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Research Article

A Hybrid Technique for the Detection of Broken Rotor Bar of Induction Motor

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Abstract: A hybrid technique for diagnosing broken rotor bar fault of induction motor using Multi-Wavelet Transform (MWT) and radial basis neural network is presented. The stator currents of induction motor are preprocessed using multi-wavelet transform and the decomposed components are obtained. Then, these features are given as input to the neural network to identify fault. This paper compares the proposed hybrid technique with MWT-Feed Forward Neural Network (FFNN) and Discrete Wavelet Transform-FFNN techniques. These techniques are compared using the concept of classifier performance. From the simulation results, it is evident that the proposed method is superior to other methods with regard to objective proposed.

Keywords: Broken rotor bar, classifier performance, multiwavelet transform, radial basis neural network

INTRODUCTION

Squirrel cage induction motors are considered to be workhorse in number of industrial applications (Aderiano *et al*., 2008). Induction motors are used in hazardous locations and severe environments and for a variety of general purpose applications. High reliability, low maintenance and high efficiency are some of the characteristics of induction motors, which made them very popular. Induction motors are available in the range from hundreds of watts to megawatts. This range of power satisfies the production needs of a number of industries, which is also the reason for the popularity of induction motors (Jinjiang *et al*., 2012).

The most prevalent faults in AC induction motors are winding faults, unbalanced stator and rotor, broken rotor bar, Eccentricity and Bearing faults. Broken rotor bar fault in the Induction motor have to be monitored and diagnosed in industries which are using these motors. It is important to identify failure of induction motor before they become catastrophic because catastrophic failures often lead to cascading systems failure, which in turn may cause production shut downs. Such shutdowns result in the reduction in production time, wastage of raw materials, and increase in maintenance cost (Mirafzal and Demerdash, 2004). In the past three decades, there has been substantial amount of research to provide new condition monitoring techniques for ac induction motors. Current signals can easily be monitored for condition monitoring and control purposes. The stator current of Induction motor can be modulated by a number of factors. Vibrations caused by bearing defects and broken rotor bar are some of the factors (Shnibha *et al*., 2012). The non-stationary nature of the stator current of induction motor leads to the use of wavelet transform for condition monitoring. Wavelet transform and wavelet packet transform can provide better analysis under various conditions (Benbouzid, 2000).

The condition monitoring of electrical machines is increasingly becoming important asset management tool (Kathir *et al*., 2012). Broken rotor bars rarely cause immediate failures, especially in large multi-pole motor (Mehmet and Ilyas, 2011). In terms of condition monitoring, fault detection in motor is studied in two categories: steady-state condition and during start-up transient condition (Seyed and Majid, 2011). Broken rotor bars are one of the easiest induction motor faults to be detected using steady-state stator current condition monitoring. The diagnosis of rotor bar failures in induction machines by means of analysis of the stator current during startup transient conditions is illustrated in Didier *et al*. (2006).

The stator current of induction motor has rotor speed dependent component and saturation induced component. Damages in rotor create more amount of speed dependent component during the startup transient. The fault detection in induction machines using fuzzy and neural network techniques and digital signal processing techniques is explained in Jordi *et al*. (2011). From the review of related works, it can be realized that neuro-fuzzy and neural network (NN)-based fault detection schemes are performed well for large machines, but they are expensive and complex.

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The wavelet analysis is performed using a single prototype function called a wavelet. This function is analogous to the sine function that is used in Fourier transforms but is structured to suit transient applications (Mazur and Trojnar, 2003). The wavelet-based functions are tuned to specific fault frequencies taking into account motor speed and load torque.

The multiwavelet transform is the extension of wavelet transform which consists of multiple scaling functions. The multiwavelet transform will be used to extract the feature from stator current of the healthy and faulty induction motor. The multiwavelet transform is accurately decomposing the stator current signal when compared to scalar wavelet. Hence, the features of the signal are extracted effectively. The radial basis neural network is used for detecting the rotor condition of the motor by using the output of multiwavelet transform.

ANN is one of the Artificial Intelligence (AI) techniques which can be used to classify the signal in terms of features. In this paper, the Radial Basis Neural Network (RBNN) is used, which uses radial basis functions as activation functions. Initially, the stator current signal of healthy induction motor and the stator current signal of motor with broken rotor bar are analyzed using the Multiwavelet Transform (MWT). The extracted feature will be applied to radial basis neural network and the rotor condition of the motor is analyzed. The proposed technique is implemented and simulated in MATLAB environment and the performance of detection algorithm is evaluated.

The broken rotor bar identification is performed by monitoring the stator current. The stator current of induction motor is analyzed using multiwavelet transform. Multi Resolution Wavelet Analysis (MRWA) based on MWT is applied in order to obtain low and high frequency bands of the stator current signals of induction motor. The stator current feature is extracted by decomposing the signal. The wavelet components of the stator current are used to detect the broken rotor bars. The feature of the decomposed signal is applied to radial basis neural network. Using the multiwavelet transform, the conditions of the stator current signal for normal case and for broken rotor bar are analyzed.

STATOR CURRENT FEATURE EXTRACTION BY PROPOSED MULTIWAVELET TRANSFORM METHOD

In general, three phase stator currents of induction motor are non-stationary. The non-stationary nature of stator current can be analyzed using wavelet transform (Kim and Parlos, 2002). Visual inspection reveals that original stator currents of the three phase induction motor are quite similar and may not be discriminated easily due to the presence of the strong fundamental component. Consequently, these waveforms may not be directly employed in detection and classification of motor faults (Bashir *et al*., 2012).

If the frequency spectra of the three phase stator currents are calculated, they can be analyzed in the frequency domain. In order to reduce the large amount of spectral information to a usable level, multiwavelet transform is used for extracting the feature components pertinent to the detection of broken rotor bar fault. For differentiating the broken rotor bar signal, the stator current of the induction motor is selected. According to the rotor bar faults, the signal is identified from the stator current variation. The multiwavelet transform is the extension of the generalization of the scalar wavelet. The scalar wavelet has only one scaling function and hence, the rotor effect cannot be extracted clearly. But, using the multiwavelet transform, the rotor effect can be extracted clearly because, it has multiple scaling functions. The multiple scaling functions is denoted as Φ (t), where t is the different sampling time. The wavelet function is denoted as $\psi(t)$. The vector notation of the scaling function and wavelet function are given by:

$$\Phi(t) = [\Phi_1(t), \Phi_2(t), \ldots.., \Phi_n(t)]^T \quad (1)$$

$$\psi(t) = [\psi_1(t), \psi_2(t), \psi_3(t), \ldots \ldots \ldots \ldots \psi_n(t)]^T \quad (2)$$

where, T denotes the transpose of the vector and n>1 is an integer.

The relation between wavelet functions and filter coefficients are given by:

$$\Phi(t) = \sqrt{2} \sum_{n \in Z} H_n \Phi(2k - n) \quad (3)$$

$$\Psi(t) = \sqrt{2} \sum_{n \in Z} G_n \Psi(2k - n) \quad (4)$$

where,
H_n = The low pass filter coefficient
G_n = The high pass filter coefficient

The stator current of each phase of the induction motor is applied to the input of the multiwavelet. In multiwavelet transform, the decomposition produces two low-pass sub-bands, two high-pass sub-bands and two sets of wavelet coefficients for each level of decomposition.

$C_{j-1,k}^{(r)}, C_{j-1,k}^{(y)}$ and $C_{j-1,k}^{(b)}$ are the input vectors of low pass sub-band signal, which form the initial expansion coefficients of the given multiwavelet transform. After the input signal vector is filtered using the matrix filters, four output streams are generated. Each of these streams is then down sampled by a factor of two. $d_{j-1,k}^{(r)}, d_{j-1,k}^{(y)}$ and $d_{j-1,k}^{(b)}$ are the high-pass sub-band signal vector, which is the multiwavelet coefficients of the input signal vector. The tree diagram

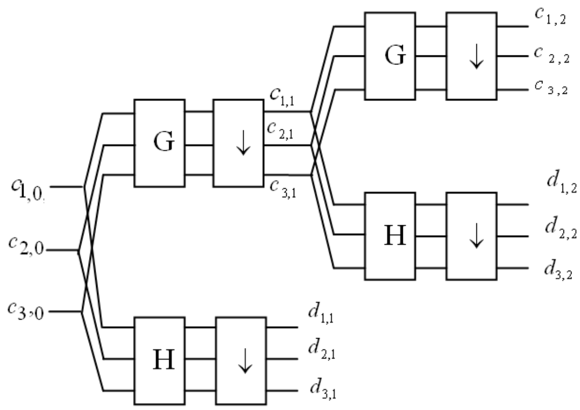


Fig. 1: Decomposition of multiwavelet transform

showing the decomposition of multiwavelet transform is shown in Fig. 1.

From the output of multiwavelet transform, the feature of the stator current is extracted. The extracted features of the stator current signals are formed as vectors which are denoted as $X_{1,}$ X_2 and X_N. The vectors are trained by neural network and the condition of the rotor is thereby predicted.

ROTOR CONDITION PREDICTION BY RADIAL BASIS NEURAL NETWORK

The neural network is one of the artificial intelligence techniques which can predict output from the trained data based on the target (Vilas and Sanjay, 2011). The neural network is trained in order to predict whether the condition of rotor is normal or broken. The input for the network is the extracted feature of the stator current which are denoted as $X_{1,}$ X_2 and X_N. The output of the network is the condition Y (i.e.,) whether rotor bar is broken or normal and are denoted as $Y_{1,}$ Y_2 and Y_m. The radial basis neural network is used which consist of input, hidden and output layer. The performance of a neural network depends upon type of architecture used in the system. The structure of the neural network is shown in Fig. 2.

In Fig. 2, the weights of the network from input layer to hidden layer is denoted as $V_{11}, V_{22}, \dots \dots V_{1n}$ and V_{pn}. Then, the weights between hidden and output layer is denoted as $W_{11}, W_{22}, \dots \dots W_{1n}$ and W_{mp}. The network is trained by back propagation training algorithm, which are the commonly used training method for FFNN and it has propagation and weight update phases.

Once the training process is completed, the network is trained well to provide the target output i.e., whether the rotor is broken or not. In the testing phase, the stator current of the induction motor is applied as an input and the rotor condition is determined as the output.

DETECTION PERFORMANCE EVALUATION BASED ON ROC ANALYSIS

When comparing two or more diagnostic tests, ROC curves are often the only valid method of comparison. An ROC curve is a detection performance evaluation methodology and demonstrates how effectively a certain detector can separate two groups in a quantitative manner. An ROC curve is plotted between the true positives rate (tpr) versus the false positive rate (fpr) (Fawcett, 2006). The broken rotor bar identification of the proposed hybrid technique (MWT-RBNN) is compared with MWT-FFNN and DWT-FFNN techniques.

The terms tpr and fpr are defined as (Fawcett, 2006):

True Positive (TP): Broken rotor bar signal is correctly identified as broken rotor bar signal

False Positive (FP): Normal signal is incorrectly identified as broken rotor bar signal.

True Negative (TN): Normal signal is correctly identified as normal signal.

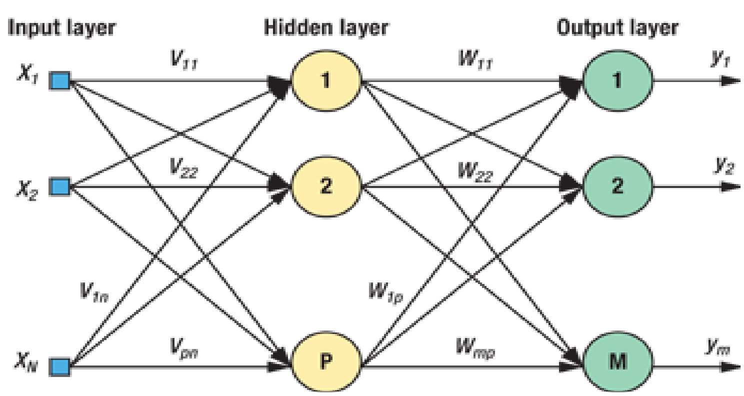


Fig. 2: Structure of neural network

False Negative (FN): Broken rotor bar signal incorrectly identified as normal signal.

Accuracy: Number of correctly classified patterns/total number of patterns:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{5}$$

Sensitivity (tpr): Number of correctly detected positive patterns/total number of actual positive patterns:

$$Sensitivity = \frac{TP}{(TP + FN)} \tag{6}$$

Specificity: Number of correctly detected negative patterns/total number of actual negative patterns:

$$Specificity = \frac{TN}{(FP + TN)} \tag{7}$$

fpr = 1-specificity

SIMULATION RESULTS AND DISCUSSION

The proposed broken rotor bar identification technique has been implemented in MATLAB/ Simulink working platform. With the help of Finite Element Method, the machine parameters of healthy induction motor are estimated. Initially, the multiwavelet transform is applied to the stator current signal and features are extracted by decomposing the signal. The decomposed features are trained by neural network to classify whether the rotor bar is broken or not. The specification and parameters of the induction machine are given in Table 1 and 2.

Table 1: Specification of induction motor

Specifications	Values
Power	3 Hp
Voltage	430 V
Speed	1430 RPM
Current	4.5 A

Table 2: Parameters of induction motor used for simulation

Parameters	Values
Rotor resistance	2.5 Ω
Rotor reactance	3.19 Ω
Number of Rotor bars	28
Number of Broken Rotor bars	4
Poles	4

The stator current for healthy induction motor is shown in Fig. 3. The stator current for induction motor with broken rotor bar is shown in Fig. 4.

The stator current signals are applied to the multiwavelet transform. The multiwavelet transform decomposes this signal into low frequency and high frequency components. The decomposed low frequency and high frequency components of stator current for healthy induction motor are shown in Fig. 5. The low and high frequency components in phases A, B and C are shown in Fig. 5a to c, respectively.

The decomposed low frequency and high frequency components of stator current for faulty induction motor are shown in Fig. 6. The low and high frequency components in phases A, B and C are shown in Fig. 6a to c respectively.

The decomposed signals are applied to neural network and for learning the network, the levenberg-marquardt back propagation training algorithm has been used. Then, the validation, training state, regression and error histogram are analyzed and are shown in Fig. 7.

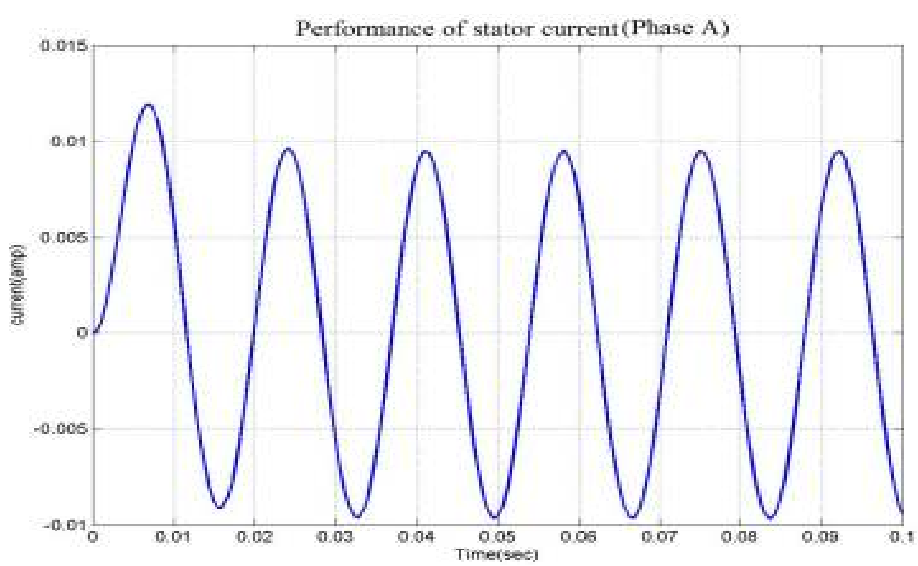


Fig. 3: Stator current for healthy induction motor

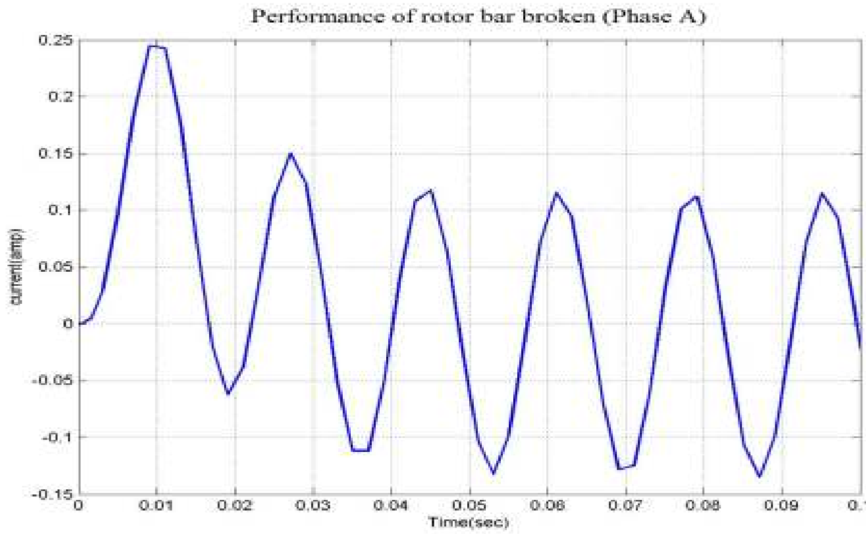
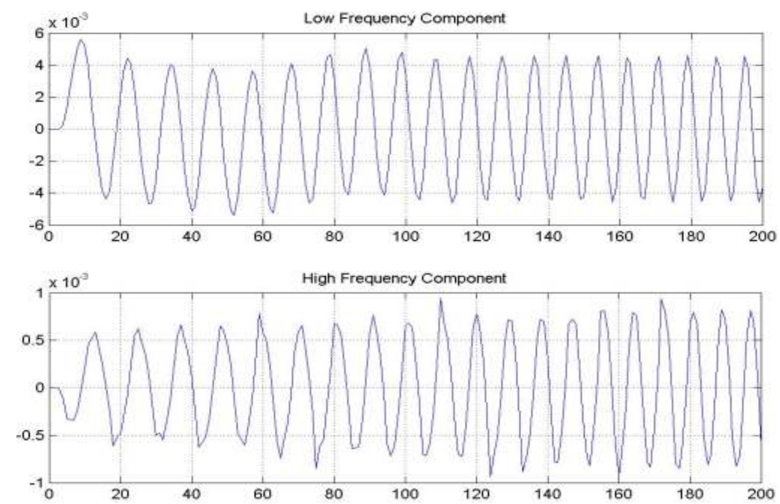
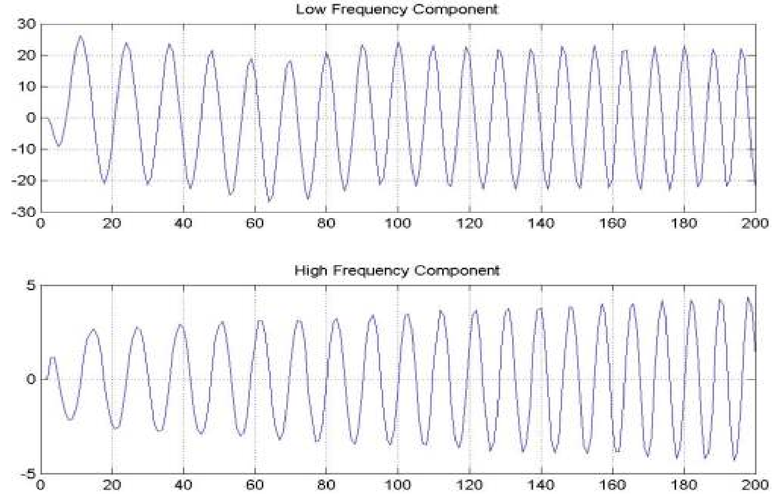


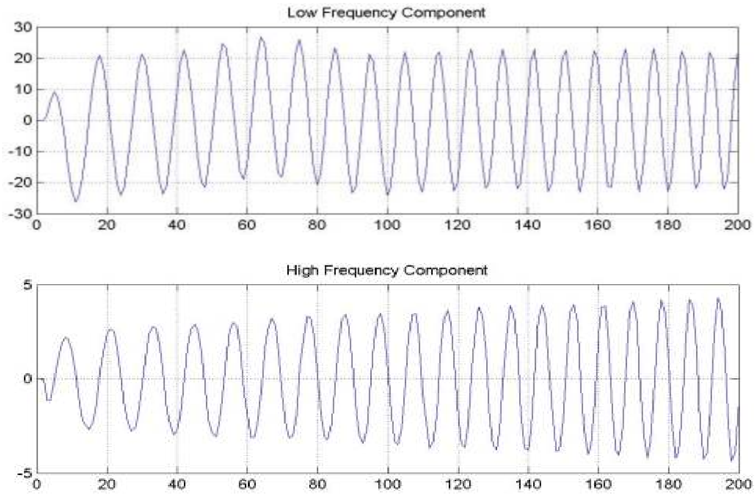
Fig. 4: Stator current for induction motor with broken rotor bar



(a)

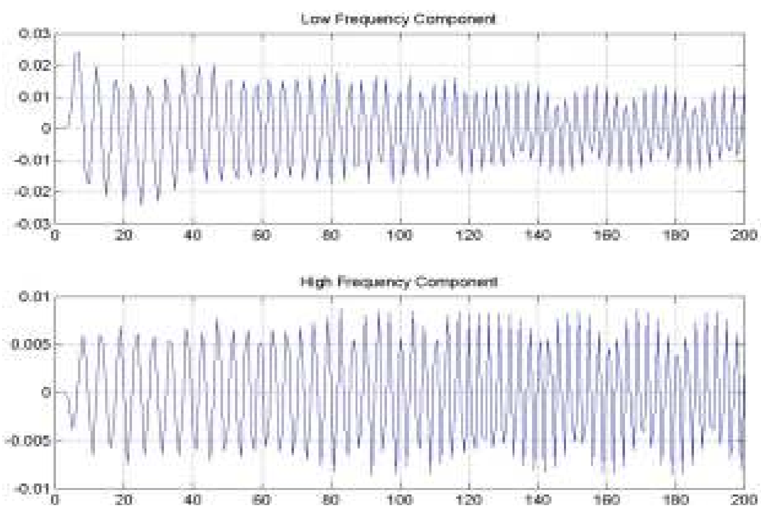


(b)

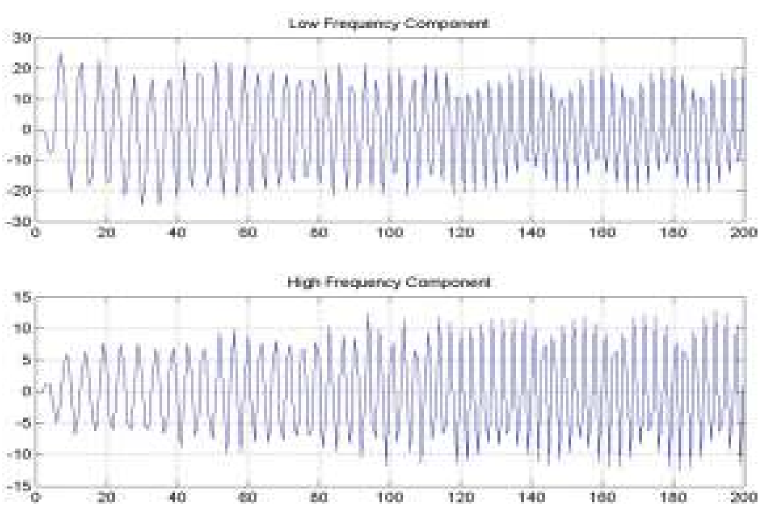


(c)

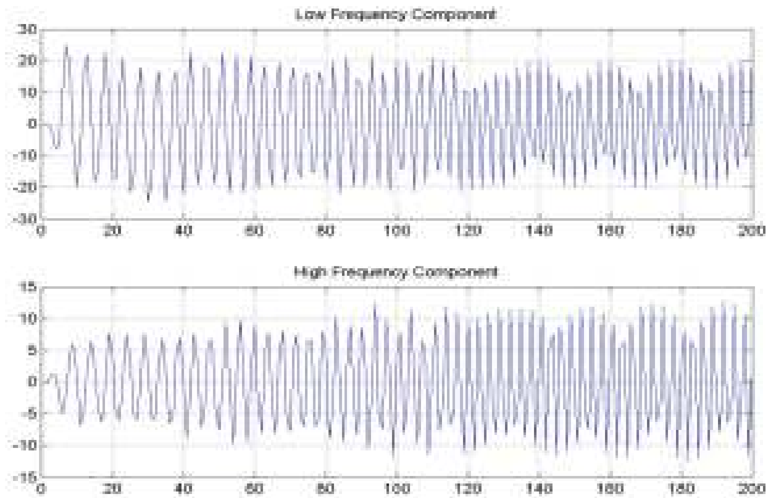
Fig. 5: Low and high frequency components of stator current for healthy induction motor; (Scale factor for x-axis of low frequency component in Fig. 5. a – c is 2)



(a)

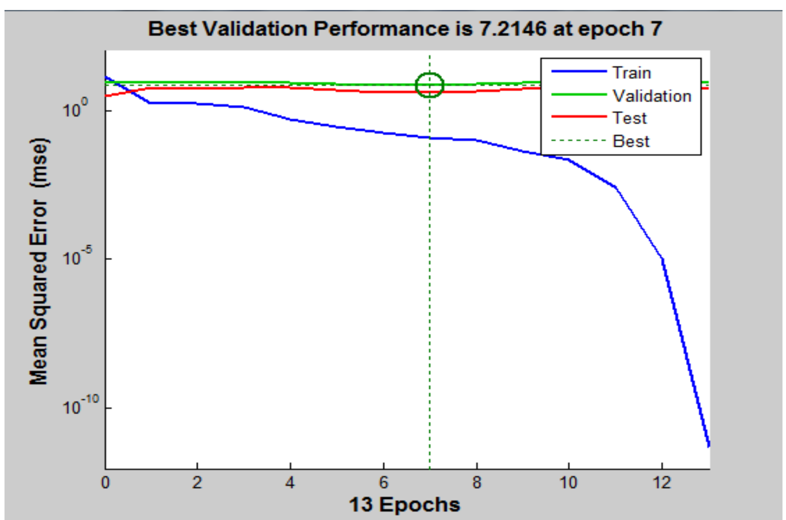


(b)

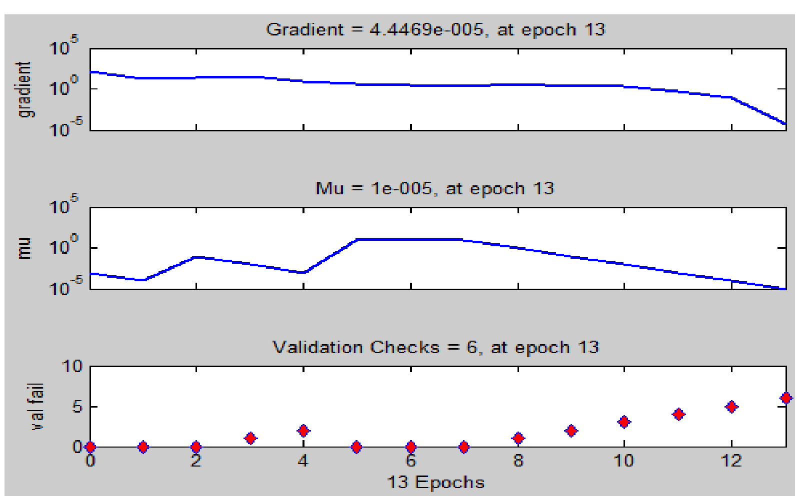


(c)

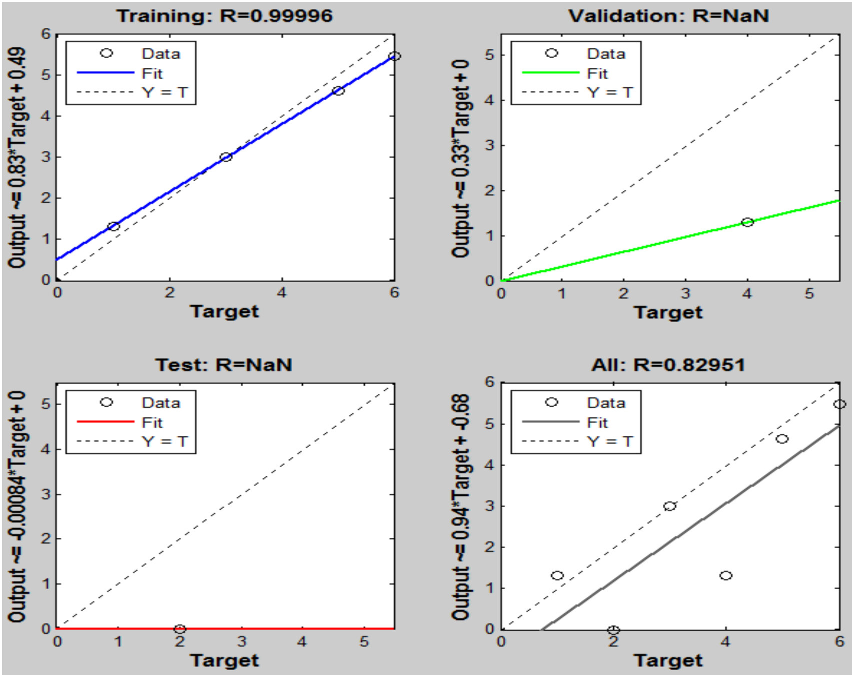
Fig. 6: Low and high frequency components of stator current for faulty induction motor; (Scale factor for x-axis of low frequency component in Fig. 5. a – c is 2)



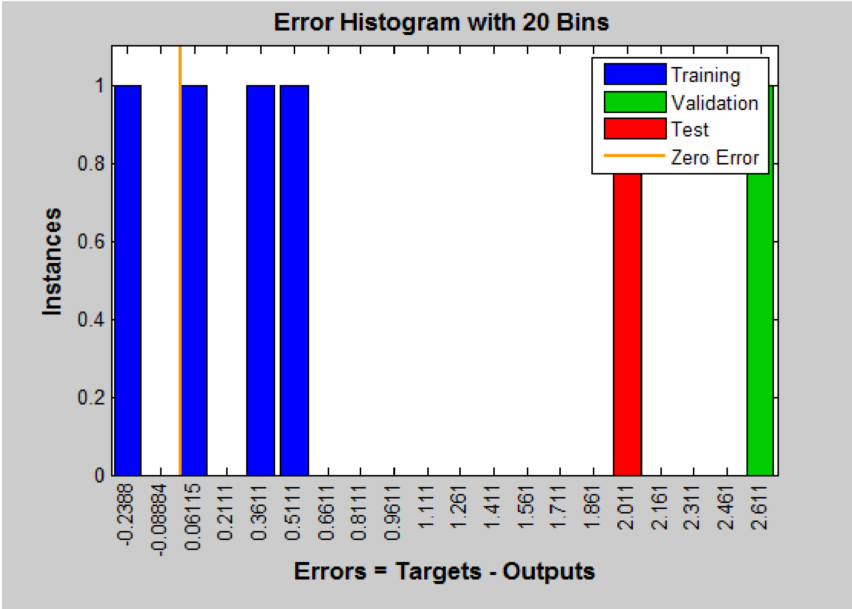
(a)



(b)



(c)



(d)

Fig. 7: (a) Validation, (b) Training state, (c) Regression and (d) Error histogram

Table 3: Accuracy, sensitivity and specificity for MWT-RBNN technique

Phase	TP	TN	FP	FN	Accuracy	Sensitivity	Specificity
A	2	3	1	0	0.833	0.75	1
B	3	3	0	0	1.000	1.00	1
C	3	3	0	0	1.000	1.00	1

Table 4: Accuracy, sensitivity and specificity for MWT-FFNN technique

Phase	TP	TN	FP	FN	Accuracy	Sensitivity	Specificity
A	2	2	1	1	0.667	0.667	0.667
B	2	3	1	0	0.833	0.750	1.00
C	3	2	0	1	0.833	1.000	0.75

Table 5: Accuracy, sensitivity and specificity for DWT-FFNN technique

Phase	TP	TN	FP	FN	Accuracy	Sensitivity	Specificity
A	1	1	2	2	0.333	0.333	0.333
B	2	1	1	2	0.500	0.500	0.500
C	2	2	1	1	0.667	0.667	0.667

For analyzing the performance of proposed hybrid technique, the features of rotor broken bar signal is applied to the neural network. From the output of neural network, the rotor broken bar identification is done. The values of TP, TN, FP and FN are evaluated from the output of the neural network. Based on the TP, TN, FP and FN values, the accuracy, sensitivity and specificity are calculated. The evaluated output of proposed hybrid technique, MWT-FFNN technique and DWT-FFNN technique are tabulated in Table 3 to 5 respectively.

The accuracy, sensitivity and specificity of the proposed hybrid techniques are 94.4, 91.67and 100%, respectively. But, the accuracy, sensitivity and specificity of MWT-FFNN method are 77.78, 80.56 and 80.56%, respectively. Also, the accuracy, sensitivity and specificity of DWT-FFNN method are 50, 50 and 50%. The analysis showed that the proposed hybrid technique (MWT-RBNN) is better than that of MWT-FFNN and DWT-FFNN. From the statistical results, it is clear that the proposed hybrid technique is effective in detecting the broken rotor bar of induction motor.

CONCLUSION

The broken rotor bar fault of a 5 Hp induction motor has been diagnosed by hybrid technique. The stator current of the induction motor was applied to the multiwavelet transform. The output of the multiwavelet transform was the extracted features of the input signal. The extracted features were in the form of vector and were applied to the radial basis neural network. When compared to MWT-FFNN and DWT-FFNN methods we can say that the proposed hybrid technique has high value for accuracy, sensitivity and specificity.

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