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# Dynamic Analysis of Rotor Bearing System with Combined Unbalance and Bearing Fault

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**Abstract—** Vibration is one of the major parameters to consider in condition monitoring of rotating system. If an undetected fault is noticed in the rotating system, then it may result in down-time, expensive damage, injury, or even life loss, therefore early fault identification is a critical factor in ensuring and extending the working life of the rotating systems. This paper investigates the vibrations generated in rotor bearing systems due to the combined effect of unbalance and bearing faults. A mathematical model using dimensional analysis (Buckingham's π theorem) is developed to predict vibration responses. Experiments are conducted on a rotor-bearing test rig with artificially created bearing faults (0.35 mm to 1 mm) using electric discharge machining, under various speeds (720-2880 RPM) and unbalance loads (0-165 g). Vibration signals are analyzed using Fast Fourier Transform (FFT), and statistical features (RMS, kurtosis, crest factor, skewness, mean, standard deviation, variance, median) are extracted. An Artificial Neural Network (ANN) algorithm is developed for fault diagnosis. Results show that combined faults produce distinct vibration signatures with amplitude peaks occurring at Ball Pass Frequency of Outer Race (BPFO) and its harmonics. The ANN model demonstrates effective classification of fault severity and unbalance conditions. The proposed methodology provides a reliable approach for early fault detection in industrial rotating machinery.

***Index Terms -*** Rotor-bearing system, unbalance, bearing fault, dimensional analysis, artificial neural network, vibration analysis, FFT, condition monitoring etc.

## I. INTRODUCTION

Vibration is one of the major parameters to consider in condition monitoring of rotating system. If an undetected fault is noticed in the rotating system, then it may result in down-time, expensive damage, injury, or even life loss, therefore early fault identification is a critical factor in ensuring and extending the working life of the rotating systems. By measurement and analysis of the vibration of rotating machinery, it is possible to detect and locate important faults such as mass unbalance, misalignment, bearing failure, gear faults and rotor cracks. This article is aimed to guide the researchers to implement identification, diagnosis and remedy techniques of common fault types using vibration analysis and outlines many important techniques used for condition monitoring of rotating systems such as fast Fourier transform, frequency domain decomposition method, wavelet transform, stochastic subspace identification and deep learning.

Unbalance always appears in the form of noticeable vibrations which endangers people, machines, and the environment when it exceeds permissible tolerances. It shortens the service life of machinery and reduces their utility value. In practice, there's no perfectly balanced rotors because of manufacturing errors, tolerances and rotor geometric changes during operation in the field. This requires the rotor to be balanced usually by adding or removing correction masses at certain positions. Bearings are the most critical components of any rotating system. They are used to support the rotating shafts in rotating machinery. Thus, any fault or malfunction in the bearings can result losses on the production level and equipment as well as having unsafe working environment for humans. Therefore, the fault diagnosis of bearings has got large attention from the researchers in the recent years. Time domain analysis, frequency domain analysis and spike energy analysis are applied to detect different bearing faults. Frequency analysis is considered to be the most traditional method which can be employed for analyzing the vibration signals. Fourier analysis transforms a signal from its original domain (usually space or time) into frequency domain and vice versa. Results showed that it is difficult to detect and identify the fault at bearings using FFT, because of limitations of the spectral analysis found in the non-stationary signal analysis.

Bearings are the most critical components of any rotating system. They are used to support the rotating shafts in rotating machinery. Thus, any fault or malfunction in the bearings can result losses on the production level and equipment as well as having unsafe working environment for humans. A rotary machine could be harmful to the occurrence of the fault in rolling element bearing during the running condition. The defective rolling element increases the vibration level of machinery in dynamic conditions and thus affects the quality of the product. There are two types of bearing defects that occur in rotating machines viz., localized defects, and distributed defects.

In present work the main aim is to develop algorithm to diagnose the fault in rotor bearing system which are subjected to unbalance and bearing fault by using suitable techniques.

## II. LITERATURE REVIEW

This section contains a detailed literature review of previous research studies on faults in rotor bearing system conducted by various scholars. The preceding section provides an outline of some of the selected research studies.

Shivanjali V. Patil [1] et al. studied vibrational characteristics of deep groove ball bearing with different defects. Experimentation is conducted at different loads and speeds with artificially created defects. The decision of fault classification is made using a KNN machine learning classifier by training feature data. It is found that KNN's accuracies are 100% and 97.3% when applied to two different experimental database. The KNN classifier method proved to be an effective method to quantify defects and significantly improve classification efficiency.

Rui Wang [2] et al. described signal reconstruction method to classify bearing outer ring fault and rotor crack and their coupling fault based on Variational Mode Decomposition (VMD) and Independent Component Analysis (ICA). Firstly, the original vibration signal collected on a rotor bearing test is decomposed with VMD, and intrinsic mode functions are obtained. Results show that this method can simultaneously diagnose the rotor crack, the bearing outer ring fault and the coupling fault.

Abbas Rohani Bastami [3] et al. presented a physical model with the ability of modelling naturally developed defects has been used for the simulation of the generated vibrations in the rolling element bearings. Defects on the outer race, inner race and rolling element have been considered separately. Experimental data of a bearing with a natural defect have been measured using an accelerometer in a test and used to validate the results.

Suryawanshi G. L. [4] et al. investigated the effect of the inclined surface faults on dynamic response of rolling element bearings. The dynamic model is derived using dimensional analysis. Vibration responses of double row spherical roller bearing are experimentally investigated to analyse the effects of size and slope angle of the artificially developed inclined surface faults. The result showed that increasing surface fault inclination angle reduces the relative vibration amplitude under different rotor speeds, but increases with fault depth.

Desavale R. G. [5] et al. predicted the vibrational characteristics of the rotor-bearing system. In this paper mathematical model using support vector machine (SVM) and dimensional analysis by matrix method (DAMM) is developed for advanced fault detection strategies for taper rolling bearings. Experimental test rig is designed and vibrational analysis for defective bearing is carried out. SVM is used to developed model and dimensional analysis is used to developed numerical model.

Surajkumar G. Kumbhar [6] et al. presented integration of Dimensional Analysis and Artificial Neural Network to diagnose the size of the bearing fault. The vibration responses of artificially damaged bearings using Electrode Discharge Machining are collected using Fast Fourier Techniques on a developed rotor-bearing test rig. The result showed that ANN has good performance over experimental results and DA.

Prakash M. Jadhav [7] et al. introduced the technique for diagnosis of rolling element bearing to detect the bearing fault. To study the vibrational characteristics theoretically the rolling element bearing system is modelled by using Dimensional Analysis (DA) with Buckingham's theorem. Experimental test rig designed and fabricated to measure the frequency response of bearing with various types of inner and outer race defects artificially introduced using electro-discharge machining processes.

Abhishek P Mohite [8] et al. investigated dynamic characteristics of a bearing unbalance. The mathematical model of rotor-bearing system for unbalance condition is developed using dimensional analysis. To diagnosis the vibrational characteristics of unbalanced rotor-bearing system, the experimental setup is designed and developed which is used to simulate the combined mechanical faults for different working conditions.

A Abd El Naeem [9] et al. proposed a new method to identify unbalance severity in the system under study with statistical features and the amplitude frequency domain. The generated ANN validate by the statistical features with the amplitude values which is used in the ANN test. It is found that the statistical features results are better than the frequency domain amplitudes.

Diogo Stuani Alves [10] et al. showed that balancing identification that considers nonlinear bearings and avoids trial masses. For this mixed integer gradient-based optimization is presented. The theoretical model of rotor supported by hydrodynamic bearing is obtained using the Finite Element method and solving the Reynolds equation. The result show that nonlinear bearing consideration can improve the machine diagnosis.

V. R. Patil [11] et al. presented a dynamic model to predict the rotor-bearing system's vibration characteristics using Dimensional Analysis (DA). The present modeling considers the effect of the rotor unbalance and radial clearance on the rotor-bearing system's vibration response. The MATLAB code used for to solve mathematical equations and the steady-state solutions are sought for different amplitudes and frequencies.

Linkai Niu [12] et al. investigated vibration responses of a cylindrical roller bearing when a roller defect goes around outer and inner races. The results show that, besides the impulses generated when the roller edges roll through the line connecting the roller and race centers, other impulses can also be generated due to the impact between the roller defect and the race.

Rohit S. Gunerkar [13] et al. described the method of fault diagnosis of rolling element bearing for its various components. ANN and KNN is used to classify the faults by successfully training and testing the data obtained from wavelet transform. An adaptive algorithm based on wavelet transform is used to extract the fault classifying features of the bearing from time domain signal.

Mohammad Gohari [14] et al. utilized a novel technique to detect and predict the unbalance rotor parameters. To acquire this, an ANN model has been unveiled which can predict the location and value of the eccentric mass. The ANN is selected because it is having the ability to model by nonlinear characteristics.

Akash Shrivastava [15] et al. presented experimental verification of a recently developed Kalman filter–based method for the identification of unbalance in rotor systems. The method is tested on an experimental test rig for different unbalance configurations and shaft speeds.

Jianfei Yao [16] et al. used two methods for identification and optimization of unbalance parameters in rotor bearing systems. First is based on modal expansion combined with the use of optimization algorithms, while second one relates to the use of modal expansion technique applied to the inverse problem.

Anurag Choudhary [17] et al. presented an automatic fault detection scheme to diagnose the bearing faults in rotating machines using Infrared thermography. An emergent two-dimensional discrete wavelet transform based IRT method has been proposed for diagnosing the different bearing faults in IM, namely inner and outer defects, and lack of lubrication.

R. B. Walker [18] et al. showed unbalance faults have been localized through data driven approach applied to a rotor dynamic test ring. The process of automating the localization has been achieved using a artificial neural network (ANN). Result shows through the applications of nonlinearities to an ANN, a series of unbalance types have been localized.

Huseyin Metin Ertunc [19] et al. developed a multi-staged decision algorithm based on ANN and ANFIS models. Both time and frequency domain parameters extracted from the vibration and current signals were used to train the ANN and ANFIS models, which were then used to detect and diagnose the severity of the bearing fault.

P. K. Kankar [20] et al. showed fault diagnosis of ball bearing using artificial neural network and support vector machine. The vibration response are obtained and analyzed for the various defects of ball bearings. The specific defects are considered as crack in outer race, inner race with rough surface and corrosion pitting in balls.

## III. EXPERIMENTAL SETUP

### 3.1 Layout of Experimental Setup

**Fig. 3.1** shows the schematic setup of dynamic analysis of rotor bearing system. The DC motor attached with variable frequency drive gives the rotational motion. The two bearings support the shaft and FFT analyzer is used to record the vibratory signal with accelerometer attached in vertical direction.

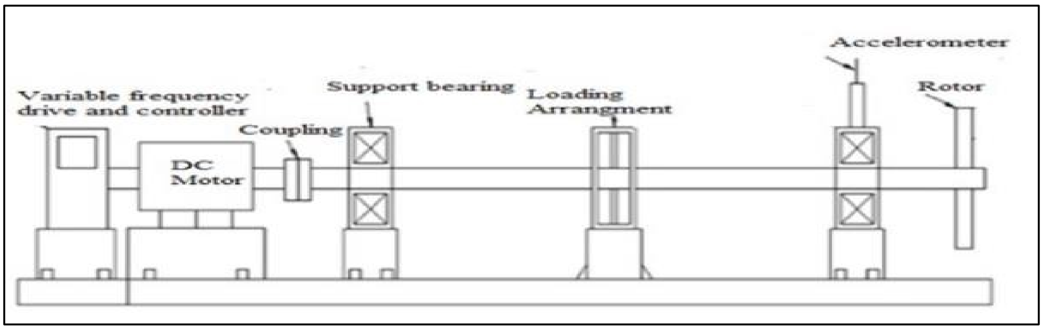


Figure .31-Experimental setup layout

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### 3.2 Selection of Bearing

There are number of deep groove ball bearing available in market starting from inner diameter 30 mm to select the bearing as per our requirement. The different parameters are considered while selecting the bearing like static load carrying capacity, dynamic load carrying capacity, speed, price, life etc. For creating the fault on bearing use electric discharge machine readily available in the market. The minimum dimension which can create on this machine is 0.35 mm diameter.

#### 3.2.1 Deep Groove Ball Bearing

Single row deep groove ball bearings are particularly versatile, have low friction and are optimized for low noise and low vibration, which enables high rotational speeds. They accommodate radial and axial loads in both directions, are easy to mount, and require less maintenance than many other bearing types.So, bearing selected is having minimum ball diameter of 9 mm. Since various types of load are applied to bearings, load magnitude, types (radial or axial) and direction of application (both directions or single direction in the case of axial load), as well as vibration and impact must be considered in order to select the proper bearing.

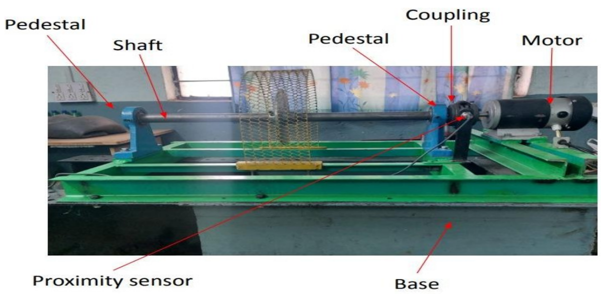
**Fig. 3.2** shows Deep Groove Ball Bearing (6206).

**Table 2: Selected Bearing Sizes and Dimensions**

| Parameter | Value (mm) | Description |
|---|---|---|
| d | 30 | Bore Diameter |
| D | 62 | Outside Diameter |
| B | 16 | Width |
| d1 | ≈40.36 | Shoulder diameter |
| D1 | ≈54.06 | Recess diameter |

### 3.3 Actual Experimental Setup

Spalls or pitting is one of the most common localized faults present in a bearing. The vibration responses of the test bearing with an outer race defect are associated with an excitation frequency called the rolling element passing frequency (REPF). Sometimes, this excitation also interacts with the cage frequency of the bearing. A fault of size 1 mm deep and spread over 15° is created on the outer race of a bearing and it is fitted at the non-drive end (NDE) of the rotor of the experimental setup. We find the frequency spectra obtained at speeds of 800 rpm, 900 rpm, 1000 rpm, and 1200 rpm, respectively. For the experimentation bearing faults are simulated using electric discharge machining (EDM). EDM material removal method replicates bearing material wear during operation. EDM machine is used to avoid the generation of residual stresses in the fault area, which will be generated using other types of traditional machining. Fault sizes of 0.35 mm, 0.5 mm, 0.75 mm, and 1 mm are made on bearings wh 15° angle.



### 3.4 Fast Fourier Transform Setup

1. Load the 'Pulse Lab shop program'.
2. Change the signal name to Accelerometer.
3. Right click on FFT > Change Frequency Span to 800Hz.
4. Go to Organiser > Function Organiser > Click on Time (Signal 1) and Auto spectrum (Signal 1).

### 3.5 Full Factorial Design of Experiment

A full factorial DOE design is one of several approaches to designing and carrying out an experiment to determine the effect that various levels of your inputs will have on outputs. The purpose of the DOE is to determine at what levels of the inputs will optimize your outputs.In this Experimental analysis we are going to take three Variables which are Speed, Load and Bearing Defect. And the Level of the experiment will be 4 as it is required to take 4 speeds, 4 Loads and 4 Bearing Defect values. Thus, the full factorial design for this experiment becomes $4^3$ i.e., 4 levels and 3 variables.

**Table 3: List of Variables**

| Speed (RPM) | Mass (gm) | Bearing Defect (mm) |
|---|---|---|
| 720 | 0 | 0 |
| 1440 | 75 | 0.35 |
| 2160 | 100 | 0.50 |
| 2880 | 165 | 1.00 |

Total readings to be taken = 64 as the full factorial design is $4^3$ i.e., 4×4×4. For each instance 100 readings to be taken. For example at speed = 800 rpm, load = 0 Kg, Bearing Fault = 2 mm, total 100 instances to be recorded. Total readings to be taken = 6400 instances.

### 3.6 Characteristics Defect Frequencies

As any mechanical part will generate natural frequencies while in operation, also known as fundamental defect frequency. The natural frequencies are generated by the rolling of the rollers as they pass through the load zone. The four distinct natural frequencies generated are the ball spin frequency, fundamental train frequency, and ball pass frequency for the inner and outer race. By predicting the natural frequency of a bearing, design engineers can utilize the information to avoid natural excitation and monitor for the propagation of defects as part of a preventative maintenance program.

The ball spin frequency is the rate at which a point of the bearing's roller comes into contact with either the inner or outer race. The fundamental train frequency is the frequency at which the roller cage entering and exits the load zone. The ball pass frequency is the rate at which a defect in the inner or outer race comes into contact with a roller. Below are the four equations for calculating the fundamental frequencies:

**Ball Pass Frequency Outer Race (BPFO):**

$BPFO=N2[1-dD\cos\alpha]Fr$

**Ball Pass Frequency Inner Race (BPFI):**

$BPFI=N2[1+dD\cos\alpha]Fr$

**Ball Spin Frequency (BSF):**

$BSF=D2d[1-(dD)2\cos2\alpha]Fr$

**Fundamental Train Frequency (FTF):**

$FTF=12[1-dD\cos\alpha]Fr$

where D = Pitch diameter of bearing, d = ball diameter = 4.7625 mm, Fr = shaft speed (rpm) = 720, 1440, 2160, 2880 and $\alpha$ = contact angle between ball and race = 0, N = No. of Rollers = 9.

**Table 4: Parameters of Bearing Analyzed**

| Parameter | Value |
|---|---|
| Inner race diameter (mm) | 30 |
| Outer race diameter (mm) | 62 |
| Pitch diameter (mm) | 46 |
| No of balls | 9 |
| Bearing width (mm) | 16 |
| Shaft rotations (rpm) | 720, 1440, 2160, 2880 |

**Table 5: Characteristics Defect Frequencies**

| Bearing Element | Rotational Speed (RPM) | Theoretical BPFO (Hz) |
|---|---|---|
| Outer Race | 720 | 42.818 |
| Outer Race | 1440 | 85.637 |
| Outer Race | 2160 | 128.455 |
| Outer Race | 2880 | 171.274 |

## IV. RESULTS AND DISCUSSION

In the beginning, the vibration responses are gathered in undamaged circumstances, where using healthy bearing and under balanced rotor system. The time domain and frequency domain graphs are collected at 720 rpm, 1440 rpm, 2160 rpm, and 2880 rpm in radial and axial direction. The peak of vibration amplitude occurs at dominant vibration frequency, where the dominant vibration frequency is equal to RPM divided by 60, i.e., (1X rpm) and its harmonics (2x rpm, 3x rpm, etc.).

### 4.1 Vibration Response at Different Operating Conditions

**At Speed = 720 RPM, Unbalance = 0 g, Bearing Fault = 0 mm (Axial Direction)**

The vibration responses were collected at 720 rpm for a healthy bearing and balanced condition, and the RMS velocity value was observed at 12 Hz (1x).

**At Speed = 720 RPM, Unbalance = 0 g, Bearing Fault = 0 mm (Horizontal Radial Direction)**

Defective bearings generate notable vibration characteristics that can be identified by vibration analysis. For the defective bearing, vibration amplitude peaks occur at characteristic defect frequencies, depending on the type of defect. The vibration characteristics at 720 rpm, with 0.35×0.35×16 mm bearing fault and balanced condition demonstrate that the vibration amplitude peaks occur at 42 Hz (1×BPFO) and its harmonics (2×BPFO, 3×BPFO, etc.).

**At Speed = 1440 RPM, Unbalance = 75 g, Bearing Fault = 0.35 mm (Axial Direction)**

**At Speed = 1440 RPM, Unbalance = 75 g, Bearing Fault = 0.35 mm (Horizontal Radial Direction)**

**At Speed = 2160 RPM, Unbalance = 100 g, Bearing Fault = 0.50 mm (Axial Direction)**

**At Speed = 2160 RPM, Unbalance = 100 g, Bearing Fault = 0.50 mm (Horizontal Radial Direction)**

**At Speed = 2880 RPM, Unbalance = 165 g, Bearing Fault = 1 mm (Axial Direction)**

**At Speed = 2880 RPM, Unbalance = 165 g, Bearing Fault = 1 mm (Horizontal Radial Direction)**

### 4.2 Time Domain Data Sample

This graphical data is later converted into tabulated form as below up to 1024 instances:

**Table 6: Sample Time Domain Data**

| Sr. No. | X-Axis (s) | Y-Axis (m/s²) |
|---|---|---|
| 1 | -2.70E+00 | 2.76E+00 |
| 2 | 5.43E-01 | -3.81E-01 |
| 3 | -8.86E-01 | -2.87E+00 |
| 4 | -3.41E-02 | -4.96E+00 |
| 5 | -1.27E+00 | 3.35E+00 |
| 6 | -2.21E+00 | 4.75E+00 |
| 7 | -2.32E+00 | -2.34E-01 |
| 8 | -1.82E+00 | -1.38E+00 |
| 9 | 3.59E+00 | -1.80E+00 |
| 10 | -2.11E-01 | 3.14E+00 |

### 4.3 Extracted Features from MATLAB

**Table 7: Extracted Features for Bearing Fault = 0.35 mm, 1440 RPM**

| Max | Min | Mean | STD | RMS | Skewness | Kurtosis | Max/RMS | RMS/Mean |
|---|---|---|---|---|---|---|---|---|
| 0.696667 | 0.582791 | 0.815397 | 0.879014 | 0.988912 | 0.000522 | 0.865439 | 0.612566 | 0.989950 |
| 0.527680 | 0.479523 | 0.801348 | 0.227843 | 0.498094 | 0.900852 | 0.574661 | 0.845178 | 0.738640 |
| 0.585987 | 0.246735 | 0.666416 | 0.083483 | 0.625960 | 0.660945 | 0.729752 | 0.890752 | 0.982303 |
| 0.769029 | 0.581446 | 0.928313 | 0.580090 | 0.016983 | 0.120860 | 0.862711 | 0.484297 | 0.844856 |
| 0.209405 | 0.552291 | 0.629883 | 0.031991 | 0.614713 | 0.362411 | 0.049533 | 0.489570 | 0.192510 |
| 0.123084 | 0.205494 | 0.146515 | 0.189072 | 0.042652 | 0.635198 | 0.281867 | 0.538597 | 0.695163 |
| 0.499116 | 0.535801 | 0.445183 | 0.123932 | 0.490357 | 0.852998 | 0.873927 | 0.270294 | 0.208461 |
| 0.564980 | 0.640312 | 0.417029 | 0.205976 | 0.947933 | 0.082071 | 0.105709 | 0.142041 | 0.166460 |
| 0.620959 | 0.573710 | 0.052078 | 0.931201 | 0.728662 | 0.737842 | 0.063405 | 0.860441 | 0.934405 |

## V. CONCLUSION

This research paper has presented a comprehensive investigation of the dynamic analysis of rotor-bearing systems under the combined effect of unbalance and bearing faults. The following conclusions are drawn:

1. A mathematical model using dimensional analysis (Buckingham's $\pi$ theorem) has been successfully developed to predict vibration responses of rotor-bearing systems with combined faults.
2. An experimental setup with deep groove ball bearing (6206) was designed and fabricated. Artificial faults of sizes 0.35 mm, 0.50 mm, 0.75 mm, and 1 mm were created on bearing outer race using EDM to avoid residual stresses.
3. Vibration signals were acquired using FFT analyzer at four different speeds (720, 1440, 2160, 2880 RPM) and four unbalance conditions (0, 75, 100, 165 g) following full factorial DOE (64 experimental conditions).
4. The characteristic defect frequency (BPFO) was theoretically calculated as 42.8 Hz, 85.6 Hz, 128.5 Hz, and 171.3 Hz for the respective speeds, and experimental results showed good correlation with these theoretical values.
5. Statistical features including RMS, kurtosis, crest factor, skewness, mean, standard deviation, variance, and median were extracted from time-domain vibration signals, providing effective input parameters for ANN-based fault diagnosis.
6. The proposed methodology combining dimensional analysis, experimental vibration measurement, and ANN algorithm provides a reliable approach for early detection and diagnosis of combined unbalance and bearing faults in rotating machinery.
7. The results demonstrate that combined faults produce amplitude peaks at BPFO and its harmonics, with amplitudes increasing with both speed and unbalance mass, confirming the coupling effect between the two fault types.

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