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Application of Artificial Neural Networks for Identification of Unbalance and Looseness in Rotor Bearing Systems

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Abstract: Rotating machinery is common in any industry. Rotating machinery in the modern era are designed for higher running speeds, tighter clearances and working under extreme conditions enhancing efficiency of the system to produce and transmit more power. All these lead to many rotordynamic challenges. Main cause of vibrations is faults in the rotating systems like unbalance, looseness, etc. In this paper a method is proposed to identify unbalance and looseness in rotor bearing system using artificial neural networks (ANN) by two different methods; one is by statistical features and the second by amplitude in frequency domain. In the first case statistical features are used to train and test the ANN, and in the second case amplitude in frequency domain is used to train and test the ANN. Experiments are conducted on the rotor bearing system running at 40 Hz and vibration data is collected by simulating different unbalance conditions in the rotor. And also experiments are conducted by creating looseness in the system by loosening the pedestal bolt. Various statistical features and amplitudes in frequency domain are extracted separately from this vibration data and are fed to neural network. It is observed that statistical features are giving good results over frequency domain amplitudes. ANNs are used to identify the unbalance severity and looseness. These results are useful for making maintenance decision.

Keywords: Unbalance; looseness; rotor; vibration analysis; neural networks.

1. Introduction

Rotating machinery is very popular in industrial applications. Most of the mechanical failures are due to vibrations. It is more so in case of rotating machinery. Main cause of vibrations is faults in the rotating systems. An unexpected failure of rotating machinery may result in significant economic losses in terms of maintenance cost as well as huge production losses in continuous process industry. One of the principal tools for diagnosing rotating machinery problems is the vibration analysis. There are many vibration-based diagnosis techniques available for rotating machinery [1]. Lei et al. [2] proposed a new approach to intelligent fault diagnosis of rotating machinery based on statistics analysis, and adaptive neuro-fuzzy interface system (ANFIS).

Some faults that usually occur in rotor-bearing systems are: unbalance in rotors, shaft-to-shaft misalignment, mechanical looseness, bearing defects, etc. Each fault has different characteristic behaviour on the system and thus the vibration response. Unbalance is one of the important faults needs to be monitored to maintain the designed efficiency of the system. Rotors have some

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residual unbalance, in practice, because of manufacturing errors, gain or loss of material during operation, porosity in castings, and manufacturing tolerances [3].

In literature, different techniques are used for modeling and identification of unbalance response of the system. Genta and Bona [4] obtained unbalance response of the system using a modal approach. Considering one loose pedestal in a rotating machine, unbalance response has been studied using experimental, analytical and numerical approaches in [5]. There are lot of methods used for determining the periodic response of the non-linear rotor systems, such as the series expansion[6] and the harmonic balance method [7,8]. Curti *et al.* [9] used dynamic stiffness method for the rotor-bearing system and obtained unbalance response. Sekhar [10] proposed a model-based method for the on-line identification of unbalance and crack in a rotor and simulated identification process when both unbalance and crack are acting simultaneously on the rotor. Vibration monitoring, though found to be a useful technique for diagnostics in rotating machines, becomes too complex in the presence of faults and machine's operating environment because the relation between machine operating variables and fault phenomena shows uncertainty. In this context researchers were forced to pay their attention to AI tools viz. artificial neural networks (ANN), support vector machines (SVM), genetic algorithms, hidden Markov models etc. Zio and Gola [11] proposed neuro-fuzzy approach for fault diagnosis of rotating machinery. A new technique based on auto-associative neural networks and wavelet transforms is presented by Javier Sanz et al. [12] for fault diagnosis of rotating machinery. The contributions of some authors [13-16] reveal the application of neural networks to online condition monitoring of rotating machinery with very high success rates. Very recently, Kankar et al. [17] carried out fault diagnosis of ball bearings using machine learning methods, such as ANN. A *K*-means clustering approach is proposed by Yiakopoulos et al. [18] for the automated diagnosis of defective rolling element bearings. Fault parameters arising from mechanical systems may be determined by analyzing dynamic responses of the system [19]. Sinha and Elbhbah [20] presented a method to reduce the number of sensors per bearing pedestals by enhancing the computational effort in signal processing. Wang et al. [21] studied the auto regressive coefficients and its difference values were used to learn samples by using Back Propagation Neural Network and determined fault types and were compared with the distance of autoregressive coefficients method.

In the present study a method is proposed to find unbalance severity identification, and looseness identification in rotor bearing system using neural networks. Vibration data are collected as a time domain signals for the nil unbalance (residual unbalance) and for different unbalance conditions like 4 gm, 6 gm, and 8 gm unbalance at 5.3 cm radius and for pedestal looseness. The signals obtained are processed for machine condition diagnosis as shown in the flow chart Figure 1. ANNs are trained and tested by two different methods; one is statistical features extracted from the time domain signal and second is by amplitude of the frequency domain signal.

2. Experimental study

2.1. Experimental setup

Experiments are carried out on the Machine fault simulator as shown in Figure 2. This is a simple rotor system in which a shaft with a disc mounted at the center and supported on ball bearings. Various instruments are used to acquire the vibration data. Proximity probes are used for unbalance identification process and accelerometers are used for unbalance and looseness identification.

2.1.1. Instrumentation

Following instruments are used for obtaining and processing the vibration signals.
(a) Four channel National Instruments (NI) Data acquisition card. (NI-Card : NI 9215 with BNC 16 bit)
(b) Proximity probes (two), one in horizontal direction and the other in vertical direction.
(c) DEWESoft 7.02 software
(d) DEWE 43 Data acquisition card (24 bit, 8 channel, ± 10 V)
(e) Signal conditioner (ICP type)
(f) ICP type Accelerometers
(g) 1024Hz is the sampling frequency with 500 Hz Frequency range

2.2. Unbalance identification

The different unbalance conditions are considered such as (i) no additional unbalance (ii) 4 gm unbalance (iii) 6 gm unbalance and (iv) 8 gm unbalance each at 5.3 cm radius on the disc. The unbalance mass is considered at an arbitrary position on the disc, however, the additional masses are added at the same location each time in the experiment. In each case 20 sets of data are taken. The pre processing is performed on the whole signal to extract the required statistical features like mean (μ), root mean square (rms) and variance (σ^2), standard deviation, skewness and kurtosis using MATLAB. Training and testing of the neural network is done with the experimental data and confusion matrix is obtained in four different cases: one is with statistical features in horizontal direction, second is with statistical features in vertical direction, third is with frequency domain amplitude in horizontal direction, and fourth is with frequency domain amplitude in vertical direction. Unbalance severity of the rotor bearing system is classified based on the above mentioned four methods and using ANNs.

2.3. Unbalance and looseness

Unbalance and looseness are simulated on the machine fault simulator. Experiments are conducted on the MFS at a rotor speed of 2400 rpm. An 8 gm unbalance is placed at 7.04 cm radius. Pedestal bolt is loosened, in the rotor system for creating the looseness. In each case 20 sets of data are taken. Statistical features like mean (μ), root mean square (rms) and variance (σ^2), standard deviation, skewness and kurtosis are extracted using MATLAB by performing the pre processing on the whole signal. Neural network is trained and tested with the experimental data and confusion matrix is obtained in two cases: one is with statistical features in horizontal direction, second is with statistical features in vertical direction. Unbalance and looseness of the rotor bearing system is classified based on the above mentioned two methods and using ANNs.

3. Feature extraction

Using statistics a set of features are calculated from the vibration signals. The statistical features are described below.
(a) Mean value: Mean value is the average value of a signal.

$$\text{Mean} = \int p(x)x \tag{1}$$

p(x) is probability density function.

(b) rms value: The rms value is given

by $$y_j = \sqrt{\frac{\sum_{i=1}^{M} |U_{ij}|^2}{M}} \tag{2}$$

(c) Standard deviation: Measure of energy content in the vibration signal is termed as standard deviation Standard deviation = $$\sqrt{\frac{n\sum x^2 - \left(\sum x\right)^2}{n(n-1)}} \tag{3}$$

(d) Variance: Variance is the square of the standard deviation.

(e) Skewness: Measure of symmetry is skewness, or the lack of symmetry

$$\text{Skewness} = \frac{n}{(n-1)(n-2)} \sum \left(\frac{x_i - \bar{x}}{s}\right)^3 \tag{4}$$

(f) Kurtosis: Kurtosis is a degree of whether the data are peaked or flat analogous to a normal distribution Kurtosis = $$\frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum \left(\frac{x_i - \bar{x}}{s}\right)^4 - 3\frac{(n-1)^2}{(n-2)(n-3)} \tag{5}$$

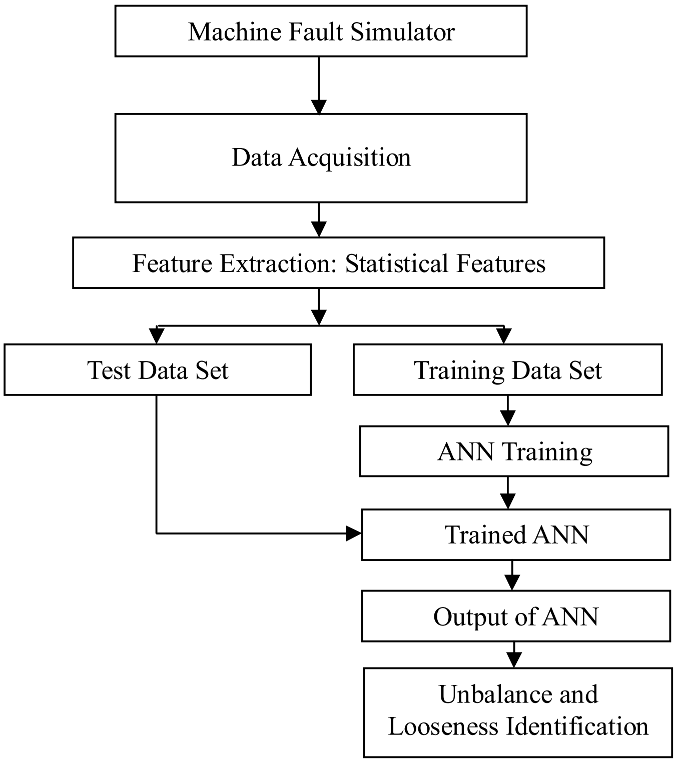


Figure 1. Flow chart of unbalance severity Identification

4. Application of neural networks

ANNs are practical to use, because they are non-parametric. Artificial neural networks are encouraged by biological findings depicting to the convention of the brain as a network of units called neurons and have been found to be an adequate tool for pattern recognition in many situations where data are incomplete or fuzzy. Artificial neural networks offer advantages for automatic detection and diagnostics of rotating machines. However they require a large number of training examples. The basic building block for an artificial neural network is the neuron. Each neuron consists of many inputs and outputs. A typical neuron model is shown in Figure 3. In the model the activation value (x) is given by the weighted sum of its M input values (a_i) and a bias term (θ_N). The output signal (S) is typically a nonlinear function $f(x)$ of the activation value. A two layered feed forward neural network consists of two layers:

(i) The hidden layer which processes the data
(ii) The output layer that provides the result of the analysis, i.e. unbalance severity class.

The data processed by hidden layer is vibration data in the present study, where as the output layer provides the unbalance severity class. The Figure 4 shows a multilayered feed forward neural network.

The configuration of the feed forward neural network is explained here. Input layer consists of 6 neurons, Hidden layer 1 consists of 8 neurons, Hidden layer 2 consists of 15 neurons and output layer consists of 4 neurons. Tansigmoidal function is used as an activation function for both the hidden layers. Number of epochs is 2000. The initial weights are chosen from randomly generated rational numbers between 0 to 1. Gradient descendent method with momentum factor is used as learning algorithm for optimizing/updating the initial weights of neural network.

5. Results and discussion

ANN training and classification of faults is carried out using MATLAB software. The defects considered in the study, i.e., unbalance severities and looseness are classified using ANN as shown in the confusion matrices.

5.1. Unbalance severity identification

As explained in section 2.2, the experiments are conducted with different unbalances like nil unbalance (some residual unbalance will be there, but no added unbalance), 4 gram have been added on the disc at 53mm radial distance from the shaft centerline, 6 gram and 8 gram added at 53 mm radial distance from the shaft centerline. Each case is considered as a separate class, like class 1, class 2, class 3 and class 4.

From the experimental data various statistical features are extracted in both horizontal and vertical directions. And also frequency domain amplitudes are derived. The rotor is run at 40 Hz (2400 rpm). Neural network is modeled as a classification problem. Data is fed to the neural network and confusion matrices in all the four cases are obtained.

Some typical ANN training data are shown in Table 1 and 2. Table 1 gives the statistical features at 6 gm unbalance in horizontal direction. Similar results have been generated for other unbalances and in both horizontal and vertical directions, these are however not shown in here. Table 2 gives the frequency domain amplitudes at different amplitudes in horizontal direction. In this case also similar data for vertical direction have been developed. Features extracted and amplitude in frequency domain are used for training and testing of ANN. The result on a test set is often displayed as a two dimensional confusion matrix with a row and column for each class. Each matrix element shows the number of test examples for which the actual class is the row and the predicted class is the column.

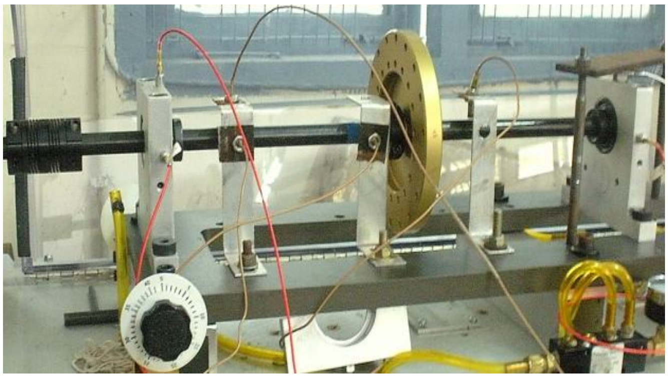


Figure 2. Experimental set-up

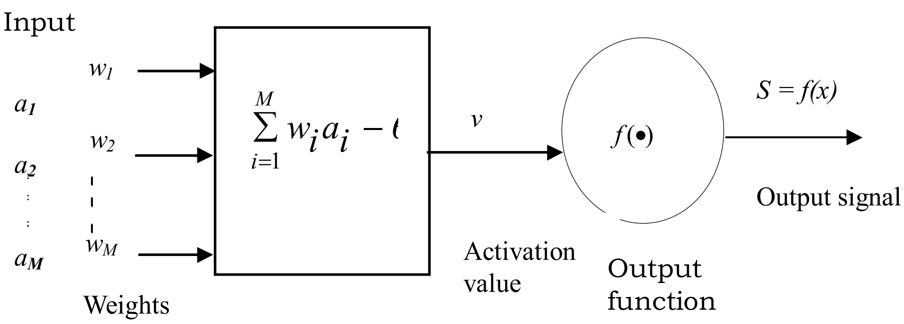


Figure 3. Typical neuron model

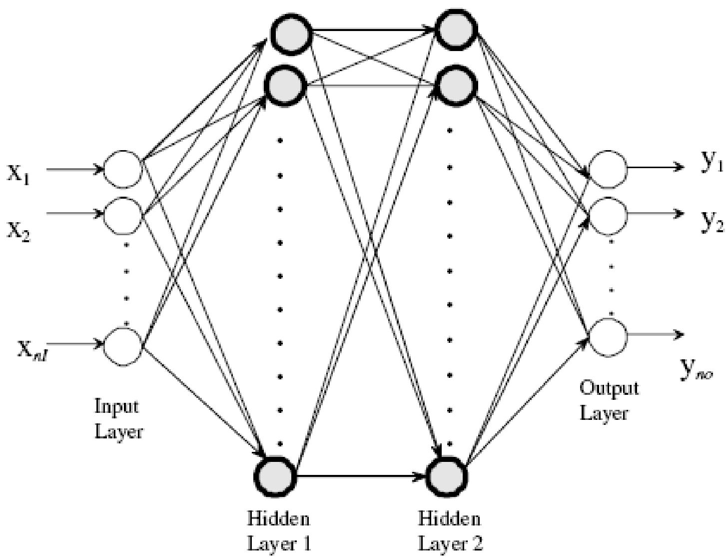


Figure 4. Multilayered feed forward artificial neural network [18]

The Confusion matrix shown in Figure 5 corresponds to the statistical features in horizontal direction while the Figure 6 corresponds to that of in the vertical direction. Figure 7 and Figure 8 are the confusion matrices correspond to the amplitude in frequency domain in horizontal direction and vertical direction respectively.

From the Figure 6 it can be inferred that ANN has correctly predicted 17, 20, 20 and 18 cases for nil unbalance, 4 gm unbalance, 6 gm unbalance and 8 gm unbalance respectively with statistical features in vertical direction. It can be noticed from Figure 5 to 8, that statistical features are giving better results over amplitude in frequency domain. Further statistical features in vertical direction are giving much better results with 93.8 % accuracy (Figure 6) than those of horizontal directions. In confusion matrix the percentages are calculated in the last rows and columns as number of samples correctly classified divided by total number of samples classified.

The vibration responses at rotor speed 2400 rpm with different unbalance conditions are shown in Figure 9. The FFT plots at rotor speed 2400 rpm are shown in Figure 10 for different unbalances. The signal characteristic of unbalance is 1x component in FFT. However, in the horizontal readings 1x components is not predominant, compared to 2x components as can be seen in Figure 10. The 2x components can be attributed to some other rotor faults in addition to unbalance. Hence the horizontal ANN results are not accurate. In Vertical directions, 1x components which correspond to unbalance are predominant. Hence Neural Networks results are more accurate in vertical direction. For comparing the performance of the proposed methodology some works are found on gears and bearings, however similar work for rolling element bearings is done by Lei et al. [2]. They achieved 91.42% classification accuracy, whereas in the present method, 93.8% accuracy in unbalance case and 97.5% accuracy in looseness case have been achieved.

5.2 Unbalance and looseness

As explained in section 2.3, experiments are conducted with unbalance and looseness. Looseness is quantified by tightening torque of the bolt, initially the pedestal bolts are tightened to 40 N-m torque and while taking the looseness measurements the pedestal bolts are loosened to 5 N-m torque. Each case is considered as a separate class, like class 1 and class 2. From the experimental data various statistical features are extracted. Neural network is modeled as a classification problem. Data is fed to the neural network and confusion matrices are obtained as shown in Figure 11 and Figure 12 in horizontal and vertical directions respectively. It shows that 95 % of the data is classified accurately in horizontal direction and 97.5% of the data is classified accurately in the vertical direction. It shows how classification is done between target class (actual class) and output class. Once the neural network is stabilized, that can be used to take the new values and it tells which class it belong to. From this we can make decision by knowing the fault to which it belongs to, whether unbalance or looseness depending on the class to which it belongs to.

Data sets used for training and testing were different. 70% of the data points were used for training and 30% of the data points were used for testing. There are 20data points were there in each set. Data is acquired with only one fault at a time. The network is modelled as a two class problem and trained and tested accordingly. Here unbalance and looseness faults are separately simulated. It is a two class problem, it just tells whether the fault is unbalance or looseness. From time domain vibration signals FFT plots are obtained and clear peaks are seen in vertical direction than in horizontal direction readings. Because of clear peaks in the vertical data, may be vertical data classification is better than horizontal. Here we will not get the severity of the problem, we get only type of problem i.e., unbalance or looseness. Based on the input (statistical features) given to the ANN and the ANN tool box of matlab program will form the confusion matrix. Here it is formulated as a two class problem, and it gives whether the fault is unbalance or looseness. The Time domain vibration signals with looseness at 2400 rpm are shown in Figure 13. The FFT plots with looseness at 2400 rpm are shown in Figure 14.

Table 1. Statistical features at 6gm unbalance in horizontal direction

S.No.	Mean (mm)	Rms (mm)	Variance (mm^2)	Std Deviation (mm)	Skewness	Kurtosis
1	2.2800E-02	3.2000E-02	5.0079E-04	2.2400E-02	1.3300E-02	1.7674E+00
2	3.1600E-02	3.8300E-02	4.7239E-04	2.1700E-02	-4.5000E-03	1.7579E+00
3	2.2500E-02	3.1300E-02	4.7232E-04	2.1700E-02	1.8100E-02	1.8617E+00
4	2.7200E-02	3.5000E-02	4.8817E-04	2.2100E-02	-2.8000E-02	1.7221E+00
5	2.9700E-02	3.7000E-02	4.8332E-04	2.2000E-02	-3.6741E-04	1.7583E+00
6	2.9700E-02	3.7100E-02	4.9658E-04	2.2300E-02	4.3900E-02	1.7215E+00
7	3.6500E-02	8.8900E-02	6.6000E-03	8.1100E-02	1.1916E+01	1.6195E+02
8	4.3700E-02	1.2800E-01	1.4500E-02	1.2040E-01	9.0327E+00	8.5938E+01
9	7.0800E-02	2.2980E-01	4.7900E-02	2.1880E-01	4.9794E+00	2.6303E+01
10	4.6900E-02	1.5480E-01	2.1800E-02	1.4760E-01	7.7098E+00	6.2064E+01
11	3.2500E-02	6.0600E-02	2.6000E-03	5.1200E-02	1.6803E+01	3.5209E+02
12	3.1600E-02	1.3430E-01	1.7100E-02	1.3060E-01	8.6488E+00	7.8714E+01
13	4.3600E-02	1.8020E-01	3.0600E-02	1.7490E-01	6.2338E+00	4.1102E+01
14	5.8700E-02	2.2830E-01	4.8700E-02	2.2070E-01	5.0034E+00	2.6472E+01
15	4.9800E-02	1.2100E-01	1.2200E-02	1.1030E-01	9.6914E+00	1.0244E+02
16	8.2000E-02	2.4050E-01	5.1200E-02	2.2620E-01	4.8848E+00	2.5190E+01
17	9.4000E-02	2.7900E-01	6.9100E-02	2.6290E-01	3.9902E+00	1.7275E+01
18	4.5600E-02	1.0110E-01	8.1000E-03	9.0200E-02	1.1107E+01	1.3903E+02
19	4.9900E-02	1.3060E-01	1.4600E-02	1.2080E-01	8.5344E+00	7.8163E+01
20	2.2600E-02	3.2400E-02	5.3715E-04	2.3200E-02	-1.2100E-02	1.7146E+00

Table 2. Frequency domain amplitudes at different unbalances in horizontal direction

	Class1 (Nil unbalance)	Class2 (4gm unb at 5.3cm)	Class3 (6gm)	Class4 (8gm)
S.No.	FFT Amp	FFT Amp	FFT Amp	FFT Amp
1	2.0700E-02	6.1000E-03	5.6000E-03	1.3300E-02
2	2.0300E-02	5.3020E-03	1.0400E-02	1.1200E-02
3	2.1300E-02	5.8000E-03	8.0000E-03	1.1400E-02
4	2.0500E-02	5.6000E-03	7.4000E-03	1.0000E-02
5	2.0200E-02	4.7000E-03	6.7000E-03	1.2900E-02
6	1.7200E-02	4.9000E-03	8.5000E-03	9.1000E-03
7	1.8080E-02	5.5000E-03	8.5000E-03	9.5000E-03
8	1.7710E-02	6.5000E-03	8.1000E-03	6.8000E-03
9	1.6980E-02	5.4000E-03	7.1000E-03	7.6000E-03
10	1.8310E-02	5.9000E-03	7.9000E-03	8.1000E-03
11	2.5500E-02	6.2000E-03	7.8000E-03	9.2000E-03
12	3.9100E-02	5.9000E-03	7.5000E-03	9.5000E-03
13	4.1500E-02	7.4000E-03	8.6000E-03	8.1000E-03
14	3.4400E-02	8.8000E-03	8.2000E-03	9.5000E-03
15	1.4300E-02	7.1000E-03	8.1000E-03	8.3000E-03
16	4.4550E-02	8.8000E-03	8.1000E-03	8.4000E-03
17	2.8600E-02	9.9000E-03	7.9000E-03	7.9000E-03
18	2.8700E-02	7.1000E-03	8.4000E-03	8.5000E-03
19	2.4960E-02	7.2000E-03	8.3000E-03	1.1100E-02
20	6.0200E-02	8.0000E-03	8.5000E-03	8.1000E-03

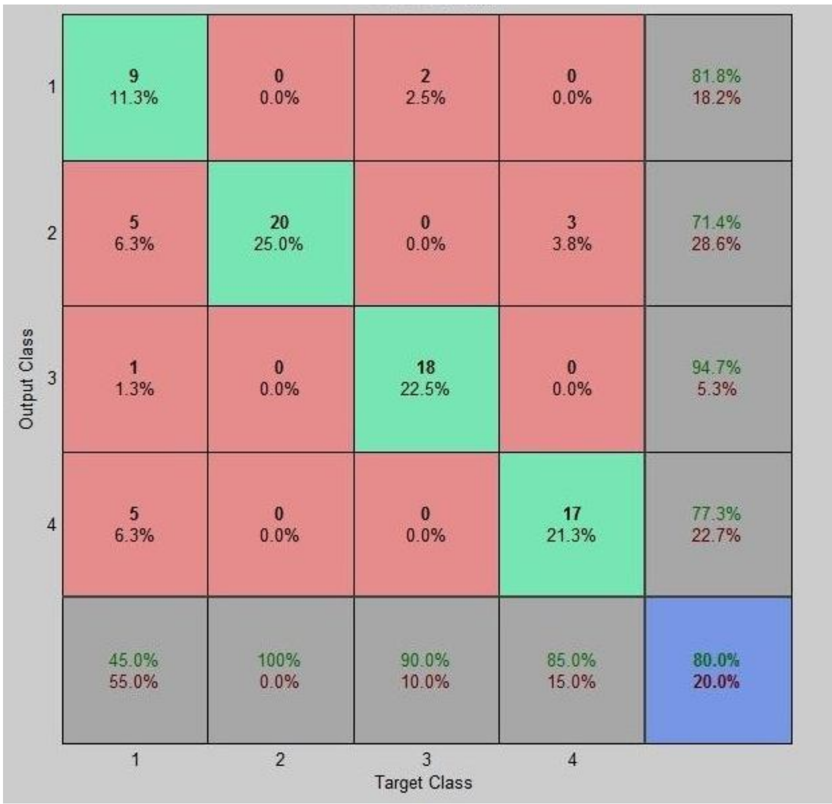


Figure 5. Confusion matrix (statistical features in horizontal direction)

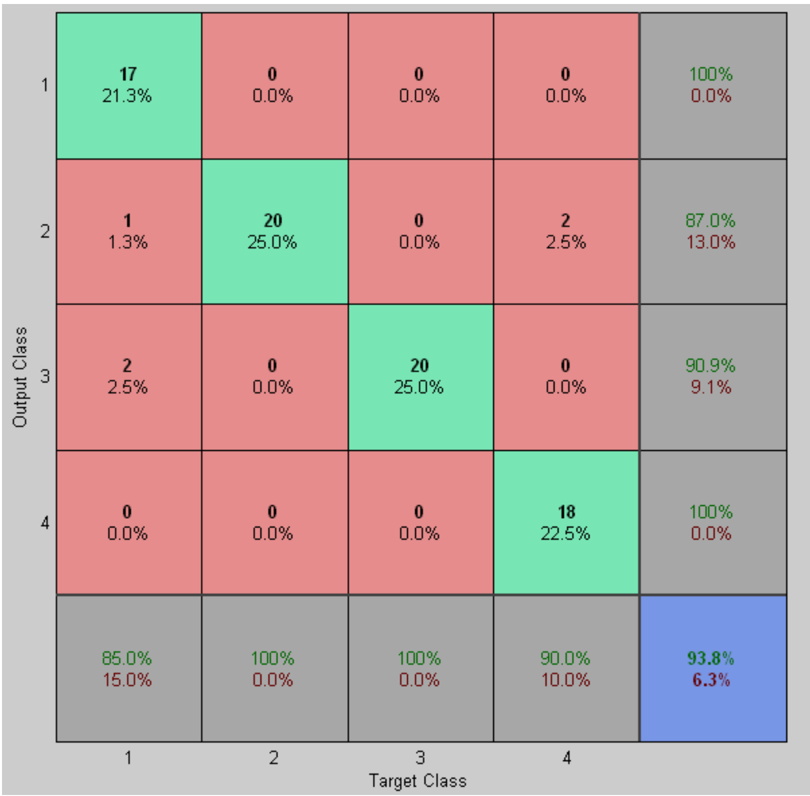


Figure 6. Confusion matrix (statistical features in vertical direction)

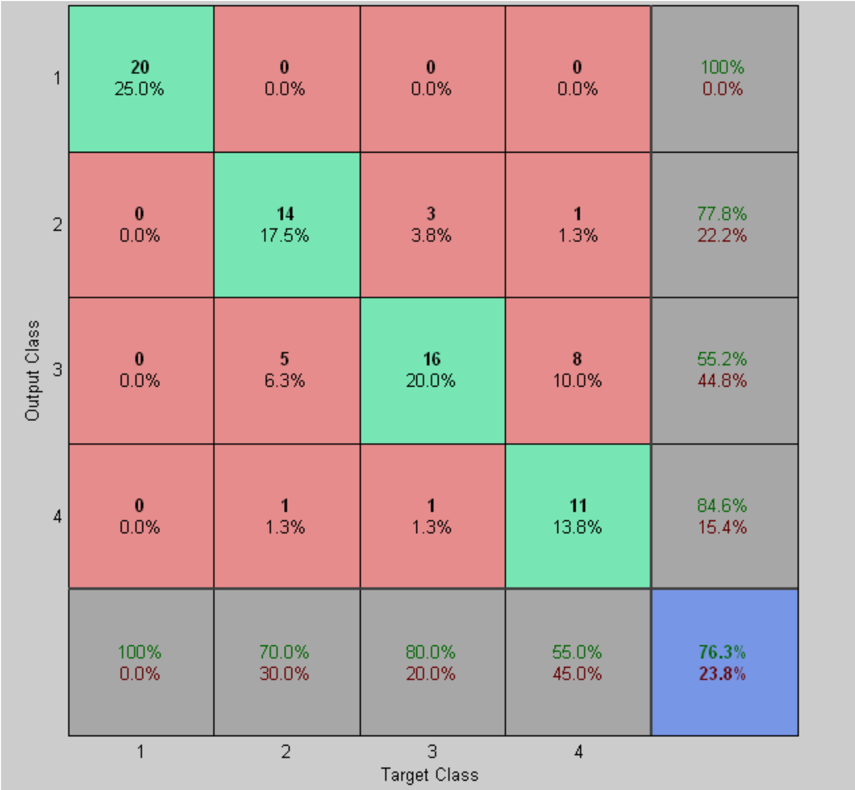


Figure 7. Confusion matrix (frequency domain amplitude in horizontal direction)

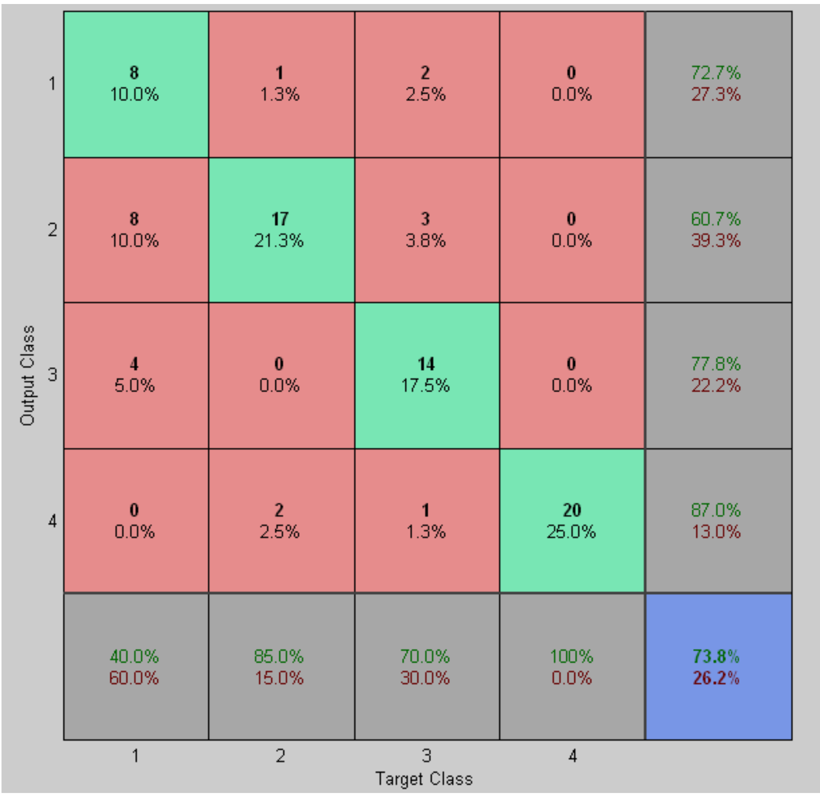
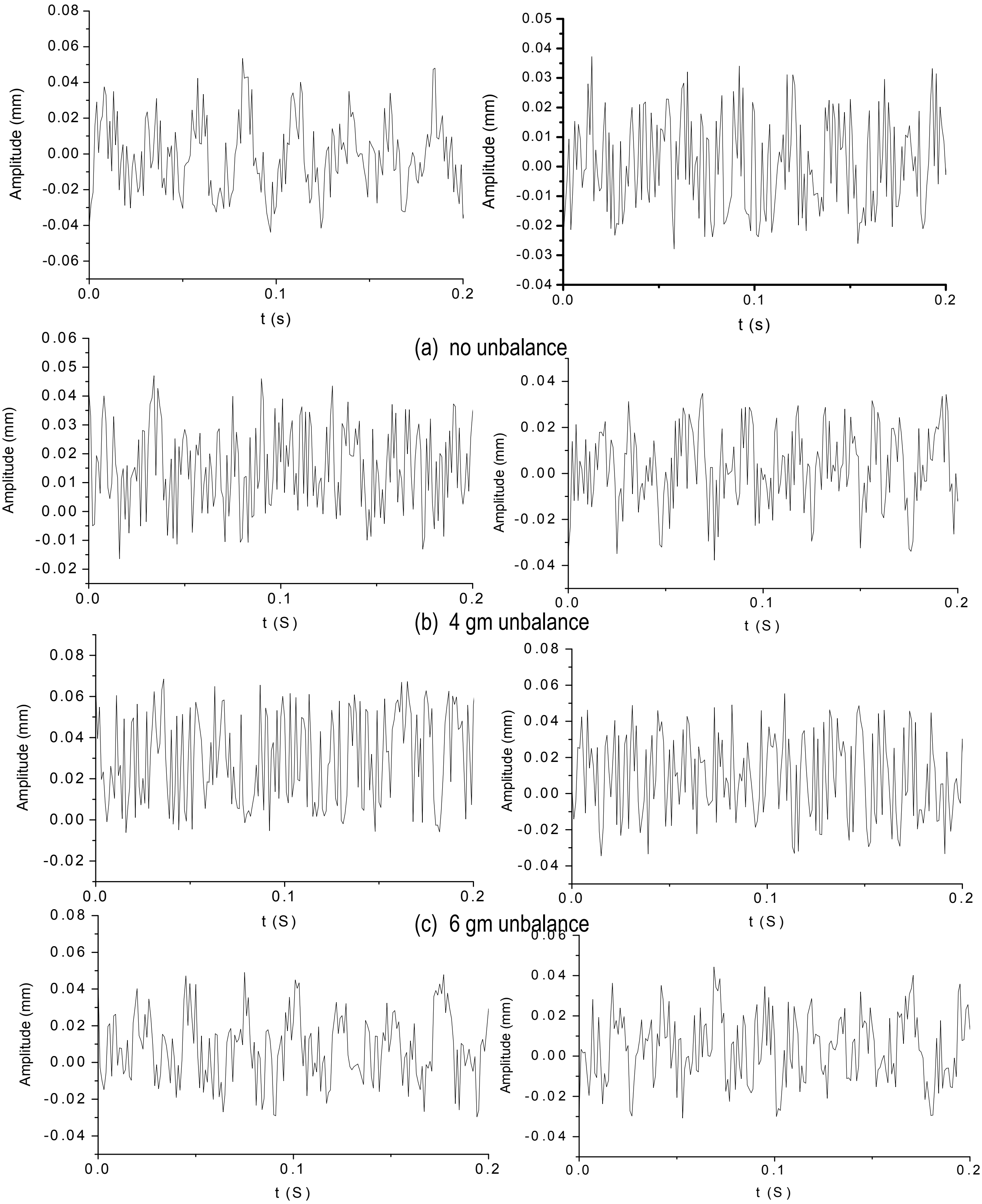


Figure 8. Confusion matrix (frequency domain amplitude in vertical direction)



(a) no unbalance

(b) 4 gm unbalance

(c) 6 gm unbalance

(d) 8 gm unbalance

Horizontal Response   Vertical Response

Figure 9. Time domain vibration signals for various unbalances at 2400 rpm

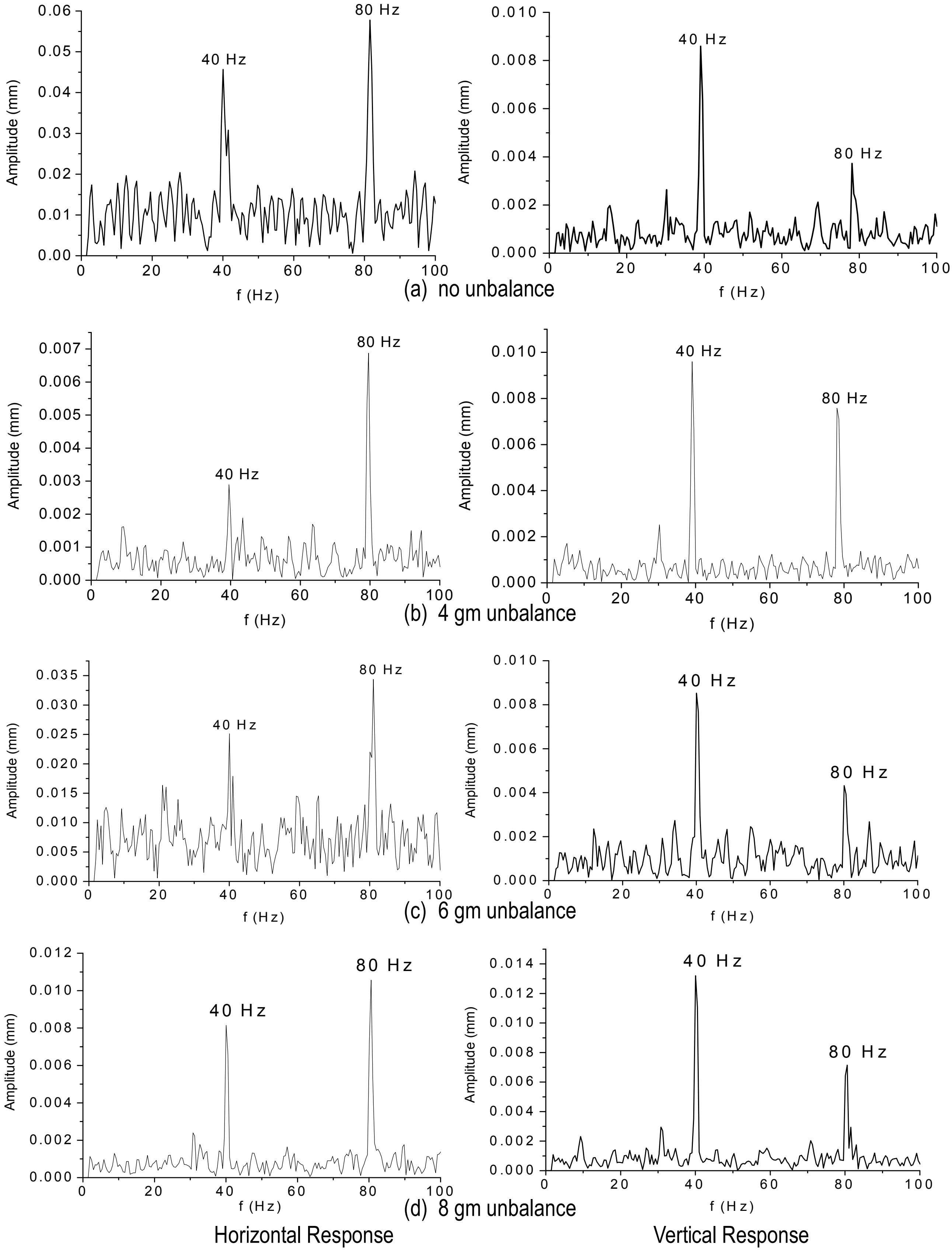


Figure 10. FFT plots for various unbalances at 2400 rpm

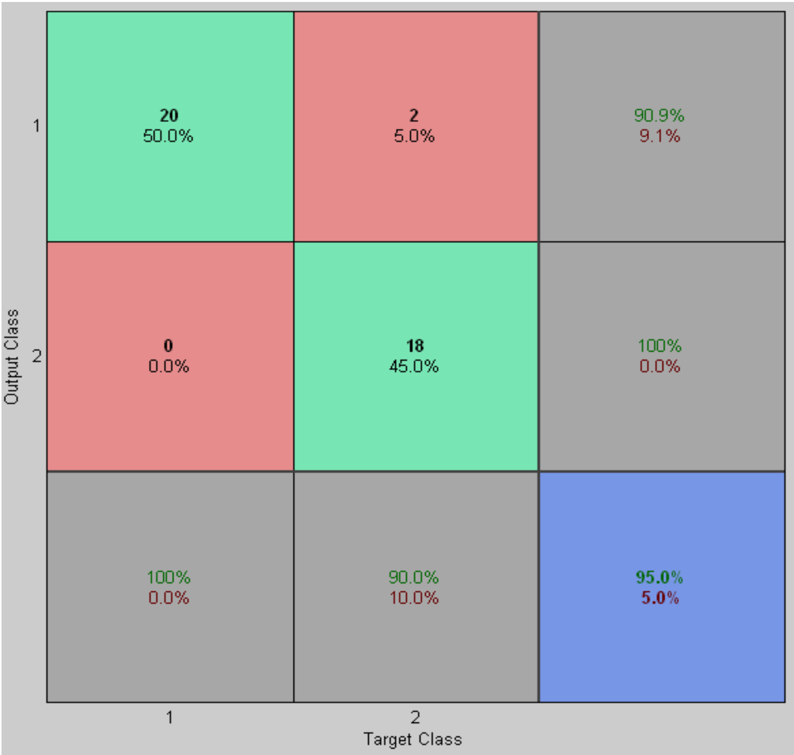


Figure 11. Confusion matrix for looseness (statistical features in horizontal direction)

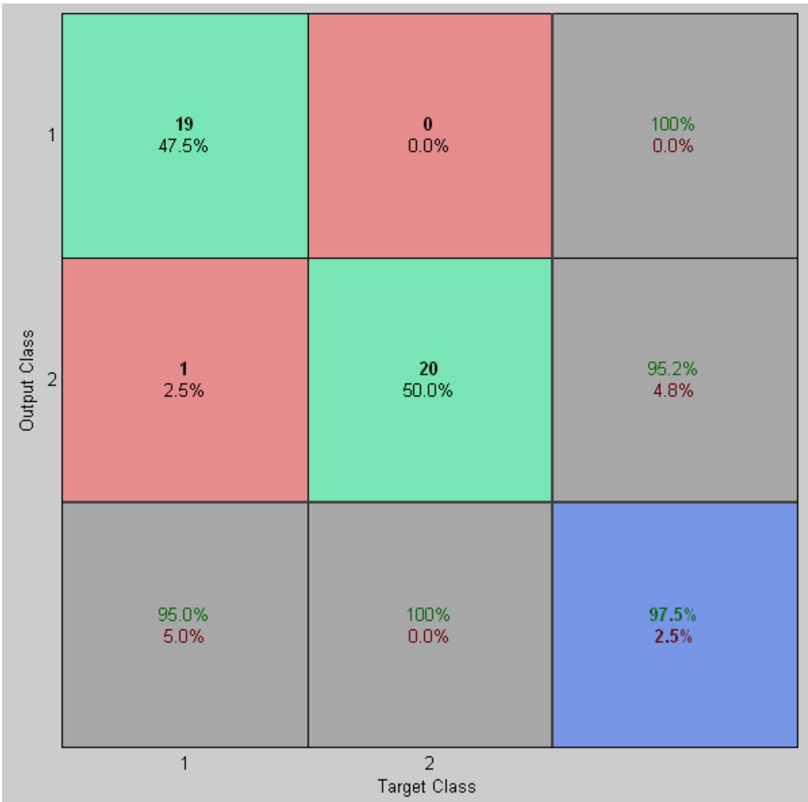


Figure 12. Confusion matrix for looseness (statistical features in vertical direction)

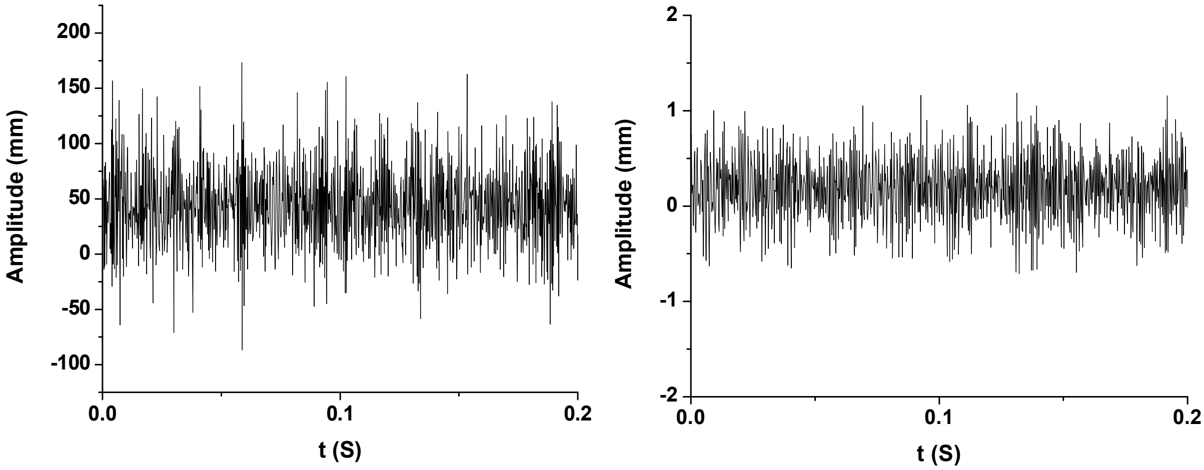


Figure 13. Time domain vibration signals with looseness at 2400 rpm

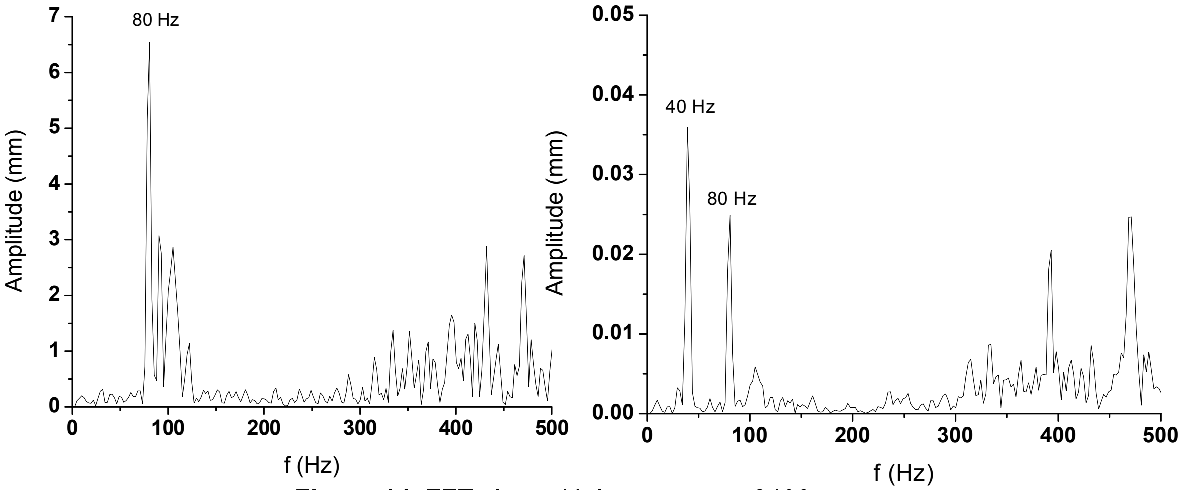


Figure 14. FFT plots with looseness at 2400 rpm

6. Conclusions

This study presents a procedure for identification of unbalance severity and looseness using ANNs. Experiments are conducted by simulating different unbalances and looseness in the rotor bearing system. From the vibration signals obtained various statistical features are extracted and fed to the neural network in one case and in the second case frequency domain amplitude is used to train and test the ANN. In both the cases ANNs are trained and tested by both horizontal and vertical readings. By modeling the neural network as a classification problem the data is classified. ANNs are used to classify the unbalance severity and looseness. It is observed that statistical features are giving good results over frequency domain amplitudes. It is also observed that vertical direction readings are giving good classification results over horizontal direction vibration readings. These results are useful for making a maintenance decision based on unbalance severity, whether the machine is allowed to run or not. The present neural network is classified with 93.8 % accuracy by statistical features in vertical direction for unbalance identification and with 97.5% accuracy by statistical features in vertical direction for looseness.

The present study can be extended to other fault identification and also can be extended to multi fault identification simultaneously.

Nomenclature

μ or $\bar{x}$	mean	n	sample size
σ	standard deviation	N	total number of samples
σ^2	variance	a_i	inputs
x	vibration displacement	w_i	synaptic weights
p(x)	probability density function	θ	bias or threshold
y_j	rms value	v	activation value
U_{ij}	input matrix	S	output signal

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