International Journal of Robotics and Control Systems
Vol. 4, No. 1, 2024, pp. 139-150
ISSN 2775-2658
http://pubs2.ascee.org/index.php/ijrcs

Prognostic Real Time Analysis of Induction Motor

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ARTICLE INFO

Article history
Received December 09, 2023
Revised January 18, 2024
Accepted February 28, 2024

Keywords
Induction Motor;
Discrete Wavelet Transform;
Artificial Neural Network;
MEMS Sensor;
Fault Prediction

ABSTRACT

Variable speed induction motors controlled by variable frequency drives are used for a variety of industrial applications. Monitoring and prognostic occurrence of faults in induction motors is vital for reducing the downtime and accidents. The proposed work focuses on failures in induction motors owing to bearing misalignment and insulation failure in the stator that results in abnormal vibration and temperature rise in the motor. This research intends to improve the dependability and safety of industrial operations by identifying faults in their early stages using advanced methods such as vibration analysis and thermal monitoring. This work focuses on fault prognosis in induction motor through vibration data, which is analyzed using Daubechies orthogonal db10 wavelet transformation. The neural network algorithm optimizes the analyzed results to enable real time fault detection. The temperature of the stator is measured to estimate the expected lifetime of the insulator. The real time vibration and temperature data is measured and transferred to prognostic model build in MATLAB using ATMEGA 32 controller and the results are validated for good, allowable and not permissible conditions of motor based on ISO 10816 vibration levels for Class I motors. The improved accuracy and efficiency of real-time fault detection have the potential to reshape maintenance strategies and enhance the overall reliability of variable speed induction motors.

1. Introduction

For prognostic fault identification of induction motors an efficient fault predicting technique must be used to detect faults in the early stage without affecting the system. Industries are widely dependent on induction motors for automation and failure in these motors leads to huge revenue loss for the industry [1]. The driveline in industry consists of induction motor gear boxes, couplings and brakes controlled by variable frequency drives. Faults occurring in any part of the system affect induction motor performance to a great extent. The transmission of cyclic forces in the drive system causes vibration in the system.

The electrical faults include rotor and stator faults. There are two different rotor faults which are pronounced in induction motors [2]. They can be categorized as end-ring and broken bar fault [3].

Similarly, there are two distinct forms of stator faults. There are defects in the frame, the stator lamination, and the stator winding. If an inter-turn short circuit occurs high currents run through the shorted coil, causing a lot of damage [4], [5]. The mechanical fault incorporates rotor mass unbalance, air-gap eccentricity, bearing fault and so on. Mass unbalance in the rotor is because of unequal dissemination of mass around the focal point of revolution of the rotor for which focus of gravity of the rotor does not harmonize with the focal point of turn. The lopsided attractive draw because of radial power created produces unnecessary vibration in the rotor and also in the stator. Un-balance may likewise happen by non-symmetrical expansion or subtraction of mass because of wear and tear, producing deformity, misalignment and so on.

Air gap eccentricity means the unequal distribution of air gap between the stationary and the rotating part [6]. The air-gap in any rotating machine also serves a cooling purpose. When the air gap is reduced, this cooling phenomenon will also be hampered. This might result in heating of windings. The bearing of rotor is an essential part to reduce the friction between the moving components [7], [8], [9]. In addition to these faults, there are some miscellaneous faults in an induction motor. They are primarily caused by outside factors such as ambient temperature and air humidity. Vibrations in machines are even caused owing to failure in installation or defects in foundation. The faults lead to rise in current magnitude and cause more losses in the machine by rise in temperature [10].

To address these challenges and enhance motor health monitoring, condition monitoring becomes imperative through the analysis of vibration and temperature data. The vibration of the machine is measured using MEMS Accelerometer whereas the temperature of the stator can be measured using the temperature sensor. The sensor values are converted into signals for obtaining the features of the signal. The features of the signal describe the parameters used for condition monitoring. The features can be extracted by using transforms like FFT and Wavelet transform. For analysis of faults in an induction motor, the different technique like Motor Current Signature Analysis (MCSA), vibration analysis, torque-signal analysis, and temperature-based analysis, etc., are used. Among which MCSA and vibration analysis are considered due to its advantages [11], [12], [13].

The health of a motor and the type of fault that has occurred can be correctly diagnosed by analyzing the vibration signals of the motor. The analysis of the vibration signal can be done by FFT in which the result widely varies based on the load and transient characteristics of the motor. Vibration signals can be measured non-intrusive and can be measured from the surface of the body [14], [15], [16], [17]. Signal processing and conditioning circuits are necessary for identifying the fault condition and avoid errors in computation.

The time-domain signals of either Fourier transforms or Short Time Fourier Transform (STFT) is converted to frequency domain and are used for signal processing, had drawbacks in frequency domain and to detect transient fault conditions occurring in a motor. Analysis of vibration data using wavelets is a powerful signal processing technique in time domain and frequency domains [18], [19], [20].

Wavelets are used for analysis of signals of varying frequency with multi-resolution capability and can analyze transient characteristics for non-linear signals. The type of fault based on low frequency or high frequency can be correctly detected, and acts as a mathematical tool for prognostic failure analysis [21], [22]. The three main ways to transform wavelets are the continuous, discrete, and wavelet packet types. Continuous Wavelet Transform (CWT) analyses vibration data in two dimensions instead of one dimension as in FT. CWT gives redundant information when translational and scale parameters are modified. In DWT signals are separated into components of low frequency and high frequency [23], [24], [25]. WPT provides detailed analysis of signals in high frequency regions by generating sub-bands and each sub-band provides detailed frequency analysis. The second-generation wavelet transforms use lifting scheme to provide detailed coefficient by splitting into subsets of odd and even samples and prediction is done with odd and even sample data, approximation coefficients are computed using the updating operator and approximation part of signal is further decomposed. Artificial neural networks are used to analyze the vibration signals in order to identify faults from the vibration signals.

In this paper, we propose a novel approach that integrates MEMS Accelerometer, temperature sensors, and advanced signal processing techniques, including Wavelet Transform and Artificial Neural Networks, for efficient fault prognosis in induction motors.

2. Method

The small-scale industries use induction motor for most of its applications. They need an alternative method for vibration monitoring where costly vibration analyzer cannot be used. For analysis of overheating due to faults instead of using the expensive Infrared thermal camera, temperature sensors seem to be the best alternative. Thus, this paper serves the purpose which is considered to be cost-effective and used for prediction of fault at an early stage.

The accelerometer is a device that measures acceleration. It is used to detect and monitor vibration in rotating machinery. There are different types of accelerometers. The mostly preferred accelerometers are the piezoelectric type (ADXL335) and accelerometer that uses MEMS (Micro Electro Mechanical System) technology [26]. The piezoelectric accelerometer uses the piezoelectric effect to measure dynamic variations in acceleration. It has an excellent frequency response despite its small dimensions. It has a negligible phase shift. Apart from all these advantages, it has high-temperature sensitivity, and hence piezoelectric type is not preferred. Instead, an accelerometer that uses MEMS technology is preferred. In specific, capacitive accelerometers are preferred.

The temperature sensor used is MLX90614. This is a non-contact type infrared sensor which is small in size and easy to integrate. The temperature is calibrated based on emissivity of the stator material. This sensor works on the logic that it marks infrared light reflecting from remote objects so that it can detect temperature by absorbing the discharged IR waves without touching them physically [27].

The selection of MEMS-based accelerometers, specifically the capacitive type, is based on factors such as frequency response and cost. Similarly, the MLX90614 temperature sensor was chosen due to its non-contact nature, small size, and wide temperature range. While the selected sensors offer numerous advantages, the potential limitations are with sensor placement and the impact of ambient temperatures may affect the accuracy of the collected data.

2.1. Proposed Method

To monitor the condition of the motor, temperature, and vibrations of the motor are measured. The setup is made in a 3 HP, 3-Phase, Class B, Slip ring Induction motor. The vibration sensor is placed on the surface of the motor bearing cap, and temperature sensor is mounted near the stator winding. The defects in bearing are artificially induced to create dataset for allowable and not permissible conditions for training and testing the proposed system.

The overall idea of the paper is represented as a block diagram in Fig. 1. The sensor data is acquired through ATMEGA 32 and is transmitted through serial communication to the proposed model built in MATLAB. The vibration signal in time domain is converted to frequency domain using Daubechies orthogonal db10 wavelet transformation and the coefficients are used by the neural network model to predict the condition of the motor. The rise in temperature data is utilized to predict the life of stator winding insulation.

2.2. Signal Analysis

The signal sent to the processor board from the accelerometer is amplitudes of vibration with respect to the ground. They are measured in terms of unit ‘g' which has an equal representation as mm/sec^2. The collected data is analyzed using MATLAB software. The flowchart of the proposed work is shown in Fig. 2.

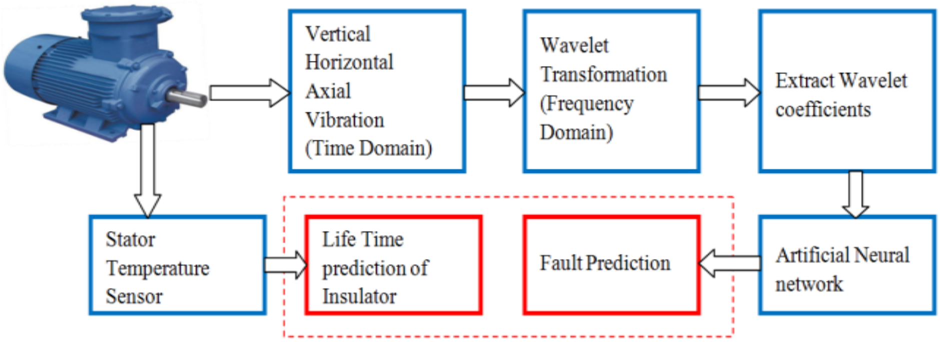


Fig. 1. Block diagram of proposed system

2.3. Wavelet Transformation

The plotted curves are analyzed using wavelet transforms. Analysis of vibration signal requires the precise value of frequency, which changes abruptly from time to time. Considering Fourier transform as an analysis method in spite of converting time signals to frequency signals it fails to tell precisely where specific frequency rises. To extract a small portion of the signal where there is a sudden change in frequency another method called short time Fourier transform evolves.

Though STFT seems to meet the requirement, it cannot detect the signals with the very low-frequency component. Thus, Wavelet transform overcomes the previous problem. The wavelet function balances time and frequency domains. This technique allows for the exact localization of both extremely low-frequency and very high-frequency components. This flexibility increases the time-frequency analysis. Considering the advantages of wavelet transform this method is chosen as an analysis method for the vibration signal of the induction motor [28].

$$cwt(s,\tau) = s^{-1/2} \int x(t) \Psi^* \left(\frac{t-\tau}{s}\right) dt \tag{1}$$

Where $x(t)$ is Measured signal in time domain, τ is Translational parameter, s is scale function, $\Psi^*$is Complex Conjugate, and Ψ is Shifted Wavelet function.

$$cwt(s,f) = F\{cwt(s,\tau)\} \tag{2}$$

$$cwt(s,f) = \frac{s^{-1/2}}{2\pi} \int_{-\infty}^{\infty} \left(\int_{-\infty}^{\infty} x(t) \Psi^* \left(\frac{t-\tau}{s}\right) dt \right) e^{-j2\pi f\tau} d\tau \tag{3}$$

$$cwt(s,f) = s^{1/2} X(f) \Psi^*(sf) \tag{4}$$

$$cwt(s,\tau) = \frac{1}{F\left(CWT(s,f)\right)} \tag{5}$$

$$cwt(s,\tau) = s^{1/2} F^{-1}\{X(f) \Psi^*(sf)\} \tag{6}$$

It has become a powerful tool of the non-stationary signal. In wavelet transform among its two types namely continuous and discrete wavelet transforms. The Continuous wavelet transform is used to split a continuous-time function into wavelets as given in (1)–(6). Better time and frequency representation can be achieved by using the continuous wavelet transform compared to the Fourier transform. The Discrete Wavelet Transform (DWT) extracts the features from a signal. The features of the signals are extracted using this transform. The signal to be analyzed is divided into ‘n’ levels by filtering and decimation. Thus, coefficients of the signals are obtained. This can be classified as an approximation and detailed coefficients. The feature extraction of signals includes a few steps. Using DWT, the acquired vibration signals are separated into four distinct frequency bands.

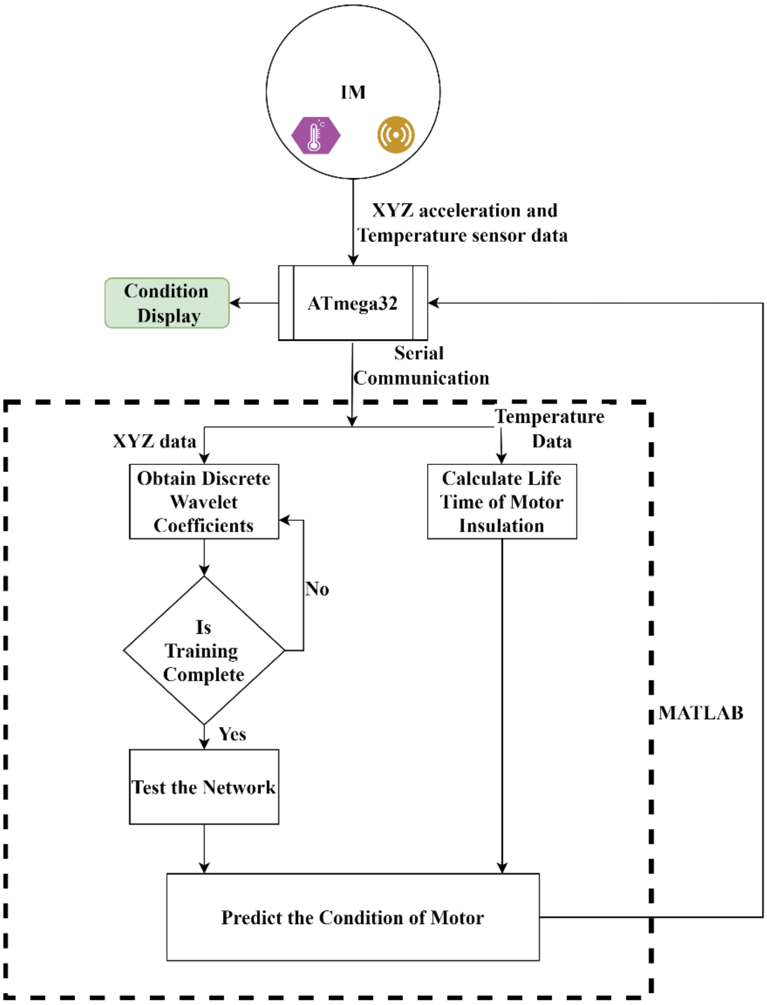


Fig. 2. Flow chart of proposed system

The sub-bands containing high-frequency are detailed band coefficients, and sub-bands with low frequency are approximation band coefficients. The approximation coefficients are further decomposed to extract localized information about detail coefficients. The analyzed signal gives both approximate and detailed coefficients represented as a_0 and d_0 to d_9 respectively.

The obtained wavelet coefficients are from the level 1 to level 9. The feature extraction of signals includes a few steps. The vibration signals obtained are divided into four individual sub-bands using Discrete Wavelet Transform as given in (7)-(8). The sub-bands containing high-frequency are detailed band coefficients, and sub-bands with low frequency are approximation band coefficients. The approximation coefficients are further decomposed to extract localized information about detail coefficients.

$$\left[[W_{\psi}f](s,\tau) = \frac{1}{\sqrt{|s|}} \int_{-\alpha}^{\alpha} \overline{\psi(\frac{t-\tau}{s}} f(t) \right] \tag{7}$$

$$dwt(j,k) = 2^{-\frac{j}{2}} \int \psi(s^{-j}x - k\tau) \tag{8}$$

where $s > 1$, $\tau > 0$ and j, $k \; \varepsilon \; Z$. DWT is defined as the transformation of the square-integral function, f. The bar above function, Ψ series, stands for conjugation. For the given s and τ, the transform result is a single real number, a wavelet coefficient.

Each level separates the frequency of the signal by '2n' times. This gives the frequency feature of the signal. These coefficients are obtained for all the conditions of the motor and used as the input to the neural network for training and testing purpose [29].

2.4. Optimization

A neural network is a mathematical system modeled by the framework, processing technique, and learning ability of a biological neuron. ANN gathers its knowledge by detecting the patterns and relationships in data. They learn or train through experiences, not from programming. The ANN is preferred because of its massive parallelism, their ability to learn, distributed representation, generalization ability, and fault tolerance. ANN is characterized by many simple processing elements that are neuron-like in nature, many weighted connections between these elements, and the acquisition of a distributed representation of knowledge over these connections and knowledge through a learning process [30].

The neural network comprises an input layer with 300 neurons corresponding to the extracted wavelet coefficients. The hidden layers consist of 10 neurons each, utilizing sigmoid. The output layer has 3 neurons representing the three classes: good, allowable, and not permissible as shown in Fig. 3. The neural networks predict the exact working condition of the motor [32], [33]. The results are validated as per ISO 10816 standard [34].

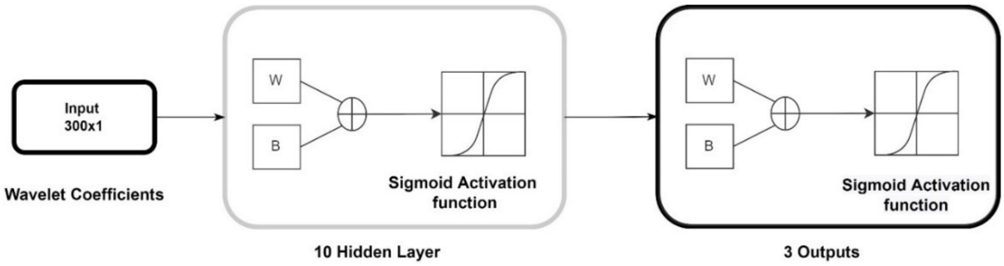


Fig. 3. Architecture of neural network

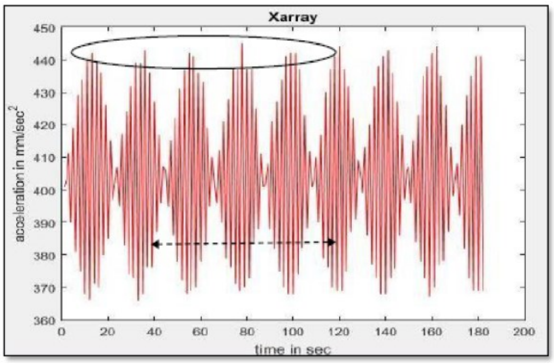
The numerical coefficients are collected and formed into a dataset array in MATLAB. These arrays play the role of inputs in the neural network. The wavelet coefficients which are extracted from the wavelet transform used to train the neural. The dataset is created in order to train the neural and for the particular dataset, targets are also given. The neural network is trained using the Levenberg-Marquardt algorithm with an 80:20 split for training, and testing datasets. The Mean Squared Error (MSE) is used to evaluate the performance of the trained model [31].

3. Results and Discussion

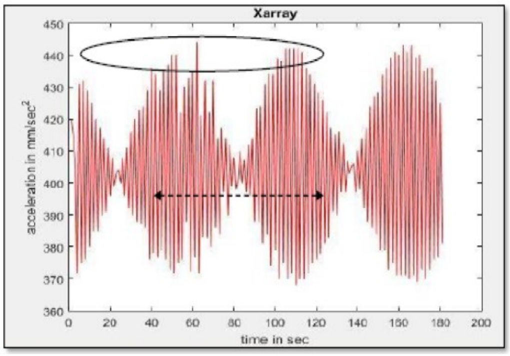
These values are collected for different conditions of motor such as good, allowable and not permissible as per ISO 10816 standard. The good condition indicates that the motor runs perfectly well without any vibrations, in allowable condition the motor have some vibrations but it doesn't affect the performance and life of the motor. In not permissible condition, the motor vibrates to the greater extent which damages the windings and may even reduce the life of the motor. The amplitude of the signals is plotted in a graph as amplitude vs. time basis as shown in Fig. 4. They can be grouped as X-array, Y-array, and Z- array. The values of wavelet coefficients during good, allowable and not permissible condition are given in Table 1. During not permissible condition, the amplitude and frequency of vibration changes and also the temperature of the motor rises abruptly which may cause insulation failure. It is observed that the decomposed Daubechies orthogonal wavelets d2 and d3 in Y- array shows significant variations during good and not permissible conditions as shown in Fig. 5 and 6 respectively. During not permissible conditions there is rise in temperature of the motor and hence in addition to the vibration data, the temperature of the motor is also measured in degree Celsius for monitoring the condition of the motor. Decomposition of the Y-array original signal when the motor is in not permissible condition shown in Fig. 6.

Table 1. Coefficients of signals for fault prediction

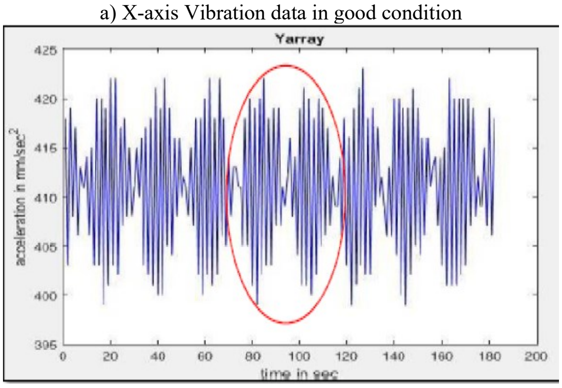
X_Good	3208.419	3210.171	3208.794	3210.222	3209.046	320.888	3209.265	3209.443	3208.586
X_Allowable	539.271	537.571	538.134	537.125	537.454	537.904	537.501	538.363	538.325
X_Not permissible	3301.281	3254.567	1.801	-3.075	-4.083	1.438	3.908	-4.391	-2.924
Y_ Good	3263.747	3263.747	3263.747	3263.747	3263.763	3264.276	3264.379	3263.736	3263.68
Y_ Allowable	539.271	537.571	538.134	537.125	537.454	537.904	537.501	538.363	538.325
Y_ Not permissible	3273.601	3272.045	3271.908	3271.438	-0.524	0.895	1.164	-0.406	-1.276
Z_ Good	3202	3199.967	3201.406	3200.645	3201.981	3200.144	3201.204	3200.792	3202.035
Z_ Allowable	539. 271	537. 571	538. 134	537. 125	537. 454	537. 904	537. 501	538. 363	538. 325
Z_ Not permissible	3185.514	3199.582	-2.417	3.739	4.248	1.082	0.002	3.780	2.934



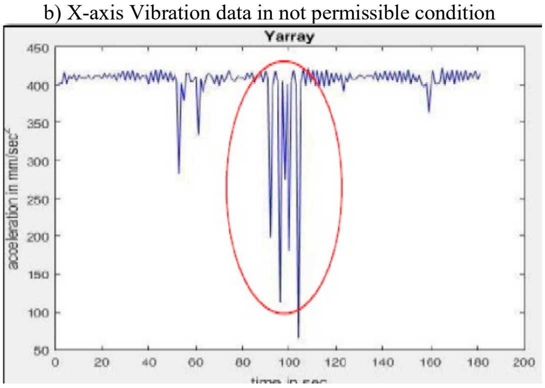
a) X-axis Vibration data in good condition



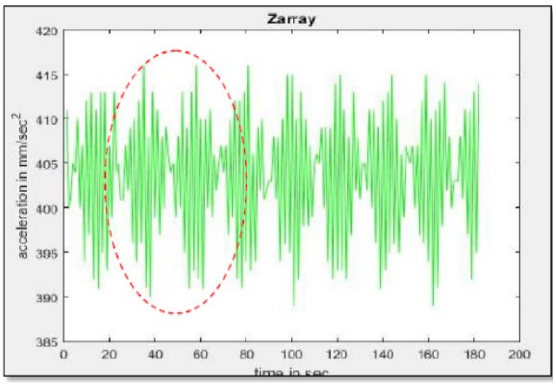
b) X-axis Vibration data in not permissible condition



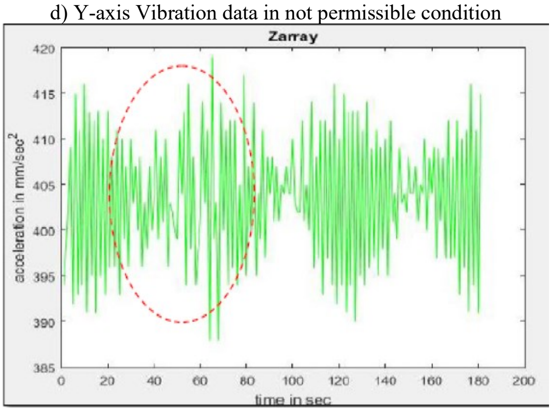
c) Y-axis Vibration data in good condition



d) Y-axis Vibration data in not permissible condition



e) Z-axis Vibration data in good condition



f) Z-axis Vibration data in not permissible condition

Fig. 4. Comparison of vibration data in different axes in good and not permissible conditions

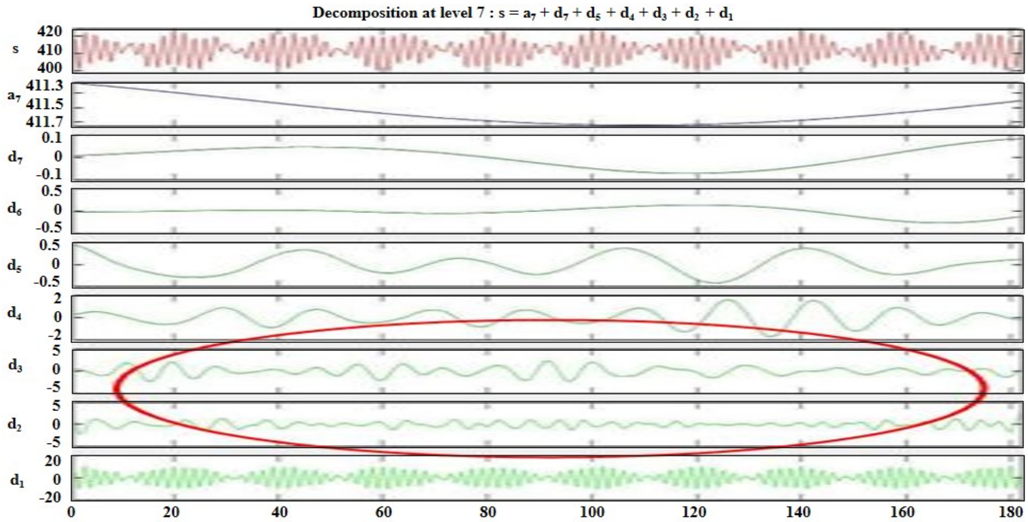


Fig. 5. Decomposition of the Y-array original signal when the motor is in good condition

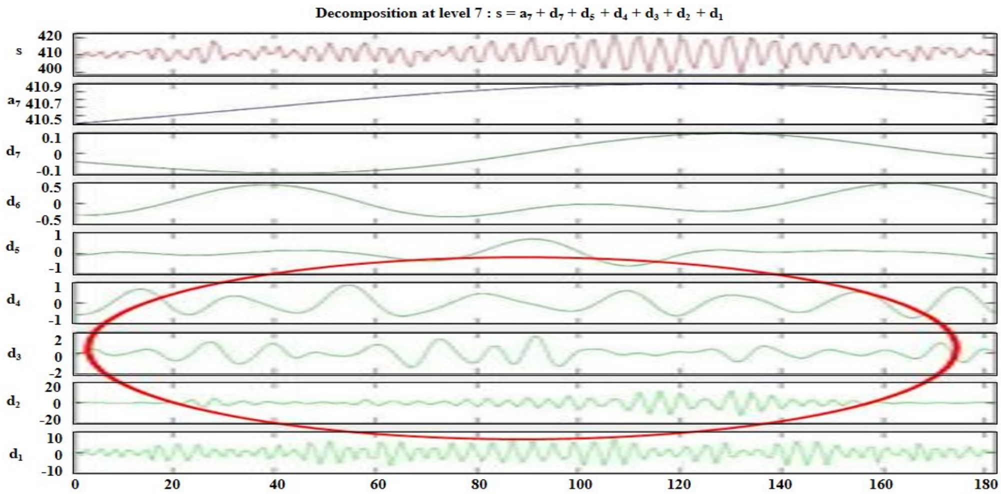


Fig. 6. Decomposition of the Y-array original signal when the motor is in not permissible condition

3.1. Results from Temperature Sensor

The temperature rise is associated with vibrations and faults occurring in the windings and other mechanical faults which lead to an increase in current magnitude. Increase in current causes more losses and temperature rise. The rise in hot spot temperature of the motor is associated with the insulation life [35]. The life of insulation can be predicted as given in (9) for less than rated load and for more than rated load is given by (10).

$$L_X = L_{100} \times 2\ exp\ \left[\frac{T_C - T_X}{HIC}\right] \tag{9}$$

$$L_X = \frac{L_{100}}{2\ exp\left[\frac{T_C - T_X}{HIC}\right]} \tag{10}$$

L_x represents the lifetime percentage at $x\%$ load, L_{100} represents the lifetime percentage at rated load, and Tc represents the total permitted temperature for insulating Class. T_x is the insulation Class hot-spot temperature, and HIC is the halving interval [36].

The hot spot temperature is measured using a temperature sensor and the readings are tabulated in Table 2 for various load conditions for duration of one hour. It can be observed that if load varies, the temperature also varies which can be used for estimating the lifetime of the motor.

Table 2. Temperature of the stator with various loads

LOAD	Temperature (Celsius)	
	Starting	Hot Spot Temperature
No load	28.18	60.28
¼ load	30.18	73.77
½ load	30.22	81.21
¾ load	30.98	94.63
Full load	31.23	104.9

The observed temperature variations under different load conditions have significant implications for motor health. The rise in temperature, particularly at higher loads, is indicative of potential faults and can be utilized to estimate the remaining lifetime of the motor's insulation, aligning with IEEE Std 1-2000 standards [37].

The accuracy of the neural network model is 98%. The confusion matrix of the test data is shown in the Fig. 7. The proposed method performs good compared to methods as shown in Table 3.

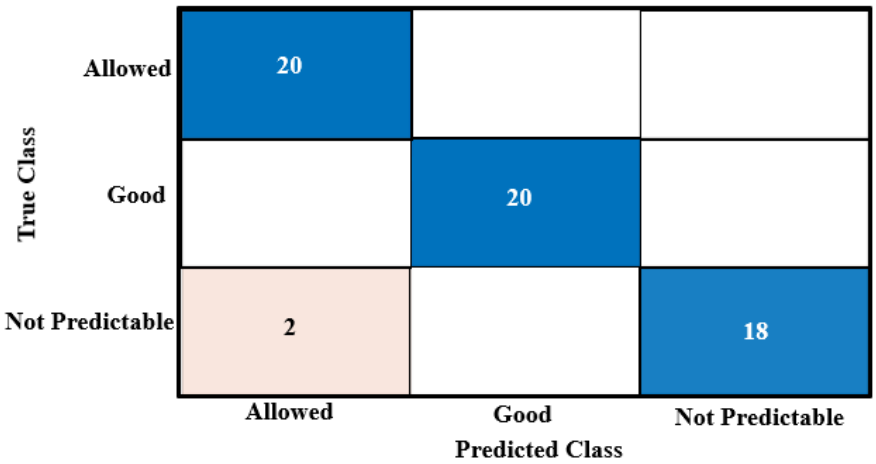


Fig. 7. Confusion matrix of the test data of proposed model

Table 3. Performance comparison

Schemes /References	Accuracy
Proposed	98%
CNN [38]	97.74%
CNN [39]	97.37%
CNN [40]	94.8%

4. Conclusion

Vibration analysis plays a significant role in finding the fault in the motor in advance by analyzing the vibration signal's frequency level. This proposed idea paves the way for easy monitoring of the motor's condition. In addition to vibration, the temperature of the motor is also monitored continuously. The data are continuously collected from the corresponding sensors and analyzed by MATLAB software. The faults occurring in the motor can be predicted using vibration as per ISO 10816 standard and the life time of insulator used can calculated by measuring temperature and verified using IEEE Std 1-2000 standard. In addition to this, the condition monitoring can be done by wireless communications using Internet of Things (IoT). The wireless technology will help in remote and online monitoring of faults from remote locations.

Furthermore, the integration of Internet of Things (IoT) technologies enables wireless communication for real-time monitoring from remote locations. This advancement not only enhances the accessibility of fault information but also opens avenues for proactive maintenance strategies. Exploring the scalability of this approach in larger industrial settings and its integration with emerging technologies may open new avenues for comprehensive motor health management. The implementation of this methodology not only enhances predictive maintenance capabilities but also holds the potential to significantly reduce downtime and associated costs. Industries adopting this approach may experience more proactive fault management and prolonged equipment lifespan.

Author Contribution: All authors contributed equally to the main contributor to this paper. All authors read and approved the final paper.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

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