Application of Neural Network in Condition Monitoring of Ball Bearings

Atul Andhare, Tejas Lakhe, Vishal Vadabhat, Tejas Umbarkar

Abstract

This paper presents the use of neural network for condition monitoring of ball bearings using statistical parameters. The time domain vibration data corresponding to normal running and various fault conditions (ball fault, inner race fault, outer race fault in O3, O6, and O12 relative position) were used. The data were segmented into groups and statistical features like Kurtosis, Skewness, Variance, RMS and normalized 6th moment were calculated for each of these groups. These five parameters were used as input for a neural network consisting of one hidden layer with sixteen neurons and one output layer with one neuron. The network was first trained for single faults and then by combination of faults. This trained network was then tested by another set of data which was unknown to the network and the success rates were calculated for each type of input. The results proved the effectiveness of the neural networks in diagnosis of the bearing condition. After testing success of the network for fault diagnosis, the effectiveness of each parameter was tested. This helped to relatively grade the five parameters and also confirmed that only a single parameter was not sufficient for accurate fault diagnosis. Also, relative grading of the parameters provided flexibility to eliminate less significant parameters, leading to lesser number of inputs, thus reducing the computation required. This makes the neural network suitable for being adopted for on-line condition monitoring.

Keywords: Neural Network, Ball Bearing, Condition Monitoring, Vibration Data, Statistical Parameters.

1 Introduction

Condition monitoring is a process of monitoring a parameter of condition in machinery, such that a significant change is indicative of developing failure. It is a major component of preventive maintenance. The use of vibration signals is quite common in the field of condition monitoring and diagnostics of rotating machinery [1-6]. Detection of machine faults like mass unbalance, rotor rub, shaft misalignment, gear failures and bearing defects is possible by comparing the vibration signals of a machine operating with and without faulty conditions. It is difficult to detect bearing condition using time domain

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vibration signals because of the presence of variety of noise and wide spectrum of bearing defect signals. So, it is imperative to identify the characteristic features relevant to the bearing conditions [3]. Scheer *et al* [7] and Samanta *et al* [3] studied fault diagnostics using vibration analysis and concluded that an automated system like neural network is more efficient and time saving than manual trend setting of results.

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems and are called as neurons. We can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements [8]. The vibration signals obtained from a group of sensors are subjected to direct and simple processing for extraction of features that are subsequently used as inputs to the Artificial Neural Networks (ANNs) for diagnosing bearing condition. Good predictability, low generalization error and reduced amount of computation, so as to allow the user to experiment with larger networks and train them on larger data sets were the main reasons for selecting ANN for the present study.

There are many types of neural networks like feed-forward back-propagation, radial basis network, dynamic network, etc. Amongst these, the feed-forward back-propagation type of neural network was selected. Because, the literature [8] indicated that this type of network has higher generalization capacity, ability to develop a relation between an input vector and corresponding target during training and it can classify input vectors in an appropriate way as defined by the user. Also, properly trained back-propagation network give reasonable answers when presented with inputs unknown to it.

2 Data Acquisition

Large data are required for training and validation of neural networks. The data for the present study was borrowed from the Bearing Data Centre website of the Case Western Reserve University [9]. The data is basically vibration amplitudes for various positions and types of faults for ball bearings using an experimental set up. It consisted of a 1.5 kW electric motor, running at 1797 rpm, coupled to a dynamometer and the test bearings supporting the motor shaft. The details of the test bearings used are shown in Table 1& 2.

The data were acquired at two sampling rates: 12 kHz and 48 kHz for drive end bearing faults, by sensors mounted at DE and FE, both. The bearing defect sizes used were: 0.178 mm diameter & 0.28 mm depth. Defects in inner race, ball and outer race (at different positions relative to the load) were used to acquire the data..

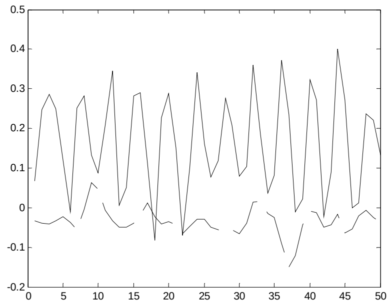
Table 1: Drive end bearing: 6205-2RS JEM SKF, deep groove ball bearing [9]

Inside diameter	Outside diameter	Thickness	Ball diameter	Pitch diameter
25 mm	52 mm	15 mm	8 mm	40 mm

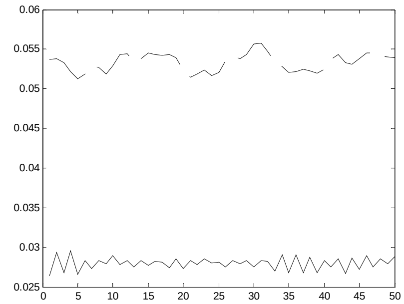
Table 2: Fan end bearing: 6203-2RS JEM SKF, deep groove ball bearing [9]

Inside diameter	Outside diameter	Thickness	Ball diameter	Pitch diameter
18 mm	38.5 mm	12 mm	6.5 mm	28.5 mm

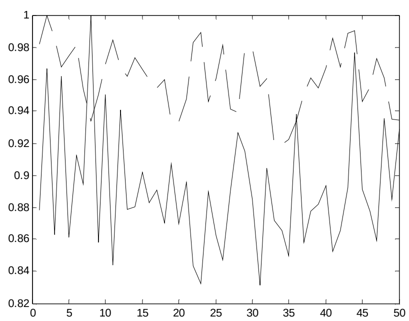
3 Data Segmentation and Selection of Parameters



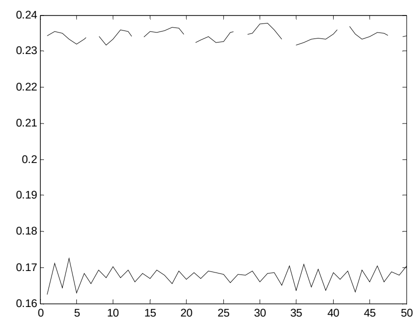
a. Skewness



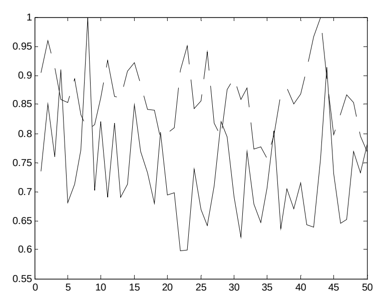
b. Variance



c. Kurtosis



d. RMS



e. 6th moment

Figure 1: Variation of parameters for normal (dotted line) & faulty (solid line) data sets. (X-axis: Input data sets; Y-axis: Selected Parameter)

The 121000 data points obtained for each running condition were normalized in the range of 0.0 and 1.0 and then divided into 50 data sets of 2420 data points each. For each data set, five parameters viz. Kurtosis, Skewness, Variance, Root Mean Square & Sixth moment were obtained [3] by using MATLAB. Values for the kurtosis and 6th moment within a group were again normalized between 0 & 1. The data sets were arranged in the matrix of (50x5) in such a way that each column represented a particular parameter (RMS, Variance, etc.) and each row represented all the five parameters of a group. Out of the 50 groups, 30 were used for training and the remaining 20 for simulation (testing). For ascertaining the suitability of these parameters as inputs to the neural network, graphs as shown in Fig. (1) were plotted, clubbing parameters for both -normal & faulty running conditions. From the graphs, it is observed that there is a clear distinction between the values of the selected parameters for normal running and faulty bearing conditions. Hence these parameters could be used as diagnostic parameters.

4 Network Architecture

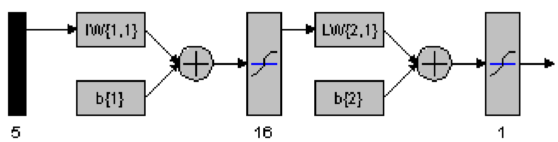


Figure 2: Network architecture

The architecture of the network is shown in Fig. (2). The feed-forward, back-propagation network consists of 5 Input elements, 16 neurons in the hidden layer and 1 output neuron. The training function was TRAINLIM, transfer function - TANSIG and performance function was MSE. Levenberg-Marquardt algorithm being the fastest back-propagation algorithm, the TRAINLIM function was used for training. Numbers of neurons in the hidden layer were varied and training was attempted. The optimum results were found for 16 neurons in the hidden layer. The five input elements were chosen to correspond to each of the five statistical parameters. The input to the network was in form of matrix shown in Fig. (3).

[Kurtosis1……………………………………………Kurtosis30
Variance1……………………………………………Variance30
Skewness1……………………………………………Skewness30
RMS1………………………………………………..RMS30
6thmoment1…………………………………………6th moment30]

Figure 3: Input matrix

5 Training of Network

The training of the neural network was carried out using the NNTOOL user interface in MATLAB. The initial weights & biases were automatically generated by the user interface. The parameters of the network were Target mean square error (MSE): e^-15, Minimum gradient: e^-10, Maximum iteration number (epochs) :1000. First, a single type of fault was fed as input to the network. The dimension of the input matrix was 5x60 which comprised of 30 fault condition data sets & 30 normal condition data sets. A sample input matrix for single fault is shown in Fig. (4).

[fault (30x5)'   normal (30x5)']

Figure 4: Sample input matrix for single fault

The target matrix for single type fault fed to the network had a dimension of 1x60. It was desired that for fault data input, the ideal output should be 0 and for normal data input, it should be 1. A schematic of ideal output is shown in Fig. (5). It means, in the target matrix, the variable corresponding to faulty input is given a value 0 while the variable corresponding to normal bearing data input is given a value 1. Sample target matrix for single input is shown in Fig. (6).

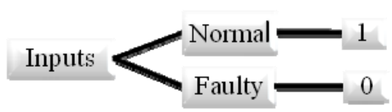


Figure.5: Ideal output

[0000 . . . 0 1 111 . . .1]

{30}   {30}

Figure 6: Sample target matrix for single input

In the next step, a combination of two types of fault was fed as input to the network. The schematic of input matrix for two faults is shown in Fig. (7). The corresponding targets were also fed. A sample target matrix for double input is shown in Fig. (8).

[Fault data (60x5)' normal data (30x5)']

Figure 7: Sample input matrix for two faults

[0000 . . . . . .   0 1 111 . . . . . .1]
{60}   {30}
Figure 8: Sample target matrix for double input

The network was trained for all possible combination of faults taken two at a time. In the same way, the network was trained by feeding a combination of three, four & five faults as inputs in incremental steps. Training performance graphs were obtained for each case & training success was computed. This training process was carried out for faults at driving end (DE) as well as faults at fan end (FE).

6 Testing of Network

After the network was trained, the testing of the network was carried out. For testing of the network NNTOOL user interface was used again. During testing, the network was simulated by feeding a known fault data to the network in incremental steps of one, two, three, four & five types of faults. During testing, no targets were fed to the network. Graph of target output v/s input were plotted for gauging the test success and all the graphs showed good test results. Due to lack of space these graphs are not included here. Instead, the training and test success results for faults at driving end and fan end bearings are tabulated and shown in Tables 3 and 4 respectively.

Table 3: Training & Test success results for driving end bearing data

S. No.	Fault data used	Training Success	Test Success
1	Ball	60/60 (100%)	16/20 (80%)
2	Inner Race	60/60 (100%)	20/20 (100%)
3	Outer race - O3	59/60 (98.3%)	20/20 (100%)
4	Outer race - O6	60/60 (100%)	20/20 (100%)
5	Outer race - O12	56/60 (93.4%)	20/20 (100%)
6	Outer race - O6 ,O12	90/90 (100%)	40/40 (100%)
7	O6, O12 and Inner Race	120/120 (100%)	60/60 (100%)
8	O6 , O12, Inner Race, Ball	150/150 (100%)	76/80 (95%)
9	All faults	179/180 (99.4%)	96/100 (96%)

Table 4: Training & Test success results for fan end bearing data

S. No.	Fault data used	Training Success	Test Success
1	Ball	60/60 (100%)	17/20 (85%)
2	Inner Race	60/60 (100%)	20/20 (100%)
3	Outer race - O3	60/60 (100%)	20/20 (100%)
4	Outer race - O6	60/60 (100%)	20/20 (100%)
5	Outer race - O12	60/60 (100%)	20/20 (100%)
6	Outer race - O6, O12	90/90 (100%)	40/40 (100%)
7	O6, O12 and Inner Race	120/120 (100%)	60/60 (100%)
8	O6, O12, Inner Race, Ball	144/150 (96%)	77/80 (96.25%)
9	All faults	174/180 (96.6%)	97/100 (97%)

6.1 Performance of Statistical Parameters in Defect Diagnosis

To decide the relative significance of the statistical parameters and their contribution to network performance, the individual parameters were tested on a new network. This network consisted of 5 input elements, 16 neurons in the hidden layer and 1 output neuron. This network was trained, tested and the results were analyzed. The test results for individual parameters for each type of fault at driving end are shown in Table 5.

Table 5: Test success for individual parameter for each type of fault - DE data

Parameter	Ball fault	Inner race	Outer race-O3	Outer race-O6	Outer race-O12
Kurtosis	19/20 (95%)	19/20 (95%)	20/20 (100%)	20/20 (100%)	18/20 (90%)
Skewness	18/20 (90%)	20/20 (100%)	20/20 (100%)	20/20 (100%)	20/20 (100%)
Variance	20/20 (100%)	17/20 (85%)	20/20 (100%)	20/20 (100%)	20/20 (100%)
RMS	20/20 (100%)	20/20 (100%)	20/20 (100%)	20/20 (100%)	18/20 (90%)
6^{th} moment	17/20 (85%)	19/20 (95%)	14/20 (70%)	18/20 (90%)	16/20 (80%)

7 Results and Discussion

From Tables 3 and 4, it is seen that training of network using single fault data gives almost 100 % test and training success in all cases, with few exceptions like ball faults, outer race O3 & O12 positions. Combination of faults also results in good performance of the network. It is seen that the test success rate of the network in predicting ball faults is less than 100 %. The possible reason for this is - as the ball is constantly rotating and revolving, the fault may not always produce impacts due to ball defect and hence the vibration amplitudes don't change. These tables also show deviation in the test success rates for O3 and O12 type of faults. The decrease is probably because the bearing load zone is outside the positions of sensors and hence vibration signals may be weak. This is shown in Fig. (9).

Table 5 shows the test success for each of the parameters for each type of fault. From this table it is seen that the parameter 6^{th} moment gave the least amount of success rate and hence this parameter is less significant. This was validated by finding the success rate, after removing this parameter from the input to the network. Table 5 also shows that kurtosis is the next insignificant parameter. We can also conclude that Skewness, Variance, RMS were relatively consistent in the success rate and thus contributed significantly to the testing success. After comparing table 3 and table 5 it is observed that single statistical parameter cannot be independently given to the network as input.

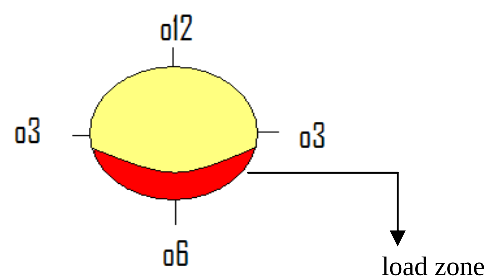


Figure 9: Bearing load zone and sensor locations.

8 Conclusion

From the results obtained, it can be concluded that a properly trained neural network can diagnose faults in the bearing to a high level of accuracy. For getting a good performance from the network, the input should have data for normal running along with all faulty running conditions of bearing. Out of the various statistical parameters used, the 6th moment of the vibration data can be safely dropped from the input matrix as it has very less effect on the performance of the network. Hence, the network can also be trained by a smaller input matrix, reducing the computation time. This increases its suitability for on-line condition monitoring. One needs to find out the best parameters and the optimum number of parameters to be used for input to the network for getting accurate results from the network.

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