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Research Article

Detection of broken rotor bar faults in induction motor at low load using neural network

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ABSTRACT

The knowledge of the broken rotor bars characteristic frequencies and amplitudes has a great importance for all related diagnostic methods. The monitoring of motor faults requires a high resolution spectrum to separate different frequency components. The Discrete Fourier Transform (DFT) has been widely used to achieve these requirements. However, at low slip this technique cannot give good results. As a solution for these problems, this paper proposes an efficient technique based on a neural network approach and Hilbert transform (HT) for broken rotor bar diagnosis in induction machines at low load. The Hilbert transform is used to extract the stator current envelope (SCE). Two features are selected from the (SCE) spectrum (the amplitude and frequency of the harmonic). These features will be used as input for neural network. The results obtained are astonishing and it is capable to detect the correct number of broken rotor bars under different load conditions.

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1. Introduction

Nowadays, induction motors have a crucial importance in industry. Internal faults such as broken rotor bars can cause serious damage to the motor itself as well as to motor-related equipment, which can lead to unexpected shutdown of the industrial processes causing then considerable economic losses. To avoid such problems, reliable diagnostic systems should be installed. Generally, a diagnostic system must include a robust fault detection algorithm, which allows detecting all defects, or any undesirable changes on the machine performances before a total failure occurrence [1,2].

There are a great number of papers presenting many techniques used to detect broken rotor bar in induction motors due to noninvasive properties. Signal processing tools such as Fast Fourier Transform (FFT) [3], Short time Fourier Transform (STFT) and Prony Analysis (PA) [4] have been introduced to extract fault related information from the stator current signals. However, the application of these methods has some drawbacks, which especially affect the diagnosis of rotor asymmetries at very low slip. This paper addresses these difficulties with an innovative method based on the properties of the Hilbert transform (HT).

It is well known that broken rotor bars produce geometric and magnetic unbalances which induce sidebands, $(1 \pm 2ks)f$, in the stator current spectrum (s is the rotor slip, f is the fundamental frequency and $k = 1,2,3\ldots$). Therefore, the identification of the sideband frequencies and the evaluation of their amplitudes can be used as an efficient and reliable approach to diagnose rotor bar faults. However, at low slip these sidebands are usually quite close to the fundamental frequency, which makes their detection much more difficult. To remedy this problem, the modulation of the three-phase stator current is the so-called envelope and that is cyclically repeated at a rate equal to $2sf$ [5]. In fact, the rotor fault effect can be localized in the stator current envelope spectrum which is expressed by the components $2ksf$.

On the other hand, one can observe a growing interest on using neural network (NN) in the motor fault diagnosis [6–9]. 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 that have nonlinear complicated structures. Besides, they present generalization capability, which lets them deal with partial or noisy inputs. The neural networks are able to handle continuous input data and the learning must be supervised in order to solve the fault detection and diagnosis problem. Hence, it is extremely important to exploit this advantage.

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In this context and in order to improve the broken rotor bar diagnosis in induction motors at low load, a method is proposed; it combines between the Hilbert transform and the neural network, then, from their advantages. The Hilbert transform is used to extract the stator current envelope. Then this signal is processed via Fast Fourier Transform (FFT). To extract the fault frequency components ($2sf$) form the stator current envelope spectrum. The position of the harmonic ($2sf$) and its amplitude will be used as input for the neural network. This technique is used for the detection of the number of broken rotor bars under different load conditions.

2. Stator phase current envelope

Typically, the stator current envelope can be extracted via different methods as Hilbert transform, filter demodulation and others. HT is a well known signal analysis method, used in different scientific fields such as faults diagnosis [10], signal transmission, geophysical data processing, detection of mechanical load faults in induction motors [11], diagnosis of rotor cage faults in induction motors [12], and others.

The HT of a real signal $x(t)$, such as the phase current, is used to emphasize its local properties. Mathematically, it is defined as a convolution with the function $1/t$, as follows [13]:

$$HT\ \ (x(t)) = y(t) = \frac{1}{\pi t} \times x(t) = \frac{1}{\pi} \int_{-\infty}^{+\infty} \frac{x(\tau)}{t-\tau} d\tau \tag{1}$$

The divergence at $t=\tau$ is allowed for by taking the Cauchy principal value of the integral. By coupling the $x(t)$ and its HT, the so-called analytic signal (AS)$\vec{x}(t)$ is created

$$\vec{x}(t) = x(t) + jy(t) = a(t)e^{j\theta(t)} \tag{2}$$

where

$$a(t) = \left[x^2(t) + y^2(t)\right]^{1/2} \qquad \theta(t) = \arctan(x(t)/y(t)) \tag{3}$$

where $a(t)$ is the instantaneous amplitude of $\vec{x}(t)$, which can reflect how the energy of $x(t)$ varies with time, and $\theta(t)$ is the instantaneous phase of $\vec{x}(t)$.

3. Extraction of fault indicators

3.1. Broken rotor bars faulty model

Fig. 1 illustrates rotor fault circuit diagram of induction machines, with the equivalent resistance, in the case of broken bars. The model of a three phase induction motor in the reference frame (d–q) related to the rotor is [14]:

$$\begin{cases} \dot{x}(t) = A(\omega) \cdot x(t) + Bu(t) \\ y(t) = Cx(t) \end{cases} \tag{4}$$

With

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

$$A(\omega) = \begin{bmatrix} -(R_s + R_{eq})L_f^{-1} & \omega_r & R_{eq}L_m^{-1}L_f^{-1} & \omega_r L_f^{-1} \\ -\omega_r & -(R_s + R_{eq})L_f^{-1} & \omega_r L_f^{-1} & R_{eq}L_m^{-1}L_f^{-1} \\ R_{eq} & 0 & R_{eq}L_m^{-1} & 0 \\ 0 & R_{eq} & 0 & -R_{eq}L_m^{-1} \end{bmatrix}$$

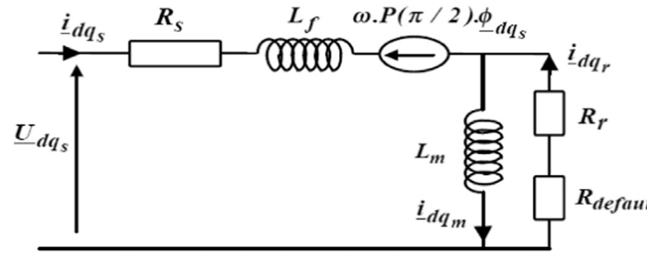

Fig. 1. Broken rotor bars mode.

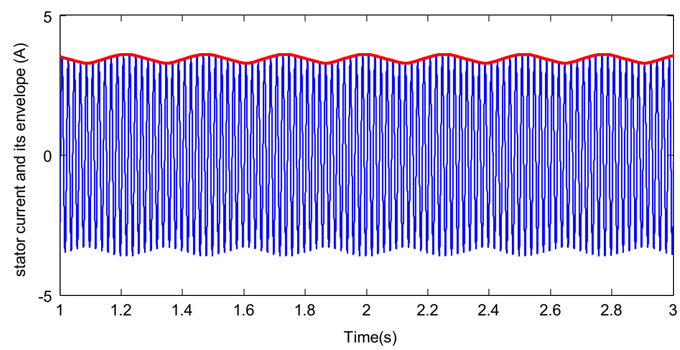

Fig. 2. Stator current and its envelope for two broken rotor bars.

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

$$R_{eq} = R_r + \frac{\alpha}{1-\alpha} Q(\theta_0) R_r$$

$$Q(\theta_0) = \begin{bmatrix} \cos\ (\theta_0)^2 & \cos(\theta_0)\sin(\theta_0) \\ \cos(\theta_0)\sin(\theta_0) & \sin\ (\theta_0)^2 \end{bmatrix} \text{and}\ \ \alpha = \frac{2}{3}\eta_0, \eta_0 = \frac{3n_{bc}}{n_b}$$

$\Omega = \frac{\omega_r}{P}$: is mechanical speed of the motor.
n_{bc} and n_b represent the number of broken bars and the total number of bars in the rotor respectively.
θ_0: an absolute localization of the faulty winding according to the first rotor phase.

The expression of the torque is given:

$$T_e = p(i_{qs}\phi_{dr} - i_{ds}\phi_{qr}) \tag{5}$$

3.2. Spectrum of stator current envelope

The motor used in the simulation study is a 1.1 kW, 220 V, 50 Hz, 4-pole induction motor, with a rotor with 28 bars. The system parameters of the induction motor tested in this study are given in Appendix A. Fig. 2 illustrates the stator current and its envelope.

Figs. 3 and 4 show the evolution of the amplitude and the frequency of the harmonic $2sf$ according to the defect severity and the load. It is obvious that the position of the harmonic $2sf$ is extremely sensitive to the load. On the other hand, the amplitude is sensitive at the same time to the defect severity (number of broken bars) and to the load varies. Consequently, by the observation of this amplitude and its position, the rotor state can be deduced.

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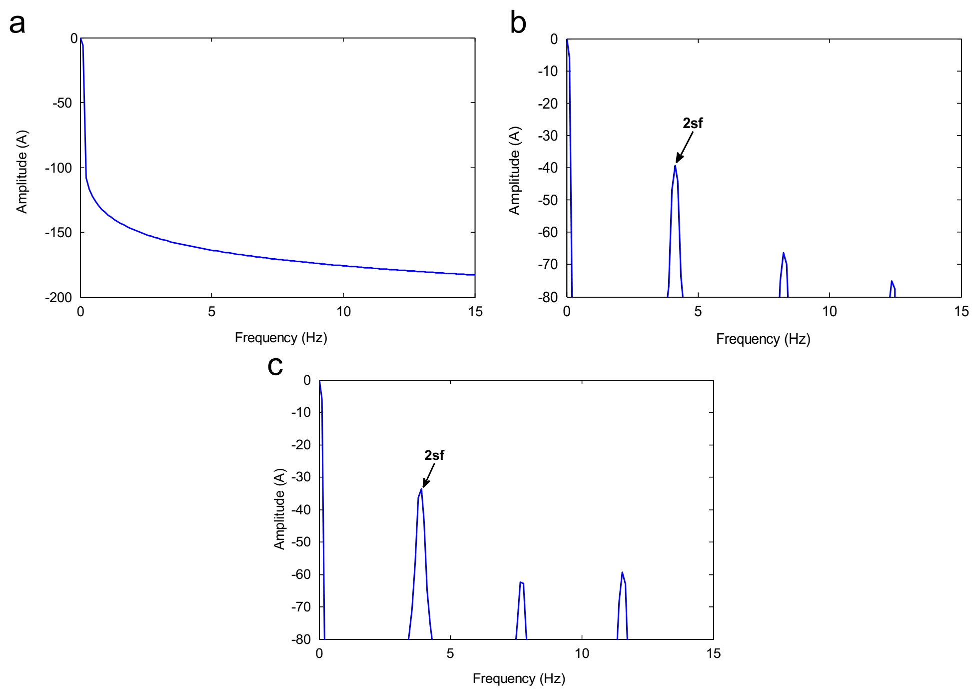

Fig. 3. Spectrum of stator current envelope: (a) healthy rotor; (b) one broken rotor bar; and (c) two broken rotor bars.

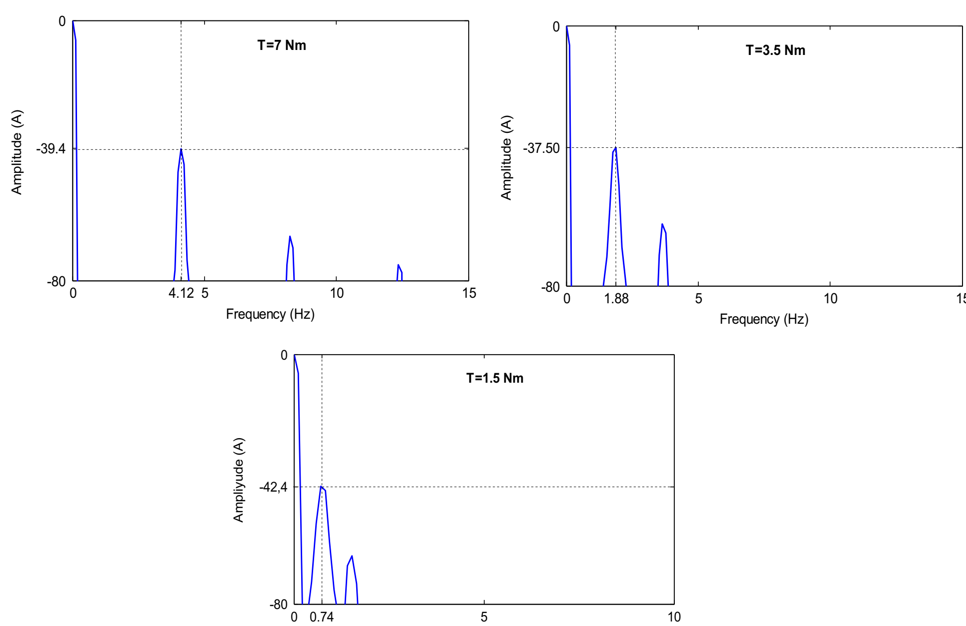

Fig. 4. Spectrum of stator current envelope for one broken bar fault under different load conditions.

4. Neural network simulated results

In this paper, the adopted NN is a feedforward MultiLayer Perceptron (MLP), which is extensively employed in classification problems. It is based on off-line learning principle using back propagation (BP) algorithm, which is one of the most powerful learning algorithms in NN [15]. BP training is a gradient descent algorithm with adaptive learning rate. It tries to improve the performance of the NN by reducing the total error on changing the weights along its gradient. In this paper, the error is expressed by the Mean Square Error (MSE).

4.1. Training database

The first and more critical step for developing an effective NN consists in defining an appropriate training database constituted by an input data set (I_i) and output data set (T_i) (Target). The select input data set is collected through simulations by Matlab, under different operating conditions of the induction machine.

The selected NN inputs are the amplitude $A(I_1)$ and the frequency $f_{bb}(I_2)$ of the harmonic $2sf$ (Fig. 5), as it is mentioned in the previous section. The NN has three outputs (O_1, O_2 and O_3) to indicate the number of broken bars in the rotor.

The input data set represented in Fig. 6, is composed by a successive range of 12 samples representing three states of the operating conditions of the induction machine under 4 load conditions (Torq = 1–3–5–7 Nm) as follow:

- healthy motor (4 samples),
- one broken bar faulty motor (4 samples),
- two broken bars faulty motor (4 samples).

An output data set is necessary to achieve a supervised learning. This data set is built by corresponding each sample in the input data set by its desired output T_i. The obtained targets $T=[T_1; T_2;T_3]$ are coded in binary and are represented in Fig. 7, as follow:

- $T=[0;\ 0;\ 0]$ for $N=0$; healthy rotor cage,
- $T=[0;\ 1;\ 0]$ for $N=1$; one broken bar in fault,
- $T=[0;\ 0;\ 1]$ for $N=2$; two broken bars in fault.

It is not necessary to learn the NN faults of more then two broken bars because, detecting a fault in an early stage of development, without false alarms, is crucial to prevent machine breakdown. So, it is very important to detect the first broken bar in the rotor of the machine.

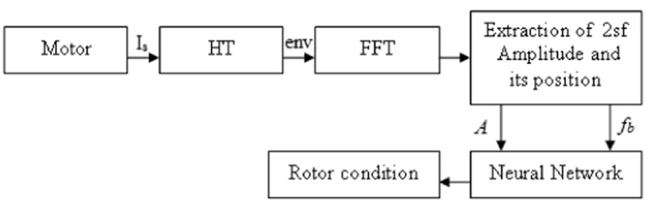

Fig. 5. Motor fault diagnosis using neural network.

4.2. Training and test results

The selected NN has one hidden layer with 6 neurons and 3 neurons at the output layer which represent the number N of the broken rotor bars. The transfer function of the hidden and the output layer are respectively "tansig" and "logsig".

The training outputs and errors of NN are shown in Fig. 8. The training errors are very low, proving that the NN has well learned the input data and has correctly reproduced the desired outputs.

The test data set is presented to the NN under three load torques ($T=2$–4–6 Nm) which corresponds to the following different operating cases of the induction motor:

- 5 samples for healthy operating
- 5 samples for an induction machine operating with one broken rotor bar
- 5 samples for an induction machine operating with two broken rotor bars.

The tests and outputs errors are illustrated in Figs. 9–11. The error is almost null. This proves that the network has learned the presence of the fault sequences quite well, and has been able to correctly reproduce the desired outputs.

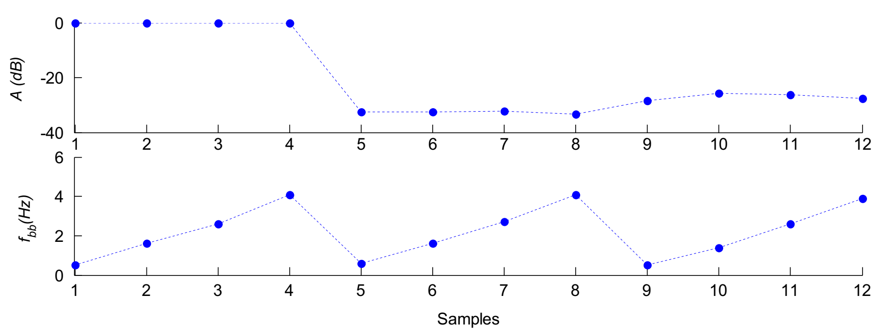

Fig. 6. Training input data set of NN.

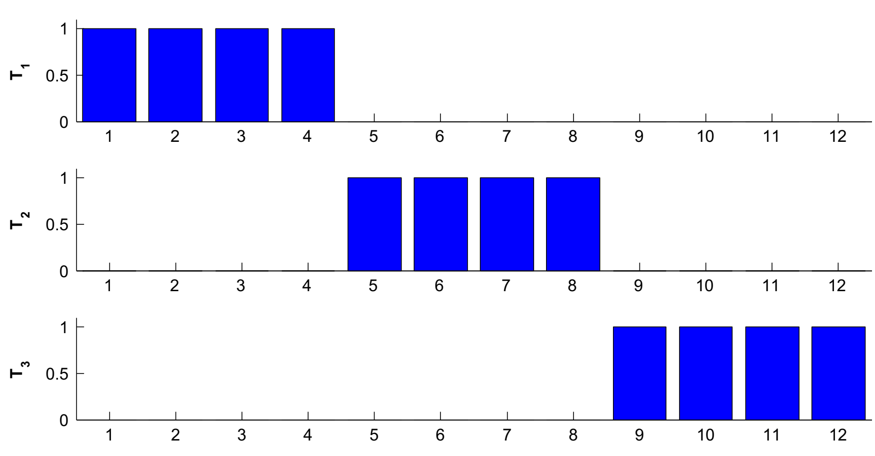

Fig. 7. NN output data set (Target).

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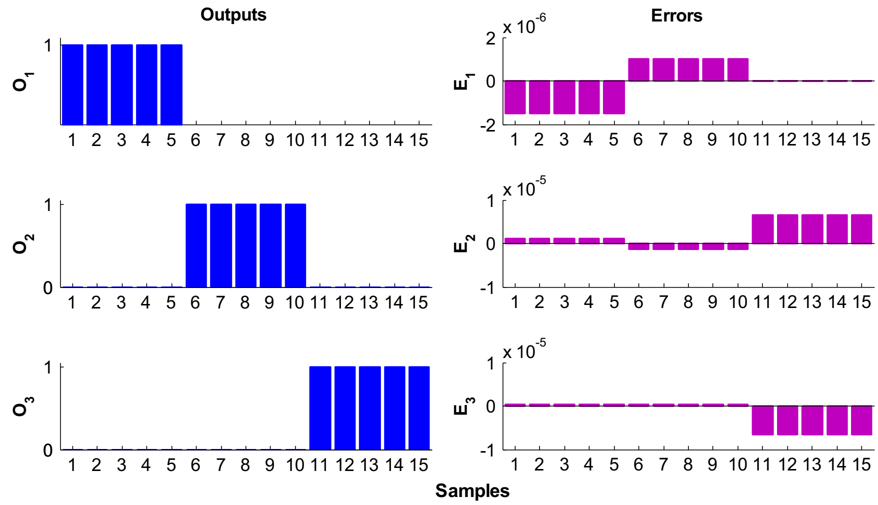

Fig. 8. Training and errors outputs of the NN.

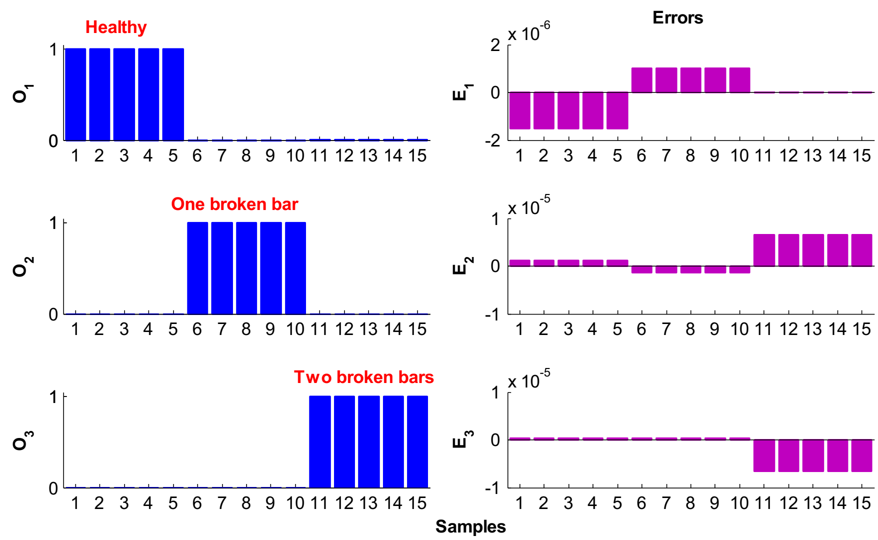

Fig. 9. Test and errors outputs of the NN for $T=2$ Nm.

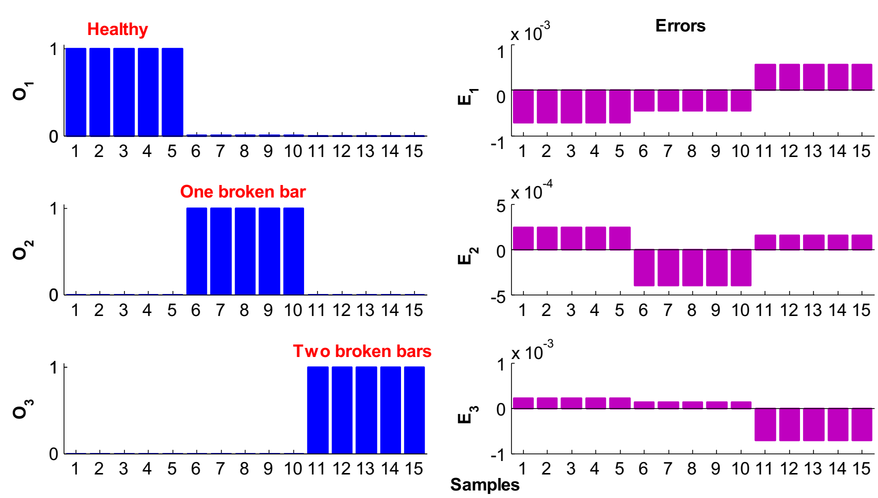

Fig. 10. Test and errors outputs of the NN for $T=4$ Nm.

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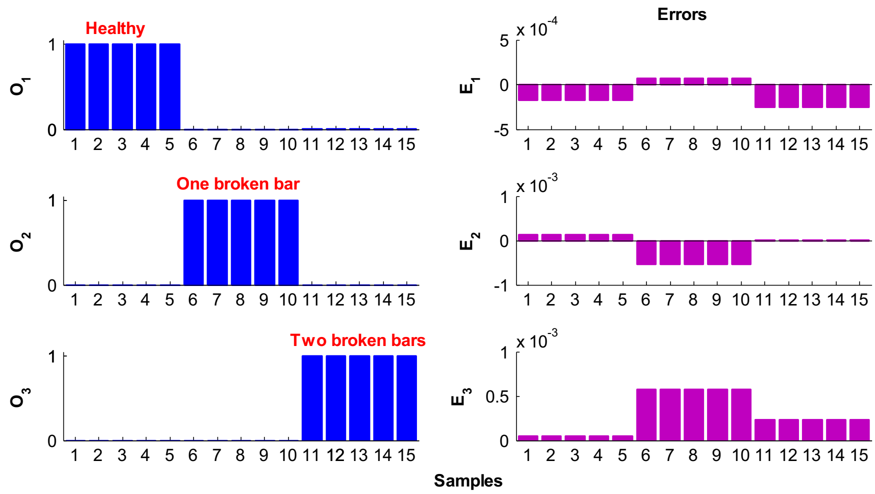

Fig. 11. Test and errors outputs of the NN for $T=6$ Nm.

5. Conclusion

This paper presents an accurate and effective method to quantify the number of the broken rotor bars in induction motor under different load conditions. In order to make an efficient diagnosis at low slip; the current envelope obtained via Hilbert transform has been used as diagnostic signal. The position of the harmonic $2sf$ and its amplitude are used as inputs of the NN. The system was tested under different load conditions and for different number of broken bars. The results obtained with this proposed system are efficient and accurate to detect the correct number of broken rotor bars.

Appendix A

For the simulated induction machine.

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

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