Abstract— Machine fault diagnosis from detection of early symptoms and prediction of fault development avoids severe machine damages and high cost of maintenance. In this study a Multi Layer Perceptron Neural Network (MLPNN) has been designed for detection of four basic faults in rotating machineries namely: 1) Unbalance 2) Misalignment 3) Bearing Faults and 4) Looseness. MLPNN uses feature vectors from vibration time waveform and vibration spectrum. Measurements have been used for training MLPNN. Because of the enormous amount of input data, Principle Coordinate Analysis (PCA) has been used for input data reduction. This technique showed 78% successful fault prediction.

Keywords— Fault Diagnosis, Rotating Machineries, Neural Network, Multi Layer Perceptron, Principle Coordinate Analysis (PCA).

I. INTRODUCTION

Maintenance is referred to all the activities which increases useful machine life, decrease spare part consumption, and increase machine efficiency. Generally the most important aim of maintenance systems is optimizing machine capabilities to reach maximum production and decrease wear and break down [1]. Rapid technology progress, increase in industrial investments and limitation of resources make efficiency as the most important issue among top industrial managers [2].

Rotating machineries fault diagnosis is done with various methods such as: Statistical Methods [3, 4], Vibration Analysis [5, 6], Time Domain Analysis [7], Finite Element Analysis [8], Multi Layer Neural Networks, and Adaptive-Neuro Fuzzy Inference Systems [9].

Among these different methods, Multi Layer Neural Network Systems are developing rapidly because of their high capabilities in nonlinear function approximations, use of knowledge of experts in finding input, output relations, and so on [10].

In 2009 Wang et al have used a BPNN for diagnosing four major faults namely, unbalance, misalignment, bearing faults and oil whip. The BPNN used in their study consists of three layers with 20 neurons in input layer 30 neurons in hidden layer and 4 neurons in output layer. Lei et al in their research for fault diagnosing of deep groove bearing used both statistical methods and ANFIS and MLP. The results showed ANFIS was more efficient than the other methods. In this research MLPNN has been used for diagnosing four major faults of rotating machineries which are: unbalance, misalignment, fault bearing and looseness. Because of the enormous amount of input data, Principal Component Analysis (PCA) has been used as the data reduction technique to consider the most important data as the input.

II. METHODOLOGY

2.1) Rotating machine Design and Construction

In order to measure and analysis data a test rig including a motor, coupling, shaft and two disk constructed as shown in figure 1.

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Fig. 1 Test rig

Based on rotating machinery faults statistics, unbalance, misalignment, faulty bearings and mechanical looseness constitute more than 85% of the total faults. There for in this research these faults have been considered. Two rotating wheels have been mounted on a rotor which is balanced precisely. For producing unbalance, different holes have been made on the two disks and nut and bolts from 5 gram to 50 gram have been used. Also in the test rig a mechanism for precise aligning of motor to rotor shaft have been implemented. Also four VC204 bearing two of them correct and two faulty (with fault on outer race) have been used for simulation of faulty bearings. The looseness fault was

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simulated by loosening bearing bolts on the test rig. The test rig rotor should also have the capability to be run at various speeds to provide enough data for training MLP, so a 0.25 kw 3 phase electromotor with a speed control have been used to provide a speed range from 1 to 1500 rpm. After simulation of each fault independently on the test rig, the desired vibration features has been measured with a four channel ADASH vibration analyzer.

2.2) Choosing appropriate vibration feature for fault diagnosis

Selections of appropriate features are very important. If the numbers of selected features are high it may lead to excessive time and cost for fault detection. On the other hand choosing fewer features than that is required may lead to false results. In this research 12 vibration features have been considered as follows:

1) Peak Value

\[ \Delta r = \frac{1}{2} \left[ \max_{n} |v[n]| - \min_{n} |v[n]| \right] \]  

(1)

2) Average

\[ \mu = \frac{1}{N} \sum_{n=1}^{N} v[n] \]  

(2)

3) Absolute Average

\[ |\mu| = \frac{1}{N} \sum_{n=1}^{N} |v[n]| \]  

(3)

4) Energy

\[ E = \sum_{n=1}^{N} |v[n]|^2 \]  

(4)

5) Normalized Energy

\[ E_n = \frac{1}{N} \sum_{n=1}^{N} |v[n]|^2 \]  

(5)

6) Root Mean Square

\[ \text{RMS}_v = \left( \frac{1}{N} \sum_{n=1}^{N} (v[n] - \bar{v})^2 \right)^{1/2} \]  

(6)

7) Peak to Average Ratio

\[ \text{PAR}_v = \frac{1}{|\mu|} \max_{n} |v[n]| \]  

(7)

8) Crest Factor

\[ CF_v = \frac{\Delta v}{\text{RMS}_v} \]  

(8)

9) Impulse Factor

\[ IF_v = \frac{\Delta v}{|\mu|} \]  

(9)

10) Shape Factor

\[ SF_v = \frac{\text{RMS}_v}{|\mu|} \]  

(10)

11) Clearance Factor

\[ CLF_v = \frac{\Delta v}{\frac{1}{N} \left( \sum_{n=1}^{N} |v[n]| \right)^2} \]  

(11)

12) Kurtosis Value

\[ \kappa_v = \frac{1}{\text{RMS}_v^4} \left( \sum_{n=1}^{N} (v[n] - \bar{v})^4 \right)^{1/4} \]  

(12)

From these selected features 10 was in time domain and two in frequency domain. Each 84 final measurements for four faults, consists of 12800 samples each of which was divided to 128 intervals of 100 measurements. For each 128 intervals 12 features extracted. So the feature matrix consists of (12×128) elements. Because 21 measurements have been done for each fault the final matrix is (251\(\times\)12)×128). This matrix is the input to MLPNN. For dimension reduction of the input matrix and therefore increase speed and precision of computation, PCA method has been used and its program has been written as an m-file in MATLAB. For training and test of the network 2/3 and 1/3 whole data have been used.

III. DESIGN MULTI LAYER PERCEPTRON NEURAL NETWORK (MLPNN)

To use MLP the following algorithm has been used:

1) Choosing initial weights from small random numbers.
2) Presenting inputs and the desired outputs to the network.

3) Each output from each layer is computed from the following equation and transferred to the next layer.

\[ y_{jk}^{l} = f \left( \sum_{i=1}^{n} w_{ij}^{l}x_{i} \right) \]  

(13)

Weight adjustments for different layers will be started from output layer and continues to the backward layers from equation 18:

\[ w_{ij}^{l+1} = w_{ij}^{l} + n \delta_{j}^{l+1}x_{i} \]  

(14)

In this model \( w_{ij}^{l} \) represents weights from node I to node j at time t, n is gain and \( \delta_{j}^{l+1} \) shows the error of the p pattern in j’s node.

Equations have been used for output and hidden layers.

\[ \delta_{j}^{l} = k_{2}e_{j} \left( 1 - e_{j} \right) \left( t_{j} - y_{j} \right) \]  

(15)

\[ v_{j}^{l} = k_{1} \sum_{k} \delta_{k}e_{j} \]  

(16)

In this network from 512 features related to different faults, number 1, 2, 3, 4 is for unbalance, angular displacement, looseness and bearing fault respectively. From all the faults some of them are chosen randomly as training data and the rest are used as testing data. The whole data are divided to two groups randomly one with 342 data as training data and the second one with 170 data. The designed network consists of three layers, input, hidden and output layers. For determining optimum neurons in hidden layer, trial and error method has been applied. To control the contribution of each of the features in modifying the weights and training the network, data are normalized so the magnitudes of the parameters are in the range [-1, 1]. Due to four different categories for the faults output layers has four neurons. For optimizing training trend and presence of all the perceptrons in this trend (avoidance of perceptrons death) the desired output have been presented to the network in the following form:

Fault number one = \([0.9, 0.1, 0.1, 0.1]\)

Fault number two = \([0.1, 0.9, 0.1, 0.1]\)

Fault number three = \([0.1, 0.1, 0.9, 0.1]\)

Fault number four = \([0.1, 0.1, 0.1, 0.9]\)

The network output is in the form of a 4×342 matrix for the training mode and a 4×170 matrix for the test mode. For training of the network the Levenberg-Marquardt (LM) algorithm has been used. Also tan-sigmoid function has been used for each perceptron. Mean square error as described in Eq (17) is used

\[ f = mse = \frac{1}{N} \sum_{i=1}^{N} (o_i - t_i)^2 \]  

(17)

In this model \( e_{i} \) is network error, \( t_{i} \) is desired output and \( o_{i} \) is the actual output. Considering the acceptable error and number of epochs as the two conditions for training stoppage, the network has been trained. Results from testing the designed network have been shown in the following figures:
IV. CONCLUSIONS

As can be seen in the figures 2 to 4 the designed MLPNN is capable of predicting the actual fault from the acquired data with 78% correctness. This can be a valuable tool for the operator or technician of the machine to detect the machine fault and make the correct decision.

V. REFERENCES


