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Fault Prognosis of Induction Motor Using Multi Resolution Current Signature Analysis

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ABSTRACT- There are various methods for the condition monitoring and this paper focuses on the multi resolution current signature analysis for fault prediction of induction motors. Variable frequency drives-based induction motors are used widely in industries. Monitoring the health of the motors is of great importance to reduce downtime and increase productivity. The multi resolution coefficients features from current signal are extracted using empirical wavelet transform. The extracted features are fed as input to artificial neural network to do prognosis on the data obtained for finding the condition of the motor. Hall Effect based system is used to measure the current signal and the features are extracted and trained to predict the condition of system using MATLAB in real time. The experimental findings reveal that the suggested technique achieves better accuracy in induction motor fault prognosis.

Keywords: Fault Prediction, Neural Network, Wavelet Transform, Multi Resolution Empirical Wavelet Transform, MATLAB.

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1. INTRODUCTION

A significant number of industrial applications use induction motors as the driving mechanism. Failure of these induction motors leads to failure of the mechanical system and cause downtime in industry and affects productivity. Monitoring the condition of the induction motor is essential for increasing the system's efficacy. The diagnostics of fault in induction motor can be made online to ensure safe operation [1].

The faults occur in the mechanical driving system or in the induction motor. The faults in mechanical system are owing to the irregularities in the air-gap, failures in the gearbox or driving system, defect in shaft [2]. The motor faults can be classified based on the fault on the stator side or rotor side. The broken bar fault on squirrel cage rotor, cracks in end ring, faulty bearings or faults in stator winding or failure of insulation are predominant faults that occur. These faults occurring in the system leads to increase in current taken by the stator winding, increases vibration of the system and produces different acoustics signals [3].

The prognosis of faults is performed by measuring the vibrations, change in acoustics of the system, and change in temperature or by change in current signatures [4]. Analysis of the change in acoustic signal between a healthy and defective motor leads to predict the occurrence of a fault. The spectrum of acoustic signal varies for different types of faults [5]. Similarly, the faults occurred induces mechanical vibrations into the system and analysing the vibration signals can be used for fault prediction. The most significant drawback of these techniques is that they are only effective for diagnosing mechanically induced defects. Even though conventional methods of fault prognosis are used for fault diagnosis, they have drawbacks of being costlier due the usage of vibration analyser and precise sound sensors and effective algorithms for processing of the sound signals to find the faults [6]. The placement of sensors affects the prediction of faults and sensors need to be embedded inside the motor. The faults occurred owing to the winding or flux changes are not analysed by these methods [7].

In this paper the faults occurring in an induction motor are predicted early by Motor Current Signature Analysis (MCSA). This technique is a non-invasive technique for predicting the faults and current is measured from the input line to the stator winding [8]. The change in profile of current waveform is instantaneous and dynamic to the changes in fault or load that has occurred. The fault that has occurred mechanically or electrically will cause in change in current and this can be used for accurate prognosis [9]

MCSA determines the frequency component associated with the working of healthy motor and finds the fault occurring in the motor for which the frequency band lies outside this range. The reliability of MCSA depends on the quality of data extracted. The data can be influenced by electrical noises, varying operating conditions such as load variation and speed changes. These affect the fault prediction accuracy. The fault identification process involves stages of feature extraction from

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the current waveform to process the signal using techniques for signal processing and to classify and recognize the pattern for the fault [10].

The frequency of signals obtained are processed using fast Fourier transform, multiple signal classification method, statistical methods, Welch method, regressive model, entropy-based classification, principle component analysis and wavelet transforms are widely used for the generating the patterns for different working conditions of the motor. The recognition of faults using patterns obtained are being done by using artificial neural network, fuzzy logic, optimization techniques, support vector machines [11]. The high sensitivity and specificity of the model ensures early prediction of bearing faults and avoiding false predictions.

In this paper, Empirical Wavelet Transformation (EWT) is used for processing the input current waveform and artificial neural network is used for pattern recognition of fault. EWT has improved time frequency resolution, suited for nonlinear and non-stationary signals. The bearing faults occur due to wear and tear and this causes fissures in the bearing leading to excessive vibrations. This fault is analysed at initial stages for failure based on the current signature analysis.

2. METHODOLOGY

Hall effect based current sensors are utilized for current measurement in the stator winding from the supply mains, where voltage is generated in direct proportion to current. This sensor provides more accurate results compared to shunt resistors or current transformers [12]. The sensor has a bandwidth of 80 kHz and sensitivity of 185 mV/A of current, the motor has peak current of 11 A. The sampling rate of 15 kilo samples per second. The input obtained in time domain has to be converted into frequency domain for further processing. FFT analysis can be done but has drawbacks of sensing the instant change in input signal. Wavelet transform analyzes the signal, which are nonlinear and can identify instantaneous changes in input. In continuous wavelet transform, the mother wavelet is further divided to multiple wavelet coefficients to increase the resolution of the input [13]. Then discrete wavelet transform is used discretize the continuous scaling function and displacement functions to discrete wavelets.

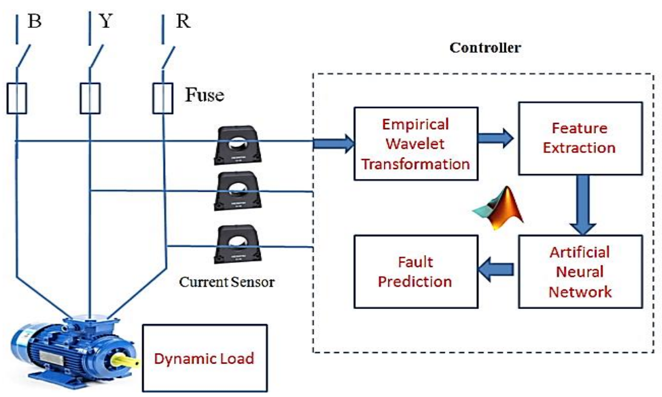


Figure 1. Block Diagram of Proposed System

Figure. 1 shows the block diagram of the proposed system in which the three phase currents are measured using Hall Effect sensors. The drawback of using wavelet transformation for decomposition of time frequency signal is that rapid changes in input parameters cannot be detected accurately and the sensitivity to noises, time consuming are limitations for using CWT [14]. In CWT, the cutoff frequency is constant for all the decomposition signals. The proposed EWT technique for fault prognosis is adaptive to change in input condition, and can process non- linear, non-stationary signal and is less time consuming. The cut-off frequency signals are not constant and varies based on the input signal applied.

2.1 Empirical Wavelet Transform

In FFT algorithm, the cut-off frequency is obtained by marking the local maxima based on the number of decomposition levels and the mid-points between the maxima whereas in EWT the input signal $i(t)$ is decomposed into intrinsic mode sub signal $in(t)$ and mean residue $mr(t)$. [15 - 17]

$$i(t) = \sum_{i=1}^{N} in(t) + mr(t) \tag{1}$$

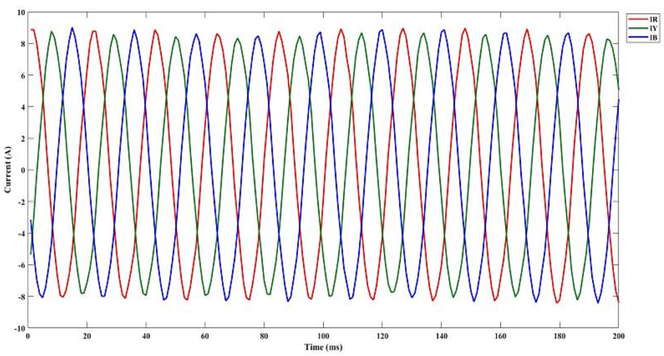
EWT decomposes the signals the main signal into sub-signal $is(t)$, which is being modulated in both frequency and amplitude.

$$i(t) = \sum_{i=1}^{N} is(t) \tag{2}$$

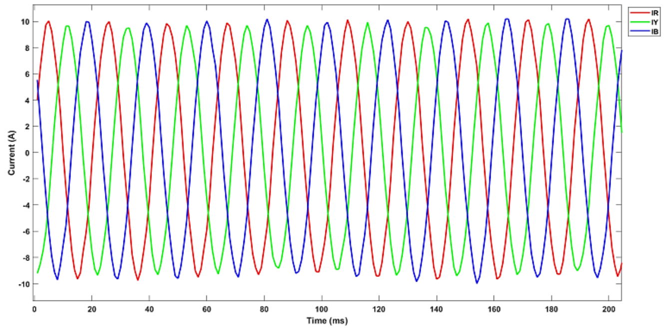
$$is(t) = K_i(t)\cos(\emptyset_i(t)) \tag{3}$$

Segmenting based on the Fourier spectrum makes it possible to isolate amplitude and frequency components, and then extract the wavelet filter bank in the center of the local maxima. The empirical functions for wavelet and scaling function are given by the *equations (4) -(5.)*

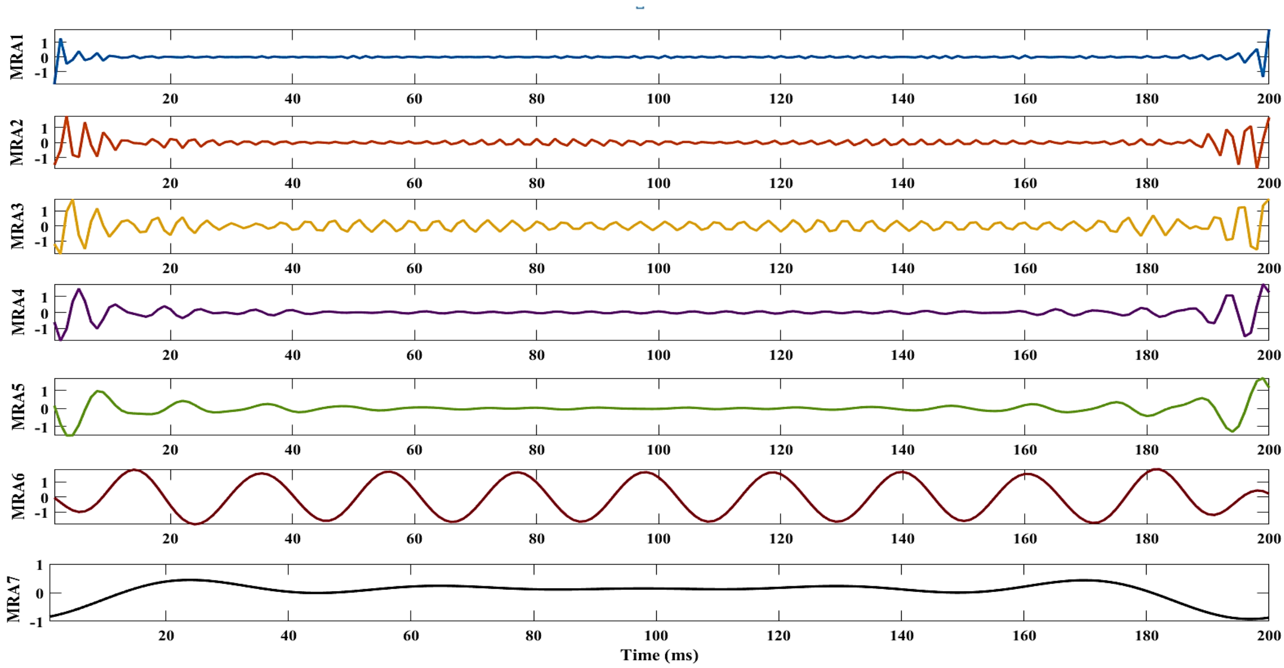
$$\vartheta_n(\omega) = \begin{cases} 1, & if\ |\omega| \le (1-\gamma)\omega_n \\ \cos\left[\frac{\pi}{2}\beta\left(\frac{1}{2\gamma\omega_n}(|\omega| - (1-\gamma)\omega_n)\right)\right] & \\ if\ (1-\gamma)\omega_n \le |\omega| \le (1+\gamma)\omega_n & \\ 0, & otherwise \end{cases} \tag{4}$$



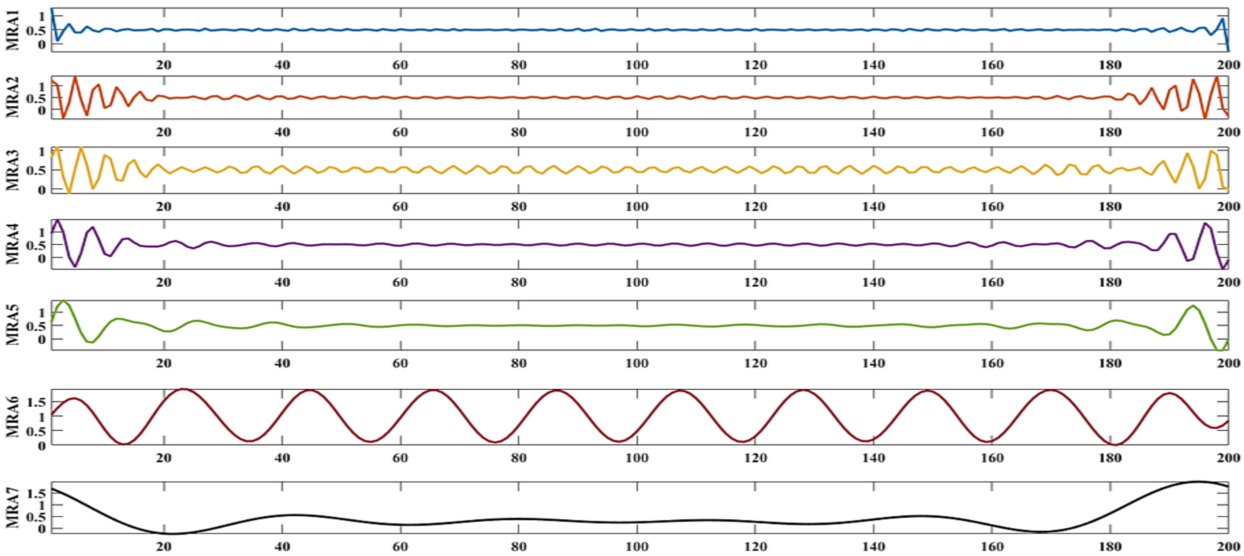
(a) Three-phase line current plot under normal operating condition



(b) Three-phase line current plot under faulty operating condition



(c) Current Signature Analysis using Multi-resolution Analysis of Empirical Wavelet under normal operating conditions



(d) Current Signature Analysis using Multi-resolution Analysis of Empirical Wavelet under Faulty operating conditions

Figure 2. Analysis of Current Waveform

$$\Psi_n(\omega) = \begin{cases} & if\ (1+\gamma)\omega_n \le |\omega| \le (1-\gamma)\omega_{n+1} \\ \cos\left[\frac{\pi}{2}\beta\left(\frac{1}{2\gamma\omega_{n+1}}(|\omega| - (1-\gamma)\omega_{n+1})\right)\right] & \\ & if\ (1-\gamma)\omega_{n+1} \le |\omega| \le (1+\gamma)\omega_n + 1 \\ \sin\left[\frac{\pi}{2}\beta\left(\frac{1}{2\gamma\omega_n}(|\omega| - (1-\gamma)\omega_n)\right)\right] & \\ & if\ (1-\gamma)\omega_n \le |\omega| \le (1+\gamma)\omega_n \\ 0, & otherwise \end{cases} \quad (5)$$

$$W_h^\epsilon(n,\tau) = \langle h, \Psi_n \rangle = \int h(\tau)\overline{\Psi_n(\tau - t)}\, d\tau \quad (6)$$

$$W_h^\epsilon(n,\tau) = \langle h, \Psi_n \rangle = \left(\hat{h}(\omega), \overline{\widehat{\Psi_n}(\omega)}\right)^v \quad (7)$$

$$W_h^\epsilon(0,t) = \langle h, \emptyset_1 \rangle = \int h(\tau)\overline{\emptyset_1(\tau - t)}\, d\tau \quad (8)$$

$$W_h^\epsilon(0,t) = \langle h, \emptyset_1 \rangle = \left(\hat{h}(\omega), \overline{\widehat{\emptyset_1}(\omega)}\right)^v \quad (9)$$

The adaptive decomposition result of the EWT Method depends on the accuracy of the spectral segmentation of the Fourier transform. Modes that operate on a narrow frequency range correspond to specific spectral regions. Inner products with empirical wavelets provide the detail coefficients and with scaling functions to provide the approximate coefficient as given in *equations (6)-(9).*

3. RESULTS AND DISCUSSION

The experiment was performed on three-phase, 5 HP, 415 V, slip ring induction motor coupled to a mechanical load through a belt pulley arrangement. Three Hall Effect sensors and data acquisition system were used for simultaneous measurement of the three-phase currents. The data was acquired by running the motor at rated load with normal and faulty bearings.

Figure. 2 (a) and *figure. 2(b)* shows the current plot for three phases measured in normal operating conditions and under influence of faulty bearing. *Figure. 2 (c) and figure. 2 (d)* shows the multi-resolution empirical wavelet analysis for one phase of the measured current. The sampling of data is done 20 times with a scan length of five seconds, under normal and faulty bearing operating conditions. The *Table 1* shows the pseudo-code of the proposed work.

Table 1: Pseudo-code

Log the current signal
Read the current signal of three-phase in MATLAB
Apply EWT to extract multi resolution features
Train the data using Neural network tool box until desirable accuracy is obtained
Export the trained model
Predict the condition of motor using the test data

In order to perform a multi-resolution analysis (MRA), the EWT employs an adaptive wavelet subdivision strategy. Using MRA, the signal is decomposed into smaller, time-independent segments, or frequency bands, such that the whole may be reconstructed from the sum of its elements. The current signal is split into MRA components based on the filter pass-bands determined using seven largest peaks. EWT extracts the suitable features for change in signal patterns compared to traditional wavelet methods.

These MRA components are used as features to train the neural network to classify the normal and faulty operating conditions [18-19]. Ten cycles of the current waveform are used to create feature vector of length 1200, which consists of the fifth and seventh component of MRA signals of three-phases. The dataset comprises of 1000 x 1200 points, in this 80 % (800 x 1200) of data is used for training and 20 % (200 x 1200) is used for testing. *Figure 3* depicts the neural network, which consists of 125 hidden layers. The proposed system has sensitivity and specificity of 0.99 and 0.97 and has high accuracy of 0.98. The ANN input layer has 1200 neurons corresponding to the extracted EWT features. There are 125 hidden layers and one output layer.

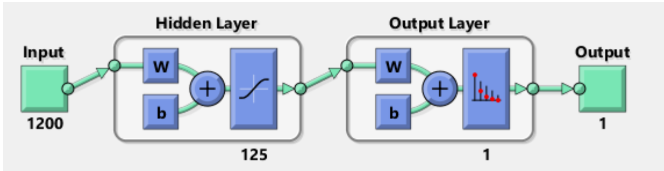


Figure. 3 Neural Network Structure

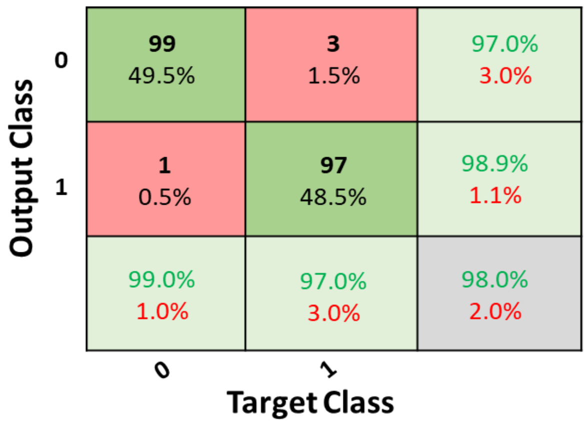


Figure. 4. Confusion matrix

Table 2: Performance Comparison

Schemes / References	Accuracy
Proposed EWT	98 %
SVM	90 %
CNN [20]	97.74 %
CNN [21]	97.37 %
CNN [22]	94.8 %

Figure. 4 depicts the confusion matrix, which is trained and tested. The system has predicted 99 % true positive conditions and 97 % as true negative conditions. The sensitivity and specificity are 99 % and 97 % respectively with an overall accuracy of 98 %. The adaptive feature extraction of EWT and fault pattern recognition of ANN has improved the system accuracy. *Table 2* shows the comparison the proposed system with existing techniques explained in literature.

4. CONCLUSION

This paper has presented the bearing fault prediction of induction motor by extracting features using multi-resolution empirical wavelet transform and predication of fault is performed using neural networks. The current signal of the motor is considered for normal and faulty operating conditions. This method has an accuracy of 98 % for predicting the fault condition of motor. The proposed system is validated for ISO 10816 standard. The approach is also applicable for prediction of different mechanical and electrical fault conditions by employing only the current sensor. The proposed system can predict multiple faults occurring in induction motor at reduced cost and easy placement of current sensors. The system is adaptable for use with multi-motor machines by training the appropriate machine data. The ensemble-based ANN model can be used to improve accuracy and robustness. The proposed system can integrate with Internet of Things (IoT) enabling real-time monitoring from remote locations.

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