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Blade Fault Diagnosis using Artificial Neural Network

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Abstract

Fourier and wavelet analysis of vibration signals are the two most commonly used techniques for blade faults diagnosis in turbo-machinery. However, blade faults diagnosis based on visual comparison of vibration spectrum and wavelet maps are very subjective as it required experiences and knowledge to interpret the results. To overcome these challenge, new approaches for blade fault diagnosis based on artificial intelligent vibration analysis need to be devised to achieve a more objective and repeatable blade fault diagnosis. In this study, continuous wavelet transform was used to analyse the vibration signals and its results were subsequently used for feature extraction. Features extracted based on the statistical parameters calculated from the wavelet coefficients were then fed into the artificial neural network (ANN) model for blade faults diagnosis. Results of ANN classification show that the features obtained from the wavelet coefficients achieved classification accuracy of 88.43%. The proposed method can therefore use as an alternative method for blade fault diagnosis.

Keywords: Fourier, wavelet, blade fault, artificial neural network.

INTRODUCTION

Turbine and compressor that utilise blades to extract energy are of importance in power generation, petrochemical plants, and aerospace industries. Over the years, blade related failures have caused significant problems for rotating machinery operators in the industry [1]. Even a single blade failure can lead to significant financial losses, severe damages, and catastrophic failure. To reduce the turbine failures caused by blade faults, research on the condition monitoring methods and signal processing techniques used to diagnose various types of blade faults (e.g., blade deformation, blade rubbing, loose blade, blade fouling, and blade fatigue failure) have been widely reported in the open literature.

Condition monitoring methods; commonly used for blade faults diagnosis, include but are not limited to temperature analysis [2], vibration analysis [3], acoustic analysis [4], and pressure analysis [5]. Among these, the most widely used for blade faults diagnosis is vibration analysis because it is the most practical method to use under field conditions. The success of vibration analysis in blade fault diagnosis is highly reliant on the signal processing methods used to process the vibration signal and the pattern classification methodology.

Frequency domain (Fourier analysis) and time-frequency domain (wavelet analysis) vibration analysis are the most widely deployed signal processing techniques for both blade faults detection and diagnosis. The application of Fourier analysis [6-9] and wavelet analysis [10-13] has been successful in blade fault detection and diagnosis, comparing the amplitude or pattern of the vibration spectrum or the wavelet map for a faulty condition to a healthy condition. Changes in the operating frequency and blade passing frequencies, however, require individuals to detect and diagnose blade faults. Previous studies showed that wavelet analysis is more reliable and sensitive for blade fault diagnosis [14]. Interpretation of vibration spectrum and wavelet results is however difficult and challenging [15]. Blade faults diagnosis becomes difficult when the interpretation of vibration spectrum or wavelet results is not possible. Furthermore, these methods are very subjective as it required experiences and knowledge to interpret the results.

Recently, a number of researchers have shown an increased interest in developing artificial intelligence-based pattern recognition techniques for rotating machinery fault diagnosis, especially for bearings and gears [16, 17]. In-depth interpretation of vibration spectrum and wavelet map requires human intervention, which can be minimised by an artificial intelligence-based classification system. The artificial intelligence method has also been employed by previous researchers for blade fault detection and diagnosis. Features extracted from frequency domain analysis are usually used as input to the classifier [18-20]. The application of features extraction using time-frequency domain analysis for blade fault diagnosis is, however, still lacking. In this paper, a novel blade fault diagnosis method based on time-frequency features extraction and artificial intelligence approaches was proposed.

The rest of the paper is structured as follows: Section 2 summarizes the theory of wavelet analysis and ANN. The experimental study is presented in Section 3. In Section 4, the proposed novel blade fault identification approach is described in detail, followed by the results and discussion in Section 5. Finally, the conclusion is drawn in Section 6.

THEORETICAL BACKGROUND

Wavelet Analysis

Generally, wavelet analysis is divided into three types: discrete wavelet transform (DWT), wavelet packet transform (WPT) and continuous wavelet transform (CWT). DWT and WPT perform a down-sampling operation at each decomposition step, which leads to the loss of valuable information. CWT, on the other hand, operates at every scale. During computation of CWT, the wavelet is scaled and shifted over the entire domain of the analysed signal. Therefore, a wavelet map derived from a CWT is smoother and loses no information. The following formula defines CWT,

$$CWT(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} x(t)\varphi * \left(\frac{t-b}{a}\right) dt \tag{1}$$

where *x(t)* represents the analysed signal, *a* and *b* represent the scaling factor and translation along the time axis, respectively, and the superscript asterisk denotes the complex conjugation.

The relationship between the scale and its corresponding pseudo-frequency depends on the mother wavelet and is given by the following formula:

$$F_a = \frac{\Delta . F_c}{a} \tag{2}$$

where a is the scale level, Δ is the sampling period. F_c is the centre frequency of the wavelet and F_a is the pseudo-frequency corresponding to the scale a.

Artificial Neural Network

Artificial Neural Network (ANN) is one of the most popular supervised learning methods which is based on the behaviours of biological neurons. Over the year, the history and theory of artificial neural networks have been widely available in the open literature so will not be described in this paper except for an overview of the network architectures. In general, a neural network will consist of an input layer, hidden layer and output layer as shown in Fig. 1. Each layer is inter-connected through the neuron. The number of neurons in the input layer is usually equivalent to the number of inputs, and the number of neurons in the output layer depends on the desired output, while the number of neurons in the hidden layer is usually optimised through trial-and-error approach [21].

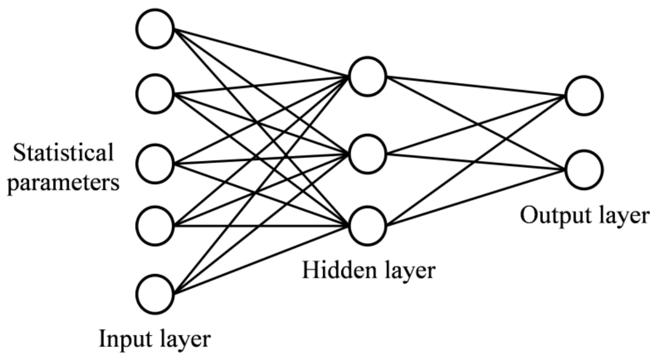


Figure 1 Overview of ANN architecture.

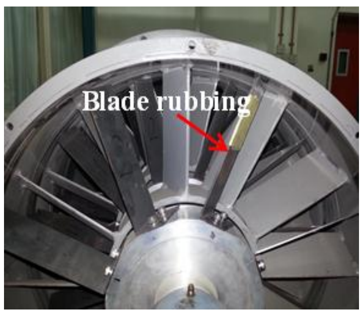
EXPERIMENTAL STUDY

In this study, a multi-stages rotor system was used to simulate various blade fault conditions. The multi-stages rotor system consists of 8, 11, and 13 pieces of rotor blades each located at the first, second and third row of the rotor. In addition, three rows of stator blades each with 12, 14, and 16 pieces of blades were also arranged in the rotor system to simulate the typical rotor-stator arrangement found in the industrial turbo-machinery.

For all blade fault configurations, two types of signals were measured: vibration and tacho. Two accelerometers were attached to the rotor casing to obtain vibration signals in two directions. In addition, an optical laser probe with reflective tape was used to capture the tacho signal. A photograph showing the multi-stages rotor system and the data acquisition setup of the experiment is depicted in Fig. 2.

Figure 2 Multi-stages rotor system and the data acquisition system set up in the experiment

Three different blade faults were investigated: blade rubbing, loss of blade part, and twisted blade. Blade rubbing was induced in the test rig by attaching a piece of sheet metal (1 mm thickness) to one of the standard blades to extend the length of the blade. The loss of blade part fault was introduced in the experiment by replacing one of the blades with another blade that had a partial loss. In order to study the vibration response due to a twisted blade, one piece of the standard blade was replaced with another blade tightened into the rotor disk in the reverse direction. Fig. 3 shows the three different types of blade faults introduced in a multi-stage rotor system.



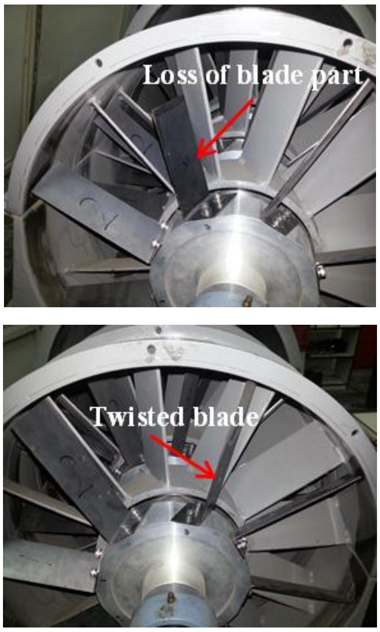


Figure 3 Type of blade faults

A total of 12 different blade conditions (3 baseline conditions and 9 blade-faulted conditions) were examined in this study, as illustrated in Table 1. Blade fault was simulated in different locations in a multi-stages rotor system with three different conditions including blade fault occur in row 1, row 2 and row 3 respectively. In summary, three different locations, each with three different types of blade faults were simulated in this study. It should be mentioned that vibration signals and tacho signals for healthy condition (no blade fault) was acquired before any blade fault was induced onto the rotor system. Two data sets (data set A and data set B) were acquired on two different days for all the designed blade fault conditions. All blade conditions were measured with a sampling rate of 5 kHz under a steady-state condition with a rotating speed set to 1200 rpm (20 Hz).

Table 1 Blade conditions induced onto the rotor system

Blade condition	Fault description
Healthy condition	No blade fault, N1
	No blade fault, N2
	No blade fault, N3
Blade rubbing	Blade rubbing in row 1
	Blade rubbing in row 2
	Blade rubbing in row 3
Loss of blade part	Loss of blade part in row 1
	Loss of blade part in row 2
	Loss of blade part in row 3
Twisted blade	Twisted blade in row 1
	Twisted blade in row 2
	Twisted blade in row 3

ANN BASED BLADE FAULTS DIAGNOSIS

The development of the new method for blade faults diagnosis was described in this section. This method begun with capturing vibration and tacho signals; follow by feature extraction using the results of continuous wavelet transform. Features extracted based on the statistical parameters calculated from the wavelet coefficients were then fed into the ANN model for training and testing. The network with the lowest cross-validation error was selected as the final network.

Feature Extraction

In this section, the proposed feature extraction method is explained. In this study, the important statistical features are extracted from the wavelet coefficients of the operating frequency and its corresponding blade passing frequencies for blade faults diagnosis. The steps for its implementation are further explained as follows:

1. Raw vibration signals and tacho signals were recorded from a multi-stages rotor system. The experiment was begun by measuring the effects of blade faults on the vibration of the rotor one at a time.
2. Using the raw vibration signal obtained, all frequencies, other than the operating frequency and its corresponding blade passing frequencies, were filtered. In this study, the operating frequency was 20Hz, and the blade passing frequencies for rows 1, 2, and 3 were 160Hz, 220Hz, and 260Hz respectively.
3. The vibration signal was converted from acceleration to velocity with high pass filtering of the signal followed by integration.
4. The signal was divided into 780 smaller segments (which represented 780 complete rotation cycles) using the tacho signal as the marker.
5. Synchronized Time Averaging (STA) operation was then applied to every 10th vibration segment to produce the STA signal, which represented the averaged vibration signal of one cycle of rotation.
6. Each STA signal was then used as the input for continuous wavelet transform to yield the corresponding wavelet coefficients. The Morlet wavelet was chosen because it has been shown to achieve good performance for machinery fault problems [22, 23].
7. Wavelet coefficients of the operating frequency and the blade passing frequencies were extracted to calculate statistical parameters.

In this study, wavelet coefficients of the operating frequency and the blade passing frequencies were extracted to calculate 11 statistical parameters, which consisted of mean, variance, standard deviation, root mean square, skewness, kurtosis, energy, Shanon entropy, crest factor, central moment, and energy to Shanon entropy ratio. For each vibration signal, a total of 78 samples are considered. Each sample consists of 88 statistical features (from operating frequency and blade passing frequencies) as shown in Table 2.

Table 2 Statistical features extracted from the wavelet coefficients

Wavelet coefficients	Total features (dataset A)	Total features (dataset B)
Operating frequency	22	22
Blade passing frequency of row 1	22	22
Blade passing frequency of row 2	22	22
Blade passing frequency of row 3	22	22

ANN Modelling

As mentioned earlier, a total of 12 different blade conditions (3 healthy conditions and 9 blade faulted conditions) were examined in this study. Two datasets (dataset A and dataset B) were acquired on two different days for all the designed blade conditions. Experimental dataset A was used for training, validation and testing purpose. Meanwhile, experimental dataset B, an entirely new testing data set was used to determine the network performance and generalization capability.

For each blade condition, 60 samples from dataset A were used for training and validation, while 18 samples each from datasets A and B were used to test the network. In summary, a total of 720 samples (12 different blade conditions x 60 samples) from dataset A had been used to train and validate the network, whereas 432 samples (12 different blade conditions x 18 samples x 2 datasets) from datasets A and B were used to test the network performance. The number of the training and the testing samples were shown in Table 3.

Table 3 The number of training and testing samples for blade fault diagnosis

Data	Blade condition	
	Healthy condition	Faulty condition
Training data (from dataset A)	180	540
Testing data (from dataset A)	54	162
Testing data (from dataset B)	54	162

In this study, feed-forward neural network with two hidden layers had been used to classify four-classes classification problem (healthy, blade rubbing, loss of blade part, and twisted blade) based on the statistical parameters calculated from the continuous wavelet coefficients. The number of neurons in the input layer equals the total number of features, and the number of neurons in the hidden layer was fixed to 10 neurons. In addition, the number of neurons in the output is 4. The training process was repeated 35 times with random generation of initial weights and biases. After that, ten-fold cross-validation was performed to train the network with stratified sampling. The network with the lowest cross-validation error was selected and tested with testing data. The architecture specifications of the ANN were summarized in Table 4. This study was performed on MATLAB software.

Table 4 Architecture specifications of the ANN

ANN parameters	Selected parameter
Training function	Scaled conjugate gradient (*trainsig*)
Transfer function	*tan-sigmoid* function in hidden layer and output layer
Number of neurons in input layer	Total number of features
Number of neurons in hidden layer	10
Number of neurons in output layer	4

RESULT AND DISCUSSION

Blade Fault Diagnosis using Conventional Method

In this section, the capabilities of Fast Fourier Transform (FFT) and wavelet analyses (using the Morlet wavelet) for blade fault diagnosis are presented. Fig. 5 show the vibration spectra for various types of blade conditions as tabulated in Table 1 (the results presented here are extracted from data set A and involved blade fault occur in row 1 only). It was found that the amplitude of the operating frequency (20 Hz) for all three faulty conditions is higher compared to the healthy condition. However, the pattern of FFT spectra for all three faulty conditions did not provide information needed to identify the type of blade fault.

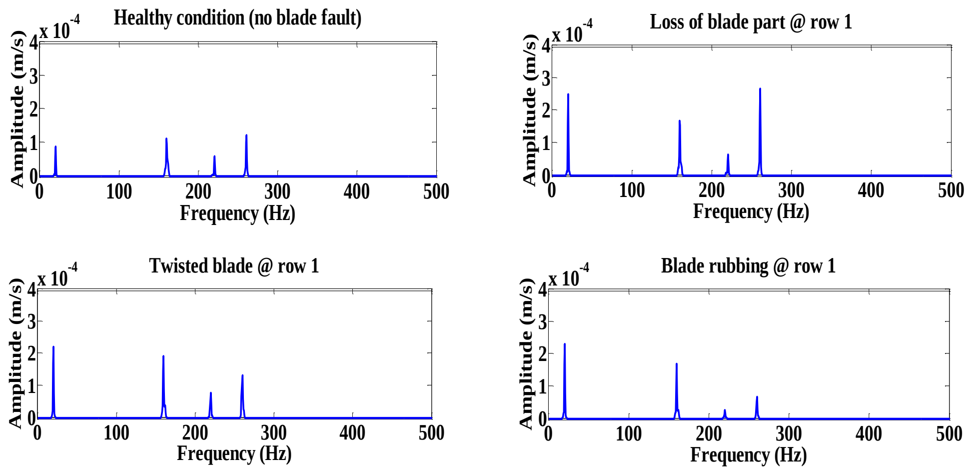


Figure 5. FFT spectra for various types of blade fault conditions.

Wavelet maps for different blade conditions are presented in Fig. 6. The findings obtained from the wavelet maps are consistent with the results of FFT spectra in which the blade faults were detected by monitoring the change of wavelet coefficients in the region of the operating frequency. However, no other significant singularity had been found from the wavelet maps to identify the type of blade fault.

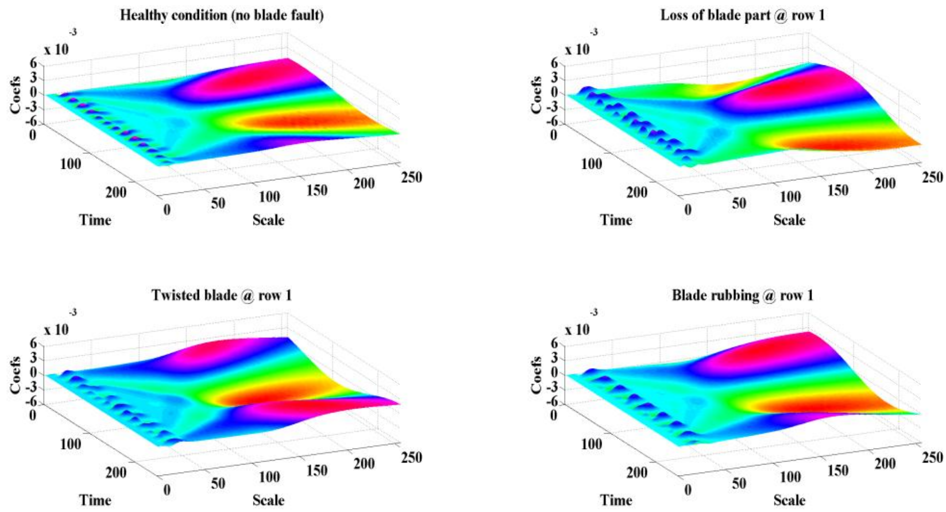


Figure 6 Wavelet map for various types of blade fault conditions.

All the above results show that the change or pattern of FFT spectra and wavelet coefficient amplitudes are been visible, but it is difficult to recognise the differences, which makes blade fault diagnosis difficult. So, it is evident that a new method for blade fault diagnosis is indeed necessary.

Blade Faults Diagnosis using ANN

In this study, the effectiveness of statistical features obtained from the continuous wavelet coefficients for blade fault diagnosis is compared. Three different feature sets were considered as the input for ANN, as shown in Table 5. Case A consisted of statistical features extracted from operating frequency, and Case B considered only the statistical features extracted from the blade passing frequencies. In Case C, all the extracted statistical features are considered. The number of neurons in the input layer for Case A, Case B, and Case C were 22, 66, and 88 respectively. The other architecture specifications of the ANN were similar to those mentioned in the previous section.

Table 5 Three different feature sets as input for ANN

Case	Feature set	Total features
Case A	Statistical features from operating frequency	22
Case B	Statistical features from blade passing frequencies	66
Case C	Statistical features from operating frequency and blade passing frequencies	88

Three ANNs were trained by using the same ANN parameters with different statistical feature sets. The effectiveness of these feature sets in identifying the types of blade faults is compared, and the results are shown in Table 6. In addition, as mention earlier, two sets of testing data from datasets A and B were used to evaluate the performance of the network. The overall accuracy represented the average accuracy of both testing datasets.

From the results, it had been observed that Case B had the lowest overall accuracy among the three different cases. The low classification accuracy for testing dataset B showed poor generalization capability of the trained network. This indicated that the features extracted from the blade passing frequencies fail to identify the type of blade fault. This observation is in line with the works of Louis et al. [24] in which only the information of the operating frequency was extracted for blade fault diagnosis. Moreover, the overall accuracy of Case A had been reported to be the best with a classification accuracy of 88.43%, followed by Case C with 80.56%, and Case B with 64.58%. In terms of network generalization, Case A was also the best as it achieved the highest classification accuracy for unseen testing data (dataset B). From all the above results, it can be concluded that Case A are more effective than Case B and Case C in blade fault diagnosis.

Table 6 Classification accuracy for Case A, Case B and Case C

Case	Testing data set A Accuracy, %	Testing data set B Accuracy, %	Overall Accuracy, %
Case A	88.89	87.96	88.43
Case B	91.67	37.50	64.58
Case C	95.83	65.28	80.56

On top of that, Tables 7-9 show the overall performance in the form of a confusion matrix for Case A, Case B and Case C respectively. The confusion matrix was often used to evaluate the performance of a classifier. The diagonal element of the confusion matrix represents the number of samples that had been correctly classified. Matrix elements, other than the diagonal element, reflect wrong classification. Besides, the sensitivity of the classifier to each class was also shown in the confusion matrix. Sensitivity is a measure of true positive rate.

Based on the confusion matrices, Case B and Case C had been incapable in identifying the blade rubbing conditions, out of 108 testing samples only 64 samples were correctly identify using Case B and 74 samples using Case C. Furthermore, the sensitivity of Case B and Case C in identifying healthy condition was also low. These results suggested that Case A was more effective than Case B and Case C in identifying different type of blade fault. Furthermore, the sensitivity of Case A in predicting each class (types of blade faults) was also good (all above 80%). Thus, all the results so far provide promising evidence for the effectiveness of Case A for blade fault diagnosis.

Table 7 Confusion matrix for Case A

Actual	Total samples	Predicted				Sensitivity (%)
		Healthy condition	Blade rubbing	Loss of blade part	Twisted blade	
Healthy condition	108	108	0	0	0	100
Blade rubbing	108	0	90	18	0	83.33
Loss of blade part	108	0	18	90	0	83.33
Twisted blade	108	0	14	0	94	87.04

Table 8 Confusion matrix for Case B

Actual	Total samples	Predicted				Sensitivity (%)
		Healthy condition	Blade rubbing	Loss of blade part	Twisted blade	
Healthy condition	108	54	0	0	54	50.00
Blade rubbing	108	5	64	8	31	59.26
Loss of blade part	108	0	13	77	18	71.30
Twisted blade	108	8	14	2	84	77.78

Table 9 Confusion matrix for Case C

Actual	Total samples	Predicted				Sensitivity (%)
		Healthy condition	Blade rubbing	Loss of blade part	Twisted blade	
Healthy condition	108	78	0	30	0	72.22
Blade rubbing	108	0	74	34	0	68.52
Loss of blade part	108	0	7	101	0	93.52
Twisted blade	108	0	13	0	95	87.96

CONCLUSIONS

In this paper, a novel blade fault diagnosis method based on time-frequency features extraction and artificial intelligence approaches was proposed. A novel feature extraction method was applied to extract statistical features from the wavelet coefficients. The effectiveness of the extracted statistical features for blade fault diagnosis was evaluated by using three different feature sets as input for ANN. The performance of the ANN trained with statistical features extracted from the operating frequency (Case A) achieved the highest classification accuracy of 88.43%, followed by features extracted from the operating frequency and blade passing frequencies (Case C) with 80.56%, and features extracted from the blade passing frequencies (Case B) with 64.58%. It can be concluded that, the features extracted from the operating frequency are more effective in blade fault diagnosis as compared to the features extracted from the blade passing frequencies. The proposed method can therefore use as an alternative method for blade fault diagnosis.

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