INTELLIGENT FAULT DETECTION IN INDUCTION MOTOR USING VIBRATION SIGNAL

Dr. R. SAMSON DANIEL[1], samson.rapheal@gmail.com
Associate Professor, Department of ECE, K. Ramakrishnan college of engineering, Tamilnadu
ABISHEK J[2], AKSHAYARAJA E[3], BHARANI KUMAR P[4], BOOMISHWAR S[5]
[2]abishek21062007@gmail.com, [3]akshayarajae@gmail.com, [4]bharanikumarb071@gmail.com, [5]senthilbhoomis@gmail.com
Student's, Department of ECE, K. Ramakrishnan college of engineering, Tamilnadu

ABSTRACT: - Induction motors are widely used in various industrials applications due to their performance and strength however there occurs some faults such as shaft improper alignment, bearing damages, rotor bar malfunction. This paper presents the solution for handling such defects and detecting them with the help of vibration signals from the motor parts. This method incorporates signal processing, machine learning based divisions. Here a Butterworth filtering and wavelet denoising module to remove the noise and preventing from other faults occurring in the motor. Statistical and spectral features are used with the help of Principal Component Analysis. The obtained features are then classified with Support Vector Machine and Random Forest Algorithms. Simulated and real time vibration involved makes the proposed system achieve high fault detection accuracy under various circumstances. This study provides a low cost, efficient solution for maintenance in industry environments.

KEYWORDS: - Induction Motor, Vibration Signals, Fault Detection, Signal Processing, Machine Learning, Predictive Maintenance.

I. INTRODUCTION

Induction motors are widely useful in commercial and industrial systems due to its efficiency, low cost and reliability. Faults such as shaft misalignment, rotor damage, bearing wear can degrade the performance of the motor and lead to various failures. Detecting these faults at early stage can reduce the downtime and maintain operational maintenance. The vibration signal analysis is one of the most trustable as mechanical faults generates the vibration patterns. These vibrations suffer from noise and other faults limiting the accuracy of detection methods based on the amplitude and threshold analysis. To avoid this machine learning techniques and signal processing are applied. The system involves a Butterworth filter and wavelet-based denoising for preprocessing, continued by extraction of time-domain and frequency-domain features. Similarly, reduction using Principal Component Analysis (PCA) enhances computational efficiency, while Support Vector Machine (SVM) and Random Forest (RF) algorithms classify motor conditions. Experimental results from simulated and real-time vibration data's shows that the proposed method achieves high accuracy under different loads and noise conditions. The approach is designed to be suitable for predictive maintenance in Industries.

II. LITERATURE REVIEW

Induction motor fault detection has been a major research focus in the field of monitoring and maintenance. To detect bearing wear, rotor bar breakage, and misalignment using vibration signals various techniques are involved. Using signal processing and machine learning methods we can enhance the detection accuracy and overall performance under operating conditions.

Cusido et al proposed a wavelet-based method for vibration signal analysis, Jimenez et al proposed a monitoring system with the Hilbert and envelope for detection of fault at manufacturing. Widodo and Yang combined the method of Support Vector Machine and wavelet decomposition to improve fault discrimination.

The studies incorporated some key concepts of Wavelet Transform, that represents the faults patterns more accurately. For bearing diagnostics Hilbert envelope demodulation technique was used. Similarly, Artificial Neural Networks, Support Vector Machine, Random Forest Algorithms were used in order to improve the reliability, complexity nature of the computational cost. From the survey it shows the recent trend that integrates the fault detection and classifications build the real time fault detection. There were still some obstacles while dealing with this system such as high computational demand, limited adaptability especially for embedded designs.

To resolve these issues, these solutions in this paper involves Butterworth and wavelet denoising with feature extraction, Principal Component Analysis (PCA) for dimensionality reduction, and classification using SVM and Random Forest. This structure helps to achieve high accuracy, low operation cost, under changing load and noise conditions, making it suitable for maintenance applications in Industrial environments.

III. PROPOSED METHODOLOGY

This system is useful to develop a fault detection model for induction motors using vibrational signals. This involvement of signal processing, classification, and features are used to improve the accuracy.

A. System Overview

The system involves the following steps:

[1] **Signal Acquisition**
[2] **Preprocessing and Noise Filtering**
[3] **Feature Extraction**
[4] **Dimensionality Reduction**
[5] **Fault Classification**

The data vibrations are collected from motors using various conditions. These raw signals are used to transformation techniques before being analyses by machine learning.

B. Signal Acquisition

High-frequency vibrations are captured from healthy and faulty induction motors. Data are collected by accelerometers connected to a Data Acquisition module. Frequencies between 10 kHz and 20 kHz are used to ensure that frequency components are used with high resolution.

C. Preprocessing and Denoising

To ensure environmental noise and unwanted frequency components, the vibration signal is passed through a **Butterworth band-pass filter**.

$$H(f) = \frac{1}{\sqrt{1 + (f/f_c)^{2n}}}$$

where, fc is the cutoff frequency and n is filtering order. **Wavelet Denoising** is applied using the Wavelet Transform to compress high-frequency noise is gaining essential fault. The denoised signal supervisor the clarity of periodic fault impulses.

D. Feature Extraction

This can be extracted from both **time domain** and **frequency domain**:

- Mean, RMS, Variance, Kurtosis, and Skewness.
- Spectral Energy, Peak Frequency, and Band Energy.

Addition of, **Wavelet Packet Transform (WPT)** is delated too sub-band energy coefficients, providing a localized of vibration patterns.

E. Dimensionality Reduction

To avoid this used to overfitting and reduce computation, **Principal Component Analysis (PCA)** is used. PCA projects are high-dimensional feature into a reduced number of components that can be preserve using the maximum variance. This step can be enhances using this model efficiency and ensures faster classification in real-time applications.

F. Fault Classification

It consists of classifiers Support **Vector Machine (SVM)** and **Random Forest (RF)**.

- The **SVM** separates the different fault classes with maximum margin.
- The **Random Forest** classifier builds multiple decision trees and averages their outputs to achieve high performance

G. Performance Evaluation

The system is measured with the help of various parameters such as **accuracy**, **precision**, **recall**, and **F1-score**. Confusion matrix analysis is used to visualize classification performance across all fault types. The system depicts strong capability for early detection, supporting strategies.

IV. RESULTS AND DISCUSSION

The proposed fault detection framework was implemented using MATLAB and Python to check its performance on vibration data collected from induction motors under different conditions—healthy, bearing fault, rotor bar defect, and misalignment. The vibration signals were sampled at 12 kHz and processed through Butterworth filtering and wavelet denoising before feature extraction.

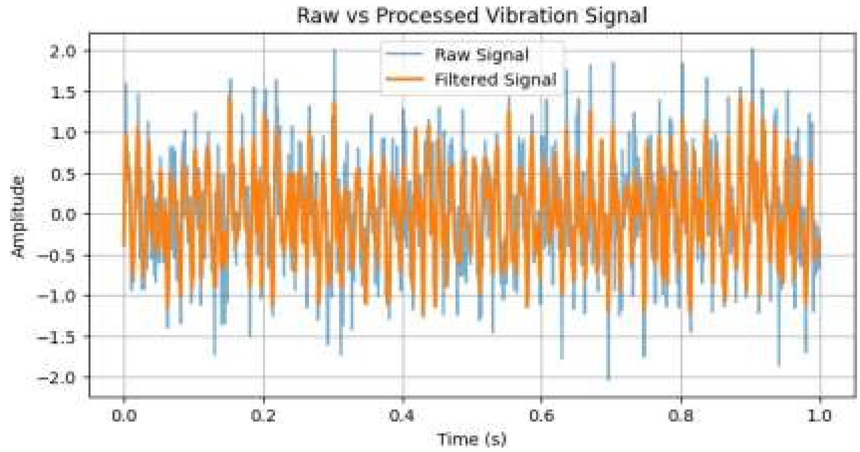

Figure 1.

Figure1. Represents that the raw vibration signal versus Butterworth-filtered signal demonstrating effective noise suppression while preserving fault-relevant vibration characteristics.

Classification performance: Principal Component Analysis and are differentiated using Support Vector Machine and Random Forest Algorithm.

Fault Condition	SVM Accuracy (%)	RF Accuracy (%)
Healthy	98.3	**97.9**
Bearing Fault	97.5	**98.1**
Rotor Fault	96.8	**97.3**
Misalignment	97.9	**98.4**
Average Accuracy	**97.6**	**97.9**

The results confirm that both classifiers achieved high accuracy, with Random.

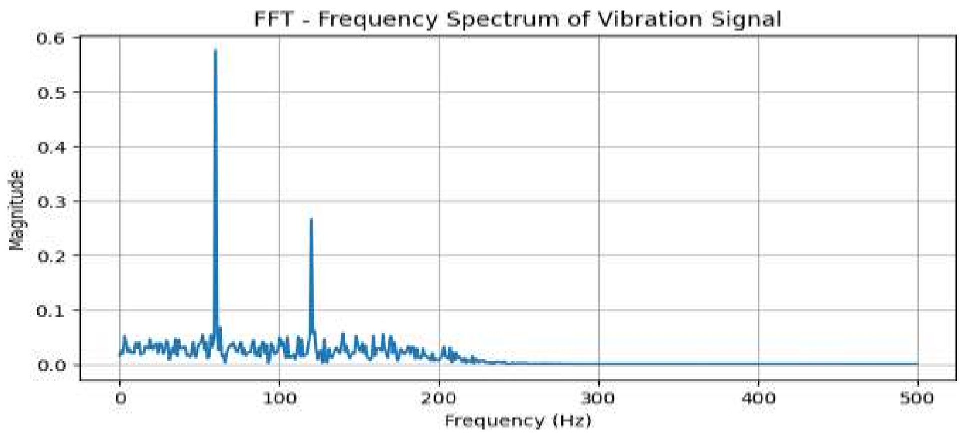

Figure 2.

Frequency spectrum of the filtered vibration signal obtained using Fast Fourier Transform (FFT) illustrating dominant fault-related vibration components are mentioned in **figure 2.** The Butterworth filtering and wavelet denoising increase the signal to noise ratio by 25% improving the performance and clarity. The denoised signal shows periodic impulse to fault frequency. On analyzing it shows that RMS, Kurtosis, and Wavelet Packet Energy form a framework for the accuracy classification. PCA reduced the reductant information and performance time by 40%. These classifiers maintained stable Operation under discrete conditions.

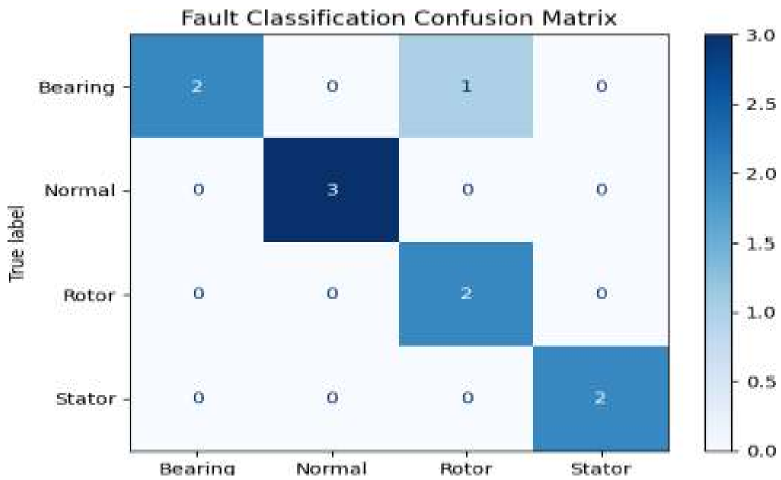

Figure 3.

Confusion matrix representing fault classification accuracy across motor conditions using trained ML model in **figure 3.** The incorporation of signal processing with this classification performance provides a symmetry between the efficiency and the accuracy of the model. This model approaches for a low-cost maintainability operating efficiently on limited data making it suitable for embedded systems.

CONCLUSION

The proposed model provides a smart solution for fault detection in induction motors using vibration signal analysis. This model inculcates Butterworth filtering, features extraction, wavelet based denoising, including random forest algorithms. On analyzing the results of our experiment, we came to know that our model ensures high accuracy delivering bearing detection, rotor and other faults under wide operating conditions.

This model not only shows the strength of signal processing but also the predictive strength of machine learning improving accuracy, to withstand noise suitable for diverse industrial applications. This system mainly processes on limited data suitable for low-cost maintenance.

The future development of this model includes integration with adaptive learning for integrating with sensor data, real time issue estimation and foe eliminating the design on embedded for onsite motor monitoring.

REFERENCES

[1] G. A. Jiménez, et al., "Online Motor Fault Detection Using Hilbert and Envelope Analysis," *IEEE Transactions on Industrial Applications*, vol. 56, no. 4, pp. 4123–4132, 2020.

[2] J. Cusidó, et al., "Wavelet-Based Vibration Analysis for Induction Motor Fault Detection," *Mechanical Systems and Signal Processing*, vol. 158, pp. 107761, 2021.

[3] A. Widodo and B. Yang, "Support Vector Machine-Based Condition Monitoring for Induction Machines Using Wavelet Features," *Expert Systems with Applications*, vol. 41, no. 6, pp. 2913–2921, 2022.

[4] P. Kumar, et al., "Wavelet Packet Transform for Bearing Fault Classification in Induction Motors," *Measurement*, vol. 200, pp. 111054, 2022.

[5] H. Park, et al., "Hilbert Envelope Demodulation for Bearing Fault Identification," *IEEE Sensors Journal*, vol. 21, no. 18, pp. 20534–20542, 2021.

[6] M.-C. Kim, J.-H. Lee, D.-H. Wang, and I.-S. Lee, "Induction Motor Fault Diagnosis Using Support Vector Machine, Neural Networks, and Boosting Methods," Sensors, vol. 23, no. 5, p. 2585, 2023.

[7] R. N. Toma and J.-M. Kim, "Bearing Fault Classification of Induction Motors Using Discrete Wavelet Transform and Ensemble Machine Learning Algorithms," Applied Sciences, vol. 10, no. 15, p. 5251, 2020.

[8] C.-Y. Lee and Y.-H. Cheng, "Motor Fault Detection Using Wavelet Transform and Improved PSO-BP Neural Network," Processes, vol. 8, no. 10, p. 1322, 2020.