the analysed dataset reflects a limited number cases of two fault types (misalignment and imbalance).

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