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Detection of Damage of Rotor-Bearing Systems using Experimental Data Analysis

R.G. Desavale[a], Asmita R. Mali[b,*]

[a]*Department of Mechanical and Automotive Engineering, ADCET, Ashta, Maharashtra, 416 301, India*
[b]*PG Student, Department of Mechanical Engineering, ADCET, Ashta, Maharashtra, 416 301, India*

Abstract

Rolling element bearings are critical components and widely used in many rotating machines such as automobiles, aerospace, weaving, machine tools that frequently fail. The vibration of the bearing-rotor influences the security, performance of the rotating machines and working life of the whole plant. In the present research work, a mathematical model of the vibration amplitude of the bearing is established through experimental data based analysis (EDBA). A new mathematical model technique for rotor-bearing systems is established. Furthermore, a model analysis on bearing system is carried out by using EDBA, the defect frequencies and vibration amplitude responses of the rotor-bearing system are obtained, and experimental result has been validated. The Neural Network (NN) is tested to verify the validation of the new EDBA. The method proposed in this paper for vibration characteristics calculation of a rotor-bearing is credible and save time and costs by timely detection of eminent bearing failure
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1. Introduction

Rolling element bearings are an integral part of many rotating machines. A bearing fault can result in unscheduled maintenance and in extreme cases, plant shutdown. In fact it was reported in [1] that rolling bearing faults accounts for almost 30% of faults in rotating machinery. These failures can be quite costly in industries. As such there is a growing demand for a robust failure diagnosis scheme for rolling element bearings. Condition based monitoring of bearing faults is typically implemented using experimental data based vibration analysis [2,3,4,5]. As an neural

* Corresponding author.
E-mail address: asmitamali01@gmail.com

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network (NN) method have been proposed in the literature for a variety of fault diagnosis applications [6,7]. The purpose of this paper is to provide a brief but effective introduction to the experimental data based analysis, so that more researchers could get familiar with its functioning and enormous capabilities in model development and empirical analysis. From the review of the relevant literature on vibration detection and analysis in rolling element bearings, it is noticed that no effort has been made in the application of experimental data based analysis using FLTθ method. The key challenge to fault diagnosis is the improvement of diagnostics accuracy based on a given amount of information. A huge work has been done on ball bearings and to identify the combination of defects in rolling bearing elements is limited. A little effort has been reported on rolling element bearings. This research paper provides an in-depth study of vibration responses in rotor bearings under single and multiple defect conditions in both inner and/or outer races using the Experimental Data Analysis (EDA). In this paper we extract feature from the time-domain vibration data and use to train a neural network (NN) and demonstrates how EDA, and NN is the most powerful, effective and efficient method for pinpointing the exact cause for bearing failure

Nomenclature

EDA experimental data analysis
NN neural network
EDM electric discharge machine

2. Model by Experimental Data Analysis

The functional dependence of vibration amplitude on the parameters can be estimated by performing a dimensional analysis on the Buckingham's π-theorem. For this problem, the involved parameters and their fundamental quantities are described in Table 1.

Table 1. Bearing studied parameters and related dimensions.

Parameter	Symbol	Unit	Dimension
Bore diameter	d	mm	L
Ball diameter	d_b	mm	L
Inner race diameter	d_i	mm	L
Outer race diameter	d_o	mm	L
Pitch diameter	d_m	mm	L
Number of balls	Z	---	---
Internal radial clearance	C_r	mm	L
Size of defect	d_s	mm	L
Speed of rotor	N_r	rpm	T^{-1}
Radial load	P	N	F
Damping factor	c	$\frac{Ns}{m}$	$FL^{-1}T^{1}$
Mass of rotor	m_r	kg	$FL^{-1}T^{2}$
Mass of the inner race	m_i	kg	$FL^{-1}T^{2}$
Mass of the outer race	m_o	kg	$FL^{-1}T^{2}$
Mass of the ball	m_b	kg	$FL^{-1}T^{2}$
Cage frequency	f_c	Hz	T^{-1}
Ball spinning frequency	f_b	Hz	T^{-1}
Inner race defect frequency	f_{id}	Hz	T^{-1}
Outer race defect frequency	f_{od}	Hz	T^{-1}
Ball defect frequency	f_{bd}	Hz	T^{-1}
Young's Modulus	E	$\frac{N}{m^2}$	FL^{-2}
Density of bearing	ρ	$\frac{\text{kg}}{\text{m}^3}$	$FL^{-4}T^{2}$
Vibration amplitude	V	$\frac{mm}{s}$	LT^{-1}

The vibration amplitude in RMS (mm/s) of the bearing can be given by the equation

$$V = f(d_b \; d_i \; d_o \; d_m \; Z \; C_r \; d_s \; c \; m_r \; m_i \; m_o \; m_b \; f_c \; f_b \; f_{id} \; f_{od} \; f_{bd} \; E \; \rho \; d \; N_r \; P) \tag{1}$$

It may be assumed that the vibration amplitude of bearing depends on the speed, load, defect size, damping factor (c) and density of material. In rotor bearing system, speed, load and defect size has significant role to play in changing the vibration amplitude and defect frequencies. The dimensions of all these quantities are reported in F, L, T, θ system are shown in Table 1. All the above variables considered for the problem are assembled using Buckingham's π-theorem in a number of dimensionless products (π_j) as

$$f(\pi_1, \pi_2, \ldots, \pi_m) = 0 \tag{2}$$

Dimension formula for relation (1) is

$$[L]^a[L]^b[L]^c[L]^d[L]^e[L]^f[L]^g[T^{-1}]^h[F]^i[FL^{-1}T^1]^j[FL^{-1}T^2]^k[FL^{-1}T^2]^l[FL^{-1}T^2]^m[FL^{-1}T^2]^n [T^{-1}]^o[T^{-1}]^p[T^{-1}]^q[T^{-1}]^r[T^{-1}]^s[FL^{-2}]^t[FL^{-4}T^2]^u[LT^{-1}]^v = [F^0L^0T^0\theta^0] \tag{3}$$

where $a, b, c, d, e, f, g, h, i, j, k, l, m, n, o, p, q, r, s, t, u$ and v are indices of the variables in Eq. (3). According to Buckingham's π-theorem, the relation between the dimensionless products can be given as

$$f(\pi_1, \pi_2, \pi_3, \ldots \ldots \ldots \pi_{23}) = 0 \quad \text{or} \quad \pi_1 = f(\pi_2, \pi_3, \pi_4, \ldots \ldots \ldots \pi_{23}) \tag{4}$$

keeping d, N_r, P common in each group and take one of the remaining variables one at a time in each group.

3. Modelling the Dynamic Response

The variables chosen are d,$\mathbf{N_r}$,P and V

$$\boldsymbol{\pi_1} = \mathbf{V d^a N_r{}^b P^c} \tag{5}$$

Where a, b and c are constants to be determined. In terms of fundamental dimension, Eq. (5) may be written as,

$$\boldsymbol{\pi_1} = \mathbf{L(L)^a(T^{-1})^b(F)^c} \tag{6}$$

In order to determine the values of a, b and c, the balancing of units may be done as

$$F^0L^0T^0 = F^cL^{1+a}T^{-b-1} \tag{7}$$

This gives rise to three equations as

$$c = 0, \qquad 1 + a = 0, \qquad -b - 1 = 0 \tag{8}$$

Solving these equations the values of unknowns may be obtained as

$$a = -1 \quad b = -1 \quad c = 0 \tag{9}$$

Therefore, the first dimensionless group may be expressed as

$$\pi_1 = \frac{V}{dN_r} \tag{10}$$

Similar procedure is adopted and the remaining nineteen dimensionless groups are formed. These may be listed as in Table 2.

Table 2. Dimensionless π-products.

Variable	Dimensionless π-products	Variable	Dimensionless π-products	Variable	Dimensionless π-products
d, N_r, P and d_b	$\pi_2: \frac{d_b}{d}$	d, N_r, P and c	$\pi_9: \frac{c\,d\,N_r}{P}$	d, N_r, P and f_{id}	$\pi_{16}: \frac{f_{id}}{N_r}$
d, N_r, P and d_i	$\pi_3: \frac{d_i}{d}$	d, N_r, P and m_r	$\pi_{10}: \frac{d\,m_r N_r}{P}$	d, N_r, P and f_{od}	$\pi_{17}: \frac{f_{od}}{N_r}$
d, N_r, P and d_o	$\pi_4: \frac{d_o}{d}$	d, N_r, P and m_i	$\pi_{11}: \frac{d\,m_i N_r}{P}$	d, N_r, P and f_{bd}	$\pi_{18}: \frac{f_{bd}}{N_r}$
d, N_r, P and d_m	$\pi_5: \frac{d_m}{d}$	d, N_r, P and m_o	$\pi_{12}: \frac{d\,m_o N_r}{P}$	d, N_r, P and E	$\pi_{19}: \frac{Ed^2}{P}$
d, N_r, P and Z	$\pi_6: \frac{1}{Z}$	d, N_r, P and m_b	$\pi_{13}: \frac{d\,m_b N_r}{P}$	d, N_r, P and ρ	$\pi_{20}: \frac{\rho d^4 {N_r}^2}{P}$
d, N_r, P and C_r	$\pi_7: \frac{C_r}{d}$	d, N_r, P and f_c	$\pi_{14}: \frac{f_c}{N_r}$		
d, N_r, P and d_s	$\pi_8: \frac{d_s}{d}$	d, N_r, P and f_b	$\pi_{15}: \frac{f_b}{N_r}$		

Out of twenty higher level groups, some of them $(\pi_2, \pi_3, \pi_4, \pi_{10}, \pi_{11}, \pi_{12}, \pi_{13}, \pi_{15})$ may be considered to form a constant β as

$$\beta = (\pi_2, \pi_3, \pi_4, \pi_{10}, \pi_{11}, \pi_{12}, \pi_{13}, \pi_{15}) \tag{11}$$

It is to be noticed that β contains several constant parameters of bearing. A change in the value of β can be due to appropriate change in any of the constant parameters involved in β. According to Buckingham's π-theorem, the relation between the dimensionless products can be given as

$$f(\pi_1, \pi_2, \pi_3) = 0 \quad \text{or} \quad \pi_1 = f(\pi_2, \pi_3) \tag{12}$$

Combining $\pi_1, \beta, \pi_a = \frac{\pi_6}{\pi_7}, \pi_b = \frac{\pi_8}{\pi_5}, \pi_c = \frac{\pi_{19}}{\pi_{20}}, \pi_d = \frac{\pi_{17}}{\pi_{16}}, \pi_e = \frac{\pi_{18}}{\pi_{14}}, \pi_f = \frac{\pi_{19}}{\pi_9}$ into the above equation gives the following,

$$\frac{V}{dN_r} = f\left(\beta \times (\pi_a)^a \times (\pi_b)^b \times (\pi_c)^c \times (\pi_d)^d \times (\pi_e)^e \times (\pi_f)^f\right) \tag{13}$$

Substituting for various dimensionless groups Eq. (13) may be rewritten as,

$$\frac{V}{dN_r} = f\left(\beta \times \left(\frac{d}{ZC_r}\right)^a \times \left(\frac{d_s}{d_m}\right)^b \times \left(\frac{\rho d^2 {N_r}^2}{E}\right)^c \times \left(\frac{f_{od}}{f_{id}}\right)^d \times \left(\frac{f_{bd}}{f_c}\right)^e \times \left(\frac{Ed}{cN_r}\right)^f\right) \tag{14}$$

The above functional relationship needs to be determined experimentally. Dependence of the amplitude of vibrations on dimensionless parameters in Eq. (14) the experiments are to be planned and conducted for different values of parameters. For each set of value of parameters, the amplitude of vibrations is to be measured. From this data the constants a, b, c, d, e, f involved in Eq. (14) is to be determined through the regression analysis. With the values of constants thus calculated, Eq. (14) may be written as,

$$\pi_1 = 0.9037 \times {\pi_a}^{-0.8920} \times {\pi_b}^{-1.7515} \times {\pi_c}^{0.7012} \times {\pi_d}^{2.1220} \times {\pi_e}^{-0.1135} \times {\pi_f}^{-0.5824} \tag{15}$$

For model expressed in Eq. (15), the value of R^2 is obtained as 0.92. This shows that nearly, 92 percent of the total variability is accounted for by the model. It is observed that the mathematical model is representing a good fit for the experimental values.

4. Experimental and Numerical Analysis

In order to evaluate the proposed model, experiments are carried out on faulty bearings (Bearing No. 1209K), as shown in Fig. 1(a). Defects are created on races of the test bearings by electric discharge machining (EDM).The depth of hole are termed as size of defect. The experiments performed with 0.5 mm, 1mm, 1.5 mm and 2 mm defects are only presented, as shown in Fig. 1(b). The experiments are performed at shaft rotational speed of 1500 rpm with 200 N radial loading on the test bearing having surface defects (single) in a ball. A Bruel and Kjaer type 4368 accelerometer has been used for measuring the vibration signals.

a b

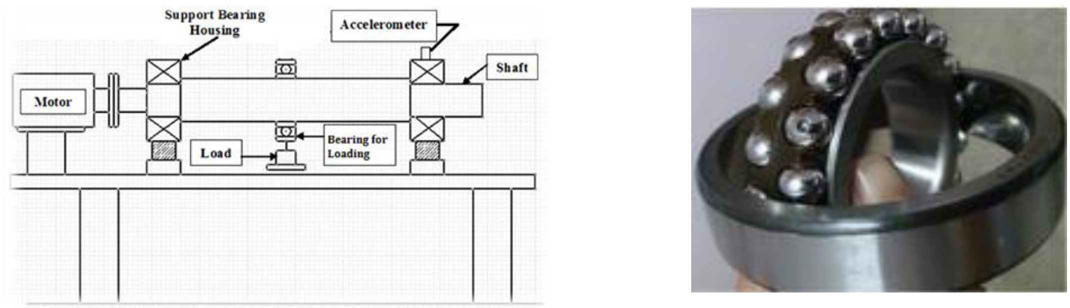

Fig.1.(a) Experimental setup. (b) Photograph of single defect on ball

5. Artificial Neural Network Modelling

A multi-layer Perceptron trained with the back propagation algorithm may be viewed as a practical way of performing a linear input–output mapping of a general nature as shown in Fig. 2. Back-propagation neural networks are usually referred to as feed forwarded, multilayered networks with a number of hidden layers trained with a gradient descent technique. This algorithm is based on the error correction learning rule. Basically, the error back-propagation process consists of two passes through the different layers of the network: a forward pass and a backward pass. In the forward pass, an activity pattern (input vector) is applied to the sensory nodes of the network, and its effect propagates through the network layer by layer. Finally, a set of outputs is produced as the actual response of the network. During the backward pass, all synaptic weights are adjusted in accordance with the error correction rule. Specifically, the actual response of the network is subtracted from the desired response to produce an error signal. The synaptic weights are adjusted so as to make the actual response of the network move closer to the desired network.

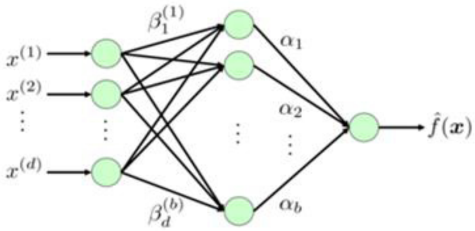

Fig.2. Structure of three layered neural network

6. Results and Discussion

The vibration amplitude is observed to increase with increase in size of the defect is shown in Fig. 3(a) and (b). The reason could be a defect reduces the stiffness which in turn reduces the natural frequency. Hence it may be justified to have π_b with d_s in its numerator, in Eq. (15) are shown in Fig.3 (a). Overall good matching of model, NN and experimental results develops good confidence in the proposed experimental data based analysis. Hence, the experimental, NN and EDBA results shows good agreement may be seen in Fig.3 (b).

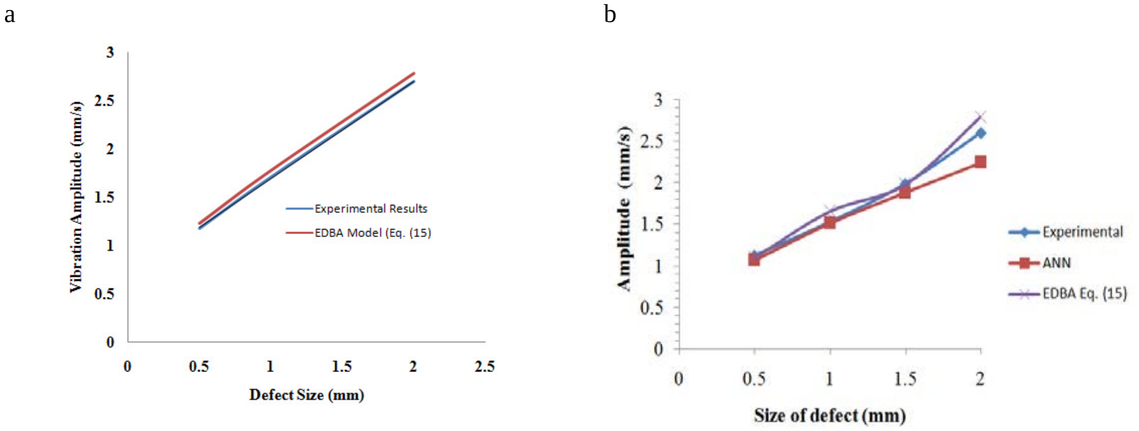

Fig.3. (a) Effect of defect size on vibration amplitude. (b) Comparison of models, NN and experimental results

The relation shows there exit a non-linear relation of all parameters on vibration amplitude. The Eq. (15) shows that apart from damping factor, surface defect, load and speed have a reasonable effect on the vibration amplitude. It is obvious that as surface defect increases the vibration amplitude produced will be bigger. The increase in surface defect, speed and load causes the vibration amplitude to increases and decreases respectively. Thus it can be noticed that the mathematical model obtained reasonably agree with the experimental results.

7. Conclusions

A mathematical model for deep groove ball bearing considering single defects on races and ball is developed and vibration of the housing are studied. Vibration amplitudes (velocities) are obtained by solving equation of motion in MATLAB. Theoretical and experimental results of the housing vibrations of faulty bearings are compared and interpreted. The amplitude of defective frequency is larger in case of 2 mm defect in comparison with 1 mm defect on races. Experimental and theoretical modal analysis showed a good fit which indicates the versatility of the mathematical equation obtained using dimensional analysis.

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