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Feed-Forward Neural Network with Backpropagation Training Based Fault Detection in Rolling Element Bearing using Time Domain Features and Frequency Domain

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Abstract

Bearings are one of the most usual elements in rotating machinery, and as a consequence, bearing failure is likewise one of the main causes of breakdown in rotating equipment. The robustness and durability of the rollers are essential qualities for a machine's safety. Deficiencies in bearings may occur during use or during manufacturing. The identification of these defects is therefore critical for condition monitoring as well as for inspecting the quality of the bearings [1]. This paper exhibits a strategy for flaw discovery in moving component bearing utilizing time-space highlights and recurrence area highlights of vibration signals. This system involves two sequential processes: feature extraction and decision-making. Vibration signals were recorded in this process. Neural Network Feed Forward Back Propagation was used for the classification. The 12 extracted features such as Mean, Peak, Mean Square, Variance, Standard Deviation, RMS, Shape Factor, Skewness, Kurtosis, Impulse Factor, Clearance Factor, Crest Factor were used to train and check the neural network for four bearing conditions namely: healthy, outer race fault, inner race fault and defective ball & outer race fault condition.

Keywords*- Time Domain Features, Frequency Domain Feature, Feed Forward Back Propagation Neural Network.*

I. Introduction

Most of the mechanical failure is due to fault with the bearing. Serious bearing failure can cause vibration, noise, low efficiency and even device breakdown. Standard treatment of bearings is a periodic replacement, possibly resulting in 90 percent of effective life waste bearing. Active maintenance is to develop a condition monitoring program to test the bearings satisfactory operation and conduct repair, according to realistic running condition and diagnosis of faults.

Currently, rolling bearing monitoring and diagnostic techniques include vibration, temperature, grindings, acoustic emission, resistance to oil film. Among them, measurement of the vibration is the most widely used and effective method. The use of vibration diagnosis can effectively diagnose common bearing defects such as crushing, cracking, indentation, wear [2].

This paper presents a technique for fault detection in rolling element bearing using time-domain features and frequency domain features of vibration signals.

II. RELATED WORK

Tandon and Choudhury [3], They calculated time-domain vibrations through parameters like total RMS level, crest factor, probability density, and kurtosis. In acoustic measurement both the sound pressure and the intensity of sound used to detect the bearing defect. Acoustic measurements of emissions used to detect defects in rolling element bearings, too.

Pratesh Jayaswal, A.K.Wadhwani and K.B.Muchandani [4] examined the feasibility of Rapid Fourier Transform (FFT) & Band Pass Analysis to classify REB faults with multiple faults. They dealt with three bearing faulty & safe conditions. They also reported that the filtered signals under three frequency bands can be useful signatures for erroneous detection, and the RMS values of the filtered signals can also be used as important diagnostic parameters.

M Amarnath, R Shrinidhi, A Ramachandra, and S B Kandagal [5], keys out the appropriateness of vibration detection and analysis techniques for detecting antifriction bearing defects. Analysis of the

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time domain, analysis of the frequency domain, and analysis of the spike energy was used to classify various defects in bearings.

B. Samanta and K. R. Al-Balushi [6], presented a procedure for rolling element bearings fault diagnosis via Artificial Neural Network (ANN). The characteristic features of rotating machinery time-domain vibration signals with regular and defective bearings that are applied as inputs to the ANN.

Bo Li, Gregory Goddu, and Mo-Yeun Chow [7] presented an approach of using neural networks to detect common bearing defects from motor vibration data. They used the frequency spectrum of the vibration signal to train an artificial neural network and achieved excellent results with minimal data.

D.H. Pandya, S.H. Upadhyay, and S.P. Harsha [8] Presented an automation methodology for the diagnosis of ball bearings with localized deficiencies (spalls) on the different components of the bearing. The machine used the decomposition of the wavelet packet using the real mother wavelet function ' rbio5.5 ' to extract features from the vibration signal, recorded for various conditions of bearing fault. The degree of decomposition was determined by the sampling frequency and the frequency of the characteristic defect. For selecting the best node of the wavelet packet tree, maximum energy to minimum criteria for the Shannon entropy ratio was used. For selected WPT nodes, the two functions kurtosis and energy were extracted from the wavelet packet coefficient. For fault classification, the total 10 data sets were registered at five different speeds corresponding to each bearing state. Therefore, extracted features were used to train and check a multi-layer perceptron neural network to identify the state of the rolling item bearing as HB, ORD, IRD, BD, and CD.

III. VIBRATION-BASED CONDITION MONITORING OF ROLLING ELEMENT BEARINGS

Since the last 50 years, vibration has been used to assess the mechanical state of equipment and parts thereof. Several researchers have experimented with different methods and descriptors under different environments and have attempted to investigate the relationship between the tested bearing and changes in vibration response under operating conditions [9].

A. Vibration Measurement Techniques

Vibration analysis can be divided into a time-domain technique, frequency-domain technique and time-frequency technique [9].

1) Time Domain Technique:

Some of the time domain techniques, such as Root Mean Square (RMS), Mean, Peak Value, Crest Factor, Skewness Kurtosis, Variance, Standard Deviation, Clearance Factor, Impulse Factor and Shape Factor may be used or applied for condition monitoring [10].

a) Root Mean Square

Root Mean Square (RMS), measures the frequency of a single signal as a whole.

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} f_n^2}$$

Where N is the discrete number of points and represents the signal from each sampled point.

RMS is a powerful tool for estimating average vibrational strength in the device. RMS has employed a considerable amount of research to successfully recognize bearing defects using accelerometer and AE sensors.

b) Mean

The acceleration signal in Mean is the standard mean statistical value. Like RMS, the Mean is only recorded for rectified signals, since the Mean remains close to zero for raw time signals. As the Mean rises, the bearing condition tends to worsen.

$$\mathrm{Mean} = \frac{1}{N} \times \sum_{i=1}^{N} f_n$$

c) Peak Value

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Peak Value is measured in the Domain of Time or Frequency. Peak Value is the limit in the amplitude of the signal.

$$P_v = \frac{1}{2}[\max(f_n) - \min(f_n)]$$

d) Crest Factor

Crest Factor is a peak acceleration ratio over RMS. This measure measures bursts of acceleration even when the RMS signal hasn't shifted. Crest factor may be counter-intuitive though. Bearing damage propagates, RMS increases, and Crest Factor decreases at advance stages of material wear. But to locate defects in rolling elements is unreliable with Crest Factor.

$$\text{Crest Factor} = \frac{\mathrm{P_v}}{\mathrm{RMS}}$$

e) Skewness

Machined or ground surfaces in bearings display a random distribution of asperities commonly described in the normal function of the distribution. Therefore, specific statistical moments will characterize the form of distribution curves, assessing the extent of surface damage at the bearing. The equation defines the third moment or Skewness as

$$\text{Skewness} = \frac{\frac{1}{\mathrm{N}}\sum_{\mathrm{n=1}}^{\mathrm{N}}(\mathrm{f_n} - \bar{\mathrm{f}})^3}{\mathrm{RMS}^3}$$

Where the mean value is f. The odd moments for normally distributed data sets are zero unless the time domain signal is rectified. Therefore, forbearing conditions skew can easily track.

f) Kurtosis

The fourth, uniform moment with regard to the fourth power of standard deviation is quite useful in the diagnosis of the fault. This quantity is called Kurtosis which is a measure of the balance between the lower intensive moments and other more sensitive moments. Kurtosis has been reported as being a good criterion for distinguishing between damaged and healthy bearings. A Kurtosis value of around 3 will be the safe bearing with Gaussian distribution. This value goes up when the bearing deteriorates to show damaged condition which reduces again when the defect is well advanced. One of the advantages of this method is that there is no need to know the time history of the signal, and it is possible to monitor the bearing condition by observing kurtosis. A strong surface finish has a theoretical Kurtosis of 3, and the skew and kurtosis are resistant to loads and speeds as Kurtosis increases the surface finish deteriorates. The noise level between individual readings however hampered the detection of damage to the bearing.

$$\text{Kurtosis} = \frac{\frac{1}{\mathrm{N}}\sum_{\mathrm{n=1}}^{\mathrm{N}}(\mathrm{f_n} - \bar{\mathrm{f}})^4}{\mathrm{RMS}^4}$$

g) Variance

$$\text{variance} = \sigma^2 = \frac{\sum_{\mathrm{n=1}}^{\mathrm{N}}(\mathrm{f_n} - \mu)^2}{\mathrm{N}}$$

h) Standard Deviation

$$\mathrm{s} = \left(\frac{1}{\mathrm{N}-1}\sum_{\mathrm{n=1}}^{\mathrm{N}}\left(\mathrm{f_n} - \bar{\mathrm{f}}\right)^2\right)^{\frac{1}{2}}$$

i) Clearance Factor

$$\mathrm{Cl_f} = \frac{\mathrm{P_v}}{\left(\frac{1}{\mathrm{N}}\sum_{\mathrm{n=1}}^{\mathrm{N}}|\mathrm{f_n}|\right)^2}$$

j) Impulse Factor

$$\mathrm{I_f} = \frac{\mathrm{P_v}}{\frac{1}{\mathrm{N}}\sum_{\mathrm{n=1}}^{\mathrm{N}}|\mathrm{f_n}|}$$

ISSN: 2233-7857 IJFGCN

Vol. 13, No. 3s, (2020), pp. 1351–1358

k) Shape Factor

$$S_f = \frac{RMS}{\frac{1}{N}\sum_{n=1}^{N}|f_n|}$$

2) Frequency Domain Technique

The conventional approach is for detecting the frequency domain vibration signals. In rolling element bearings, the interaction of defects produces pulses of very short duration whenever the defect strikes or is struck due to the system's rotational motion. The natural frequencies of the bearing elements and housing structures are excited by these pulses. These frequencies depend on the properties of the bearing and are calculated according to the relationships as shown below [4][9].

a) Shaft rotational frequency

$$(FOR) = \frac{N}{60} \tag{1}$$

b) Inner race defect frequency

$$(FID) = \left(\frac{n}{2}\right)\left(\frac{N}{60}\right)\left[1 + \left(\frac{bd}{pd}\right)\cos ø\right] \tag{2}$$

c) Outer race defect frequency

$$FOD = \left(\frac{n}{2}\right)\left(\frac{N}{60}\right)\left[1 - \left(\frac{bd}{pd}\right)\cos ø\right] \tag{3}$$

d) Ball defect frequency

$$FBD = \left(\frac{pd}{bd}\right)\left(\frac{N}{60}\right)\left[1 - \left(\frac{bd}{pd}\right)^2 (\cos \emptyset)^2\right] \tag{4}$$

Where,

n = Number of balls.

ϕ = Contact angle.

pd = pitch diameter.

bd = ball diameter.

N= rotational speed in rpm.

FFT converts the convolution in one domain into a multiplication in the other domain. FFT simplifies the solution of many problems, but it is also useful in graphical illustrations of many relationships. Convolution is the operation by which the output (response) of a linear system is obtained from the input (forcing function) and the transfer properties of the physical system, in the time domain represented by its impulse response function. The impulse response function (IRF) of a system is its output when excited by a unit impulse at time zero. FFT shows the graphical representation of the data and interpretative the data, frequency v/s Amplitude and many more.

IV. EXPERIMENTAL SETUP

1 HP induction motor drive the machine, measuring at different speeds varying from 1000 to 4000 rpm. Variable Frequency Drive (VFD) has been used which gives fine speed adjustment over the necessary range. The configuration consists of 3 support bearings and 1 test bearing sitting on the shaft at a time from which two support bearings are SKF6205 & 1 support bearing SKF 6004, and 1 test bearing is SKF6205. The test bearing is single row Deep groove ball bearings. The main dimensions are: internal diameter (d) = 25 mm, outer diameter (D) = 52 mm, total bearing thickness = 15 mm. Figure 5.1 shows SKF6205 Deep Groove Ball Bearing Geometry[11].

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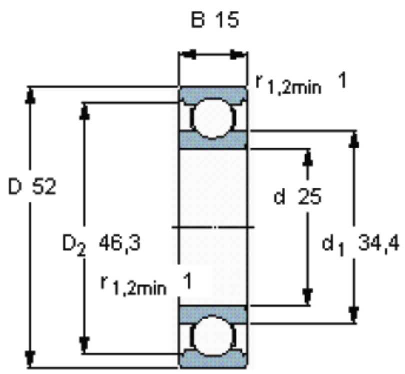

Figure 5.1 SKF 6205 Deep Groove Ball Bearing Geometry [11]

Figure 5.2 Experimental setup

The instrumentation allows for a visual inspection of the vibration signal, recording it, measuring the overall vibration level, performing the frequency analysis. Figure 5.2 shows the experimental setup.

This system involves two sequential processes: feature extraction and decision-making. In this process, vibration signals were recorded. Initially read the bearing vibration signal file on to the device and then display the signal graph for the time domain. Set the bearing parameters which have to be tested. After this calculate all the FOR, FID, FOD, FBD fault frequencies. The system displays a graph for the frequency domain. Extract time-domain features then use Back Propagation Learning to train the Feed Forward Neural Network.

V. MULTILAYER FEED-FORWARD NEURAL NETWORK AND BACKPROPAGATION TRAINING

A. Feed Forward Neural Network

A network of single-layer S logsig neurons having R inputs is shown in figure 6.1, Full detail to the left and layered diagram to the right.

Feedforward networks often have one or more hidden strata of sigmoid neurons followed by a linear neuron output layer. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear input/output vector relationships. The linear output layer is most widely used for function fitting problems (or nonlinear regression) [12].

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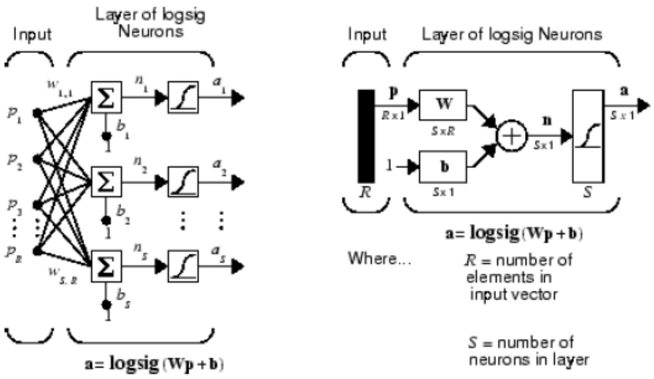

Figure 6.1: A single-layer network of S logsig neurons with layer diagram on the right side [12].

The data was then obtained, there are two steps to be done before the data is used to train the network: the data must be preprocessed and separated into sub-sets.

For preprocessing and post processing features, use mapminmax (Normalize inputs/targets to fall within the range [-1, 1]) in this network. In most cases, they don't need to be used explicitly, as the preprocessing steps are part of the network object. The preprocessing and post processing will be done automatically while simulating or training the network.

A neural network training process involves tuning the values of the network's weights and biases to maximize network performance, as defined by network performance function net.performFcn. For feedforward networks, the default performance function is mean square error mse — the average squared error between network outputs a and target outputs t. It is defined as follows:

$$F = \mathrm{mse} = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2$$

The progress is constantly being updated in the Training window during training. The performance, magnitude of the performance gradient and a number of validation checks are of most interest. To terminate the training, the magnitude of the gradient and the number of validation checks are used. The gradient will get very low as the training approaches an output minimum. If the gradient magnitude is less than 1e-5, then the training will cease. You can adjust that limit by setting the net.trainParam.min grad parameter. The number of validation checks represents the number of successive iterations that fail to decrease validation efficiency. The training will end if this number exceeds 6 (the default value).

VI. RESULT AND DISCUSSION

For test bearing analysis, the vibration signal was acquired for four conditions: Healthy, Outer race fault, Inner race fault, and defective ball fault. The theoretical characteristic frequencies were determined according to the equations shown for the above cases of a defect as in table 7.1 and Summary of overall fault classification as shown in table 7.2.

Table 7.1: Theoretical Characteristic Frequencies (Hz)

Speed in rpm	**fs**	**BPFO Fod**	**BPFI fid**	**BPFR fbd**
1800	30	105	165	144
2100	35	122.5	192.2	168
2400	40	144	220	192
2700	45	156.6	247	216
3000	50	175	274.5	240

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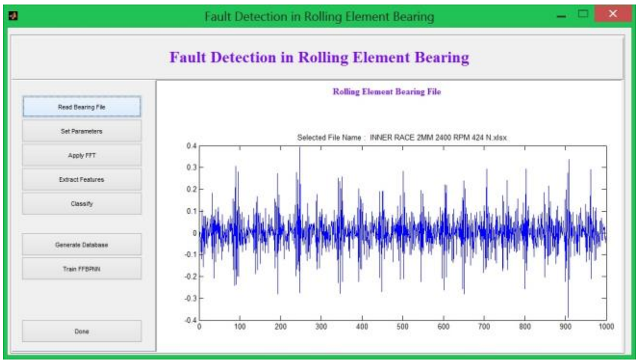

Figure 7.1 Time Domain Signal of Inner Race Bearing Fault Signal

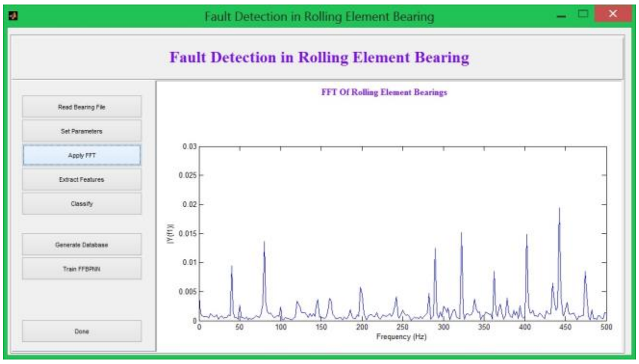

Figure 7.2: FFT of Inner Race Bearing Fault Signal

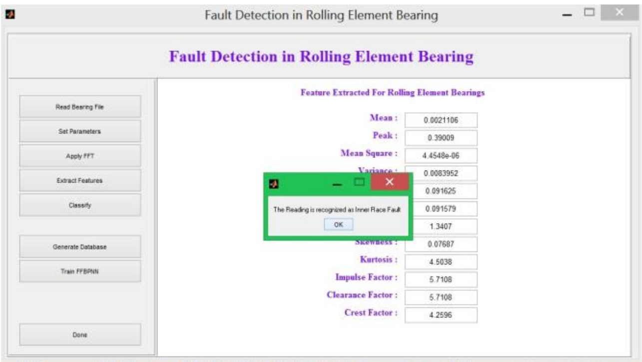

Figure 7.3 Extracted Features and Classification Result

Table 7.2: Summary of overall fault classification

Sr. No.	**Bearing Condition**	**Dataset**	**Correctly classified**	**Mis-classified**	**% Accuracy**
1	Healthy Bearing	15	14	1	93.3%
2	Inner Race Fault	15	14	1	93.3%
3	Outer Race Fault	15	15	0	100%
4	Ball + Outer Race Fault	15	12	3	80%

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VII. CONCLUSION

Two sequential processes, feature extraction and decision-making were used for the detection of a fault in rolling element bearing using feed-forward propagation neural network. For the detection of faults, SKF6205 deep groove ball bearing was chosen, then vibration signals were registered and the device was fed into. The program will read the registered bearing vibration signal file and will map the time domain signal graphs. The parameters of SKF 6205 Deep Groove Ball Bearing were then set, and the machine also plotted the frequency domain graphs. 12 Time-domain features were extracted from the system: Mean, Peak, Mean Square, Variance, Standard Deviation, RMS, Shape Factor, Skewness, Kurtosis, Impulse Factor, Clearance Factor, Crest Factor. Using the Back Propagation Training method these parameters were used to train the Feed Forward Neural Network. Then they classified different bearing faults. For Healthy Bearing Classification Accuracy was 93.3%, for Inner Race Fault 93.3%, for Outer Race Fault 100%, for Ball & Outer Race Fault 80%.

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