EFFECTS OF ARTIFICIAL NEURAL NETWORK PARAMETERS ON ROLLING ELEMENT BEARING FAULT DIAGNOSIS

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Abstract

To ensure asset reliability the industries have been focused on the condition based maintenance (CBM). Fault detection and diagnosis are two of three condition based maintenance mainstays. Rolling Element is one of the major and essential components of rotating machinery. Thus researchers have been shown their interest in rolling element bearing fault detection and diagnosis for few decades. They used mostly the bearing vibration as fault characteristics for fault detection and used Artificial Neural Networks (ANNs) for bearing fault classification as well. The process of fault classification involves some Neural Network (NN) geometry and parameters, thus is not quits simple. There is no any predefined formula to select the optimal values for these network parameters. These parameters affect the reliability of fault diagnosis system. This paper investigates the effects of NN geometry and parameters on rolling element bearing fault diagnosis. The vibration signals are recorded for normal bearings, bearing with inner race fault, outer race fault and rolling ball fault from an appropriate experimental setup. The RMS vibration features are calculated then using Fast Fourier Transform (FFT). Rolling element bearing faults are classified as same using Back-Propagation Neural Network (BPNN) and the results are simulated.

Keywords—Artificial Neural Network, back-propagation algorithm, Condition Based Maintenance (CBM), Fast Fourier Transform (FFT).

I. INTRODUCTION

In a production system 60 to 75 % product cost accounts for maintenance and support activities which make the systems reliability a major issue. System's reliability depends upon Condition Based Maintenance (CBM) strategy. For many production systems the old maintenance strategies like break-down and preventive hold not good any time. These days the predictive maintenance strategy has been arisen in the form of an effective mainstay of CBM. Predictive maintenance offers online as well as offline condition monitoring of the machine or part and insures the condition of machine prior to any incipient part failure or major break-down which causes the unplanned shutdown. It also provides sufficient time to repair in comparison with other.

Rolling element bearing is one of the essential components in the vast majority of rotating machines. Rolling element bearing failure may affects the quality of product line working and create wastes in many ways. Thus rolling element bearing failure results in decrease product quality and increase product cost to the customer. Rolling element bearing may get defect due to any misalignment, looseness, improper installation, assess of load, poor lubrication, contamination, electric passage, insertion of foreign matter and progressive wear as listed in [1]. Rolling element bearing defects are classified as firstly on the basis of fault location and secondly on the basis of their fault type, It may be single point defect or it may be multi point defect as in [2]. Numbers of researchers are interested in finding the location of fault.

The main purpose of installing the rolling the rolling element bearing in machinery is to hold or support an element and transmit the moment of the load to the another element. When a machine rotates by drive, the shaft bearing response to the vibrations of the drive is main cause of vibration. All drives have nature to vibrate (*Vibrations cannot be eliminate*) and itself is not a fault. However excess of vibration can be a symptom of a developing fault and an early warning of machine failure. Many methods for rotating machinery fault diagnosis are presented in the literature on the basis of their different fault characteristics listed in [3]. In the present industrial scenario 70% bearing vibration, 20% wear particles are used as fault characteristics & remaining 10% covers all the other non-destructive testing including eddy current measurement as in [4]. By taking the vibration signals as characteristics fault features the fault detection and diagnosis of gear transmission system has been performed in [5]. When the signal is analyzed as a function of time then analysis is called time domain analysis. Time domain analysis has been performed to monitor the bearing health condition in [6]. This technique has been further subdivided as time waveform analysis and waveform indices as in [5]. How to set up, acquire and manipulate time waveform data is detailed in [7]. Time indices are listed as standard deviation, Root Mean Square (RMS) value, peak value, crest factor, shape factor, impulse factor, clearance factor, skewness and kurtosis etc. and calculated in [8]. In analyzing the signal in time domain one cannot find at what frequency an event occurred. Hence researchers have been focused on en effective technique (frequency domain analysis) for many decades. Frequency domain analysis employs Fast Fourier Transform (FFT) to transforms the time domain signal in frequency domain. FFT is used in this paper to extract features from row vibration signals. Rest of the paper is organized as follows: section 2 discusses the data acquisition. Section 3 describes the back-propagation algorithm. Section 4 discusses the Artificial Neural Network. Section 5 discusses NN geometry. Section 6 discusses NN parameters. Section 7 discusses results and analysis. Section 8 contains general discussion. Section 9 concludes the paper.

II. DATA ACQUISITION

The experimental setup consists of a Machine Fault Simulator (MFS) having an induction motor coupled with a rotating shaft supported with Rolling Element Bearings (REBs), CSI accelerometer, CSI 2400 dynamic signal analyzer with cable and PC interface, vibscanner to measure shaft speed in RPM and MATLAB R2009a software. The details of specimen (Self alignment rolling element bearing) are as follows:

Inner race dia (d) =25 mm
Outer race dia (D) =52 mm
Contact angle (β) =Zero degree
Number of balls (N_b) =13 per row
Ball diameter (d_b) =7.5 mm
Pitch diameter (d_p) =38.5 mm

The defects are produced artificially as follows:

TABLE I
Bearing defect geometry parameters

S. No.	Defect type	Location and number of defects	Defect size
1	Ball Defect	2 balls in one row, one by one	1*1mm, 0.1 mm deep
2	Inner Race Defect	3 defects at each row at pitch a pitch of 3 mm, both rows with defects	1*1mm, 0.2 mm deep
3	Outer Race Defect	3 defects at each row at pitch a pitch of 3 mm, both rows with defects	1*1mm, 0.2 mm deep

These listed faults cause their certain fault frequency to appear in the bearing vibrations hence there is one characteristic fault frequency associated with each of the four parts of the bearing. The fault frequencies are calculated, using the equations as in [9]

$$F_i = [N_b F_r \{1 + (d_b \cos(\beta)) / d_c\}] / 2 \quad (1)$$

$$F_o = [N_b F_r \{1 - (d_b \cos(\beta)) / d_c\}] / 2 \quad (2)$$

$$F_b = (d_c / d_b) F_r \{1 - (d_b \cos(\beta) / d_c)^2\} \quad (3)$$

where d_i is inner diameter, d_c is pitch circle diameter, d_b is diameter of ball, N_b is number of balls, β is contact angle of ball, and F_r is the rotor frequency in Hz and F_i=Inner race fault frequency, F_o=Outer race fault frequency and F_b=Ball fault frequency.

Using the formulae (1), (2), and (3) and bearing geometry parameters listed in TABLE I, characteristics fault frequencies corresponding to each fault type are calculated. Time domain vibration signals (figure 1) are acquired at a sampling rate of 7680 Hz from the experimental setup for normal bearings, bearing with inner race fault, outer race fault and rolling ball fault by replacing one by one.

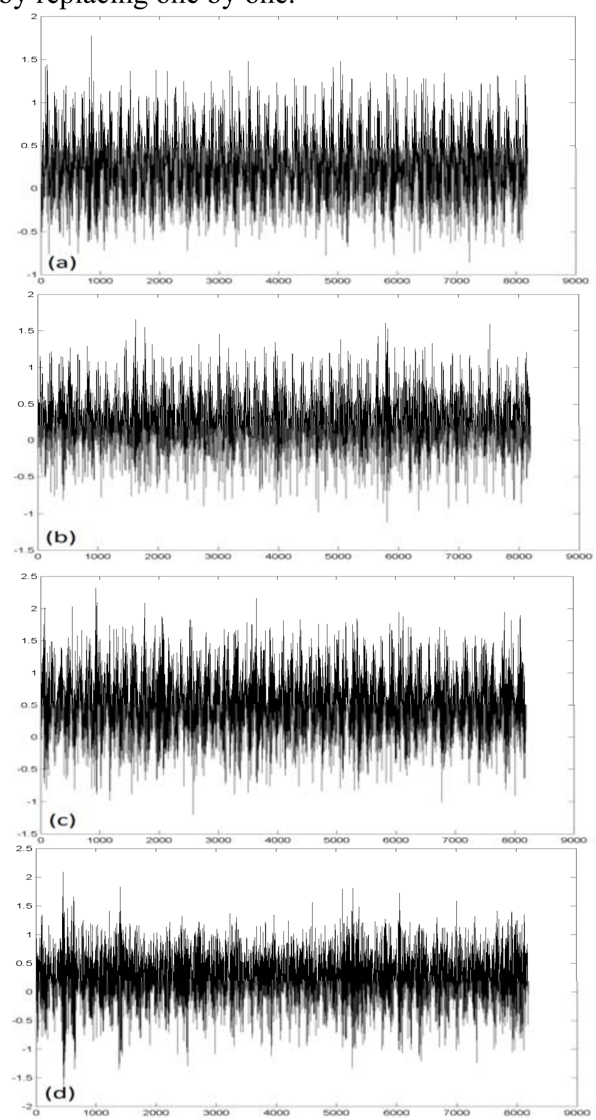


Figure 1. Vibration signals of healthy bearing (a), inner race defect (b), outer race defect (c), rolling ball defect (d).

III. BACK PROPAGATION ALGORITHM

The back-propagation algorithm is used to train the neural network in this paper follows the steps as in page 53 [10]

STEP 1: Normalize the input and output with respect to their maximum values. Neural network perform better if input and output lie between .1 and .9

STEP 2: Assume the number of neurons in the hidden neurons in the hidden layer to lie between $1<m<21$

STEP 3: $[V]$ represents the weights of synapses connecting input neurons and hidden neurons and $[W]$ represents weights of synapses connecting hidden and output neurons. Initialize the weight to small random values usually between -1 to 1 for our problem λ is taken as 1 and the threshold value θ is taken as zero.

$[V]^0$ =[random weights]

$[W]^0$ =[random weights]

$[V]^0 = [W]^0 = [0]$

STEP 4: For the training data, present one set of inputs and outputs. Present the pattern to the layer $\{I\}_I$ as input to the input layer. By using linear activation function, the output of the input layer may be evaluated as

$$\{O\}_I = \{I\}_I$$

1 x 1 1 x 1

STEP 5: Compute the inputs to the hidden layer by multiplying corresponding weights of synapsed as

$$\{I\}_H = [V]^T \{O\}_I$$

m x 1 m x 1 1 x 1

STEP 6: Let the hidden layer units evaluate the output using the sigmoidal function as

$$\{O\}_H = \begin{bmatrix} . \\ 1/(1+\exp(-I_{Hi})) \\ . \end{bmatrix}$$

m x 1

STEP 7: Computes the inputs to the output layer by multiplying corresponding weight of synapses as

$$\{I\}_o = [W]^T \{O\}_H$$

n x 1 n x m m x 1

STEP 8: Let the output layer units evaluate the output using sigmoidal function as

$$\{O\}_o = \begin{bmatrix} . \\ 1/(1+\exp(-I_{oj})) \\ . \end{bmatrix}$$

The above is the network output.

STEP 9: Calculate the error and the difference between the network output and desired output as for the i[th] training set as

$$E^P = \{\sqrt{\sum (T_j - O_{oj})^2}\}/n$$

STEP 10: Fond $\{d\}$ as

$$\{d\} = \begin{bmatrix} . \\ (T_k - O_{ok})O_{ok}(1 - O_{ok}) \\ . \end{bmatrix}$$

n x 1

STEP 11: Find $[Y]$ matrix as

$$[Y] = \{O\}_H \langle d \rangle$$

m x n m x 1 1 x n

STEP 12: Find $[\Delta W]^{t+1} = \alpha[\Delta W]^t + \eta[Y]$

m x n m x n m x n

$$\{e\} = [W]\langle d \rangle$$

m x 1 m x n n x 1

$$\{d^*\} = \begin{bmatrix} . \\ e_i(O_{Hi})(1 - O_{Hi}) \\ . \end{bmatrix}$$

m x 1 m x1

STEP 13: Find [X] matrix as

$$[X] = \{O\}_I \langle d^* \rangle = \{OI\}_I \langle d^* \rangle$$

1 x m 1 x 1 1 x m 1 x 1 1 x m

STEP 14: Find $[\Delta V]^{t+1} = \alpha[\Delta V]^t + \eta[X]$

1 x m 1 x m 1 x m

STEP 15: Fin $[V]^{t+1} = [V]^t + [\Delta V]^{t+1}$

$$[W]^{t+1} = [W]^t + [\Delta W]^{t+1}$$

STEP 16: Find error rate as

Error rate $= \sum E_P / (nset)$

STEP 17: Repeat step 4-16 until the convergence in the error rate is less than the tolerance value Once the process converges the final weights should be stored in a file.

IV. ARTIFICIAL NEURAL NETWORK

In a biological brain billions of neurons are responsible for the taken decision from the information provided by sense organs. Means the neurons are the main unit of a biological brain and convert input into output by forming a complex network between themselves and updating the weights. This idea of forming artificial neurons and updating the weights are implemented by the researchers in the field of technology to make decisions. Thus, the Artificial Neural Network (ANN) is the prototype of biological brain. Neural networks are formed by an input layer of neurons, an output layer of neurons and definite number of hidden layers of hidden neurons as shown in figure 2. ANNs have learning and generalization abilities. Numerous variations of ANNs have been proposed by the researchers in the literature on the basis of their learning algorithms, ANN structure, Transfer Function (TF) and training parameters etc. To classify the bearing faults on the basis of their location Back-Propagation Neural Network (BPNN) with single hidden layer is used in this present work.

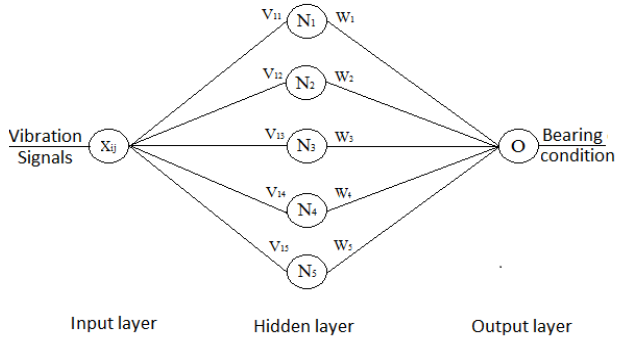


Figure 2 ANN structure

V. NEURAL NETWORK GEOMETRY

Neural networks (NN) have been used universally in function approximation. Hidden layer completes the neural network structure (Shown in figure 2) and constitutes the numbers of hidden neurons. There is no any criterion to select the optimal number of hidden neurons. Thus optimizing the number of hidden neurons for greater accuracy is one of the major & challenging tasks, hence a problem in hand. Usages of excessive hidden neurons may cause over fitting. Means the neural networks over-estimate the complexity of the given problem, which decreases the generalization capability, hence leads to significant changes in the prediction performance.

VI. NEURAL NETWORK PARAMETERS

A. Learning coefficient

Learning coefficient determines the size of the weight adjustment and influence the convergence rate. Negative value of learning coefficient causes the change of weight vector from the ideal weight vector. It cannot be zero; if learning coefficient is zero then no any learning takes place. If its value is greater than 1, the weight vector will oscillate about its ideal position. The choice of smaller learning coefficient may increase convergence time and choice of smaller value may slow the convergence process as in page 51 [10]. Hence we must keep learning coefficient constant through all the iterations.

B. Momentum coefficient

Momentum term is also used to reduce the training time and enhance the training process. The effects of momentum coefficient on weight change are given by the equation page 52 [10]

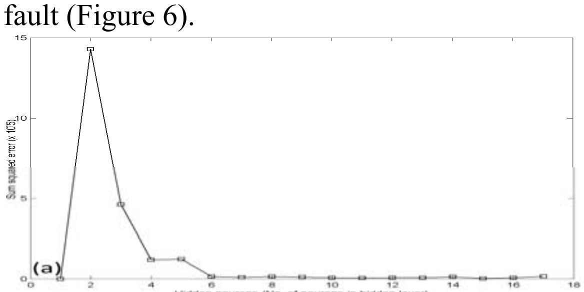
$$[\Delta W]^{t+1} = -\eta(\partial E / \partial W) + \alpha[\Delta W]^{t}$$
(4)

Where $[\Delta W]^{t+1}$ is new weight, $[\Delta W]^{t}$ is the previous weight, $\partial E / \partial W$ is change in error with change in weight, η is learning coefficient and α is momentum coefficient

The momentum coefficient produces damping effect on searching procedure and may be considered as approximation to second order method. Thus the momentum term generally improves convergence of the back-propagation algorithm by using information from the previous iteration.

VII. RESULTS AND ANALYSIS

76 RMS features (19 for healthy bearing and 19 for each type of faulty bearing) are extracted by employing FFT and then using an IIR band pass filter to extract frequencies of interest at three nodes as (725-745), (381-387), (773-793). Trained the Back-Propagation Neural Network (BPNN) for different values of number of neurons in hidden layer, learning coefficient and momentum coefficient then results are simulated and plotted as error rate versus number of hidden neurons (Figure 3), error rate versus learning rate (Figure 4), error rate versus momentum rate (Figure 5). Bearing conditions are simulated as Healthy bearing, bearings with inner race fault, outer race fault and rolling ball fault (Figure 6).



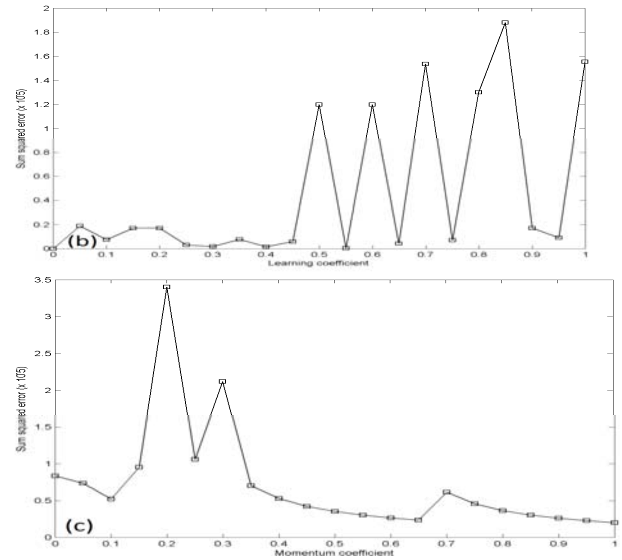


Figure 3 Error verses hidden neurons (a), error verses learning coefficient (b), error verses momentum coefficient (c)

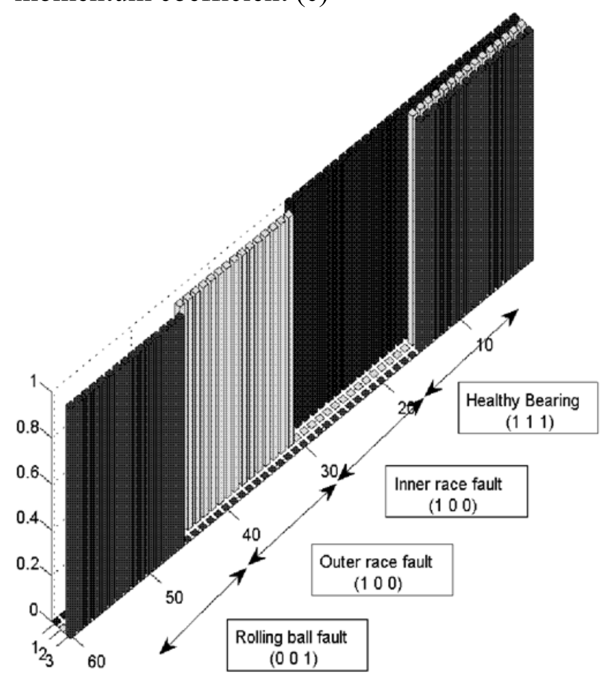


Figure 4 Bar graph showing bearing fault classification

VIII. DISCUSSION

Figure 3(a) shows very poor performance for two hidden neurons and abrupt improvement sequentially for 3, 4, 5, and 6 neurons. Whereas the best performance shown for 10 neurons. Figure 3(b) shows the small increments and decrements in the performance for the value of learning coefficient from 0 to 0.45 and large ups and downs thereafter up to 1. The best performance has shown for 0.55. Figure 3(c) shows yielding poor performance for the value of momentum coefficient at 0.2. Two performance increasing gradients for 0.36-0.65 and 0.70-1.00 also have been shown. The best performance has met for 1.00. Figure 4 shows the bearing fault classification at optimal values of hidden neuron, learning coefficient and momentum coefficient as healthy bearing, inner race fault, outer race fault, and rolling ball fault.

IX. CONCLUSIONS

Time domain vibration signals are recorded from experimental setup, transformed to frequency domain using FFT and RMS features are extracted using an elliptic IIR band pass filter. This paper generally concludes as follows:

1) Features are trained using BPNN and results are simulated.
2) Bearing faults are successfully classified as Inner Race Fault (IRF), Outer Race Fault (ORF), and Rolling Ball Fault (RBF).
3) Investigated the effects of (NN) geometry and parameters on bearing fault diagnosis.

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