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ORIGINAL ARTICLE

Wavelet transform and neural network techniques for inter-turn short circuit diagnosis and location in induction motor

Besma Bessam[1] · Arezki Menacer[2] · Mohamed Boumehraz[2] · Hakima Cherif[3]

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Abstract It is well known that stator winding faults such the inter-turn short circuit are the most frequent source of breakdowns in induction motors. Early detection of any small inter-turn short circuit and location of the faulty phase at different load would eliminate some subsequent damage to adjacent coils and stator core, reducing then the repair cost. To achieve this purpose, the present paper presents a new method of diagnosis and detection of inter turn short circuit fault using discrete wavelet transform (DWT) and neural networks (NN). This method consists in analyzing the stator current by DWT in order to compute the energy associated with the stator fault in the frequency bandwidth. Then, this energy is used as input for a NN classifier. The results obtained are astonishing and the approach is able to detect any small number of shorted turns and the faulty phase even under different load of the machine.

Keywords Diagnosis · Induction motors (IM) · Stator fault · Inter-turn-short circuit · Discrete wavelet transform (DWT) · Neural network (NN)

✉ Arezki Menacer
menacer_arezki@hotmail.com

Besma Bessam
bessambesma@yahoo.fr

Mohamed Boumehraz
m.boumehraz@univ-biskra.dz

Hakima Cherif
hakima.hakima5@gmail.com

[1] LMSE Laboratory, University of Biskra, Biskra, Algeria

[2] LGEB Laboratory, University of Biskra, Biskra, Algeria

[3] LGEB Laboratory, University of El-Oued, El Oued, Algeria

1 Introduction

Usually different types of faults can be occurred in an induction motors due to various stresses during operating conditions. These faults can be divided into two types according to the location: stator faults and rotor faults. Stator faults include stator-winding open or short circuits and stator inter-turn faults. Rotor faults include rotor winding open or short circuits for wound rotor machines and broken bar or cracked end ring faults for cage machines. Hence, the condition monitoring becomes necessary to avoid the above faults and to increase the life span of the machines.

Stator winding faults are one of the most important causes of faults in induction motors. Such faults are caused by several types of stress such as thermal, mechanical, electrical and environmental acting on the insulation system. All these stresses interact with each other in such a way that to degrade the insulation system (Siddiqui et al. 2014). Different types of stator faults can be caused by such stresses. From which inter-turn short circuit fault is one of the most common types of stator fault (Lai et al. 2014).

Usually, a short circuit of a small number of turns doesn't have great physical signs, but it can lead to a catastrophic insulation failure in a short time. Early detection of inter-turn short circuit defect occurrence and its phase during motor operation at different load torque would eliminate some subsequent damage to adjacent coils and stator core, reducing then the repair cost and motor outage time.

There are a great number of papers presenting many techniques used to detect stator inter-turn short circuit in induction motors due to noninvasive properties. Signal processing tools such as fast Fourier transform, short time

Fourier transform (STFT), wavelet transform and power spectral density estimation (Das et al. 2012) have been introduced to extract fault related information from the stator current signals. The wavelet technique is new in the field of fault diagnosis due to its ability to extract information in both time and frequency domain as well as it provides a sensitive means to the diagnosis of faults if compared to other signal processing method like Fourier Transform. A wide part of these published studies are based on the current signature analysis (Gaeid and Ping 2011; Ceban et al. 2012). A good review of machine diagnosis using wavelet technique can be found in (Dash et al. 2010; Bouzida et al. 2011; Gaeid and Ping 2011; Jawadekar et al. 2011; Menacer et al. 2011; Das et al. 2012; Talhaoui et al. 2014). By this way, a much better signal characterization and a more reliable discrimination can be obtained.

On the other hand, a growing interest in using neural network (NN) in the motor fault diagnosis has been observed recently (Kowalski and Orlowska-Kowalska 2003; Bouzid et al. 2008; Ghate and Dudul 2010; Asfani et al. 2012). This is mainly due to the fact that NN did not need a rigorous mathematical model for fault detection, and they are very flexible in solving some problems with nonlinear complicated structure. Besides, they present generalization capability, which lets them deal with partial or noisy inputs. The NNs are able to handle continuous input data and the learning ability can be used to solve fault detection and diagnosis problems. Hence, it is extremely important to exploit this advantage.

In this context and in order to improve the stator winding faults diagnosis in induction motors, a new method is proposed. The proposed approach combines DWT technique and NN and profits from their advantages. This method is based on using stator current DWT to compute the energy associated to the stator fault in the frequency bandwidth. Then, this energy is used as input for the NN classifier. The simulation results show the effectiveness of the proposed method for stator inter turn short circuit in induction motors.

2 Discrete wavelet transform and energy analysis

The DWT is an efficient and powerful technique that provides a time frequency representation of a non stationary signal with a better time resolution than a Fourier Transform. It is an extension to STFT that has constant window length. DWT allows high frequency components analysis with short time interval and low frequency components analysis with long time intervals (Dash et al. 2010).

The DWT is computed by successive low-pass and high-pass filtering of the discrete time-domain signal together

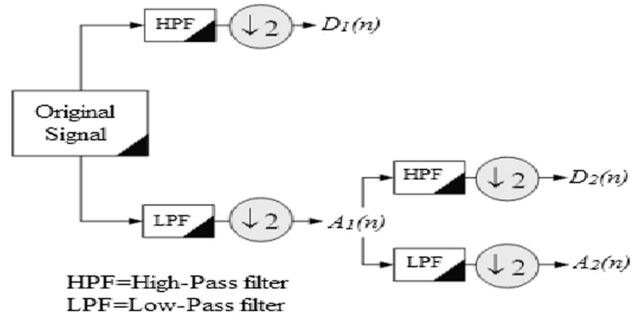

Fig. 1 DWT decomposition of a signal

with changes in sampling rates. A signal can be successively approximated by DWT with different scales. Each step of the decomposition of the signal corresponds to a certain resolution. The decomposition process can be iterated, with successive approximations being decomposed in turn.

This is called the wavelet decomposition tree. Figure 1 shows a typical two-level wavelet decomposition tree. Each wavelet scale corresponds to a frequency band given by (Mohanty and Kar 2006):

$$f = 2^{(n-m)}(f_s/2^n) \quad (1)$$

where f, the higher frequency limit of the frequency band, is represented by the decomposition level m, f_s is the sampling frequency, and 2^n is the number of data points in the signal.

The wavelet energy (WE) is very useful feature for signal analysis (Mohanty and Kar 2006). The energy eigenvalue of each frequency band is defined as:

$$E_j = \sum_{k=1}^{k=n} \left|D_{j,k}(n)\right|^2 \quad (2)$$

where $j = 1, 2, \ldots, 2^{n-1}$; n is the discrete wavelet decomposition time; D_j is the wavelet coefficient magnitude in each discrete point in the corresponding frequency band (Bouzida et al. 2011).

The eigenvalue E_j contains information on the stator current signal for a motor behavior. In addition, the deviation amplitude of some eigenvalues depends on the defect severity, which makes E_j a good candidate for diagnosing stator inter-turn short circuit faults.

3 Model of the induction motor with stator fault

The faulty model of the induction motor stator is illustrated in Fig. 2.

The Model of the three phase induction motor in the reference frame (d-q) related to the stator can described by (Bachir et al. 2006):

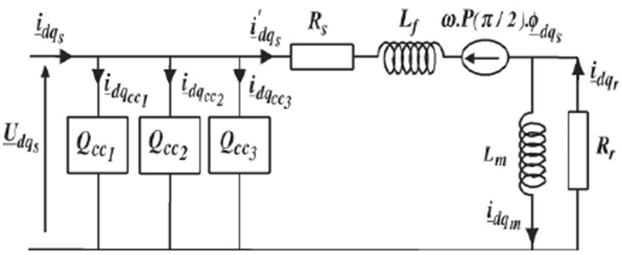

Fig. 2 Stator faulty model of induction motor

$$\begin{cases} \dot{X}(t) = A(\omega)X(t) + Bu(t) \\ Y(t) = CX(t) + Du(t) \end{cases}$$

with

$$X = \begin{bmatrix} i_{ds} & i_{qs} & \phi_{dr} & \phi_{qr} \end{bmatrix}^T, u = \begin{bmatrix} U_{ds} \\ U_{qs} \end{bmatrix}, \quad Y = \begin{bmatrix} i_{ds} \\ i_{qs} \end{bmatrix}$$

$$A(\omega) = \begin{bmatrix} -\dfrac{R_s + R_r}{L_f} & \omega & \dfrac{R_r}{L_m L_f} & \dfrac{\omega}{L_f} \\ -\omega & -\dfrac{R_s + R_r}{L_f} & -\dfrac{\omega}{L_f} & \dfrac{R_r}{L_m L_f} \\ R_r & 0 & -\dfrac{R_r}{Lm} & 0 \\ 0 & R_r & 0 & -\dfrac{R_r}{Lm} \end{bmatrix},$$

$$B = \begin{bmatrix} \dfrac{1}{L_f} & 0 \\ 0 & \dfrac{1}{L_f} \\ 0 & 0 \\ 0 & 0 \end{bmatrix} C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix},$$

$$D = \sum_{k=1}^{3} \frac{2}{3} \frac{\eta_{cck}}{R_s} P(-\theta) Q(\theta_{cck}) P(\theta)$$

and

$$\eta_{cck} = \frac{n_{cck}}{n_s},$$

$$Q_{cck}(\theta_{cck}) = \begin{bmatrix} \cos(\theta_{cck})^2 & \cos(\theta_{cck})\sin(\theta_{cck}) \\ \cos(\theta_{cck})\sin(\theta_{cck}) & \sin(\theta_{cck})^2 \end{bmatrix},$$

$Q(\theta_{cck})$: is a matrix depending on short-circuits angle θ_{cck} and the faulty winding according to the first rotor phase θ_0. n_{cck} and n_s are, respectively, the number of inter-turns short windings at healthy phase. k^{th} phase and the total number of turns in one.

The expression of the torque is given by:

$$T_e = P(i_{qs}\,\phi_{dr} - i_{ds}\,\phi_{qr}) \quad (3)$$

4 Generation of phase currents

The simulation is realized for the induction motor model: 1.1 kW, 230 V, 50 Hz, 4-pole, rotor with 28 bars and 464 turns per phase winding on the stator. The system parameters of the induction motor tested in this study are given in Table 1.

Figure 3 illustrates the simulated three phase currents profiles with no load torque and under a stator fault (15-shorted turns) on one of the three phases (a_s, b_s, or c_s) introduced at time 1 s.

Figure 3 shows that before 1 s, the current magnitudes are equal for the three phases but after that the currents become different. If a fault occurs in phase as, the current in the phase increases to its peak value as compared to that of phase b_s and phase c_s, consequently, the phase angle between the phase voltage and line current will change.

5 Application of DWT for the stator current analysis

Before the application of the DWT, first we have to select the mother wavelet type and the decomposition levels number.

5.1 Selection of the mother wavelet

In any DWT based approach, the first important step is the selection of the mother wavelet to carry out the analysis. Several wavelet families with different mathematical properties have been developed (Dash et al. 2010). For extraction of fault components, multiple tests show that a wide variety of wavelet families can give satisfactory results. In our case we have used Daubechies-40 as the mother wavelet for the DWT analysis.

Table 1 Specifications of the studied induction motor

P: Output power	1.1 kW
V_s: Stator voltage	220/380 V
I_s: Nominal current	2.6/4.3 A
n_n: Nomina speed	1425 rpm
R_s: Stator resistance	9.81 Ω
R_s: Rotor resistance	3.83 Ω
L_m: Mutual inductance	436 mH
L_f: Leakage inductance of stator	76.2 mH
P: Number of pole pairs	2
n: Number of stator slots	48
n_b: Number of rotor bars	28
n_s: Number of turns per stator phase	464

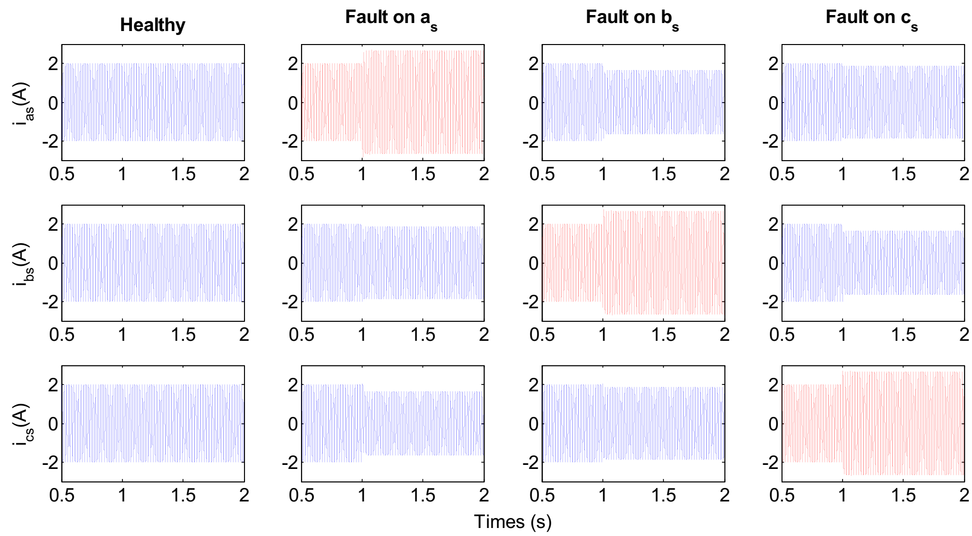

Fig. 3 Fault effect on the three phase currents of induction motor

Table 2 Frequency bands for wavelet signal

Level	Approximations		Details	
J = 1	A1	0–5000 Hz	D1	5000–10,000 Hz
J = 2	A2	0–2500 Hz	D2	2500–5000 Hz
J = 3	A3	0–1250 Hz	D3	1250–2500 Hz
J = 4	A4	0–625 Hz	D4	625–1250 Hz
J = 5	A5	0–312.5 Hz	D5	312.5–625 Hz
J = 6	A6	0–156.25 Hz	D6	156.25–312.5 Hz
J = 7	A7	0–78.125 Hz	D7	78.125–156.25 Hz
J = 8	A8	0–39.0625 Hz	D8	39.0625–78.125 Hz
J = 9	A9	0–19.531 Hz	D9	19.531–39.0625 Hz

5.2 Specification of the number of decomposition levels

The number of decomposition levels is determined by the low frequency components. For the extraction of the frequency components caused by inter-turn short circuit, the number of decomposition level should be equal. The decomposition level number N_f is given by (Bouzida et al. 2011).

$$N_f = \mathrm{int}\left(\frac{\log\left(\frac{f}{f_s}\right)}{\log(2)}\right) \tag{4}$$

Considering f = 10,000 samples/s and f_s = 50 Hz, using Eq. 4, one obtains $N_f = 9$. The frequency bands associated with each wavelet signal are shown in Table 2.

5.3 Analysis of the wavelet signals

Figure 4a shows the detail and approximation signals (D9, D8, D7, D6 and A6) obtained by db40 for the healthy machine and Fig. 4b, c show the result for a machine in inter-turn short circuit fault. From the levels (D9, D8, D7, D6 and A6) signals we observe a clear disturbance for under inter-turn faulty machine.

The features obtained from DWT will be used for training and testing the NN classifier. If the DWT coefficients are used as NN inputs, the NN structure will be more complex since the number of the DWT coefficients is a large number. Therefore, Instead of using DWT coefficients the energies of DWT coefficients have been used as inputs to the NN classifier, in order to overcome this problem while retaining important features of the motor signals.

5.4 Analysis of the wavelet energy (WE)

Figure 5 shows the eigenvalue analysis results for a healthy motor and with stator inter-turn short circuit fault. The eigenvalue E7, presents an obvious deviation caused by the fault. Table 3 shows the eigenvalue E7 under the conditions of healthy state and with stator inter turn short circuit fault. From the Table 3, it is obvious that the eigenvalue E7 depends on the stator inter turn short circuit fault. Therefore, this feature can be used as inter-turn short circuit fault indicator.

The load effect on the eigenvalue E7 had been also studied. Figures 6, 7 and 8 show the three- eigenvalue E7 in the case of stator fault in phases a_s, b_s, and c_s under two load torque (T = 3 and 7 Nm). These figures show that the eigenvalue E7 does not present any overlap between the values, even with different torques and in faulty conditions.

After this detailed analysis, we can conclude that the three Eigenvalue E7 is a distinctive feature and can be used as efficient indicator to detect a stator fault, locate the phase where this fault has occurred, and also provide the

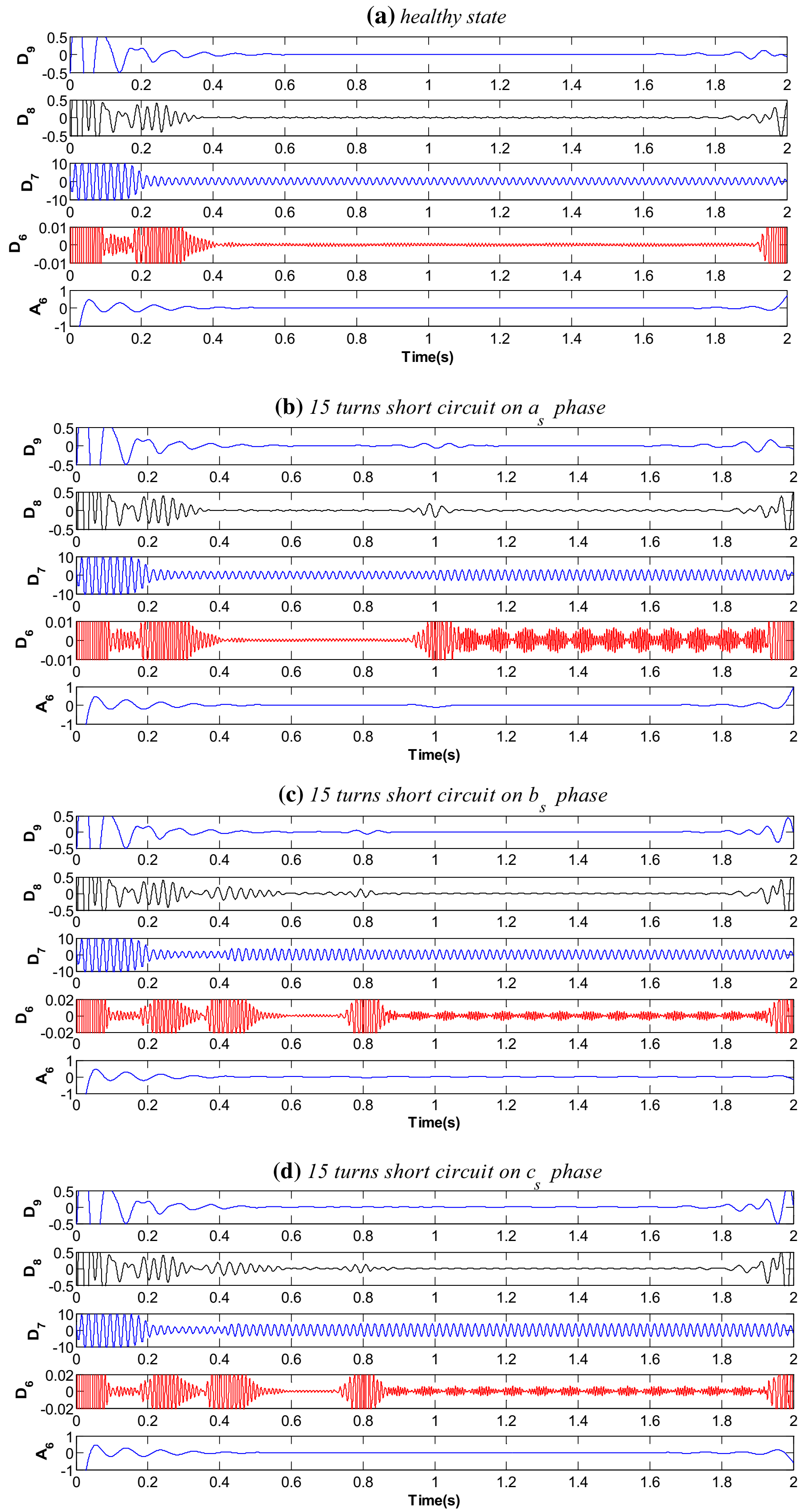

Fig. 4 Details and approximation for healthy state and with 15 turns short circuit on a_s phase, b_s phase, and c_s phase

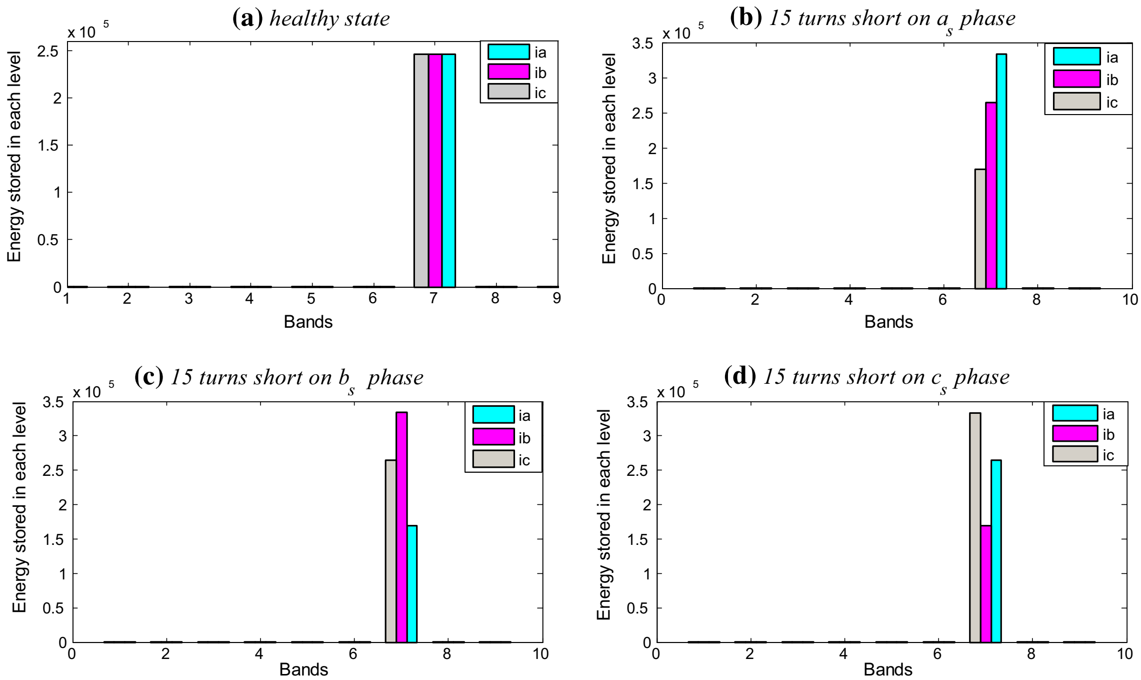

Fig. 5 Changes in various levels of decomposed signals for healthy state and with 15 turns short circuit on a_s phase, b_s phase, and c_s phase

Table 3 Eigen value E7 of each fault condition

Motor condition	The eigen value E7	
Healthy	E7ia	246,244.81
	E7ib	246,244.81
	E7ic	246,244.81
15 turns short circuit on a_s phase	E7ia	333,928.57
	E7ib	265,357.14
	E7ic	169,642.86
15 turns short circuit on b_s phase	E7ia	169,485.29
	E7ib	333,455.88
	E7ic	265,808.82
15 turns short circuit on c_s phase	E7ia	265,073.52
	E7ib	169,485.29
	E7ic	334,191.17

information about the fault severity (the number of the faulty turns). Thus, the three- eigenvalue E7 constitute an ideally noninvasive sensor, which provides the adequate data for the neural diagnosis system in order to ensure effective monitoring.

6 Neural network for the stator fault diagnosis

The aim of the proposed fault diagnosis system is the detection and the location of an inter-turn short fault on the stator windings of a three phase induction motor using NNs. The motor fault diagnosis process is shown in Fig. 9. It is composed by four parts: data acquisition, feature extraction, fault detection and post-processing. The design of the NNs based fault diagnosis system can be decomposed in the following four steps:

– Preparation of a suitable training data set for the NN;
– Selection of a suitable NN Structure;
– Training of the NN;
– Evaluation of the test pattern.

6.1 Preparation of a suitable training data set for the NN

A training database composed by input and output data sets has been used to train the NN classifier. The input data are collected through simulations, using the model presented in Fig. 2. To be efficient in the location of the induction motor faulty phase, the training data should span the complete range of the operating conditions, which contain all possible fault occurrences and even the healthy case.

A training data set constituted by input and output data sets has been used to train the NN. The input data set, which is shown in Fig. 10 are composed by a successive range of several examples in different operating conditions of the induction motor. All these examples are presented to the NNs under five load torques (0, 30, 50, 70, and 100 % of the rated load) which corresponds to the

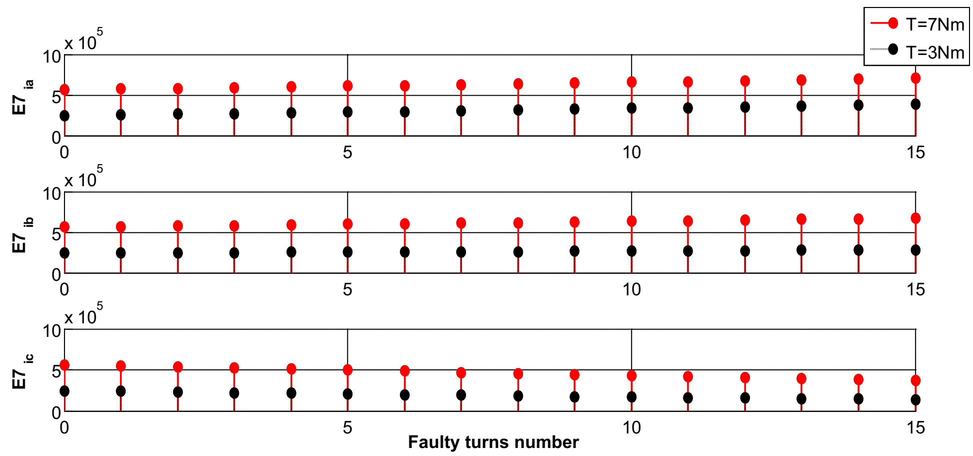

Fig. 6 Eigenvalue E7 for the fault on as phase and under two different load

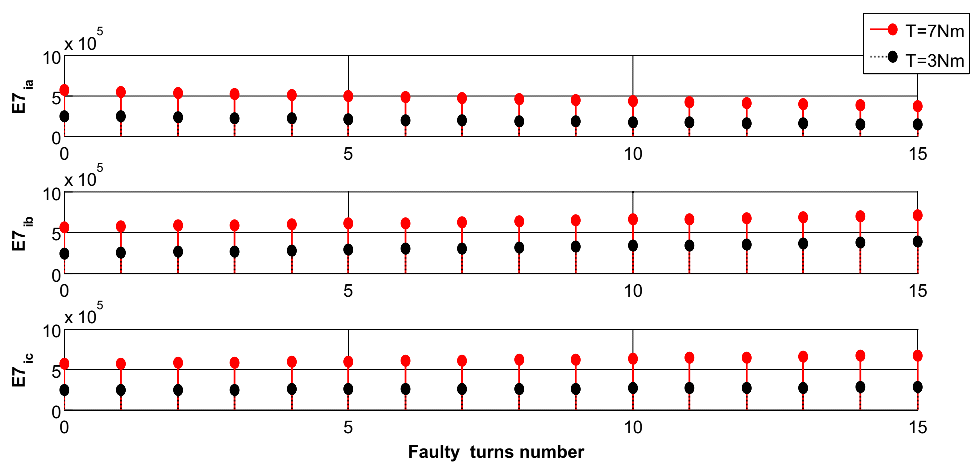

Fig. 7 Eigenvalue E7 for the fault on b_s phase and under two different load

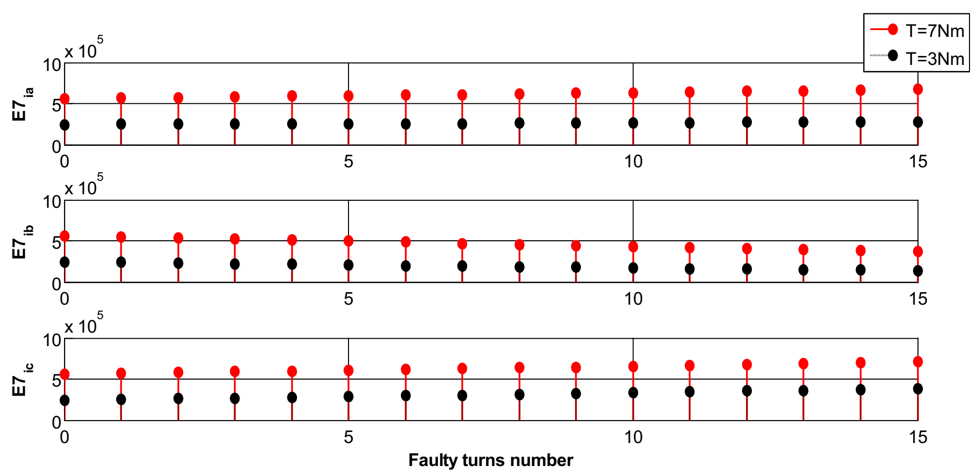

Fig. 8 Eigenvalue E7 for the fault on c_s phase and under two different load

following different operating cases of the induction motor: healthy (five samples) and fault of an odd number of shorted turns (1, 3, 5, 7, 9, 11, 13, and 15) on each stator phase [40(8 $\times$ 5) samples]. Thus, a total of 125 (40 $\times$ 3 + 5) samples have been collected and applied as the inputs to the NNs for stator inter-turn fault diagnosis.

The desired outputs (T_i) of the NN are chosen as follows:

- $T1 = 1$ for a short circuit at phase a_s; otherwise, $T1 = 0$;
- $T2 = 1$ for a short circuit at phase b_s; otherwise, $T2 = 0$;

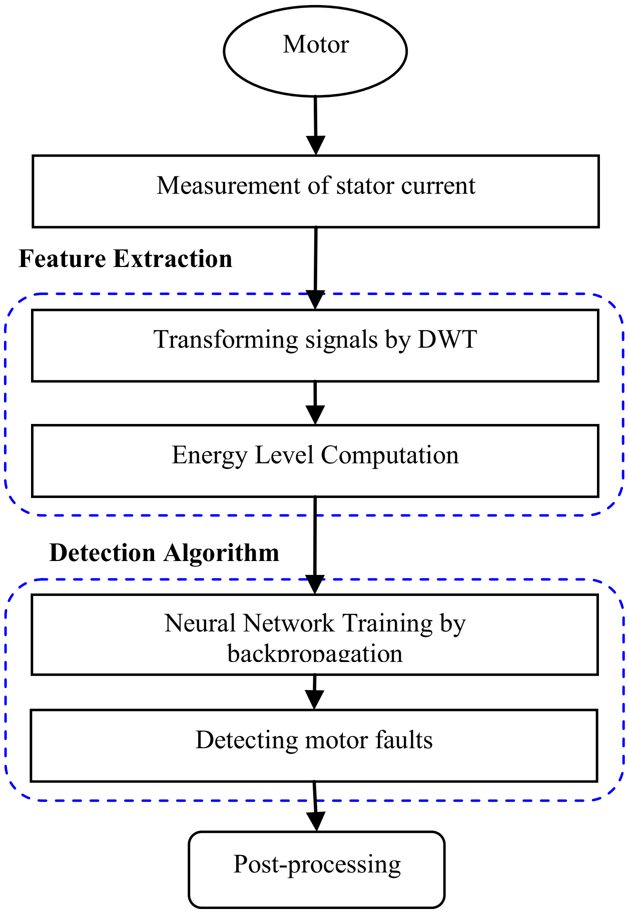

Fig. 9 Flowchart of proposed motor fault diagnosis

- T3 = 1 for a short circuit at phase c_s; otherwise, T2 = 0.

Therefore, the output states of the NNs are set as the following:

[0; 0; 0] no fault (healthy mode);
[1; 0; 0] fault occurred on phase a_s;
[0; 1; 0] fault occurred on phase b_s;
[0; 0; 1] fault occurred on phase c_s.

6.2 Selection of a suitable NN Structure

The NN paradigm used in the proposed fault diagnosis system is a feed-forward multi layer perceptron NN trained by back propagation algorithm.

The number of inputs and outputs is fixed by the number of the fault indicators and faulty states respectively. The inputs are the three- Eigenvalue E7 and the outputs are the number of fault classes, which are the three phases of the induction motor, respectively, and one hidden layer with 3 neurons. The activation functions of the hidden and output layers are "tansig" and "logsig", respectively.

6.3 Training of the NN

The multilayer perceptron NN is trained with a supervised learning algorithm called back propagation (BP). BP raining is a gradient descent algorithm with adaptive

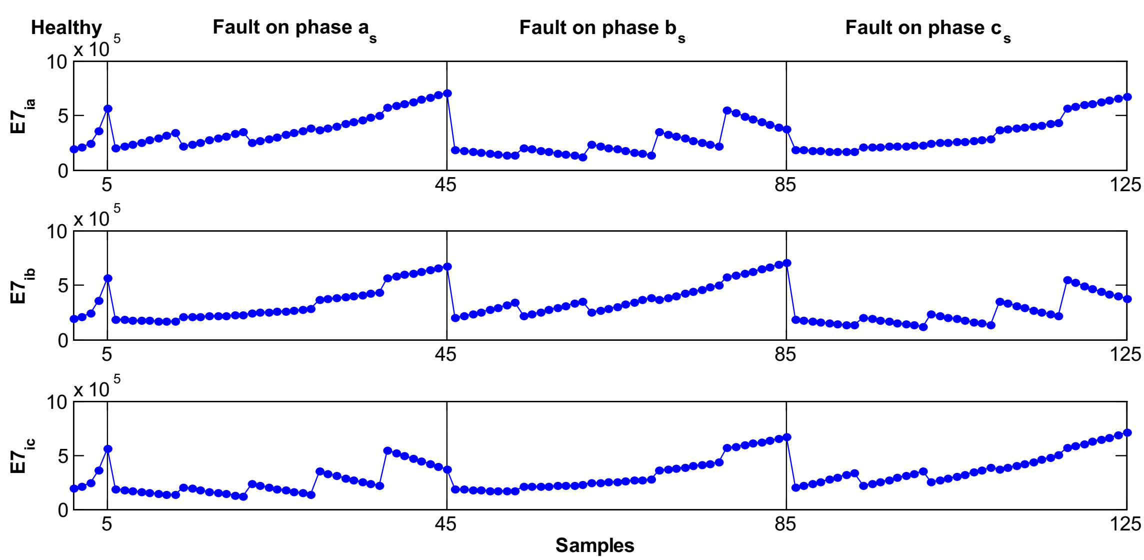

Fig. 10 Simulated training input data set of NN

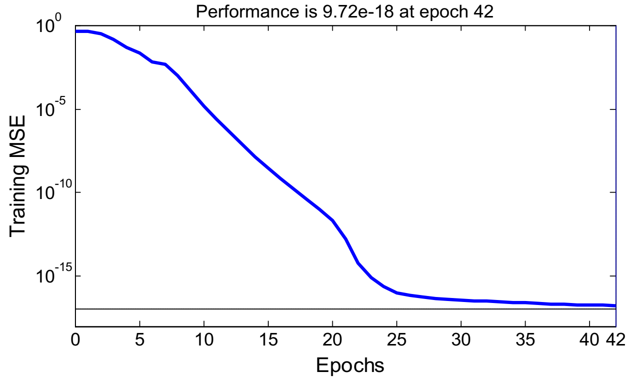

Fig. 11 Simulated training performances of the NN

learning rate. It tries to improve the performance of the NN by reducing the total error by changing the weights along its gradient. In this paper, the error is expressed by the mean square error (MSE).

The training performance is shown in Fig. 11, where after 42 epochs, a low training MSE is reached (9.72×10^{-18}). The training outputs and errors of NN are shown in Fig. 12. From Fig. 15 it is clear that the NN has been well trained and correctly reproduced the desired output with low errors.

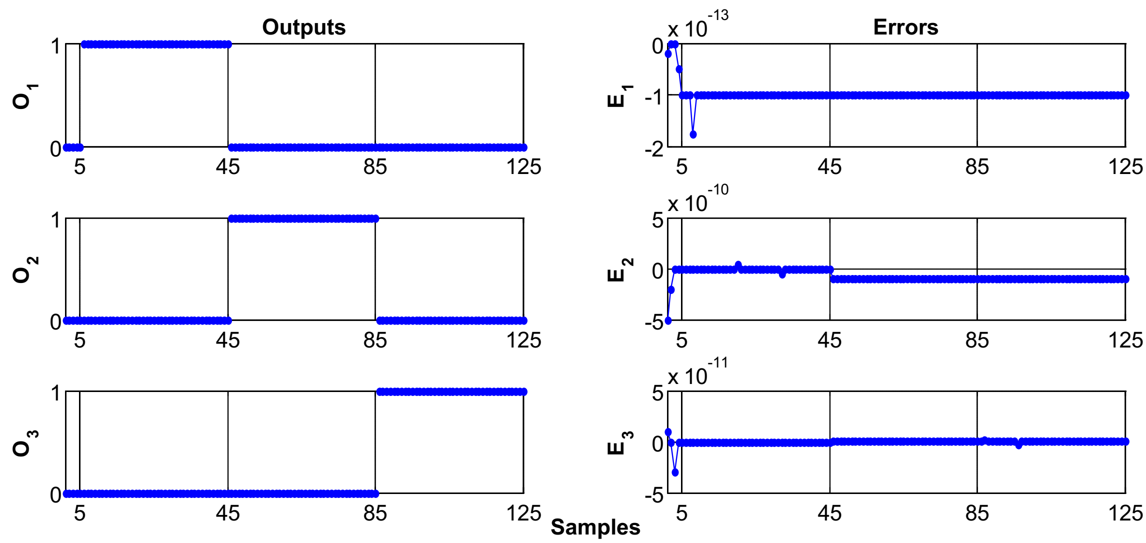

Fig. 12 Simulated training outputs and errors of NN

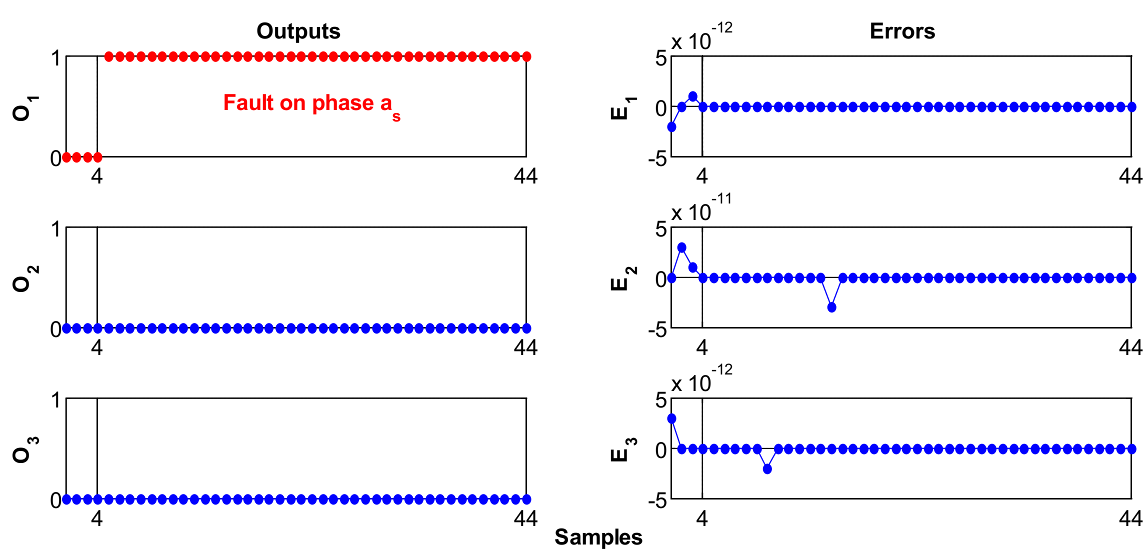

Fig. 13 Simulated test outputs and errors for faults on phase a_s

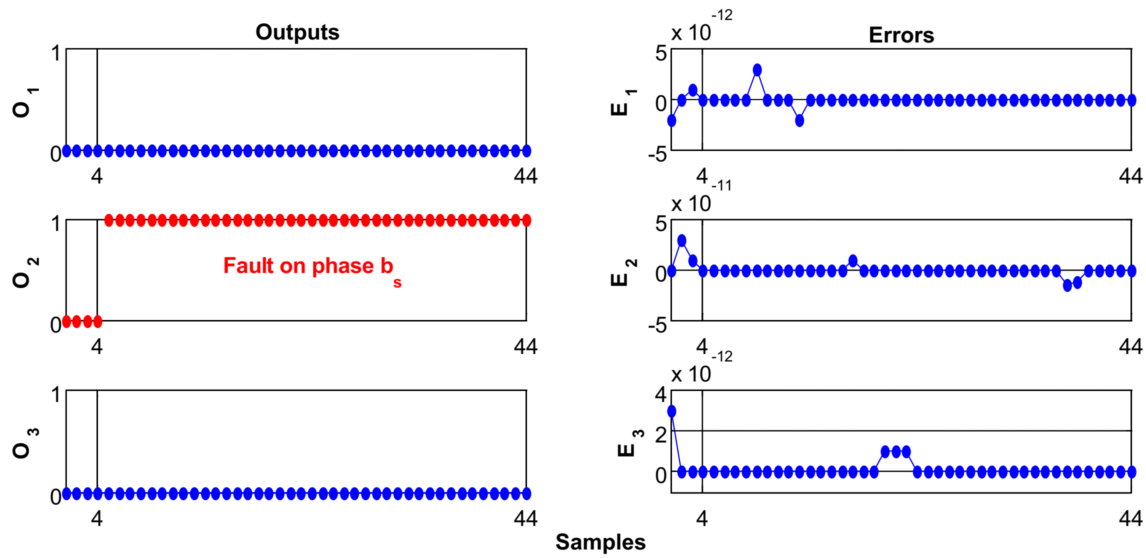

Fig. 14 Simulated test outputs and errors for faults on phase b_s

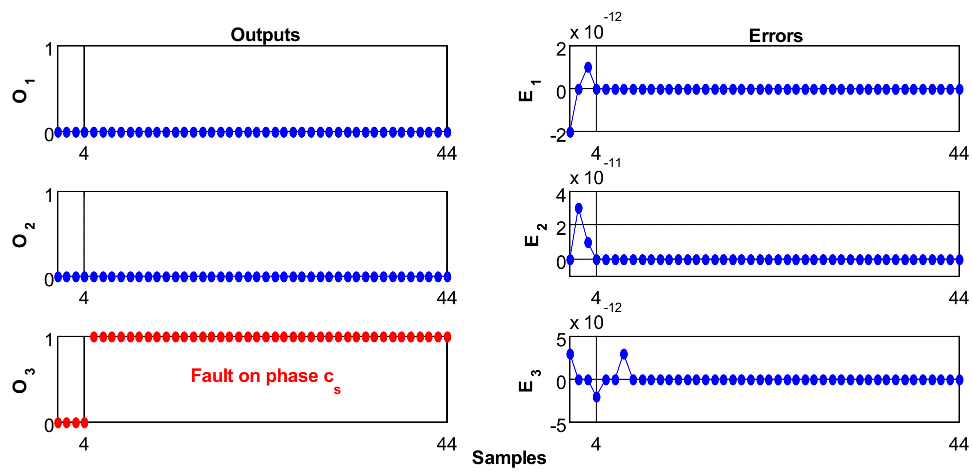

Fig. 15 Simulated test outputs and errors for faults on phase c_s

7 Simulation results

The performance of a NN on the testing data set represents its generalization ability. The data set is divided into two. One set is used for training and the other for testing. In fact a generalized NN will perform well for both training and testing data. The test procedure is conducted by a test data set that is different from the training data set to assess the generalization capacity of the adopted network.

The test data set are presented to the NNs under four load torques (20, 40, 60, and 80 % of the rated load) and corresponds to the following different operating cases of the induction motor: healthy (four samples) and fault of an even number of shorted turns (2, 4, 6, 8, 10, 12, 14, 16, 18 and 20) on each stator phase [40 (10 $\times$ 4) samples]. Thus, a total of 44 (40 + 4) testing samples have been collected for testing each phase stator inter-turn fault.

Figures 13, 14 and 15 show the NN test outputs and their errors for faults on phases a_s, b_s, and c_s, respectively.

From Fig. 13 the NN test output (O1, O2, O3) is equal to (1, 0, 0) with good accuracy. This means that the NN is able to locate correctly the fault occurring on phase a_s. The testing error for this case is very low.

In Fig. 14, the NN output is set to (0, 1, 0), indicating the presence of faults on phase b_s with low errors. Hence the NN is able to locate correctly the inter-turn short circuit fault on phase b_s.

The NN gives the output (0, 0, 1) for the third part of test data with good accuracy as shown in Fig. 15. The testing error is very low. Hence we conclude that the NN is able to locate correctly the stator inter-turn short circuit fault occurring on phase c_s.

8 Conclusion

This paper presents a technique for the inter turn short circuit fault detection and location in induction motor using wavelet energy and NNs. This method consists is applying the DWT of stator currents, to compute the energy associated to the stator fault in the frequency bandwidth. Then, this energy is used as input for a NN classifier.

The novel feature of the wavelet energy including information about the detection and the location of fault let them to be reliable indicators of inter-turn short-circuit fault in the stator windings of the induction motor.

The technique was tested for different load and for different position of phases of shorted turns of the machine. The results obtained are very significant and the technique considered is able to detect and locate automatically the inter-turn short circuit fault.

As further scope of this paper, we can extend our research to identify the number of the shorted turns on the faulty phase and, in this fact, achieve a comprehensive diagnosis procedure.

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