Application of Artificial Neural Network and Wavelet Transform for Vibration Analysis of Combined Faults of Unbalances and Shaft Bow

H. K. Srinivas

Department of Mechanical Engineering
P.E.S.C.E, Mandya, India
hksri2006@yahoo.co.in

K. S. Srinivasan

C.I.T., Ponnampet, Madikere, India
ksrim23@redifmail.com

K. N. Umesh

Department of Mechanical Engineering
PESCE, Mandya, India
ksrim23@redifmail.com

Abstract

The vibration analysis of rotating machinery can give an indication of the condition of potential faults such as unbalance, bent shaft, shaft crack, bearing clearance, rotor rub, misalignment, looseness, oil whirl and whip and other malfunctions. The diagnostics of rotor faults has gained importance in recent years. Many papers in the literature have dealt with single faults but normally, more than one fault can occur in a rotor. This paper describes the application of artificial Neural Network (ANN) and Wavelet Transform (WT) for the prediction of the effect of combined faults of unbalance and shaft bow on the frequency components of vibration signature of the rotating machinery. The characteristic features of frequency domain vibration signals have been used as inputs to the ANN consisting of one input, one hidden and one-output layers. The ANN is trained using multiplayer feed forward back propagation marquardt algorithm. It is found that marquardt algorithm is much more efficient than the other techniques. The ANN used for diagnosis and quantifying of faults. The success
rates based upon each fault have been reported. In particular, an over all success rates of unbalance 99.78%, shaft bow 99.81% and combined faults of unbalance and shaft bow 99.45% has been achieved. The wavelet transform approach enables instant to instant observation of different frequency components over the full spectrum. A new technique combining the (WT) and (ANN) for detection of faults in three phases. This method is tested successfully for individual and combined faults of unbalance and shaft bow at a rate of 99.9%.

**Keywords**: Rotor test rig, Rotor faults, vibration analysis, unbalance, shaft bow, unbalance and shaft bow, ANN, Wavelet

1. Introduction

In recent years, a variety of conditions monitoring techniques have been developed to detect the various faults at their early stages. In order to avoid failure of rotating machinery of various types including mechanical and electrical ones, condition monitoring of various machine signatures using sophisticated instrumentation has found considerable use. In industrial plants, a number of signatures like vibrations, noise, acoustic emission, wear debris, lubricant degradation, temperature, corrosion, performance parameters etc., are monitor continuously or periodically, to give an idea of the health of the machine by proper diagnosis of faults which would, if not attended to in time, can result in catastrophic failures and down time. Vibration measurement and analysis has been applied with success (1) to machine like steam and gas turbines, pumps, compressors, induction motors etc. Faults like unbalance, misalignment, looseness, rub, cracks etc., generate vibration signals. In the present work experimental study has been carried out for transient response of the rotor for individual and combined faults of unbalance and shaft bent on the rotor test rig. The vibration frequency components recorded in the horizontal, vertical and axial directions for the analysis. The study has been carried out to developed unbalance and shaft bent on the rotor system in order to predict the change in the vibration behavior due to unbalance and shaft bent. Fault identification and diagnosis has become a vigorous area of work during past decade. Vibration monitoring has been widely reported as being a useful technique for the analysis of rotating machines (2); it can help by detecting faults early, allowing parts to be replaced before significant damage occurs. Vibration response measurements yield a great deal of information concerning any faults in a rotating machine. The use of machine condition monitoring can provide considerable cost savings in many industrial applications especially where large rotating machines are involved, for example generators in power stations. The monitoring of vibration of rotating machines has been reported as being a useful technique for their analysis of their condition (3) (4) (5). Many condition-monitoring techniques require extensive analysis of large amounts of data. These data can be used to produce estimates of the vibration spectra. Analysis of the information by human specialist can reveal
indications of many faults. Vibration condition monitoring as an aid to fault diagnosis was examined by Taylor (1995), Smalley and colleagues (1996) presented a method of assessing the severity of vibrations in terms of the probability of damage by analyzing the vibration signals. Although often the measured vibration signatures of frequency domain features are adequate to identify the faults, there is a need for reliable, fast and automated procedure of diagnostics (6). Unbalance is an important cause of vibration in rotating machinery and the reduction of such vibration by balancing. In this paper the experimental studies are presented in the dynamic balancing of flexible shaft using FRM. An important example of flexible rotor is provided by the alternator rotors, which are used for the generation of electrical power. The FRM balancing uses trial mass of rotor system. In the conventional procedure functional elements of CBM monitoring system include (i) a suite of active sensors to observe phenomena such as vibration spectra. (ii) Signal processing techniques to characterize the signal data and extract the significant features from the data. Usually, rotor unbalance can be detected by spectral analysis. The vibration frequency of rotor unbalance is synchronous, i.e., one time the shaft rotation speed (1X r.p.m.), since the unbalance force rotates at the shaft running speed. Rotor unbalance has been reported occasionally to show up in the frequency domain as a series of harmonics of the shaft running speed, i.e., 1Xrpm, 2Xrpm, 3Xrpm, 4Xrpm, etc. (7).

1.1 Artificial neural networks

The neural network techniques are used in conjunction with signal analysis techniques for classification and quantification of faults [8] in some applications. Kaminski [9] has developed neural networks to identify the approximate location of damage due to cracks through the analysis of changes in the neural frequencies. McCormick and nandi [10] have used neural network method for automatically classifying the machine condition from the vibration time series. Vyas and Satish Kumar [11] carried out experimental studies to generate data for rotating machinery faults like mass unbalance, bearing cap loose and health machine conditions. Srinivasan [12] carried out extensive studies for experimental data simulating faults like parallel misalignment, angular misalignment, unbalance, crack, light and heavy rubs, looseness and bearing clearance.

The neuron (Greek: Nerve Cell) is the fundamental of the nerve system, neuron is a simple processing unit that receives and combines signals from many other neurons through filamentary input paths. Neural network consists of a number of components connected together. The building block of the system is a relatively simple computing element and is known as adaptive linear combiner. The output of this element is a linear combination of inputs, this combination being determined by the choice weight ‘W_i’ [13]. The weights are chosen such that when the element is presented with training data, the output is as close as possible to the desired response. For every epoch, weights and biases will change, bias b_i is connected to an additional input permanently set to ‘1’. The next more complex element is the linear classifier, which is a linear combiner followed by a threshold
device, which has a binary output depending on the value of the input. A further
extension to the above is to allow the output element to have a more general
behavior than just a threshold function and let it have a set of weights that can
adopt to allow the realization of the desired response. A further refinement is to
add additional elements between the input element and the output elements. These
additional elements, the existence of which cannot be deduced from the number of
input and output components are known as hidden nodes. It is sensible to regard
the network structure as being composed of layers of elements or nodes and to
refer to the first layer where the inputs enter the system as the input layer and last
layer in between these two are known as hidden layers.

The Fig-1 shows a simple network consists of three layers with one input
layer, one hidden layer and one output layer. There are no connections between
nodes in the same layer and no connection bridging the layers. Such networks
with only one hidden layer can uniformly approximate any continuous function
and hence provide a theoretical basis for the use of this type of network. The
input-output relationship of each node is determined by a set of connection weight
$W_i$, a threshold parameter $b_i$ and a node activation function $A(\cdot)$ such that

$$Y = A(W_iX_i + b_i)$$  \hspace{1cm} (1)

Where $Y$ is the output of the node and $X_i$ are the inputs. The activation function $A(\cdot)$ defines the output of a neuron in terms of activity level at its input. The
sigmoid function is the most common activation function used in neural networks.
It is defined as a strictly increasing function exhibiting smoothness and
asymptotic properties. The Tan-sigmoid activation function is used in the hidden
layer. The purelin activation function is used in the output layer.

In the present work, improved back propagation neural network has been applied
for the diagnosis of combined faults of unbalance and shaft bow. It attempts to
minimize the square of the error between the output of the network and the
desired outputs by changing the connection weights using some form of gradient
descent. During training, this method consists of a forward pass through to
determine the output, followed by a backward pass to correct the weight. Once the
network has been trained, back propagation requires only the forward pass to
obtain the network output. The back propagation method has used gradient
descent techniques, which are simply the techniques, where parameters such as
weights and biases are moved in the opposite direction to the error gradient. Each
step-down the gradient results in smaller errors until error minimum is reached.
Using an approximation to Newton’s method is called “Levenberg-Margaret
approximation”. This is an improved back propagation method. Levenberg-
Margaret algorithm has the best convergence speeds for small and medium size
networks [13, 14]. In some cases the ratio of convergence speeds of these methods
are 1, 10 and 100 respectively. This optimization technique is more than gradient
descent method. The Levenberg-Marquardt update rule is

$$\Delta W = (J^T J + \Delta \mu I)J^T e$$ \hspace{1cm} (2)

Where $\Delta W = \text{Small change in weight}$. $J$ is the n by m Jacobian matrix $J^T J$ to keep
function N rows of $J$ linearly independent and $\mu$ is a small positive constant
chosen to ensure $(J^T J + \mu I)$ is positive for all ‘n’ values. If the sector $\mu$ is very large
the above expression approximates gradient descent, while if it is small the above expression becomes the Gauss-Newton method. The Gauss-Newton method is faster and more accurate and near to an error minimum. Training continues until the error goal is met, the minimum error gradient occurs, the maximum value of $\mu$ occurs or the maximum number of epochs has finished. The MATLAB Neural Network toolbox has been applied for diagnosing the rotating machinery faults. The input for the Neural Network is the frequency domain data obtained in the experimentation of rotating machinery faults.

1.1 Wavelet Transform

The wavelet transforms acts as a “Mathematical microscope” in which one can observe different paths of the signal by “adjusting the focus”. A frequency domain of the vibration signal can indicate sufficient difference for health and fault condition. The wavelet transform approach allows the detection of short-lived frequency component in the signals. The method is logical since high frequency components such as short bursts need high frequency resolution as compared with low-frequency components, which require low-frequency resolution. This paper also describes use of wavelet transform to decompose the vibration signal into several frequency ranges at different level of resolution. The strength root mean square (RMS) of selected decomposed signals is then calculated under combined faults of unbalance mass and shaft bent conditions. The neural network is then trained with the generated database to automate the fault diagnostic process.

2. Description of The Test Rig

The experimental operator is shown in Fig.2. The experimental rotor system used in this work was composed of a motor, which were connected by a flexible coupling and a single disk rotor. The rotor shaft is supported by two identical brass bush bearings and as a length of 250mm. The diameter of the rotor shaft is 15mm. A disk of 116mm in diameter, 22mm in thickness and a disk of mass 1.65kg are mounted on the rotor shaft mid-way between the bearing supports. The disk is fixed on the rotor shaft by radial screws. There are 36 tapped holes symmetrically placed on each side of the disk flat faces at a radius of 45mm, to attach any desired amount of unbalance mass. The bearing pedestals are provided in order to fix the sensors and measure the dynamic vibration level in the horizontal directions. The rotor shaft is driven by a 0.37kW (hp) dc/ac motor and a regulator which is use to maintain a constant operating speed of 1750rpm (29.16Hz). The power supply of 140V, 15Amps, and the input of the power supply connected to the motor and the output is connected to the regulator. The motor speeds ranges from 0-8000rpm. The natural frequency of the rotor is 4.45Hz. The critical speed is 267rpm. The piezoelectric accelerometers were attached in three directions for measurement of vibration velocity. The frequency analysis was carried out using a FFT analyzer. An accelerometer enables measurement of the vibration level in the horizontal, vertical and axial directions.
The output of the accelerometer was connected to the FFT analyzer for frequency analysis. The instrumentation used in the experiment includes piezoelectric accelerometer, pre-amplifier, vibration meter, dial-indicator, taco-meter and FFT analyzer. Three special fixtures attach tightly to the bearing pedestal were used to hold the accelerometer at the desired locations. The signal is transmitted to a transducer pre-amplifier. The output of the pre-amplifier signal transmitted to the FFT analyzer. The FFT analyzer records vibrations in frequency domain. The FFT spectrums are helpful in analyzing the vibration problems. These instruments will give the necessary information about the machine conditions.

The experimental work was carried out on Rotor bearing Test-rig is as shown in Fig.1. The entire project will be carried out in two stages. In the first stage the rotor was balanced using four run methods. The unbalance was simulated in rotor test rig. The rotor was run at a speed of 1500rpm. The accelerometer pickup fixed on the bearing points was used to record the vibration at three position namely, horizontal, vertical, and axial directions. Extensive experiments were carried out in order to investigate the effects of various individual and combination of faults like unbalance, crack, and combination of unbalance and crack. The results obtained were tabulated and frequency analysis was carried out.

3. Frequency Spectrum Analysis On Effects Of Combined Faults Of Unbalance And Shaft Bow

Spectrum analysis, as the most popular diagnostic tool, provides crucial information about the amplitude and phase content of the vibration at various frequencies. Frequencies of vibration responses are related to excitation frequencies, natural frequencies, and sub-harmonic frequencies. The peaks at multiple orders of the fundamental are identified with variety of faults that are present in the rotating machinery. Many papers in the literature have dealt with single faults but, normally, more than one fault can occur in a rotor. In this
experiment, combination of mass unbalance and shaft bent were both introduced simultaneously in the rotor test rig. The unbalance mass range was from 5.5 g to 11.5g and shaft bent ranging from 8.4 to 32.4microns, with a combination of unbalance and shaft bent. Machine was run at 1750 rpm for all case. The magnitude of residual unbalance is \(3.5 \times 4.5 = 15.75\text{g-cm}\) at an angle of \(38^0\) and a radius of 45 mm. The combined faults of unbalance and shaft bent were introduced and the vibration signals of the rotor were picked up from the bearing 2 in the horizontal, vertical and axial directions. The amplitude signals were stored in a dual channel FFT analyzer for further analysis. The frequency analysis has been carried out for the frequency component of vibration signatures due to different unbalance mass and shaft bent. Values of combined faults of unbalance and shaft bent on frequency components of RMS velocity (mm/s) are listed in table 3. From the above observation the value of 1X vibration frequency component in the horizontal direction are ranges from 0.500 mm/s to 2.98 mm/s, similarly 2X, 3X and 4X components have the magnitude of 0.240 mm/s to 0.580 mm/s, 0.026mm/s to 0.029 mm/s, and 0.004mm/s to 0.014mm/s respectively. 1X frequency component in the horizontal direction was maximum of 2.98 mm/sec. Thus we can conclude that 1X vibration frequency component is seen to be predominant in the horizontal direction. The trend graphs for combined faults of unbalance and shaft bent are shown in Fig 5 (a) to 5 (d).

The shaft was bent ranging from 8.4 to 32.4microns. The unbalance mass range was from 5.5 g to 11.5 g with a combination of unbalance and shaft bent. The machine was run at 1750 rpm. It is observed that the first harmonic in the horizontal direction 1X component has increased from 0.5mm/s to 2.98mm/s. The second harmonic 2X has also increased from 0.24mm/s to 0.58mm/s. There is an increase in the level of 1X frequency component of vibration from 0.27 to 1.48mm/s in vertical direction. The 2X frequency component of vibration has also shown an increasing trend from 0.14 mm/s to 0.184mm/s in the vertical direction. It has been observed from Fig.5 (a) to 5(b), that 1X frequency component of vibration is to be seen predominant in the horizontal direction ranging from 0.5mm/sec to 2.98mm/sec for the shaft bent ranging from 8.4 to 32.4microns and unbalance ranging from 5.5g to 11.5g corresponding to a speed of 1750 rpm, phase angle of \(38^0\) and radius of rotor is 45mm. The increase in the vibration level is the highest with 1X frequency components in the horizontal direction is 2.98 mm/sec. Thus we can conclude that the horizontal forces are predominant with the occurrence of first harmonic (1X).
Table 1: Values of frequency components of RMS vibration velocity (mm/s) for various unbalance mass ranging from 5.5 to 11.5g and shaft bow ranging from 32.4 microns were obtained at a rotor speed of 1750 rpm.

<table>
<thead>
<tr>
<th>Frequency components</th>
<th>Unbalance mass in (g) + Shaft Bent in (microns)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>5.5+32.4</td>
</tr>
<tr>
<td>1XH</td>
<td>0.920</td>
</tr>
<tr>
<td>2XH</td>
<td>0.440</td>
</tr>
<tr>
<td>3XH</td>
<td>0.009</td>
</tr>
<tr>
<td>4XH</td>
<td>0.008</td>
</tr>
<tr>
<td>1X V</td>
<td>0.680</td>
</tr>
<tr>
<td>2X V</td>
<td>0.160</td>
</tr>
<tr>
<td>3X V</td>
<td>0.018</td>
</tr>
<tr>
<td>4X V</td>
<td>0.006</td>
</tr>
<tr>
<td>1X A</td>
<td>0.068</td>
</tr>
<tr>
<td>2X A</td>
<td>0.038</td>
</tr>
<tr>
<td>3X A</td>
<td>0.018</td>
</tr>
<tr>
<td>4X A</td>
<td>0.016</td>
</tr>
</tbody>
</table>

Fig. 5(a). Frequency components of RMS Velocity for an unbalance mass of 5.5g and shaft bent of 32.4microns

Fig. 5 (b). Frequency components of RMS velocity for an unbalance mass of 7.5g and shaft bent of 32.4microns
4. Applications Of ANN For Fault Diagnosis

The neural network used for rotor fault diagnosis consists of one hidden layer and one output layer. Tan-sigmoid activation function is used in the hidden layer. It is used to map a neuron input from the interval \((-\infty, +\infty)\) into the interval \((-1, +1)\). The tan-sigmoid is a fully differential function, which makes it suitable for neurons being trained with back propagation. The output layer uses a purelin transfer function. The linear activation function is often used with the neurons being trained using back propagation. The simplest transfer function, which simply passes a neuron’s input vectors on to its output, is altered only by the neuron’s bias, which is added to it. The input vectors for training the network are the RMS velocity (mm/s) frequency components of the vibration signatures measured in the horizontal, vertical and an axial direction for the faults like unbalance and shaft bow. The network performance is called generalization, which is the ratio of actual output to the desired output expressed in percentage. The network was trained and tested with different neuron combination with different error goals for the above faults. ANN toolbox of MATLAB was used for the studies.
4.1 Network training and testing of combined faults of unbalance and shaft bow data

Table 6 shows the experimental values of combined faults of unbalance and shaft bent and the frequency components of vibration (mm/s). The values of frequency components obtained in the horizontal, vertical and axial directions. Three sets of data have been used for training the network and one set is test data (11.5mm+32.4microns). The network was used 8 neurons with error goal of 0.0001. The testing set has been shown in the last column of table 3. After sum squared error has decreased and μ has increased it yielded good generalization. Using this network the combined faults of unbalance and shaft bent has been quantified as11.4428g and 32.3954 microns or 99.50% and 99.98% of the experimental value.

Table 2- Quantification of unbalance mass, error goal of 0.0001 and hidden neurons 6.

<table>
<thead>
<tr>
<th>Serial no.</th>
<th>Experimental values of unbalance mass (g)</th>
<th>Epochs</th>
<th>MSE</th>
<th>Quantification values (g)</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5.5</td>
<td>7</td>
<td>5.47511e-008</td>
<td>5.4715</td>
<td>99.48</td>
</tr>
<tr>
<td>2</td>
<td>7.5</td>
<td>3</td>
<td>1.41375e-006</td>
<td>7.4785</td>
<td>99.72</td>
</tr>
<tr>
<td>3</td>
<td>9.5</td>
<td>3</td>
<td>2.26756e-006</td>
<td>9.4574</td>
<td>99.55</td>
</tr>
<tr>
<td>4</td>
<td>11.5</td>
<td>3</td>
<td>1.16994e-007</td>
<td>11.4717</td>
<td>99.75</td>
</tr>
</tbody>
</table>

Table 3- Quantification of shaft bent, error goal of 0.0001 and hidden neurons 6

<table>
<thead>
<tr>
<th>Serial no.</th>
<th>Experimental values of shaft bent (Microns)</th>
<th>Epochs</th>
<th>MSE</th>
<th>Quantification values (microns)</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>8.4</td>
<td>3</td>
<td>9.83621e-006</td>
<td>8.3465</td>
<td>99.36</td>
</tr>
<tr>
<td>2</td>
<td>18.6</td>
<td>5</td>
<td>5.30815e-010</td>
<td>18.5647</td>
<td>99.81</td>
</tr>
<tr>
<td>3</td>
<td>25.4</td>
<td>13</td>
<td>6.17818e-007</td>
<td>25.3184</td>
<td>99.67</td>
</tr>
<tr>
<td>4</td>
<td>32.4</td>
<td>4</td>
<td>3.17993e-005</td>
<td>32.3866</td>
<td>99.95</td>
</tr>
</tbody>
</table>
Table 4- Quantification of combined faults of unbalance and shaft bent, error goal of 0.0001 and hidden neurons 6

<table>
<thead>
<tr>
<th>Serial no.</th>
<th>Experimental values of combined faults of unbalance (g) and shaft bent (microns)</th>
<th>Epochs</th>
<th>MSE</th>
<th>ANN Quantification values</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5.5 8.4</td>
<td>4</td>
<td>0.000292407 5.4008</td>
<td>98.19</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>11.5 8.4</td>
<td>5</td>
<td>1.35912e-005 11.2947</td>
<td>98.21</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>5.5 18.6</td>
<td>4</td>
<td>0.000852516 5.49901</td>
<td>99.98</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>11.5 18.6</td>
<td>7</td>
<td>0.000221832 11.3993</td>
<td>99.12</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>5.5 25.4</td>
<td>6</td>
<td>6.40257e-006 5.5000</td>
<td>100.00</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>11.5 25.4</td>
<td>17</td>
<td>0.000511523 11.3685</td>
<td>99.94</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>5.5 32.4</td>
<td>5</td>
<td>4.83345e-005 5.4385</td>
<td>99.88</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>11.5 32.4</td>
<td>8</td>
<td>0.000587234 11.4428</td>
<td>99.50</td>
<td></td>
</tr>
</tbody>
</table>

5. Wavelet Analysis

Wavelet transform is a mathematical tool with a powerful structure and enormous freedom to decompose a given signal into several scales at different levels of resolution. Figure 7(a) shows the multi-resolution signal decomposition algorithm used for implementation of discrete wavelet transform. In this figure, \( s^l(n) \) is the sampled signal of \( f(t) \), sampled at the rate of \( " fs" \) Hz. The digitized signal \( s(n) \) is then first decomposed into \( a1(n) \) and \( d1(n) \) using low pass filter \( h1(n) \), and high pass filter \( g1(n) \), respectively, where, \( d1(n) \) is called the detail function containing higher frequency terms, and \( a1(n) \) is called the approximation signal containing low frequency terms. This is called first- scale decomposition. The second scale decomposition is now based on the signal \( a1(n) \) which gives \( a2(n) \) and \( d2(n) \). The next higher scale decomposition is now based on \( a2(n) \) and so on. At any level \( "f" \) the approximation signal \( aj(n) \) will be composed of frequencies \( 0-fc \) Hz. Similarly the detail signal \( dj(n) \) at any level \( "f" \) will contain frequencies of range \( fc-2 \) Hz. The cut-off frequency \( "fc" \) of approximation signal \( aj(n) \) for a given level \( f \) is found by

\[
f_c = f_c / 2^{f-1}
\]
Also, the number of points in the decomposed detail and approximation signals decreases gradually through successive decimation. Thus, to compute the discrete wavelet transform all that is needed are filters. The signal is convolved with these filters. In contrast to the short time Fourier transform (STFT), the time resolution becomes arbitrarily fine at high frequency, while the frequency resolution becomes arbitrarily fine at low frequencies. In the present work attempt is made to use wavelet transform for identification of rotor fault, which does not depend on a single frequency, but on a band of frequencies.

**Implementation**

A Condition monitoring system performs three general tasks data acquisition, feature extraction, and fault identification. Data acquisition part includes collection of rotor fault, which are indicative of rotor health. The signals are recorded for various individual and combined faults of unbalance mass and shaft bow conditions. The faults in the rotor were introduced intentionally.

**Feature Extraction**

The aim of the feature extraction is to apply the transformation that extracts the signal features hidden in the original frequency domain. Corresponding to different characteristics of the signal, transformation should be properly selected such that specific signal structure can be enhanced in its transformed domain. The fault identification techniques are those, which compares current data with that of the known cases to reach the final diagnosis. A multi-resolution property of the discrete wavelet transform (DWT) is used to analyze the vibration signal under different fault conditions. The Daubechies wavelet was selected for the signal analysis because they provide a much more
Application of artificial neural network

effective than that obtained with the other wavelets (Haar, Coifman, etc.). When vibration signals collected under different conditions are decomposed via the wavelet, the appreciable differences between the corresponding wavelet coefficients Figure 7(b), (c), (d), and (e) can be seen. However, direct assessment from all wavelet coefficients turns out to be tedious job. Therefore, the wavelet node power $e_j$ at “f” level decomposition in defined as $e_j = 1/N_j$

Here, $N_j$ is the number of coefficients at level “f.” $w_{j,k}$ is the $k^{th}$ coefficient calculated for $j^{th}$ level $e_j$ is the RMS (root mean square) value of the decomposed signal at a level “f”. It measures the signal power contained in the specified frequency band indexed by the parameter “f”. In order to relate the RMS value of the wavelet decomposition signals with different rotor faults. For each case four sets of data are recorded.

![Figure 7(b) Wavelet decomposition corresponding to unbalance mass 5.5g + Shaft bow 32.4 microns](image)

![Figure 7(c) Wavelet decomposition corresponding to unbalance mass 7.5g + Shaft bow 32.4 microns](image)

![Figure 7(b) Wavelet decomposition corresponding to unbalance mass 9.5g + Shaft bow 32.4 microns](image)

![Figure 7(c) Wavelet decomposition corresponding to unbalance mass 11.5g + Shaft bow 32.4 microns](image)

The vibration in the RMS value of first ten decomposition for one segment from each case is shown in Table 7 the similar values are obtained for other vibration segments. From Table 7, it is clearly observed that the unbalance mass increases with a constant shaft bow.
Table 5: RMS value of vibration signal and its ten detailed coefficient wavelet decompositions

<table>
<thead>
<tr>
<th>Unbalance Mass + Shaft Bow</th>
<th>Original RMS</th>
<th>D1</th>
<th>D2</th>
<th>D3</th>
<th>D4</th>
<th>D5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unbalance Mass 5.5g+ Bow 32.4 Microns</td>
<td>0.4432</td>
<td>0.1161</td>
<td>0.0901</td>
<td>0.1891</td>
<td>0.1475</td>
<td>0.1440</td>
</tr>
<tr>
<td>Unbalance Mass 7.5+ Bow 32.4 Microns</td>
<td>0.6940</td>
<td>0.1550</td>
<td>0.1670</td>
<td>0.3550</td>
<td>0.2160</td>
<td>0.2413</td>
</tr>
<tr>
<td>Unbalance Mass 9.5+ Bow 32.4 Microns</td>
<td>1.5622</td>
<td>0.3952</td>
<td>0.4318</td>
<td>0.7721</td>
<td>0.4928</td>
<td>0.4741</td>
</tr>
<tr>
<td>Unbalance Mass 11.5+ Bow 32.4 Microns</td>
<td>3.3088</td>
<td>0.6564</td>
<td>1.1308</td>
<td>2.0926</td>
<td>0.9480</td>
<td>1.0765</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Unbalance Mass + Shaft Bow</th>
<th>D6</th>
<th>D7</th>
<th>D8</th>
<th>D9</th>
<th>D10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unbalance Mass 5.5g+ Bow 32.4 Microns</td>
<td>0.1837</td>
<td>0.3268</td>
<td>0.5846</td>
<td>1.0128</td>
<td>1.7940</td>
</tr>
<tr>
<td>Unbalance Mass 7.5+ Bow 32.4 Microns</td>
<td>0.3074</td>
<td>0.5445</td>
<td>0.9789</td>
<td>1.6935</td>
<td>2.9916</td>
</tr>
<tr>
<td>Unbalance Mass 9.5+ Bow 32.4 Microns</td>
<td>0.5919</td>
<td>1.0435</td>
<td>1.8820</td>
<td>3.2504</td>
<td>5.7505</td>
</tr>
<tr>
<td>Unbalance Mass 11.5+ Bow 32.4 Microns</td>
<td>1.3546</td>
<td>2.3703</td>
<td>4.3044</td>
<td>7.9217</td>
<td>13.1349</td>
</tr>
</tbody>
</table>

Neural Network Training

Once suitable features have been extracted and selected from the vibration data, it is necessary to determine the effect of combined faults of unbalance and shaft bow for different unbalance masses based upon these features. The neural network is trained by using back propagation algorithm [11, 12].

Data Normalization

During training of the neural network, higher valued input variables may tend to suppress the influence of the smaller one. To overcome this problem and in order to make neural network perform well, the data must be well processed and properly scaled before input to the ANN. All the components of feature vector are normalized using the following equation.

\[ x_n = \frac{x - x_n}{1.5 x_{\text{max}}} + 0.8 + 0.1 \]  

(2)

Where, \(x\) is actual data, \(x_{\text{max}}\) is the maximum value of the data and \(x_n\) is the normalized data. The maximum value is obtained from the faulty data set. The maximum value is multiplied by the factor 1.5 so that if the fault severity is more than what is consider till now, same neural network can be useful for fault identification. Table 9 shows the normalized value of RMS level given in Table 7 by using equation 2. The neural network tool box of MATLAB has been used to simulate the desired network. The “newff” function of MATLAB uses has been
used to create three-layered back propagation network. In the training process, the network is trained according to Levenberg-Marquardt optimization technique until the mean square error is found below 0.0001 or the maximum number of epoch’s (500) is reached. The result as shown in Table 9.

Table 6: Normalized training data set

<table>
<thead>
<tr>
<th>SI. No</th>
<th>Unbalance Mass + Shaft Bow</th>
<th>Input</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Unbalance Mass 5.5g+ Shaft Bow 32.4 Microns</td>
<td>W1 0.10  W2 0.103  W3 0.10  W4 0.105  W5 0.105  W6 0.107  W7 0.113  W8 0.12  W9 0.141  W10 0.1</td>
</tr>
<tr>
<td>2</td>
<td>Unbalance Mass 7.5+ Shaft Bow 32.4 Microns</td>
<td>W1 0.10  W2 0.106  W3 0.11  W4 0.108  W5 0.109  W6 0.112  W7 0.122  W8 0.13  W9 0.168  W10 0.2</td>
</tr>
<tr>
<td>3</td>
<td>Unbalance Mass 9.5+ Shaft Bow 32.4 Microns</td>
<td>W1 0.11  W2 0.117  W3 0.13  W4 0.120  W5 0.119  W6 0.124  W7 0.142  W8 0.17  W9 0.231  W10 0.3</td>
</tr>
<tr>
<td>4</td>
<td>Unbalance Mass 11.5+ Shaft Bow 32.4 Microns</td>
<td>W1 0.12  W2 0.145  W3 0.18  W4 0.138  W5 0.143  W6 0.155  W7 0.196  W8 0.27  W9 0.401  W10 0.6</td>
</tr>
</tbody>
</table>

Table 3 shows the experimental values of combined faults of unbalance and shaft bent and the frequency components of vibration (mm/s). The values of frequency components obtained in the horizontal, vertical and axial directions. Three sets of

Figure. 7(f) Neural Network training

Figure. 7 (g) Neural Network training
data have been used for training the network and one set is test data (11.5mm+32.4microns). The network was used 8 neurons with error goal of 0.0001. The testing set has been shown in the last column of table 3. After sum squared error has decreased and $\mu$ has increased it yielded good generalization. Using this network the combined faults of unbalance and shaft bent has been quantified as11.4983g and 32.3993 microns or 99.99 % and 99.98% of the experimental value. The result as shown in Table 9.

Table 7- Quantification of combined faults of unbalance and shaft bent using combined form of ANN and Wavelet transform, error goal of 0.0001 and hidden neurons 6

<table>
<thead>
<tr>
<th>Serial no.</th>
<th>Experimental values of combined faults of unbalance (g) and shaft bent (microns)</th>
<th>Epochs</th>
<th>MSE</th>
<th>AN Quantification values</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5.5 32.4</td>
<td>9</td>
<td>2.335e-006</td>
<td>5.5 32.3958</td>
<td>100.0 99.98</td>
</tr>
<tr>
<td>2</td>
<td>7.5 32.4</td>
<td>5</td>
<td>6.71342e-005</td>
<td>7.4962 32.3973</td>
<td>99.94 99.99</td>
</tr>
<tr>
<td>3</td>
<td>9.5 32.4</td>
<td>3</td>
<td>0.0008831 62</td>
<td>9.4994 32.3997</td>
<td>99.99 99.99</td>
</tr>
<tr>
<td>4</td>
<td>11.5 32.4</td>
<td>24</td>
<td>2.0738e-006</td>
<td>11.4983 32.3993</td>
<td>99.99 99.99</td>
</tr>
</tbody>
</table>

6. Conclusions

Use of amplitudes of vibration harmonics of a rotor system in horizontal, vertical and axial directions helps in indicating the presences of faults like unbalance and shaft bow. To quantify these faults the approach of using artificial neural network of multiplayer feed forward back propagation algorithm, is promising has been seen by training of the network by simulated data obtained experimentally and testing the same. Further work needs to be done by using other types of networks and algorithm. Further, there needs to be work to remove the arbitrariness in choice of the network parameters. The ANN used for diagnosis and quantifying of faults. The success rates based upon each fault have been reported .In particular, an over all success rates of unbalance 99.78%, shaft bow 99.81% and combined faults of unbalance and shaft bow 99.45% has been achieved. This paper also has been investigated the feasibility of applying discrete wavelet transform to identify the combined faults of unbalance mass and shaft bow of vibration signals. To alleviate the frequency –invariant characteristics of the wavelet coefficients and to reduce the dimensionality of the input to the neural network, RMS value at selected decomposition levels are used as feature measure
Application of artificial neural network

of the signal. The features obtained by proposed method for vibration signal yields nearly 99.99% correct when used as input to a neural network.

References


Received: June, 2009