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Neural Network based Classification of Unbalances in Rotating Machinery

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Abstract

Health monitoring for rotating machinery such as aircraft engines, motors provide economic benefits and operational efficiencies in terms of reduced downtime. In this paper we present a methodology of using artificial neural networks (ANN) and frequency-domain vibration analysis to detect and classify common types of unbalances in rotating machines. Frequency domain features are used to train an artificial neural network. The artificial neural network is trained using back-propagation algorithm with a subset of experimental data obtained from a real-world rotating machine, Machinery Fault Simulator (MFS), for known types of unbalances. The trained artificial neural network is then used to classify various types of unbalances such as static unbalance and couple unbalance. The effectiveness of the neural network to classify these different types of unbalances is tested using the remaining set of data. The advantage of this procedure is that it can be used not only to diagnose unbalance but also to identify the type of unbalance in rotating machines.

1. Introduction

A fault is an unwanted deviation of the behaviour of the system from an acceptable behaviour. Therefore, a fault may lead to a failure of the system. Fault diagnosis means to discriminate fault types using vibration signals using expert's knowledge or experiences when the machine breaks down. Early detection of faults can provide considerable cost savings in many industrial applications such as aircraft engines, wind turbines etc. The use of vibration signals is common in the field of condition monitoring and fault diagnostics in rotating machines. Vibration signal from accelerometers are usually measured and compared with nominal measurements to detect faults in rotating machines. Time domain analysis and frequency domain analysis are some of the methods used to analyse the vibration signals. Among these methods frequency analysis is the most popular one. Most of the characteristics of vibration signal are more easily noticed in frequency domain rather than in time domain.

Detection of faults like mass unbalance, rotor rub, shaft misalignment and bearing defects is possible by comparing the vibration signals of normal and faulty conditions. As the vibration signals carry important information of the fault, it is possible to extract features from the frequency spectrum of the vibration signals in order to diagnose various faults. Although visual inspection of the frequency spectrum of the vibration signals is often adequate to identify the type of unbalance, there is a need for a reliable automated procedure for diagnosis and classification of the type of unbalance.

Artificial Neural Networks (ANNs) in recent period have become an important technique to solve classification problems. ANNs have been widely used for fault detection of faults in bearings of rotating machines [1,2]. ANNs have been used for classification based on time-domain features [3] as well as frequency domain features [2]. Tao *et al.* [4] used different mode shapes as inputs to ANN to identify crack fault in a rotor shaft. Barakat *et al.* [5] used Self Adaptive Growing Neural Networks (SAGNN) to detect and diagnose various faults in bearings, gears and belts of rotating machines. ANNs have been used to detect mass unbalance in rotating machines [6]. Neural networks have also been used to classify faults in rotaing machines such as turbo-generators [7] and hydraulic generator sets [8]. In this paper we present diagnosis and classification of various types of unbalances using ANNs. A Neural network is trained to classify various types of unbalances using frequency domain features extracted from the vibration signals.

2. Extracting features

Unbalance is the most common rotordynamic fault. It normally manifests itself as 1X (synchronous) vibration and it can cause rub and wear, degradation in performance. Various types of unbalances are - static unbalance and couple unbalance.

- Static Unbalance: It is the simplest form of unbalance as detailed in Figure 1. The center of rotation is displaced parallel to the geometric center of the rotor.

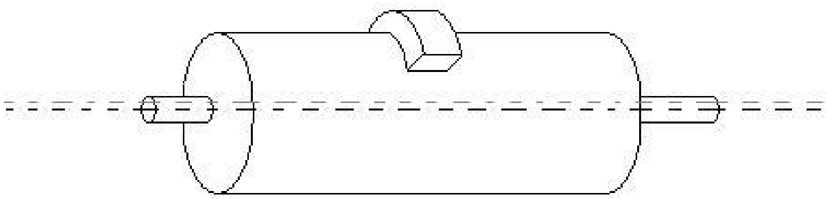

Figure 1: Static unbalanced rotor

- Couple Unbalance: As detailed by Figure 2, couple unbalance is represented by two unbalance masses separated by 180° from each other. This type of unbalance is often the result of incorrect balancing attempts on a static unbalance.

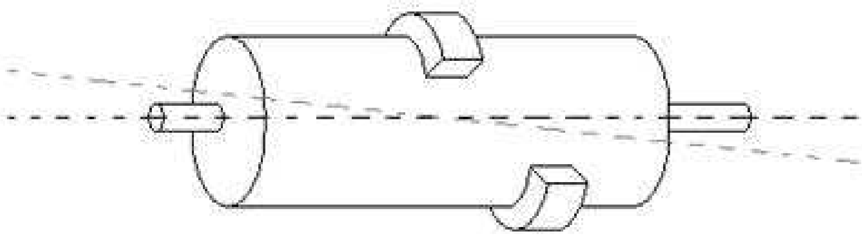

Figure 2. Couple unbalanced rotor

2.1 Frequency domain analysis

As unbalance is periodic in nature, frequency domain analysis is best suited to detect unbalance and to diagnose various types of unbalances. As the frequency components are concentrated as multiples of the fundamental frequency (or referred to as 1X), it is enough to concentrate on frequencies which are multiples of the fundamental frequency. The fundamental frequency is the shaft rotational frequency, *F*.

The vibration data is collected from the Machinery Fault Simulator (MFS), a laboratory rig shown in Figure 3, to simulate various faults in rotating machines. Balanced rotor, static unbalance and dynamic unbalances are simulated on this rig and the vibration data collected is used to train and test the effectiveness of the neural network. Two weights of 5.5 *g* each are used to create the unbalances. Each signal consists of 1 second of data gathered at a sampling rate of 25 KHz. Only frequency components from 1 to 500 Hz are considered. A low-pass Butterworth filter is used to filter out frequencies above 500 Hz. An FFT of this signal is then performed to generate a frequency spectrum of the vibration signal.

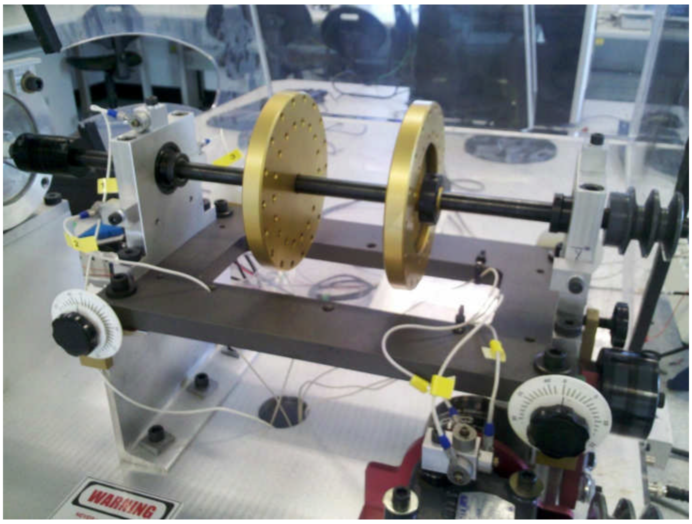

Figure 3. Machinery fault simulator

The frequency spectrograms of balanced, static unbalanced and couple unbalanced rotors rotating at a constant rotational speed of 35 Hz are shown in Figure 4 Figure 5 and Figure 6 respectively. As it can be seen from the figures, there are subtle differences in the frequency spectrum. The neural networks can be trained to pick these differences and classify the type of unbalance.

2.2 Normalization

The FFT values of the frequencies in the frequency spectrum of the vibration signal increases with increase in speed of rotation. In order to make the diagnosis algorithm insensitive to the variations in speed of rotation of the rotor, the frequency signatures are obtained by means of normalization process. Normalization is carried out by diving FFT value of each frequency from 1 to 500 Hz with the norm of the FFT vector which contains FFT values of frequencies ranging from 1 to 500 Hz. Normalized FFT value for a particular frequency is given by

$$\textit{normalized FFT value} = \textit{FFT value} / \textit{norm(FTT vector)} \qquad (1)$$

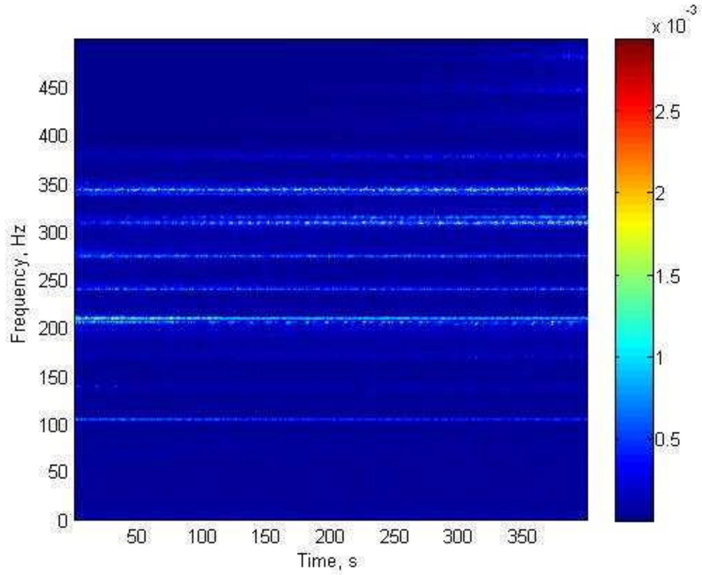

Figure 4: Spectrogram of balanced rotor rotating at 35 Hz

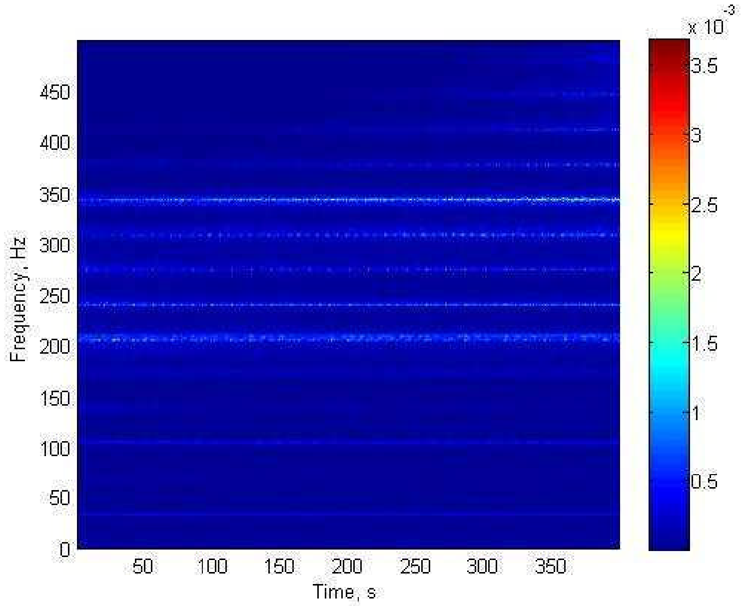

Figure 5: Spectrogram of static unbalanced rotor rotating at 35 Hz

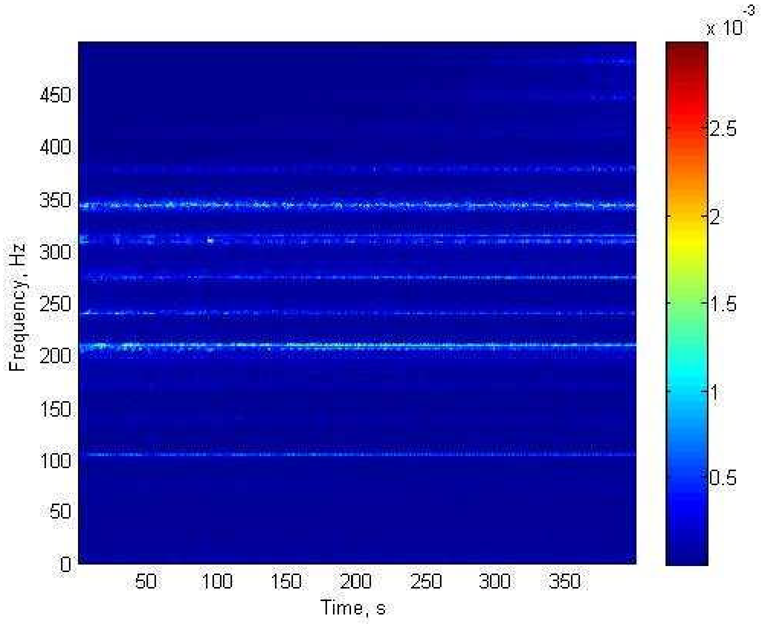

Figure 6: Spectrogram of couple unbalanced rotor rotating at 35 Hz

Normalization process makes the frequency signatures independent of the speed of rotation, but at the same time preserves the relative strengths of different frequency components in the frequency spectrum. As classification of various unbalances depends on the relative strengths of the frequency components in the frequency spectrum, normalization is crucial in developing neural network based classification.

In order to develop a classification algorithm using neural network it is important to identify the features of the frequency spectrum that can help in distinguishing between the various types of unbalances. In this research we used normalized FFT values of the frequency components which are integer multiples of *F*. Frequency content at *F, 2F, 3F*, *4F, 5F* and *6F* are considered. These frequencies corresponding to the first six harmonics, or first six orders, of the rotating machine. Because of energy leakage and slight variations in the speed of rotation of the rotor a frequency band of 2 Hz is considered around these frequencies.

$$\textit{frequency band} = [f-1\ f+1] \qquad (2)$$

where f is the centre frequency of the frequency band. x_1, x_2, x_3, x_4, x_5 and x_6 represent

the average values of the normalized FFT values in the bands centred around frequencies *F, 2F, 3F*, *4F, 5F* and *6F* respectively. In other words, these six values represent the amplitudes of the first six orders.

Vibration signals are gathered for rotating speeds of 35 Hz and 40 Hz and for different types of unbalances. In order to reduce noise in the amplitudes of orders, moving average filter is used. Figure 7 and Figure 8 shows the amplitudes of six orders before and after the filtering process respectively. The figures show the amplitudes of six orders for 200 samples of a balanced rotor rotating at 35 Hz.

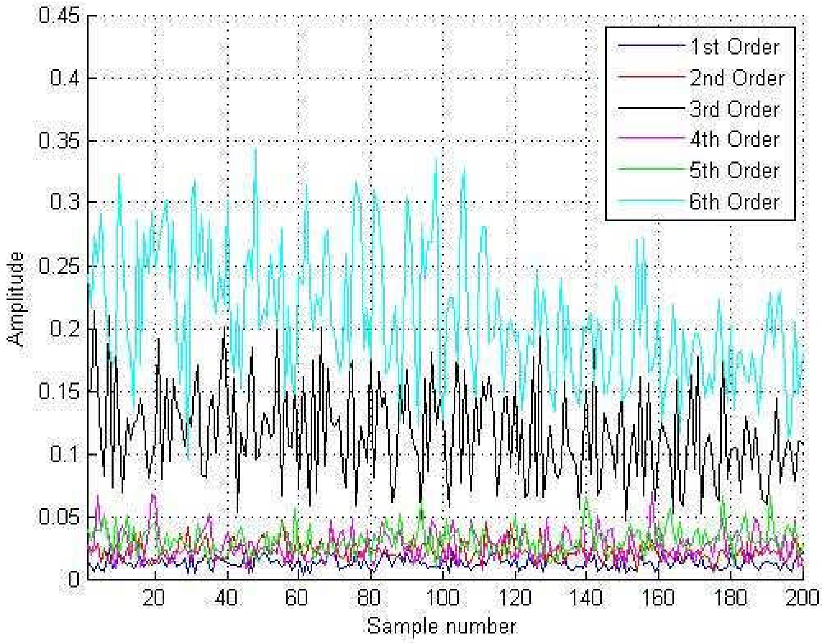

Figure 7. Amplitudes of first six orders of a balanced rotor rotating at 35 Hz before filtering

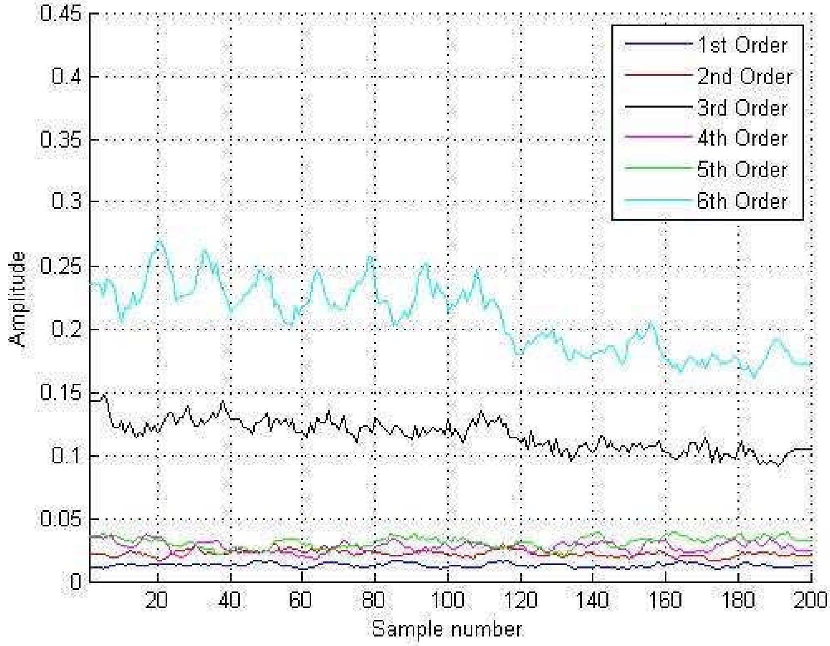

Figure 8. Amplitudes of first six orders of a balanced rotor rotating at 35 Hz after filtering using moving average filter

3. Diagnosis using artificial neural network

3.1 Training neural network

The neural network used for fault diagnosis and classification is shown in Figure 9. The input to the neural network is a vector consisting of the amplitudes of six orders and the rotational speed. Each of the three outputs serve as an indicator for the three types of unbalances – balanced, static unbalanced and couple unbalanced. The output is a classification vector corresponding to one of the three types of unbalaces. The neural network has five hidden nodes.

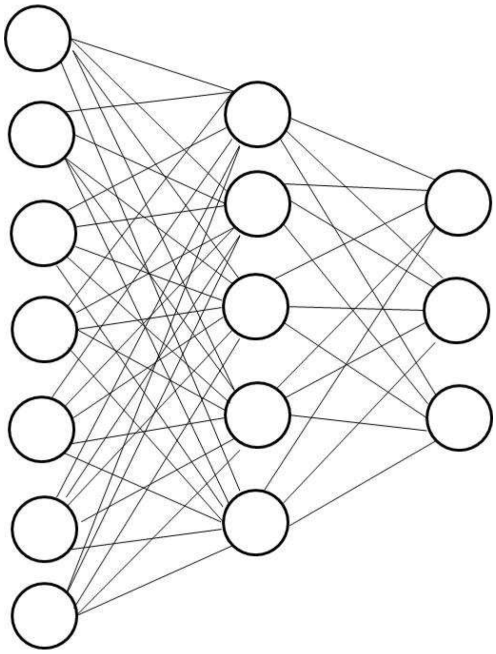

Figure 9. Artificial neural network used for classification of unbalances

The input vector to the neural network is given by

$$X = [\, x_1 \;\; x_2 \;\; x_3 \;\; x_4 \;\; x_5 \;\; x_6 \; F \,] \qquad (3)$$

The first six values correspond to the six orders and the seventh value represents the speed of rotation. The amplitues of orders varied with the rotational speed because of interaction with the structural modes of the rotating machine. Hence, speed of rotation is also used as one of the inputs to the neural network. The neural network is trained using back propagation algorithm which adjusts the weights of the connections of the neural network such that the outputs match the expected values. 200 signals for each type of unbalance for each of the two speeds - 35Hz and 40 Hz - are used to train the neural network. In total 1200 signals are used for training the neural network. After training, the neural network is able to classify the various types of unbalances.

3.2 Validating neural network

The trained neural network is validated using vibration data which has not been used during the training. Vibration data of the three unbalance conditions gathered from the MFS is used to test the effectiveness of the neural network to classify the type of unbalance. The results of the performance of the neural network are given in Table 1. The neural network is very effective when classifying unbalanced rotor compared to the other two types of unbalances. The neural network is not so effective in detecting static balanced and couple unbalanced cases. The reason for this is that - the amplitues of orders for the balanced and the couple unbalanced cases are not very dissimilar.

Table 1. Detection accuracy of the artificial neural network

Type of Unbalance	Rotational Speed (in Hz)	No of Data Sets	Detection Accuracy
Balanced	35	200	61.5 %
	40	200	100 %
Unbalanced	35	200	100 %
	40	200	100 %
Couple Unbalanced	35	200	92 %
	40	200	74.5 %

3. Conclusions

In this paper we have presented a neural network based approach to classify various types of unbalances. This approach needs training data for training the artificial neural network. However, once the neural network is trained it can diagnose unbalances. The effectiveness of the trained neural network to diagnose and classify various unbalances in rotating machines from features gathered from the vibration signal has been demonstrated.

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