Artificial neural network-based induction motor fault classifier using continuous wavelet transform

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Induction motors are used in industrial, commercial and residential applications because they have considerable merits over other types of electric motors. These motors are used in various operating stresses that give rise to faults. Most recurrent faults in induction motors are bearing faults, stator interturn faults and cracked rotor bars. Early detection of induction motor faults is crucial for their reliable and economical operation. This could be done by motor monitoring, incipient fault detection and diagnosis. In many situations, failure of critically loaded machine can shut down an entire industry process. This growing demand for high-quality and low-cost production has increased the need for automated manufacturing systems with effective monitoring and control capabilities. Condition monitoring and fault diagnosis of an induction motor are of great importance in the production line. It can reduce the cost of maintenance and risk of unexpected failures by allowing the early detection of catastrophic failures. This work documents experimental results for multiple fault detection in induction motors using signal-processing and artificial neural network-based approaches. Motor line currents recorded under various fault conditions were analyzed using continuous wavelet transform. A feedforward neural network was used for fault characterization based on fault features extracted using continuous wavelet transform.

Keywords: artificial neural networks; continuous wavelet transform; induction motor; multiple fault detection

1. Introduction

Induction motor being a principal component in most of the industrial processes, any failure in the machine affects the industries. To reduce the downtime and also for safety consideration, early detection of motor faults is highly desirable which requires condition-based monitoring of the induction motor. Major faults in the induction motor include bearing faults, stator winding faults and rotor faults. Bearing faults are responsible for approximately one-fifth of all faults. Interturn short circuit in the stator winding contributes to nearly one-third of reported faults. Broken rotor bar and end ring faults represent around 10\% of induction motor faults. The major issue concerning machine condition monitoring is machine fault diagnosis. Diagnosis refers to the determination of current ‘health’ status or working condition of the motor being monitored. A reliable diagnosis technique along with reducing the risks of unexpected machine breakdowns also helps in prolonging machine’s life. Due to this the current trend in the industry is towards condition-based preventive and proactive maintenance.

The major component of a condition-based monitoring system includes the machinery, condition-monitoring sensors, signal processors, fault classifiers, machine models and monitoring output. Errors and uncertainties in fault classification can lead to false indication which motivates the researchers to come up with a more robust and reliable condition-monitoring system.

In the present competitive market scenario, condition-based maintenance and efficient fault monitoring are gaining more importance over scheduled maintenance and routine monitoring. Many engineers and researchers have focused their attention on incipient fault detection and preventive maintenance in recent years. Different methodologies based on current and vibration spectral analysis have been proposed using Fourier transform and wavelet transform for induction motor preventive monitoring of specific faults. Most conventional methods of detecting bearing faults, rotor faults are based on the spectrum analysis of motor voltage, current and instantaneous input power (Didier et al., 2004; Liu, Yin, Zhang, & Chen, 2004). Currently, the diagnosis of induction motor uses the modern measurement techniques, data-processing techniques and spectral analysis techniques. The most commonly used fault-related feature extraction technique is Fourier spectral analysis by FFT (Benbouzid, Viera, & Theys, 1999). Barrios (1997), Gallardo (1996) and González (1998) have developed a phenomenological model to simulate broken...
bars in the rotor of an induction motor. For diagnosing stator interturn fault in three-phase induction motors using Park’s vector technique is described in Cardoso, Cruz, and Fonseca (1999). Induction motor with stator interturn fault is represented as an unsymmetrical three-phase system. In the power system, an unsymmetrical three-phase system can be modeled as a combination of three symmetrical systems, namely, positive, negative and zero sequence. Most researchers have attempted to detect interturn fault by means of calculating negative sequence current (Kliman, Premerlani, Koegl, & Hoeweler, 1996; Kohler, Sotty, & Trutt, 1992) and negative and zero sequence impedances (Lee, Tallan, & Habetler, 2003; Sotty and Kohler, 1992). The interturn fault diagnostic method based on the pendulous oscillation concept has been introduced in Mirafzal, Povinelli, and Demerdash (2006). Different approaches for motor incipient fault detection and diagnosis have been successfully proposed (Acosta, Verucchi, & Gelso, 2006; Ballal, Khan, Suryawanshi, & Sonolikar, 2007; Bouied, Seddiki, Guelton, & Akdag, 2014; Faiz, Ebrahimis, Akin, & Toliyat, 2008; Farahani, Zare Bidaki, & Enshaeieh, 2014). Most of these techniques involve vibration analysis and stator current analysis because they are easy to measure and are highly reliable. However, vibration analysis requires expensive sensors and special signal-processing tools. In the current monitoring technique, no additional sensors are required. Because voltage and current signals are the basic quantities associated with the electric machines and are readily measured with the help of potential and current transformers that are already installed in the protection system. In the proposed work, current signals are considered for induction motor fault diagnosis.

With the development of Artificial Intelligence (AI) systems, expert systems based on neural network, fuzzy logic have been employed in order to assist the fault detection task for correctly interpreting the faulty data (Filippetti, Franceschini, Tassoni, & Vas, 2004; Tung, Yang, Oh, & Tan, 2009; Yang, Han, & Sukin, 2004). Thus, it can be summarized that there are countless techniques for diagnosis of specific induction motor faults, most of them performed offline, arising the necessity for a generalized technique that allows online multiple fault detection.

Popularity and widespread use of many modern fault diagnosis techniques are hindered by cost and computational complexities and require the use of accurate, effective, economically viable technique that uses available monitoring devices, combined with modern signal conditioning and data-processing tools for monitoring faults in an induction motor. Therefore, a low-cost online non-destructive fault diagnosis and detection system is demanded to provide accurate assessment of motor faults.

The proposed work presents experimental results for detection of multiple faults in an induction motor. The algorithm proposed can be effectively implemented for online fault diagnosis. Signal processing is an important issue in machine condition monitoring. This includes time domain, frequency domain and time, frequency domain analyses. Since time domain and frequency domain analyses are limited to the analysis of stationary signals under a sinusoidal power supply condition. Whereas wavelet transform can be effective in analyzing stationary and non-stationary signals under a non-sinusoidal supply condition.

Wavelet transform is a kind of effective time frequency-processing tool, among them continuous wavelet transform (CWT) has superiorities of random wavelet base selection, finer time-scale resolution and time invariance. In this research work, CWT is proposed for feature extraction. CWT can give the user to analyze the signal at any scale, at any time translation. Any wavelet that satisfies the minimum criteria can be used for feature extraction and easily detects direction and orientation. In the present work the Morlet wavelet is used for feature extraction. The CWT approach applies to the motor current signals recorded with the help of the data acquisition system for healthy and various fault conditions such as stator interturn, bearing fault and rotor bar crack. Minimum values of CWT coefficients are selected as inputs to the artificial neural network (ANN). The ANN is a functional imitation of the brain, which simulates the human decision and draws conclusions, even when presented with complex noisy irrelevant information. The obtained results demonstrate the suitability of the proposed technique for multiple fault detection in an induction motor achieving 100% accuracy.

2.  Continuous wavelet transform

The use of wavelet transform is particularly appropriate since it gives information about the signal in frequency and time domain. Let \( f(x) \) be the signal, the CWT of \( f(x) \) is then defined as

\[
W_f(a, b) = \int_{-\infty}^{\infty} f(x) \psi_{ab}(x) \, dx,
\]

where (*) indicates the complex conjugate

\[
\psi_{ab}(x) = \frac{1}{\sqrt{|a|}} \psi \left( \frac{x - b}{a} \right) \quad a, b \in \mathbb{R}, \; a \neq 0. \tag{2}
\]

And it provides the admissibility condition as follows:

\[
C_\psi = \int_{0}^{\infty} \frac{|\psi(\omega)|^2}{\omega} \, d\omega < \infty. \tag{3}
\]

And for this reason

\[
\int_{-\infty}^{\infty} \psi(x) \, dx = 0. \tag{4}
\]

Here, \( \psi(\omega) \) is the Fourier transform of \( \psi(x) \). The admissibility condition implies that the Fourier transform of \( \psi(x) \) vanishes at zero frequency. Therefore, \( \psi \) is called
as a wave or the mother wavelet and it has two characteristics parameters dilation \(a\) and translation \(b\) which vary continuously. Translation \(b\) controls the position of wavelet in time. A narrow wavelet can access high-frequency information, whereas a more dilated wavelet can access low-frequency information, which means that parameter \(a\) varies with different frequencies.

3. Neural network classifier

The ANN represents information-processing systems formed by interconnecting simple-processing units called neurons. Each neuron is an independent processing unit that transforms its input data via a function called activation function. The connections between neurons are characterized by weight values that represent the memory of the network. By modifying these weights according to some learning rule, the ANN can be trained to recognize any pattern giving the training data. The network architecture plays a very important role in the performance of ANN and usually depends on the problem at hand. Several types of neural network structures have been proposed in the literature (Filippetti et al., 2004; Tung et al., 2009) for diagnosis purposes, the most popular one is the multilayer perceptron which is used in the present study. This network with a simple architecture may be used for both modeling and classification tasks. The layers are fully interconnected in one direction from the input layer towards the output layer. The number of neurons in the input and output layers is governed by the number of inputs and outputs of the pattern to be recognized. However, the number of neurons in the middle layer can be selected depending upon the applications. Input patterns are exposed to the network whose output is compared with the target values to calculate the error which is corrected in the next pass by adjusting the synaptic weights.

In the proposed work, a three-layer feedforward neural network is selected for fault diagnosis of an induction motor as this problem of fault diagnosis is likely a highly complex nonlinear mapping problem because both the inputs and outputs are multiple variables without clear linear relationships.

A three-layer feedforward network has proven to have the capability of approximating any function regardless of its complexity. Figure 1 shows the architecture of a feedforward neural network.

4. Experimental study and data collection

Experimental studies have been performed on 2 H.P. three-phase, four-pole, 415 V; 50 Hz squirrel cage induction motor. The experimental setup for the same is shown in Figure 2. Motor used for the experiment has 24 coils, 36 slots in all. Each phase comprises 8 coils carries 300 turns. A phase has been tapped where each tapping is made after 10 turns, near to the star point (neutral). Tapings are drawn from coils where each group comprises
approximately 70–80 turns. Spring and belt arrangement is used for mechanical loading of the motor. The motor was loaded at 75% of full load to full load conditions. To acquire the data, the Tektronix DSO, TPS 2014 B, with 100 MHz bandwidth and an adjustable sampling rate of 1 GHz is used to capture the current and voltage signals. The Tektronix current probes of rating 100 mV/A, input range of 0–70 Amps AC RMS, 100A peak and frequency range DC to 100 kHz are used to acquire the stator current signals. Approximately, 500 sets of signals were captured at different load conditions and at different main supply conditions for the following case studies.

4.1. Healthy

2 H.P motor is fed by three-phase balanced supply load on the motor is varied from 75% of full load to full load with spring and belt arrangement. Stator current signals and phase voltages are captured for no load 75% of full load and at full load conditions.

4.2. Bearing defects (inner and outer race)

Motor under test comprises two bearing numbers 6204 and 6205. Bearings having natural defects caused by regular operation of motor are used in experimental studies. The motor is fitted with different combinations of bearings having an inner race or outer race defects. Stator currents and voltages for each combination of bearing are captured to compare it with the healthy bearing condition. Different experiments were conducted with different combinations of rear side and load side bearings to assess the performance of bearings and its effect on the performance of the motor.

4.3. Stator interturn short circuit

In this case of study, stator windings of induction motor were modified to have several accessible tapings that can be used to introduce short circuits. For this experimentation phase A is tapped, where each tapping is made after 10 turns. Different experimentations were conducted with 10 turns, 20 turns and 30 turns short circuited in phase A of motor and for different loading conditions phase voltage and stator current signals are captured.

4.4. Broken rotor bars

The induction motor under test has 32 rotor bars, to carry out the rotor broken bar test, two rotor bars are broken.
Figure 4. (a): CWT spectrum for Healthy condition. (b) CWT spectrum for bearing fault. (c) CWT spectrum for interturn fault. (d) CWT spectrum for rotor bar crack.

Figure 5. Feedforward artificial neural network.

on both sides of end rings and stator current signals are captured at different loading conditions.

Figure 3(a)–(d) shows the stator current signals recorded from the motor terminals at full load during normal and under various fault conditions.

5. Feature extraction using CWT

Current signals recorded for abnormal conditions of motor are similar to normal motor signals, thus data acquired in time domain that do not reveal any information that can be used for fault detection. There is a need to come up with feature extraction. The nonstationary nature of fault signals encouraged the use of CWT to be used in this work. The CWT has been effectively used in time frequency transformations of nonstationary waves in the power system for fault diagnosis. Choosing a proper wavelet family is very important. If an improper wavelet family is chosen, it will make the wavelet transform complex and difficult. In the present study, the Morlet wavelet is selected as it has the best time frequency localization in the sense specified by the Heisenberg uncertainty principle. Current signals recorded under normal and various fault conditions of induction motor are used to get CWT spectra as shown in Figure 4. These CWT spectra are obtained at different scales such as 10, 20, 30, 40 and 50. These scale levels are found after a number of tests to get distinctive attributes from analyzing signals. There are certainly observable differences among CWT plots of healthy and faulty motor conditions. This is also reflected in minimum values of CWT coefficients. The minimum value of these coefficients is computed and fed as an input to the ANN for classifying the different faults.

6. Results and discussion

An ANN with its excellent pattern recognition capabilities can be effectively employed for the fault classification of an induction motor. In this paper, three-layer FFANN is used and trained with a supervised learning algorithm called
Table 1. Comparative analysis of artificial neural networks with various transfer functions for 7 PE.

| S. no. | Transfer function | Percentage classification accuracy (%) |
|--------|-------------------|----------------------------------------|
| 01     | Sigmoid Axon      | 69                                     |
| 02     | Linear TanhAxon   | 80.25                                  |
| 03     | SoftMax Axon      | 83.75                                  |
| 04     | BiasAxon          | 95                                     |
| 05     | TanhAxon          | 100                                    |

For generalization, randomized data are fed to the network. Various transfer functions such as TanhAxon, Sigmoid Axon, Linear TanhAxon and SoftMaxAxon are used for training the network and percentage accuracy of classification is obtained. For all transfer functions, the considered network is trained with maximum epochs of 100, training data assumed is 60%, testing data, 40% step size = 0.1 and momentum of 0.7. The minimum squared error is considered as a discriminating factor for the classification of different conditions of the motor. With these assumptions the percentage accuracy of classification for induction motor under healthy, bearing fault, interturn fault and broken rotor bar conditions with respect to the number of processing elements in the hidden layer is obtained. Figure 5 represents the feedforward neural network used for fault classification. Table 1 gives the comparative analysis of classification accuracy obtained with various transfer functions. Figure 6(a) shows variations of percentage accuracy of classification with respect to the number of processing elements.
elements in the hidden layer for the Sigmoid Axon transfer function. From the figure, it is apparent that for seven processing elements the average percentage accuracy of classification obtained is 69%. Figure 6(b) shows variations of percentage accuracy of classification for the linear TanhAxon transfer function. With seven number of processing elements in the hidden layer, the percentage accuracy of classification obtained is 80.25%. From Figure 6(c) and 6(d), it is seen that with SoftMaxAxon and the Bias Axon transfer function the average percentage accuracy of classification for seven processing elements is 83.75% and 95%, respectively. From Figure 6(e), it is seen that the TanhAxon transfer function with seven processing elements is capable of classifying induction motor faults with 100% accuracy.

7. Conclusion

This work proposes a CWT-based ANN approach for multiple fault classification in an induction motor, validating its effectiveness through different cases of study that considered the motor under diverse fault conditions such as faulty bearing, broken rotor bar and stator inter-turn fault. Line current signals recorded under normal and fault conditions are passed through a signal-processing technique. Subsequently, CWT is utilized to extract the features that derive rich information from stator current signals. Feedforward ANN with the momentum learning rule and TanhAxon transfer function and with seven processing elements in the hidden layer is the best network to classify multiple faults in an induction motor with 100% accuracy.

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