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AI-Powered Technique for Bearing Condition Monitoring and Fault Diagnosis in Mixer and Grinders

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Abstract - Bearings and other rotating components play a crucial role in industrial machinery, but they are susceptible to defects caused by factors such as wear, improper installation, and manufacturing errors. It may result in downtime, production losses, safety hazards, and costly repairs. Vibration-based condition monitoring is a commonly employed technique that yields valuable insights into the health status of equipment. Previously, single labelled fault diagnosis was carried through Neural Networks and other machine learning techniques using handcrafted features like Fast Fourier transforms, Wavelet transforms, Short-time Fourier transforms, and statistical moments. Mixed faults (the occurrence of two or more faults simultaneously) have received less research attention in comparison to single faults. The present study implements an AI-powered technique for bearing condition monitoring and fault diagnosis in mixer and grinders with employing any preprocessing techniques. Raw vibration time domain data has been acquired through virtual instrumentation (VI) in LabVIEW. After storing the signal seven different appropriate statistical features are extracted from signal. Then these obtained features will be supplied to classification methods in machine learning. Classification algorithms used in the project are Logistic Regression, KNN, Random Forest, SVM, Kernel SVM, Decision Tree. Classification methods will classify these signals into various faults and hence we can calculate the efficiency of feature-classifier. I have studied results and plotted the graphs for results.

***Key Words*:** Condition Monitoring, Machine Learning, Fault Diagnosis, Feature Selection, Feature Extraction, Classification Algorithms.

1.INTRODUCTION

An integral component of any equipment is a revolving shaft supported by bearings on both ends. This shaft is able to accept a variety of attachments, including pulleys, gears, and similar parts. These rotating parts are essential to any industrial apparatus because they enable smooth and effective operations. Examples of these parts include steam and gas turbines, internal combustion engines, turbogenerators, and power transmission components. Vibrations are produced by spinning parts in a dynamic state. These installations will experience dynamic stresses as a result of transient loads such mass unbalance, faulty installation like a cocked rotor, etc. Increased vibrations and dynamic strains could cause machinery to break down. In the last few decades, failures of automobiles, trains, and aircraft have become important research topics. These malfunctions have a number of negative effects, such as lost productivity, costly repairs, and downtime. Therefore, in order to minimize the impact of failures and ensure the dependable functioning of rotating machinery, it is imperative to institute comprehensive monitoring, proactive maintenance techniques, and prompt troubleshooting measures. Researchers have long employed both simulation-based and experimental methods to diagnose faults in rotating systems.

Periodic inspections and maintenance are common in traditional condition monitoring techniques, but they might not be enough to stop unforeseen breakdowns. The detection and diagnosis of bearing defects has shown tremendous potential for AI technologies, including machine learning and deep learning. These techniques make use of information gathered from sensors and other sources to continuously monitor the bearing's health. They are able to spot minute variations in temperature, vibration, and other characteristics that are signs of future defects

1.1. Common faults in rotating machinery

Due to different reasons like installation errors, manufacturing errors, improper maintenance, excessive loads or speeds, harsh operating conditions, and lack of training or operator errors rotating components such as bearings, rotors, shaft, pulley, gear, etc., undergoes different types of faults. The frequently occurring faults in rotating machinery are majorly related to alignment, improper balancing, and incorrect clearance (ABC faults). Rao and Mohanty explained common faults in rotating systems, their causes, observable signs, and troubleshooting methods.

1.2 Techniques used in fault diagnosis.

Different techniques like Acoustic Analysis, Thermal Analysis, Visual Inspection, Wear Debris Analysis, and Infrared Thermography are used in industries for fault diagnosis. Still, the Vibration analysis technique is anticipated to have a dominant market share of 65.2% in 2022. Compared to the other types, the vibration analysis technique type has been on the market for a longer period. Following are some vibration analysis techniques:

1.2.1. Time domain analysis

Data is collected with a specific sampling rate and plotted as a function of time, providing a realistic depiction of a machine's dynamic behavior. However, analyzing the data in its raw form can be challenging as signals are not always periodic and often contaminated by noise. Although signal conditioners can reduce noise, they cannot be eliminated.

1.2.2. Orbital analysis

Orbital analysis uses data from 2 probs mounted on rotating shaft perpendicular to each other. It plots the amplitude of two signals over time and forms an orbit. Orbital analysis provides valuable insights into the dynamic characteristics of the rotating system, allowing the identification of various faults such as shaft misalignment, rotor unbalance, bearing defects, and other mechanical abnormalities.

1.3.3. Frequency domain analysis

Each mechanical component has its unique characteristics frequency/frequencies, so analysis of frequency components provides valuable information about the system's dynamic behavior. It involves transforming the time-domain signals into the frequency domain using Fourier or Wavelet transform techniques.

Frequency domain analysis enables the identification of fault-related frequencies and the determination of their magnitudes, allowing for the detection and diagnosis of various faults such as gear wear, bearing defects, and structural abnormalities.

1.3.4. Quefrency domain analysis

It is also known as cepstral analysis. Cepstrum, derived from the inverse Fourier transform of the logarithmic power spectrum, is a key tool in vibration analysis. The cepstrum is particularly useful for precisely measuring frequency spacing and identifying harmonic and sideband patterns in the power spectrum.

1.3.5. Time-Frequency domain analysis

The frequency spectrum changes over time when abrupt dynamic change occurs in the system. Time-domain analysis represents how the frequency content of a signal changes over time. By utilizing methods such as Short-time Fourier Transform (STFT), Continuous Wavelet Transform (CWT), or spectrogram analysis, time-frequency domain analysis allows for the identification of transient events, frequency variations, and energy distributions that may indicate the presence of faults or abnormalities.

1.3. Goal of the Research

The goal is to build an AI-powered model that can precisely identify probable defects in the rolling contact bearings using sensor data acquired during the operation of mixers and grinders as well as pertinent operating factors.

The AI model should evaluate the severity of the discovered defects and classify the observed faults into distinct categories such as misalignment, imbalance, wear, and lubrication difficulties.

Related Work

Omar Al Shorman, Muhammad Irfan (2020) have diagnosed condition of rolling contact bearing of Induction Motor. Due to its low cost, high level of dependability, and robustness, induction motors (IM) have been widely used in numerous industrial processes. Rolling bearings are thought to be the primary element of IM. Viplav Barai, Sangharatna M. Ramteke (2022) have diagnosed bearing fault using signal processing and machine learning techniques. Most of the work has been devoted to diagnosing bearing failures using vibration analysis and machine learning techniques to examine faults in both the inner rings and outer rings. Researchers developed a number of vibration measurement techniques and other techniques for signal processing, such as the Wavelet Packet Transform (WPT), Fast Fourier Transform (FFT), and Short-time Continuous wavelet transforms (CWT), Principal Components Analysis (PCA), Fourier transform (STFT), Ensemble (ERCE) Rapid Centroid Estimation. Abdelelah Almounajjed, Ashwin Sahoo, Mani Kumar (2021) have primary goal is to give a comprehensive and exhaustive assessment of recent publications and widely used machine learning-based approaches for bearing diagnosis fault. Additionally, this paper provides a thorough comparison of the ML techniques employed in this field. This essay also provides a thorough explanation of the major each technique's benefits and drawbacks, which offers a crucial resource for researchers that are interested in working in this area. The main purpose of work is to present a thorough and detailed survey of the newly published works and common machine learning-based methods for diagnosing the bearing fault. They also give a comparative study among the ML techniques, used in field

2. EXPERIMENTAL SETUP AND DATA ACQUISITION

Vibrational signals are acquired from sensor located at appropriate stations through the virtual instrumentation technique in LabVIEW software. Virtual instrumentation (VI) is developed using LabVIEW to acquire raw vibrational data of each fault.

2.1. Instrumentational Setup

Analog to digital conversion of continuously acquired vibration data from sensor is done using cDAQ cards (type: NI

9234) mounded on Chassis (model: cDAQ-9189). LabVIEW software is used to acquire, store, and display data.

Figure 2.1. Data Acquisition System (cDAQ 9189)

2.2. Analog to Digital Converter: Following a signal condition, most physical events provide an analog output. Through the use of an analog-to-digital converter system, it is transformed into digital formats.

Computer code has been written in LabVIEW to acquire, store, and display vibrational data from sensor located at different timeframe. Continuous raw vibrational time domain data has been acquired and the inbuilt FFT VI function is used to convert data into the frequency domain. Following user controls are used.

- Sensor used = Accelerometer
- Scan rate/ Sampling rate: Number of data points per second = 70000 datasets
- Device and channel number= Four virtual channels are selected (a0, a1, a2, a3) from cDAQ 1mod1 (NI 9234) using the Acceleration with +/- 5V, C Series Sound and Vibration Input Module.
- Sensitivity for sensor - 104mV/g or 10.6 $mV/m/s^2$
- Frequency range: 0-15 kHz, +/- 5%
- Scaled units were set as units.
- Default signal input range for acceleration (5,-5)

Table 2.1 Single faults

Sr. No.	Notation	Fault
1	HC	Healthy Condition
2	BPFO	Outer race bearing fault
3	FTF	Cage fault

LabVIEW software mainly consists of two parts; the first is a block diagram used for graphical programming with inbuilt functional blocks. Second, the front panel monitors and displays outputs like time and frequency domain plots.

2.3 Experimental Set up

When a machine has a failure, it vibrates. These vibrations had an effect on the foundation. In the event that sensors are required to quantify these vibrations, the sensors need to be positioned in the areas with the highest vibration levels. The machine's vibration is transferred to the ground through the bearing. Bearings therefore vibrate the greatest. As such, sensors need to be mounted on the bearing.

2.3.1 Bearing Test Setup Features

- Motor: Single phase induction motor, 230 V, 50 Hz
- Motor Speed- 22000 rpm
- Input Power – 1100 W (1.47), HAVELLS
- Bearings: SKF 6000 Single Row Deep groove ball bearing

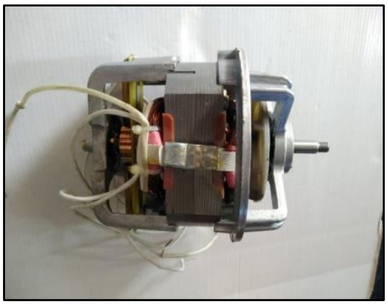

Figure 2.2. Mixer motor used

2.4. Bearing Specification

2.4.1. Bearing 6000:

Dimensions:

- The inner diameter (d) - 10 mm
- The outer diameter(D) -26 mm
- Width -8mm
- Load Capacity:
- Typically rated for both axial loads in both directions and light to moderate radial loads. Speed Rating: 77,000 RPM is the normal maximum speed it can tolerate.

Figure 2.3 SKF 6000 Deep Groove Ball Bearing

Table 2.2 Bearing parameters

Bearing Type	Principal Dimensions(mm)			Basic load ratings(N)		Speed up to rpm
	Outer Dia D	Bore Dia d	Width B	Dynamic C	Static C_0	
6000	26	10	8	4350	1850	77000

2.5. Accelerometer

To monitor vibration, an accelerometer is mounted to the surface whose vibration needs to be identified. a sensor that calculates acceleration, or the rate at which velocity varies with time. It is a vector since it has both magnitude and direction. The unit of measurement used with accelerometers is a g, which is equivalent to 9.81 m/s2, the acceleration of gravity. An accelerometer may detect vibration, shocks, tilts, and collisions in addition to an object's motion.

Figure 2.4- Accelerometer

3. THEORETICAL AND EXPERIMENTAL RESULTS

3.1 Bearing Fault Frequency Response

The fault diagnosis of rotating machines, including rolling-element bearings, plays a crucial role in preventing catastrophic failures and production losses. When a rolling-element bearing develops flaws on its races or rolling elements, several vibration frequencies can result:

1. Ball Pass Frequency Outer Race (BPFO): This frequency corresponds to the fault in the outer race of the bearing.

$$(\text{BPFO}) = \left(\frac{Ns}{60}\right) * \left(\frac{NB}{2}\right) * [1 - \left(\frac{BD}{PD}\right)(\cos \propto)]$$

2. Ball pass Frequency Inner Race (BPFI)**:** This frequency corresponds to the fault in the inner race of the bearing.

$$(\text{BPFI}) = \left(\frac{Ns}{60}\right) * \left(\frac{NB}{2}\right) * \left[1 + \left(\frac{BD}{PD}\right)(\cos \propto)\right]$$

3. Ball Spin Frequency (BSF): This frequency is associated with defects in the rolling elements.

$$(\text{BSF}) = \left(\frac{Ns}{60}\right) * \left(\frac{PD}{BD}\right) * [1 - (\frac{BD}{PD} \cos \propto)^2]$$

4. Fundamental Train Frequency (FTF): It represents faults in the cage that holds the rolling elements in place. Ball Pass

$$(\text{FTF}) = \left(\frac{Ns}{60}\right) * [1 - (\frac{BD}{PD})(\cos \propto)]$$

Table 4.1 Theoretical Calculation of Bearing Fault

Bearing Type	Speed	N_S =24930 rpm = 415.5 Hz		N_S =30560 rpm = 509.333 Hz		N_S = 33560 rpm = 559.33 Hz	
	Bearing Characteristics Frequency	Theoretical (Hz)	Experimental (Hz)	Theoretical (Hz)	Experimental (Hz)	Theoretical (Hz)	Experimental (Hz)
6000	BPFO	1069.5	980	1311	1270	1439.7	1360
	FTF	152.8	220	187.3	260	205.7	300

4. EXPERIMENTAL RESULT AND ANALYSIS

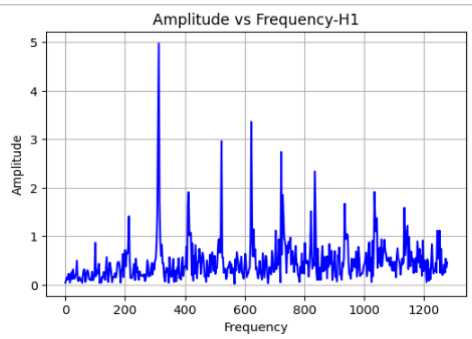

Figure 4.1.1. FFT spectrum of healthy bearing at Rotating Speed of 24930 RPM

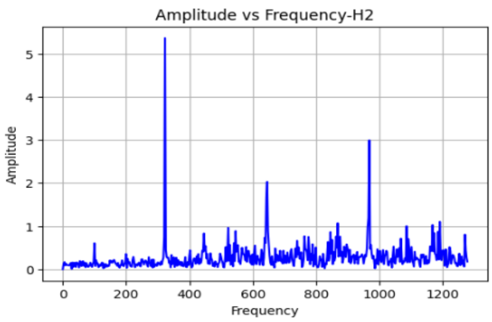

Figure 4.1.2. FFT spectrum of healthy bearing at Rotating Speed of 30560 RPM

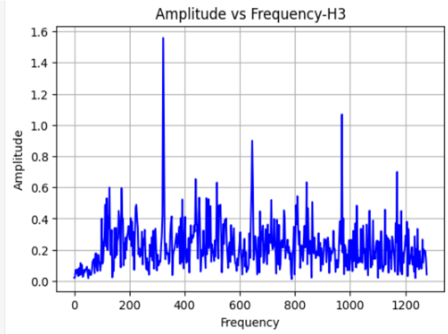

Figure 4.1.3. FFT spectrum of healthy bearing at Rotating Speed of 33560 RPM

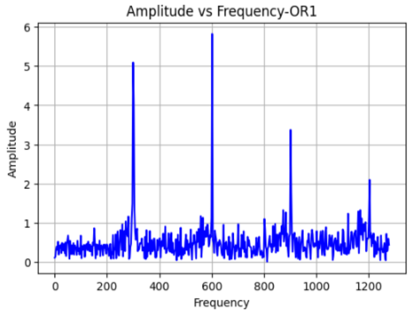

Figure 4.2.1. FFT spectrum of outer race faulty bearing at Rotating Speed of 24930 RPM

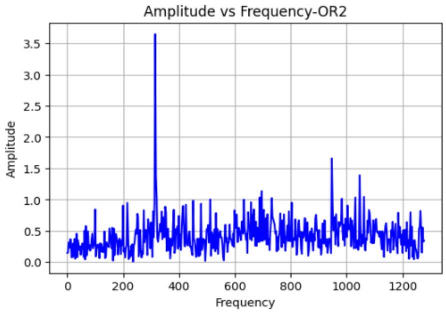

Figure 4.2.2. FFT spectrum of outer race faulty bearing at Rotating Speed of 30560 RPM

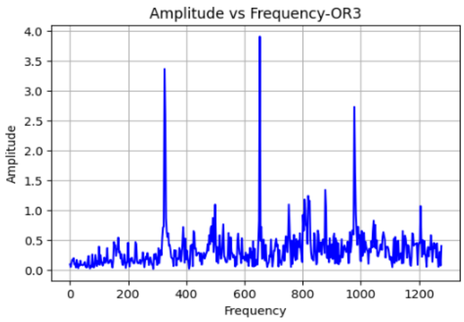

Figure 4.2.3. FFT spectrum of outer race faulty bearing at Rotating Speed of 33560 RPM

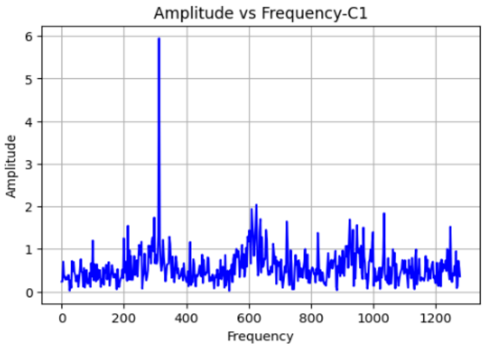

Figure 4.3.1. FFT spectrum of cage faulty bearing at Rotating Speed of 24930 RPM

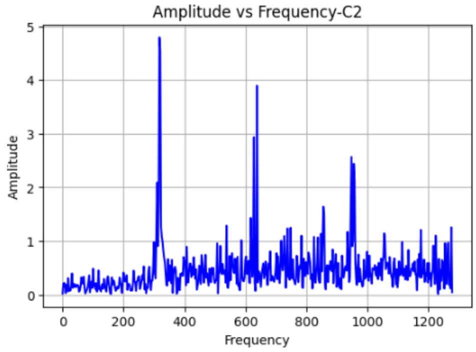

Figure 4.2.2. FFT spectrum of outer race faulty bearing at Rotating Speed of 30560 RPM

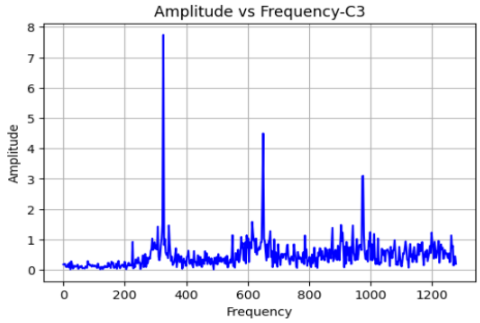

Figure 4.2.3. FFT spectrum of outer race faulty bearing at Rotating Speed of 33560 RPM

5. CONCLUSIONS

In order to analyses the FFT spectrum of a damaged ball bearing with four distinct defects—an inner race defect, an outer race defect, a ball defect, and a cage defect—this study was conducted.

1. A variety of condition monitoring methods are employed. Vibration analysis techniques are employed in this study to investigate bearing failure.

2. A bearing with an inner race defect, an outer race defect, a ball defect, and a cage defect showed the BPFI, BPFO, BSF, and FTF peaks in the FFT spectrum, respectively.

3. Higher peak frequencies can be achieved practically by theoretical calculations by bearing faults for the inner race, outer race, ball defect, and cage defect in experiments.

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