Fault Detection in Rolling Element Bearing Using Vibration Based Analysis

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ABSTRACT

In any rotating machinery, bearings are important elements. Bearing failure is one of the primary causes of breakdown in rotating equipment. Defects in bearings may occur through use or during the manufacturing process. Therefore, the detection of these defects is important for condition monitoring as well as the quality inspection of bearings. This paper propose a technique for fault detection in rolling element bearing using Time domain features and Frequency Domain features of vibration signals. This system involves two sequential processes: feature extraction and decision-making. In this process vibration signals are recorded. Fuzzy Min–Max Neural Network with Compensatory Neuron (FMCNs) will be used for classification.

Keywords*: Rolling Element Bearing, Time domain features, Frequency Domain Features, Fuzzy Min-Max Neural Network with Compensatory Neuron.*

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1. INTRODUCTION

Most mechanical failure is caused by bearing fault. Vibration, noise, low efficiency, even breakdown of equipment is because of fault present in bearing. According to practical running condition and fault diagnosis, maintenance is to establish a condition monitoring technique to check the satisfactory operation of bearings. Vibration, temperature, grindings, acoustic emission, oil film resistance are the monitoring and diagnosis techniques of rolling bearing. Among them, vibration measurement is the most widely used and effective way. Using vibration diagnosis, such common bearing faults as crushing, crack, indentation, wear can be detected effectively [1][2].

This paper propose a technique for fault detection in rolling element bearing using Time domain features and Frequency Domain features of vibration signals. This system involves two sequential processes: feature extraction and decision-making. In this process vibration signals are recorded. Fuzzy Min–Max Neural Network with Compensatory Neuron (FMCNs) will be used for classification.

2. LITERATURE SURVEY

Tandon and Choudhury [3], they considered detection of two categories of defect: localized and distributed defect. Detection of defects is then measured by vibration and noise generation in bearings. Authors discussed Vibration measurement in both time and frequency domains along with signal processing techniques such as high frequency resonance technique. In time domain, using RMS level, crest factor, probability density and kurtosis parameters authors measured the vibrations. Sound pressure and sound intensity have been used for the detection of the bearing defect in acoustic measurement. The sound intensity technique seems to be better than sound pressure measurements for bearing diagnostics.

Pratesh Jayaswal, A.K.Wadhwani & K.B.Muchandani[4] investigated the feasibility of fast Fourier Transform (FFT) & band pass analysis for fault identification of REB with multiple faults. They experimented three faulty & healthy conditions bearing. They have confirmed that the filtered signals under three frequency bands can be valuable signatures for faulty identification & the RMS values of filtered signals can be further utilized as parameters of diagnostic important.

M Amarnath, R Shrinidhi, A Ramachandra, S B Kandagal [5], describes the suitability of vibration monitoring and analysis techniques to detect defects in antifriction bearings. Time domain analysis, frequency domain analysis and spike energy analysis have been employed to identify different defects in bearings. The results have demonstrated that each one of these techniques is useful to detect problems in antifriction bearings.

B. Samanta and K. R. Al-Balushi [6], presented procedure for fault diagnosis of rolling element bearings through artificial neural network (ANN). The characteristic features of time-domain vibration signals of the rotating machinery with normal and defective bearings have been used as inputs to the ANN consisting of input, hidden and output layers. The features are obtained from direct processing of the signal segments using very simple preprocessing. The input layer consists of five nodes, one each for root mean square, variance, skewness, kurtosis and normalized sixth central moment of the time-domain vibration signals. The inputs are normalised in the range of 0.0 and 1.0 except for the skewness which is normalised between -1.0 and 1.0. The output layer consists of two binary nodes indicating the status of the machine normal or defective bearings. Two hidden layers with different number of neurons have been used. The ANN is trained using backpropagation algorithm with a subset of the experimental data for known machine conditions. The ANN is tested using the remaining set of data. The results show the effectiveness of the ANN in diagnosis of the machine condition. Their proposed procedure requires only a few features extracted from the measured vibration data either directly or with simple preprocessing. The reduced number of inputs leads to faster training requiring far less iterations making the procedure suitable for on-line condition monitoring and diagnostics of machines.

Bo Li, Gregory Goddu, 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.

3. ROLLING ELEMENT BEARING

Rolling Element bearings are the most common component in rotating machinery that utilizes the rolling action of rollers to minimize friction between stationary and moving parts. The economic loss due to bearing failure is huge compared to the cost of the bearing itself. Therefore, bearing condition monitoring and diagnosis has drawn many attentions in the last four decades.

Before discussing bearing condition monitoring and diagnosis, it is important to have a general understanding of rolling element bearings. This chapter introduces rolling element bearings, beginning with basic bearing types, their major components and its geometry [8].

3.1 Types of Rolling Element Bearings

There are many forms of rolling element bearings. Depending on the application, rolling element bearing can have various dimensions and design. For example, deep groove ball bearings perform well at high speed under moderate radial as well as axial loads. They have low friction and can be produced with high precision and in quiet running variants. Therefore, they are preferred for small and medium sized electric motors [8]. One way to classify rolling element bearings is based on the shape of rolling elements as shown in figure 1.

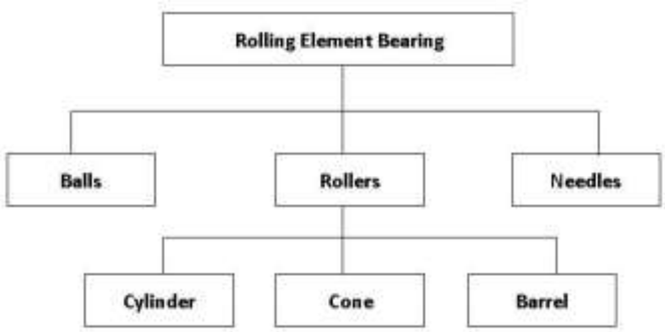

Figure 1: Classification of Rolling Element Bearing

3.2 Rolling Element Bearing Components and Geometry

Bearing geometry is a critical factor for diagnosing bearing defects because the geometry of ball bearings determines the dynamics of the bearing components and their vibration characteristics. This section will describe the components and geometry of bearing. Figure 2 shows components, applied force, load zone and load distribution.

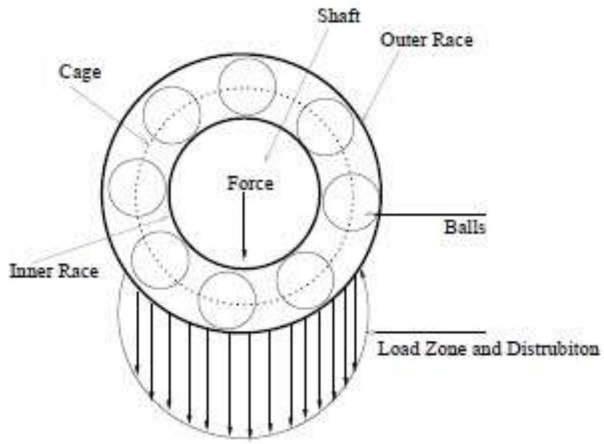

Figure 2: Ball bearing components, applied force, load zone and load distribution [8].

A ball bearing consists of an inner race, an outer race, balls, a cage holding the balls apart from each other and a shaft. The load zone and load distribution are also given with the direction of applied force in the figure. The inner race and the balls rotate and the outer race is held stationary. Cracks or pits defects occur on the inner side of outer race on the locations subject to the load zone, since they are directly under the applied force. The inner race faults on the other hand, can occur anywhere since the race is not stationary and rotating.

3.3 Bearing Failure Modes

The normal service life of a rolling element bearing rotating under load is determined by material fatigue and wear at the running surfaces. Fatigue, wear, plastic deformation, corrosion, brineiling, poor lubrication, faulty installation and incorrect design are the factors due to which premature bearing failures may occurs [9].

4. VIBRATION BASED CONDITION MONITORING

Vibration has been used to determine the mechanical condition of machinery and their parts since last 50 years. Many researchers have tried different approaches and different descriptors under different environment and tried to investigate the relationship between the tested bearing and changes in vibration response under operating condition [9].

4.1 Vibration Measurement Techniques

Condition monitoring using vibration measurement can be classified into time domain technique, frequency domain technique and time-frequency technique [9].

1) Time Domain Technique

Some of the time domain techniques can be used or applied for condition monitoring, such as root mean square (RMS), mean, peak value, crest factor, Skewness kurtosis, Variance, Standard Deviation, Clearance Factor, Impulse Factor, Shape Factor [10].

Root mean square

Root mean square (RMS), measures the overall level of a discrete signal.

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

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

RMS is a powerful tool to estimate the average power in system vibrations. A substantial amount of research has employed RMS to successfully identify bearing defects using accelerometer and AE sensors.

Mean

The mean acceleration signal is the standard statistical mean value. Unlike RMS, the mean is reported only for rectified signals since for raw time signals, the mean remains close to zero. As the mean increases, the condition of the bearing appears to deteriorate.

$$\mathrm{Mean} = \frac{1}{N} * \sum_{i=1}^{N} f_n \qquad (2)$$

Peak value

Peak value is measured in the time domain or frequency domain. Peak value is the maximum acceleration in the signal amplitude.

$$P_v = \frac{1}{2}[\max(f_n) - \min(f_n)] \qquad (3)$$

Crest factor

Crest factor is the ratio of peak acceleration over RMS. This metric detects acceleration bursts even if signal RMS has not changed. However, crest factor can be counterintuitive. At advance stages of material wear, bearing damage propagates, RMS increases, and crest factor decreases. But crest factor is unreliable to locate defects in rolling elements.

$$\text{Crest Factor} = \frac{P_v}{RMS} \qquad (4)$$

Skewness

Machined or ground surfaces in bearings show a random distribution of asperities that are commonly described with the normal distribution function. For this reason, various statistical moments can describe the shape of distribution curves therefore, assessing bearing surface damage level. Equation defines the third moment or skewness as

$$\text{Skewness} = \frac{\frac{1}{N}\sum_{n=1}^{N}(f_n - \bar{f})^3}{RMS^3} \qquad (5)$$

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

Kurtosis

The forth moment, normalized with respect to the forth power of standard deviation is quite useful in fault diagnosis. This quantity is called kurtosis which is compromise measure between the intensive lower moments and other sensitive higher moments. It was reported that kurtosis is the good criterion to distinguish between damaged and healthy bearings. The healthy bearing with Gaussian distribution will have a kurtosis value about 3. When the bearing deteriorates this value goes up to indicate 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 time history of the signal and bearing condition can be monitored by observing kurtosis. A good surface finish has a theoretical kurtosis of 3, and when kurtosis increases the surface finish deteriorates, the skew and kurtosis are insensitive to loads and speeds. However, the level of noise between individual readings hampered the detection of bearing damage.

$$\mathrm{Kurtosis} = \frac{\frac{1}{\mathrm{N}}\sum_{\mathrm{n}=1}^{\mathrm{N}}(\mathrm{f_n} - \bar{\mathrm{f}})^4}{\mathrm{RMS}^4} \qquad (6)$$

Variance

$$variance = \sigma^2 = \frac{\sum_{n=1}^{N}(f_n - \mu)^2}{N} \qquad (7)$$

Standard Deviation

$$s = \left(\frac{1}{N-1}\sum_{n=1}^{N}(f_n - \bar{f})^2\right)^{\frac{1}{2}} \qquad (8)$$

Clearance Factor

$$Cl_f = \frac{P_v}{\left(\frac{1}{N}\sum_{n=1}^{N}|f_n|\right)^2} \qquad (9)$$

Impulse Factor

$$I_f = \frac{P_v}{\frac{1}{N}\sum_{n=1}^{N}|f_n|} \qquad (10)$$

Shape Factor

$$S_f = \frac{RMS}{\frac{1}{N}\sum_{n=1}^{N}|f_n|} \qquad (11)$$

2) Frequency Domain Technique

Another conventional approach is processing the vibration signals in the frequency domain. The interaction of defects in rolling element bearings produces pulses of very short duration whenever the defect strikes or is struck owing to the rotational motion of the system. These pulses excite the natural frequencies of bearing elements and housing structures. These frequencies depend on the bearing characteristics and are calculated according to the relations as shown below [3][9].

Shaft rotational frequency

$$(\mathrm{FOR}) = \frac{N}{60} \tag{12}$$

Inner race defect frequency

$$(\mathrm{FID}) = \left(\frac{n}{2}\right)\left(\frac{N}{60}\right)\left[1 + \left(\frac{bd}{pd}\right)\cos \phi\right] \tag{13}$$

Outer race defect frequency

$$\mathrm{FOD} = \left(\frac{n}{2}\right)\left(\frac{N}{60}\right)\left[1 - \left(\frac{bd}{pd}\right)\cos \phi\right] \tag{14}$$

Ball defect frequency

$$\mathrm{FBD} = \left(\frac{pd}{bd}\right)\left(\frac{N}{60}\right)\left[1 - \left(\frac{bd}{pd}\right)^2 (\cos \phi)^2\right] \tag{15}$$

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 simplify 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.

5. FUZZY MIN-MAX NEURAL NETWORK WITH COMPENSATORY NEURON

In classification phase, we are supposed to use the Fuzzy Min-Max Neural Network with Compensatory Neuron (FMCNs) which is designed by Nandelkar and Biswas [10]. The Fuzzy Min-Max Neural Network with

Compensatory Neuron (FMCNs) uses hyperbox fuzzy sets to represent the pattern classes. It is a supervised classification technique with new compensatory neuron architecture. FMCNs is capable to learn the data online in a single pass through with reduced classification and gradation errors. One of the good features of FMCNs is that its performance is less dependent on the initialization of expansion coefficient, i.e., maximum hyperbox size. So it provides high accuracy and less computational complexity in training and testing phase of the system. It is a supervised classification technique with new compensatory neuron architecture. The concept of compensatory neuron is inspired from the reflex system of human brain which takes over the control in hazardous conditions. Compensatory neurons (CNs) imitate this behavior by getting activated whenever a test sample falls in the overlapped regions amongst different classes. These neurons are capable to handle the hyperbox overlap and containment more efficiently. The architecture of FMCN is shown in Figure 3.

The input vector is applied to the input layer for the neural network and number of nodes in the input layer is equal to the dimension of applied input vector Ah. Where the Ah1, Ah2,…..Ahn are the input sample belongs to the pattern area In. And A1,A2,…..An are the input nodes. The second layer neuron called hyperbox nodes B1, B2,…..Bj. are created at the training time which represent the Min-Max points of the hyperbox and are stored into the (V,W) matrix. The middle layer neurons and output layer nodes are partitioned into three sections: classifying neuron (CLN) section, OCN section, and CCN section.

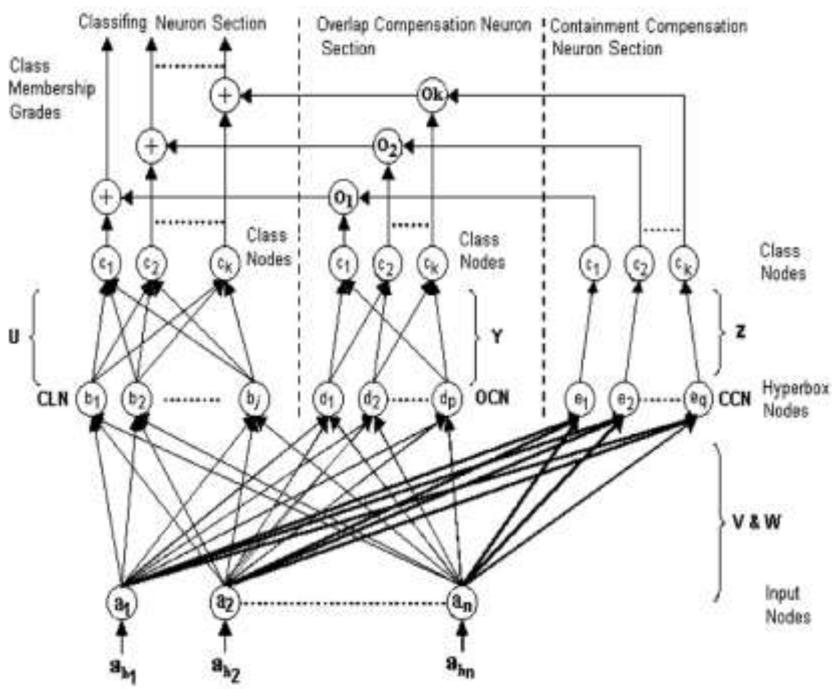

Figure 3: Architecture of FMCN [10]

A neuron in the middle layer represents an -dimensional hyperbox. The connections between an input node and a hyperbox node in the middle layer represent min-max points (V,W). Hyperbox nodes in OCN and CCN sections represent overlap and containment of hyperboxes in CLN section, respectively. All middle layer neurons are created during the training process. A hyperbox node in CLN section is created if training sample belongs to a class which has not been encountered so far or existing hyperboxes of that class cannot be expanded further to accommodate it. The connections between hyperbox and class nodes in CLN section are represented by matrix U. A connection between hyperbox nodes to a class node is adjusted by the following equation.

$$u_{ij} = \begin{cases} 1 \; if \; \{b_j \in c_i\} \\ 0 \; if \; \{b_j \in c_i\} \end{cases} \qquad (16)$$

Hyperbox nodes in the middle layer of OCN and CCN sections are created whenever the network faces problem of overlap or containment. The OCN section takes care of the overlap problem. The connections between hyperbox and class nodes in OCN section are represented by matrix Y. The connection weight from neuron dp which representing the overlap between the ith and jth class hyperbox.

o_i

$$y_{ip} \text{ and } y_{jp} = \begin{cases} 1, & \text{if } \{d_p \in c_i \cap c_j, i \neq j\} \\ 0, & \text{otherwise} \end{cases} \quad (17)$$

Similarly, a hyperbox node in CCN section is created whenever hyperbox of one class is contained within a hyperbox of other class. The connection weight of neuron in this subsection is given as,

$$z_{iq} = \begin{cases} 1, & \text{if } c_j \text{ is contained fully or partially by } c_i, i \neq j \\ 0, & \text{Otherwise} \end{cases} \quad (18)$$

The number of output layer nodes in CLN section is the same as the number of classes learned. The number of class nodes in CCN and OCN section depends on the nature of overlap the network faces during the training process. The final membership for th class is given by

$$\mu_i = c_i + o_i \quad (19)$$

Where c_i is the membership of ith class in main section given by

$$c_i = \max_{j=1}(b_j \mu_{ji}) \quad (20)$$

o_i is the compensation for the i^{th} class given by

$$o_i = \min \; (c_{oi}, c_{ci}) \quad (21)$$

Where c_{oi} is overlap compensation for the i^{th} class in OCN section given by

$$c_{oi} = \min_{j=1,k}(d_j y_{ji}) \quad (22)$$

c_{ci} is containment compensation for the i^{th} class in CCN section given by

$$c_{ci} = \min_{j=1,k}(e_j z_{ji}) \quad (23)$$

6. CONCLUSION

This paper propose a technique for fault detection in rolling element bearing using Time domain features and Frequency Domain features of vibration signals. This system involves two sequential processes: feature extraction and decision-making. In this process vibration signals are recorded. Fuzzy Min–Max Neural Network with Compensatory Neuron (FMCNs) is used for classification.

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