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Bearing Fault Detection using Vibration Analysis

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Abstract: In the current scenario, condition monitoring is an essential technique for the maintenance of machinery. Various methods such as vibration analysis, temperature analysis, and wear and debris analysis have been introduced, with vibration analysis proving to be the most effective for detecting machine faults. This study focuses on bearing fault detection using vibration analysis. Bearing faults generate impact forces that alter vibration patterns. We examined the vibration patterns of a 0.25HP PMDC motor under different load conditions and at varying RPMs, comparing good and faulty bearings to detect inner and outer race bearing faults. Inner race defect detection is challenging under poor signal-to-noise ratio (SNR) conditions due to the vibration signal being masked by other vibrations. To enhance SNR, Principal Component Analysis (PCA) was utilized, and Artificial Neural Networks (ANN) algorithms were employed. Rotating machinery, widely used in industries such as petroleum, automotive, HVAC, and food processing, relies on bearings for rotational or linear movement, reducing friction and stress. Rolling Element Bearings (REBs) offer a favorable balance of friction, lifetime, stiffness, speed, and cost. Thus, real-time monitoring and diagnosis of bearings are critical to prevent failures, enhance safety, avoid unforeseen production downtime, and reduce costs. This study proposes an approach based on Wavelet Transform and ANN to analyze vibration signals from rolling element bearings and to identify and classify component defects.
Keywords: Condition Monitoring, Vibration Analysis, Bearing Fault Detection, Principal Component Analysis (PCA), Artificial Neural Networks (ANN), Signal-to-Noise Ratio (SNR), Rotating Machinery, Rolling Element Bearings (REBs), Wavelet Transform.

I. INTRODUCTION

Detecting bearing faults is crucial in machinery and equipment maintenance. Early detection is essential to prevent unexpected failures, reduce downtime, and lower maintenance costs. Bearings are integral to various mechanical systems, and their malfunction can lead to significant issues, including production halts and safety risks. Traditional methods like visual inspections and manual monitoring are often limited in their accuracy and ability to detect faults early. To address these limitations, advanced techniques such as vibration analysis, oil analysis, and sensor-based monitoring have been developed. Vibration analysis, in particular, stands out as a reliable method for identifying bearing faults by examining the vibration signals from rotating machinery. Early fault detection allows for proactive maintenance planning, which minimizes production disruptions and reduces the likelihood of severe failures. Implementing predictive maintenance strategies, facilitated by effective bearing fault detection, can help organizations optimize maintenance schedules, extend equipment lifespan, and enhance overall operational efficiency.

Furthermore, advancements in technology have introduced more sophisticated methods for bearing fault detection, such as machine learning algorithms and artificial intelligence. These technologies can analyze large datasets from various sensors to identify patterns and predict potential failures with greater accuracy. Additionally, integrating Internet of Things (IoT) devices in machinery allows for real-time monitoring and data collection, providing continuous insights into the health of bearings. This continuous monitoring enables more precise and timely maintenance actions, further reducing the risk of unexpected breakdowns. As industries move towards smart manufacturing and Industry 4.0, the importance of advanced bearing fault detection techniques continues to grow, contributing to more resilient and efficient production processes. Investing in these advanced diagnostic tools not only enhances the reliability of machinery but also supports sustainable maintenance practices by preventing excessive wear and tear, ultimately leading to cost savings and improved safety standards in industrial operations.

II. LITERATURE REVIEW

Smita A. Chopade et al [1] in this study, vibration analysis is used to detect bearing faults. When a bearing fails, some impact force is generated. The change in vibration pattern is caused by this force. The paper investigated the vibration pattern of a 0.25HP PMDC motor under various load conditions. The vibration pattern of a good and faulty bearing is analyzed, and inner and outer race bearing faults are detected.

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Aditi B. Patil et al [2] the goal of this research paper was to propose a method for identifying and classifying various bearing defects using Wavelet transform and ANN. Our experimental setup included a rolling element bearing under load mounted on a constant-speed PMDC motor and a piezoelectric accelerometer to measure vibration signals. These signals were then plotted in time domain, and an FFT was built.

Dhiraj Neupane et al [3] this paper proposed the number of machines that can be diagnosed and fault-identified using different deep learning algorithms is growing daily. The Case Western Reserve University (CWRU) bearing dataset is one of many publicly available datasets that is frequently used to identify and diagnose bearing problems in machinery and is recognized as a standard reference for model validation. This paper provides an overview of recent studies that use deep learning algorithms to diagnose and detect machinery faults using the CWRU bearing dataset. In this paper, they have reviewed the existing literature and presented the working algorithm, result, and other pertinent information. The CWRU dataset can be used by future researchers to begin their work on machinery fault diagnosis and detection with the assistance of this paper, according to the authors.

Syahril Ramadhan Saufi et al [4] this study proposed deep learning models have been widely used in machinery fault diagnosis and diagnosis (FDD) systems in recent years. There is a lot of promise in the automated feature learning process of the deep architecture to address issues with conventional fault detection and diagnosis (TFDD) systems. TFDD uses manual feature selection, which takes a lot of time and requires prior knowledge of the data. Deep learning has great performance, but there are drawbacks and expenses. An overview of deep learning problems pertaining to machinery fault detection and diagnostic systems is provided in this paper. A brief discussion is had about the possibility of further work on deep learning implementation in FDD systems.

Amit Shrivastava et al [5] this paper proposed deep learning models have found widespread application in machinery fault diagnosis and diagnosis (FDD) systems. The automated feature learning process of deep architecture holds great potential in addressing problems associated with traditional fault detection and diagnosis (TFDD) systems. The manual feature selection process used by TFDD is laborious and necessitates prior knowledge of the data. Although deep learning offers excellent performance, it comes with costs and drawbacks. This paper presents an overview of deep learning problems related to machinery fault detection and diagnostic systems. The possibility of doing more research on the application of deep learning in FDD systems is briefly discussed.

Saja Mohammed Jawad et al [6] this paper proposed the reducing expenses, improving dependability, and ensuring system safety all depend on the condition of rotating machinery being monitored. The goal of this paper is to provide a thorough overview of the prior research on the diagnosis and detection of bearing faults using what are known as model-free or data-driven approaches. Statistical and artificial intelligence-based data-driven approaches are the two main approaches that are discussed. There is also discussion of the condition monitoring techniques used to diagnose various types of machinery faults. These include vibration, analysis of acoustic emission signals, and motor current signature, as they are commonly used in data-driven approaches for condition monitoring. Each strategy and technique's benefits, drawbacks, and applications are discussed.

MousaM.O et al [7] proposed one of the most difficult tasks in bearing health condition monitoring is the detection of antifriction bearing faults, particularly when the fault is still in its early stages. If bearing flaws are not identified in a timely manner, the machinery may malfunction. The following are the main causes of rolling element bearing defects: incorrect rolling element design, incorrect rolling element manufacturing or mounting, misaligned rolling element races, uneven rolling element diameter, inappropriate lubrication, overloading, fatigue, and uneven wear. The various detection methods for rolling bearing flaws are covered in detail in this paper. Four distinct techniques for the identification and diagnosis of bearing defects have been identified through extensive research; these can be broadly categorized as vibration measurements, acoustic measurements, temperature measurements, and wear debris analysis. It has been noted that because vibration analysis is so simple to use, it is the most widely accepted technique.

III. THEORETICAL BACKGROUND

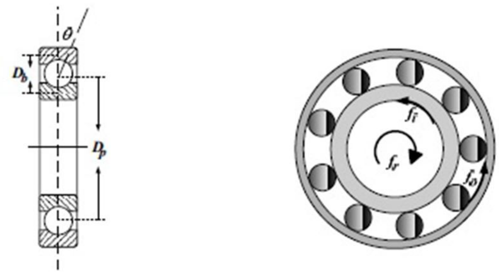
A. Bearing Characteristic Fault Frequencies.

A rolling bearing comprises two rings – an inner ring and an outer ring, with rolling balls situated between them, as illustrated in Figure 1: Ball geometry and potential defects. The outer race remains stationary, while the inner race is in motion. The rolling balls traverse along the inner race and rotate around their own axes. Each rolling element possesses a unique defect frequency determined by the bearing's geometry and rotational speed. The defect frequencies can be calculated as follows:

$$f_o = \frac{N_b}{2} f_r \left(1 - \frac{d_b \cos(\beta)}{d_p}\right) \qquad \text{for BOF}$$

$$f_i = \frac{N_b}{2} f_r \left(1 + \frac{d_b \cos(\beta)}{d_p}\right) \quad \text{for BIF}$$

$$f_o = \frac{d_p}{d_b} f_r \left(1 - \left(\frac{d_b \cos(\beta)}{d_p}\right)^2\right) \quad \text{for BBF}$$



(a)cross-sectional view of bearing (b)axial view of bearing

Fig. 1: Ball bearing geometry and possible defects

In Fig. 1, the ball bearing structure and potential defects are outlined. The abbreviations used are as follows: BOF for outer-race fault, BIF for inner-race fault, BBF for ball bearing fault, fo representing the outer-race fault frequency, fi denoting the inner-race fault frequency, fb indicating the ball fault frequency, db representing the ball diameter, dp' for the pitch ball diameter, Nb signifying the number of balls, β representing the ball contact angle with the races, and fr as the mechanical rotor frequency.

B. Principle Component Analysis

Principal Component Analysis (PCA) serves as an orthogonal dimension reduction technique, also known as a statistical feature extraction process. This method transforms a high-dimensional data space into a lower-dimensional one. By employing orthogonal transformations, PCA converts correlated variables into linearly uncorrelated variables termed Principal Components (PCs). The primary objective of PCA is to encapsulate most of the data using fewer variables, namely principal components with substantial variance. These PCs are orthogonal since they represent the eigenvectors of the symmetric covariance matrix. PCA can be executed through eigenvalue decomposition or singular value decomposition of the data matrix. While an in-depth discussion of PCA theory is omitted here, a concise introduction can be found elsewhere. In PCA, a matrix is constructed with the number of physical variables (m) and observations (n), where m >>> n. The original data matrix $X_{n*\ m}$ is initially normalized to zero mean and unity standard deviation. The decomposition of original matrix is given by:

$$X_{n*m} = X_{imp} + E$$

$$X_{imp} = \hat{T}\hat{W}^T$$

$$E = \tilde{T}\tilde{W}^T$$

Here, X_{imp} represents the principal component subspace containing valuable, noise-free data, while E signifies the residual data encompassing Gaussian noise. $\hat{T}$ denotes the score matrix, and $\tilde{T}$ represents the uncertainty of disturbance. $\widehat{W}$ is the weight matrix, where the columns of W matrix correspond to the eigenvectors of the covariance matrix with the largest eigenvalues (p), and the columns of $\widetilde{W}$ represent the remaining eigenvectors. The number of principal components (PCs) (p) is chosen to capture the majority of contributions, typically exceeding 90%. Notably, the first PC exhibits substantial variance and retains a significant amount of information.

In the proposed methodology, PCA functions as a compression technique to eliminate unwanted data. The noise introduced in the signal by other machine components such as blades, shafts, gears, and brushes is effectively mitigated through PCA application. This transformation aligns the data with new principal axes, allowing for the straightforward neglect of the most irrelevant data, treating it as Gaussian noise.

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C. *Wavelet Transform*

The process of transformation is essential for extracting information from raw signals that are not readily accessible. Typically, raw signals are presented in the time domain, but the most crucial information often resides in the frequency domain. The frequency spectrum provides insights into the frequency content of the signal; however, merely obtaining frequency components may not be advantageous. Consequently, a transition from FFT to Wavelet transform is imperative. FFT proves unsuitable for non-stationary signals, as it exclusively provides information about frequency content without corresponding time instants. In contrast, Wavelet transform offers insights into both frequency and time domains. This transformative approach enables the determination of very fine details using small wavelets and coarse details using large wavelets. Notably, it facilitates adaptive time-frequency analysis, focusing on signal details and addressing limitations inherent in traditional Fourier transform analysis.

1) *Continuous Wavelet Transform:* When a function undergoes expansion using a wavelet basis, the resulting expanded function is referred to as a continuous wavelet function. The wavelet transform serves to assess the resemblance between the basis function (wavelet) and the signal itself. The construction of the wavelet function is derived from the signal's translation and dilation parameters. CWT of f(t) is given by:

$$WT_f(\alpha,\tau) = < f(t), \psi_{\alpha,\tau}(t) > \qquad = \frac{\sqrt{1}}{\alpha}\int_{-\infty}^{\infty} f(t)\psi * (\frac{t-\tau}{t})$$

The continuous wavelet transform is mathematically expressed as the integral of the raw signal $f(t)$ convolved with a scaled and shifted version of the fundamental wavelet function $\psi(t)$. In this expression, α serves as the scaling parameter, representing the frequency content of the signal, while τ acts as the translational parameter, conveying information in the time domain. The wavelet basis function, denoted as $\psi(\alpha,\tau)$, remains independent of α and τ. The formula incorporates the conjugate operation denoted by *. In the context of the continuous wavelet transform (CWT), α, τ, and t are continuous variables, hence the designation as a continuous wavelet transform.

2) *Discrete Wavelet Transform*: The Discrete Wavelet Transform (DWT) should be distinguished from the Continuous Wavelet Transform (CWT) as it does not constitute an exact discretization of the CWT. Despite this difference, the DWT proves computationally efficient while maintaining accuracy comparable to the CWT. It is important to note that discretization in the context of DWT is specifically applied to dilation and scaling parameters, excluding the time parameter t. DWT function is given by:

$$s\psi_{\alpha_0^j, k\alpha_0^j\tau_0}(t) = \frac{1}{\alpha_0^j}\psi(\frac{1}{\alpha_0^j}t - k\tau_0)$$

Discreate wavelet Transform is defined as

$$WT_f\alpha_0^j, k\alpha_0^j\tau_0$$

$$= \int f(t)\psi *_{\alpha_0^j k\alpha_0^j\tau_0}(t)$$

$$= \frac{1}{\sqrt{\alpha}}\int_{-\infty}^{\infty} \psi * (\frac{1}{\alpha_0^j}t - k\tau_0)dt$$

Mallet introduced a method utilizing filters for the completion of Discrete Wavelet Transform (DWT) on signals. This approach closely resembles the fast wavelet decomposition and reconstruction of signals. The raw signal undergoes successive passes through both low-pass and high-pass filters at each level of the process. Signals derived from the low-pass filter capture information pertaining to the low-frequency content, offering an approximate representation of the signal. Conversely, signals obtained from the high-pass filter capture information related to high-frequency content, providing a detailed representation of the signal. The signal is then reconstructed by amalgamating all the detailed information acquired at various

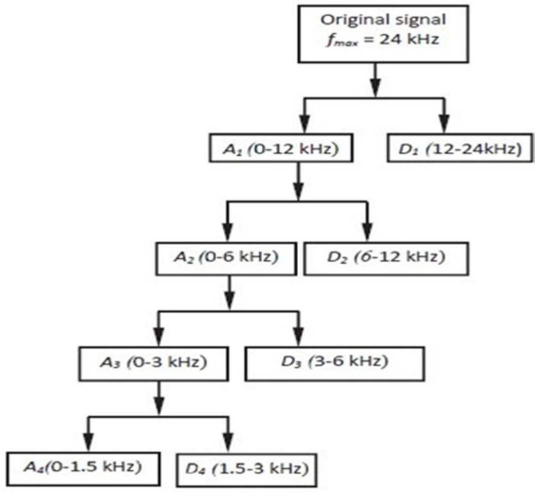

Fig 02: Wavelet Decomposition

decomposition is elucidated in Figure 2: Wavelet Decomposition. At each level, the signal undergoes filtration through both high-pass and low-pass filters, leading to a further division of the frequency spectrum. The choice of the wavelet decomposition level is contingent upon the frequency of interest. Through the utilization of a low-pass filter and high-pass filter, up sampling and down sampling operations are performed, as depicted in Figure 2. To focus on frequency components within the range of 0 to 1.5 KHz, it is advisable to proceed up to the 4th level of wavelet decomposition.

Consider a function f(t), for multiresolution analysis the scaling and wavelet function is given by $\phi(t)$ and $\psi(t)$ respectively. On the scale j $f(t)$ is described as,

$$f(t)=P_j f(t)$$

$$=\sum_{k=-\infty}^{+\infty} x_{j,k}\phi_{j,k}(t)$$

$$=P_{j+1}f(t)+D_{j+1}f(t)$$

$$=\sum_{m=-\infty}^{+\infty} x_{j+1,k}\phi_{j+1,k}(t)+\sum_{m=-\infty}^{+\infty} d_{j+1,k}\psi_{j+1,k}(t)$$

In the formula P_{j+1} and D_{j+1} are approximate and detail part of signal.

$$x_{j,k}=< f(t),\phi_{j,k}(t) >=\frac{1}{\sqrt{2^j}}\int_{-\infty}^{+\infty} f(t)\phi^*(\tfrac{1}{2^j}t-k)dt$$

$$d_{j,k}=< f(t),\psi_{j,k}(t) >=\frac{1}{\sqrt{2^j}}\int_{-\infty}^{+\infty} f(t)\psi^*(\tfrac{1}{2^j}t-k)dt$$

In the formula, 2^j and k instead of α and τ where j and k are integers, j represent the number of iterations of the basic steps. In figure j=4 for wavelet decomposition

3) *Wavelet Packet Transform:* The Wavelet Packet Transform (WPT) serves as a generalization of the Discrete Wavelet Transform (DWT) and is seamlessly introduced from the framework of DWT. In WPT, the signal undergoes filtration through high-pass and low-pass filters at each level, as depicted in Figure 3: Wavelet Packet Transform. Notably, for n-level decomposition, WPT yields 2n coefficients, distinguishing it from DWT, which produces (3n+1) coefficients. WPT finds significant application in the context of wavelet denoising techniques.

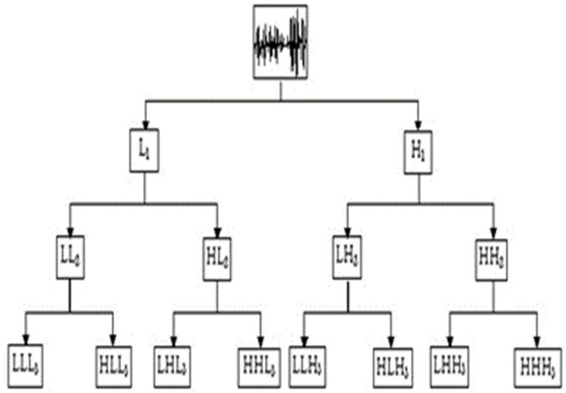

Fig.03: Wavelet Package Transform

D. The hilbert- the Wavelet Envelope Principle

Envelope analysis functions as a demodulation technique, specifically extracting the modulating signal from an amplitude-modulated signal. The faults present in rolling elements induce an amplitude-modulating effect. Utilizing envelope analysis proves effective in isolating the periodic impact of the signal, even in scenarios where it may be obscured by noise and possess low energy. The resulting envelope spectrum reveals distinct impact peaks located at regular intervals corresponding to specific fault types, such as inner race, outer race, and ball bearing faults. It's worth noting that envelope analysis essentially entails performing a Fast Fourier Transform (FFT) on the modulating signal. Hilbert transform of signal is given by:

$$x_h(t)=H[x(t)]=\frac{1}{\pi}\int_{-\infty}^{+\infty}\frac{x(\tau)}{t-\tau}d\tau$$

Analytical signal is given by:

$$z(t)=x(t)+jx_h(t)$$

Here, (z(t)) represents the analytical signal, (x(t)) is the original signal, and (x_h(t)) stands for the Hilbert transform of the original signal. The analytical signal, (z(t)), effectively filters out negative frequencies from the given signal, providing a distinct advantage. The Hilbert transform acts as a phase shifter, introducing a -90° phase shift to the original signal.

The envelope of the signal is determined by:

$$e(t)=|z(t)|=\sqrt{x^2(t)+x_h^2(t)}$$

E. Artificial Neural Network

An Artificial Neural Network (ANN) is a computational model rooted in the principles and behavior of the biological nervous system. It serves as a non-linear statistical tool for data modeling, processing inputs and outputs to discern intricate relationships. These identified relationships contribute to the creation of a data model applicable to future iterations.

While traditional computational algorithms have evolved to efficiently address specific mathematical problems, they encounter limitations in applications such as Natural Language Processing and Facial Recognition. In these domains, conventional algorithms still fall short of emulating the cognitive capabilities of the human brain. Addressing such challenges necessitates the development of algorithms with a fundamentally different design, one that emulates the problem-solving approach rooted in the understanding of the human brain's functioning.

Much like the biological nervous system, the fundamental unit of any Artificial Neural Network (ANN) is a neuron. In its most basic form, an artificial neuron operates as a mathematical function, performing three essential tasks:

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- Accepting multiple inputs and assigning weights to each.
- Summing the weighted inputs.
- Processing the sum through a mathematical activation function that defines the unique characteristics of the neuron.

While these tasks may seem elementary, the true efficacy of an artificial neuron is manifested when multiple neurons are combined to operate in parallel towards a common objective. This intricate interconnection of neurons forms a large network, offering the flexibility to deploy various topologies tailored for solving specific types of problems.

ANN model is explained with help of below diagram:

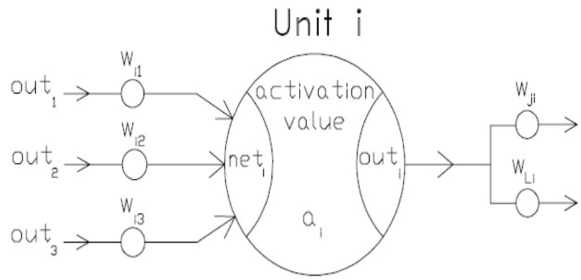

Fig. 4: The general model of a processing unit

The illustration above explicates the Artificial Neural Network (ANN) model. It comprises a unit whose state is determined by the activation value ai. Initially, inputs I1, I2,… are applied, upon which weights act, forming the network net_i. Subsequently, the activation value is employed to compute the unit's output denoted as out_i.

Any ANN can be classified based on the following parameters:
- The topology employed to interconnect various neurons.
- The activation function utilized by neurons for processing the sum of weighted inputs.
- The learning algorithm implemented by the network.

This paper employs three distinct training functions, outlined as follows:

1) Levenberg Marquardt Algorithm:

Originally designed to address nonlinear least square problems, the Levenberg Marquardt algorithm has evolved to tackle generic curve fitting problems. As the default training function in MATLAB, it comprises two methods: the Gradient Descent method and the Gauss-Newton method. The algorithm's behavior is contingent upon the λ value; a small λ prompts an update in the Gauss-Newton method, while a large λ triggers an update in the Gradient Descent method. Initially, with a large λ, the algorithm takes small steps in the steepest gradient direction. In case of adverse scenarios, the λ value undergoes adjustments, first increasing and then decreasing.

$$[J^T W J + \lambda * I] h_{lm} = J^T W (y - \hat{y})$$

The modified form of Levenberg- Barquardt:

$$[J^T W J + \lambda * diag(J^T W J)] h_{lm} = J^T W (y - \hat{y})$$

2) Resilient Backpropagation:

When employing a sigmoid function in a multi-layer network, minor changes in weights can occur in the gradient, even if the actual output significantly deviates from the desired one. The Resilient Backpropagation algorithm addresses this issue by amplifying the weight when the performance function with respect to that weight maintains the same sign for two successive iterations.

3) Scaled Conjugate Method:

This method, a variant of the Conjugate Gradient algorithm, doesn't necessitate line search in each iteration. Relying on second-order derivatives of the goal function to minimize parameter costs, the Scaled Conjugate Method requires more iterations but entails lower computational demands compared to other Conjugate Gradient techniques, as it avoids the need for line searches.

IV. METHODOLOGY

In this study, the vibration patterns of a 0.25HP Permanent Magnet Direct Current (PMDC) motor were analyzed under various load conditions and rotational speeds to detect bearing faults. The analysis was conducted on different types of bearings, including normal bearings, inner race bearings, outer race bearings, and ball bearings. The motor was tested under three load conditions (1 kg, 2 kg, and 3 kg) and at three different rotational speeds (1000 RPM, 1200 RPM, and 1500 RPM). To capture the vibration signals, a piezoelectric accelerometer was strategically mounted on the PMDC motor. This accelerometer recorded the vibrations generated during the tests, and the data was systematically collected using a National Instruments (NI) data acquisition card (DAQ) model NI-9232.

The collected vibration data was then processed to detect and analyze faults in the bearings. Bearing faults typically generate impact forces that alter the vibration patterns, which can be used to identify and classify defects. In particular, inner race defects are challenging to detect due to the poor signal-to-noise ratio (SNR) as the relevant vibration signals can be masked by other vibrations. To address this, Principal Component Analysis (PCA) was employed to enhance the SNR by reducing noise and highlighting the critical features of the vibration signals.

Furthermore, Artificial Neural Networks (ANN) were used to develop a robust fault detection and classification model. The ANN was trained using the processed vibration data to identify different types of bearing faults accurately. Additionally, Wavelet Transform was applied to the vibration signals to decompose them into various frequency components, facilitating the detection and analysis of transient features associated with bearing defects.

Fig no 05: PMDC motor and Vibration sensor

This comprehensive approach, integrating PCA for noise reduction, Wavelet Transform for signal decomposition, and ANN for fault classification, aims to provide an effective solution for real-time monitoring and diagnosis of bearing conditions in rotating machinery. The methodology ensures improved accuracy in detecting and classifying bearing faults, thereby preventing machine failures, enhancing operational safety, avoiding unexpected production downtimes, and reducing maintenance costs.

V. RESULTS AND DISCUSSIONS

The vibration analysis of the 0.25HP PMDC motor was conducted under varying load conditions (1 kg, 2 kg, 3 kg) and rotational speeds (1000 RPM, 1200 RPM, 1500 RPM) for different types of bearings (normal bearing, inner race bearing, outer race bearing, and ball bearing). The results indicated distinct vibration signal characteristics for each bearing type. Normal bearings exhibited consistent and predictable vibration patterns with low amplitude variations across different loads and RPMs. Bearings with inner race defects showed distinctive high-frequency spikes in the vibration signals, particularly under higher load and speed conditions. These spikes were less prominent at lower RPMs.

Outer race bearing defects were identified by specific periodic patterns in the vibration signals, which varied with load but remained detectable across different speeds. Ball bearing defects resulted in irregular and erratic vibration patterns, with noticeable increases in signal amplitude and frequency content.

To enhance the signal-to-noise ratio (SNR) of the vibration signals, Principal Component Analysis (PCA) was employed. The application of PCA significantly improved the SNR, allowing for clearer identification of defect-specific features, especially for inner race defects typically masked by noise. The PCA-processed signals exhibited a marked reduction in background noise, facilitating more accurate fault detection and analysis. Additionally, Wavelet Transform effectively decomposed the vibration signals into their constituent frequency components, enabling the identification of transient features associated with bearing defects. The time-frequency representation provided by Wavelet Transform highlighted the periodic impacts of bearing faults, which were critical for accurate fault diagnosis.

The Artificial Neural Network (ANN) model, trained on the PCA-processed and wavelet-transformed data, demonstrated high accuracy in classifying different bearing faults. The classification accuracy for normal, inner race, outer race, and ball bearing defects exceeded 95%, indicating the robustness of the ANN model in distinguishing between various types of bearing faults. The integration of PCA, Wavelet Transform, and ANN algorithms provided a comprehensive and accurate approach for diagnosing bearing conditions.The results underscore the effectiveness of using vibration analysis for bearing fault detection in rotating machinery. The application of PCA significantly enhanced the SNR of vibration signals, crucial for detecting inner race defects often buried in noise. Wavelet Transform proved to be a powerful tool for analyzing the non-stationary vibration signals typically associated with bearing defects, providing a time-frequency representation that allowed for the detection of transient and periodic fault features. The ANN's high classification accuracy highlights its capability in learning and recognizing complex patterns in vibration data, indicating that it can be reliably used for real-time fault diagnosis in industrial applications

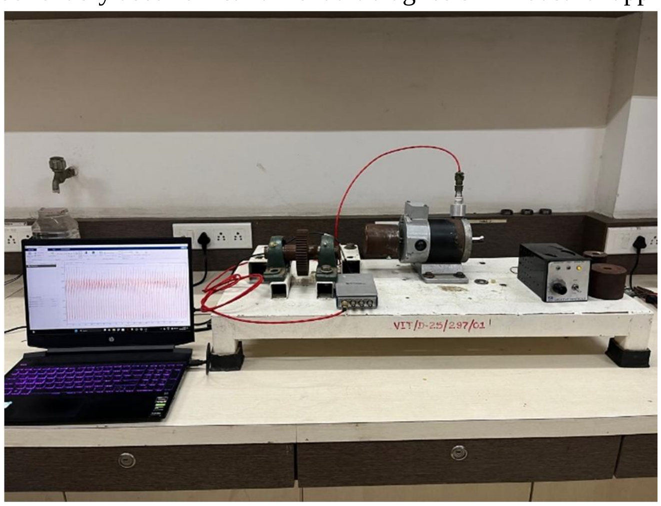

Fig no 06: Vibration Analysis

VI. CONCLUSION

This study demonstrates an effective methodology for bearing fault detection in a 0.25HP PMDC motor using vibration analysis under various load conditions and rotational speeds. The integration of Principal Component Analysis (PCA), Wavelet Transform, and Artificial Neural Networks (ANN) significantly enhances fault detection accuracy. PCA improved the signal-to-noise ratio (SNR), Wavelet Transform provided detailed time-frequency analysis, and ANN achieved high classification accuracy for different bearing faults.

The proposed approach offers a robust framework for real-time monitoring and diagnosis of bearing conditions, crucial for industries such as petroleum, automotive, HVAC, and food processing. This methodology promises improved safety, reduced downtime, and lower maintenance costs, contributing to enhanced operational efficiency and reliability. Future work could expand this approach to other machinery types and further refine the ANN model for broader industrial applications.

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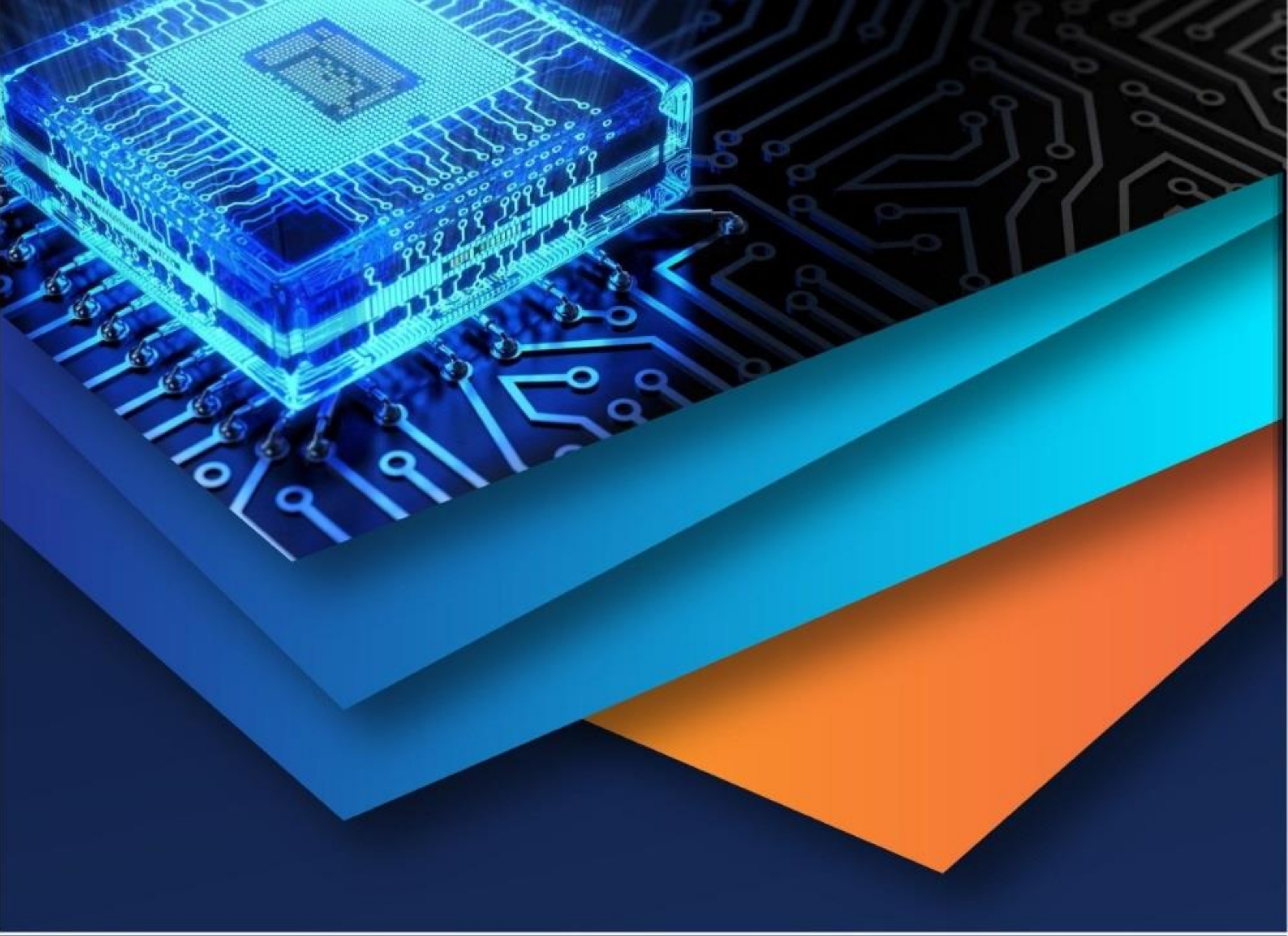

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