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# Stator inter-turn fault detection of an induction motor using neuro-fuzzy techniques

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Motivated by the superior performances of neural networks and neuro-fuzzy approaches to fault detection of a single phase induction motor, this paper studies the applicability these two approaches for detection of stator inter-turn faults in a three phase induction motor. Firstly, the paper develops an adaptive neural fuzzy inference system (ANFIS) detection strategy and then compares its performance with that of using a multi layer perceptron neural network (MLP NN) applied to stator inter-turn fault detection of a three phase induction motor. The fault location process is based on the monitoring the three phase shifts between the line current and the phase voltage of the induction machine.

**Key words:** inter-turn short circuit fault, phase shifts, adaptive neural fuzzy inference systems (ANFISs), neural network, induction motor

## 1. Introduction

Induction motors are the commonly used electrical machines in industry. Although these are very reliable, they are subjected to different modes of failure. Stator inter-turn fault is the most common type of fault in electric motor. If these faults are undetected, it may lead to the machine failure. Therefore, a monitoring system becomes necessary to increase the ability and life span of the machine.

Different researchers have proposed various fault monitoring techniques for induction motors. Some of the reported techniques necessitate mathematical model of the system [1], [2]. In [1], the modeling and simulation of induction motors with inter-turn faults for diagnosis have been reported. The models have been successfully used to study the transient and steady state behavior of the induction motor with short-circuited turns. A new model of squirrel cage induction motors under short circuit and rotor broken bar faults has been presented in [2].

A number of time frequency domain techniques have been used, which includes Short Time Fourier transform (STFT), Fast Fourier Transform (FFT), Bi-Spectrum, High resolution spectral analysis and wavelet analysis [3]-[10]. In [3], a methodology based

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on discrete wavelet transform for diagnosis of induction motor has been presented. An induction motor fault diagnosis using the stator current envelopes for broken rotor bars and inter-turn short circuits in stator windings have been proposed in [4]. In that paper, it is also identified the severity of the fault. A wavelet packet for extracting useful information from vibration signals has been employed in [5]. Though the signal is non-stationary, the Fourier transform cannot provide sufficient information to detect the fault.

Another technique used for induction motor fault detection exploits Artificial Intelligence tools, such as Expert Systems, Fuzzy Inference Systems, Artificial Neural Networks, Support Vector Machines, Genetic and ANFISs [11]-[19]. A neural network approach for the detection and location of an inter-turn short circuit fault in the stator windings of an induction motor has been applied in [11]. Pedro and Antero [12] have used fuzzy logic technique for the detection of stator winding fault in induction motor.

In [14], the adaptive neural fuzzy inference system for the detection of inter-turn insulation and bearing wear faults for a single phase induction machine has been applied. Here, in this paper, we have extended the work for the detection of stator inter-turn short circuit fault of a three phase induction motor. Then we have compared its performance with that of using a multi layer perceptron neural network (MLP NN).

The three phase shift between the line currents and phase voltages of the induction is used as the input to both the ANFIS and MLP NN. To monitor of these three phase shifts, both techniques will detect an inter-turn short circuit fault in the stator windings of an induction machines.

## 2. Generation of induction motor phase current at healthy and faulty condition

To generate the healthy and faulty currents of a three phase induction motor, we use the model which is proposed in [11]. It is described below.

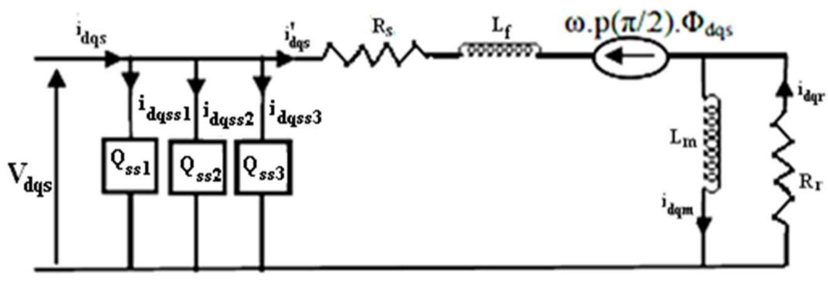


Figure 1. Stator faulty model in dq frame [11].

Fig. 1 shows the model proposed in [11], which is suitable to find out inter-turn short circuit fault in stator winding of an induction motor. In faulty condition, the model can be characterized by two modes such as common mode and differential mode. The common mode refers to the dynamic modes in healthy operation of the machine whereas the differential mode refers to the faulty operation.

The model of differential mode introduces two parameters defining the faults in the stator. These are as follows:

(i) $\theta_{ssk}$, (location parameter). It is the angle between the inter turn short circuit stator winding and the first stator phase axis. This parameter can take only three values 0, $2\pi/3$, $4\pi/3$, corresponding to the short circuit on the phase $a_s$, $b_s$, $c_s$ respectively.

(ii) $\lambda_{ssk}$, (detection parameter). It is the ratio between the numbers of inter-turn short circuit windings and the total number of turns in the healthy phase. These parameters are used to quantify the unbalance.

The state space representation of the model is given by [19].

$$\dot{X} = A(\omega)X + BU \tag{1}$$

$$Y = CX + D\left(\lambda_{ss}, \theta_{ss}\right)U \tag{2}$$

where

$$X = \begin{bmatrix} i_{ds} & i_{qs} & \varphi_{dr} & \varphi_{qr} \end{bmatrix}^T$$

$$U = \begin{bmatrix} V_{ds} & V_{qs} \end{bmatrix}^T$$

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

$$B = \begin{bmatrix} \frac{1}{L_f} & 0 & 0 & 0 \\ 0 & \frac{1}{L_f} & 0 & 0 \end{bmatrix}^T$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

$$D(\lambda_{ss}, \theta_{ss}) = \left[ \frac{2}{3R_s} \sum_{k=1}^{3} \lambda_{ssk} P(-\theta) Q(\theta_{ssk}) P(\theta) \right]$$

$$Q_{ssk} = \begin{bmatrix} \cos\left(\theta_{ssk}\right)^2 & \cos(\theta_{ssk})\sin(\theta_{ssk}) \\ \cos(\theta_{ssk})\sin(\theta_{ssk}) & \sin\left(\theta_{ssk}\right)^2 \end{bmatrix}$$

$$P(\theta) = \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix}$$

and

$i_{ds}$, $i_{qs}$ : dq stator current components,
$\varphi_{dr}$, $\varphi_{qr}$ : dq rotor flux linkage,
$V_{ds}$, $V_{qs}$ : dq stator voltage,
$\theta$ : electrical angle,
$\omega = \frac{d\theta}{dt}$,

$R_s$, $L_f$, $R_r$, and $L_m$ are the stator resistance, leakage inductance referred to the stator, rotor resistance, and magnetizing inductance respectively.

## 3. Generation of phase currents

Under normal operation and balanced conditions, phase voltages and line currents are equal in magnitude and shifted by $120^0$ electrical. However, under faulty operation, the phase currents are unequal and also their phase are shifted. To investigate the currents of the induction motor under inter turn short circuit fault, we have written respective program in MATLAB which generates phase currents of the induction motor before and after the fault condition.

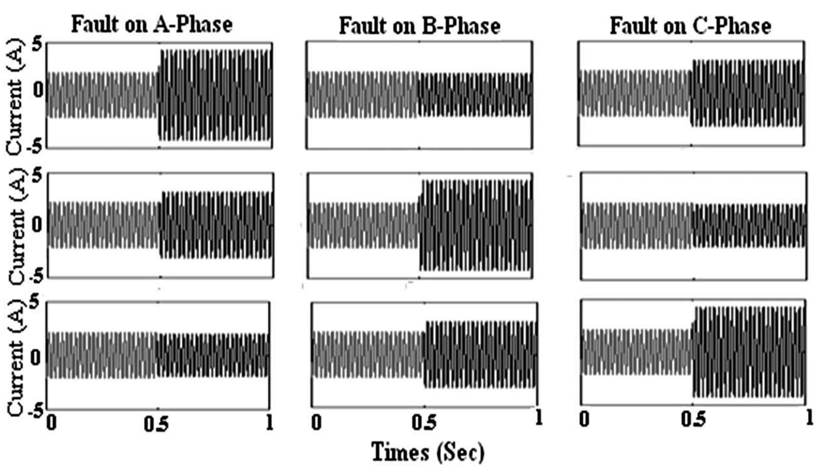


Figure 2. Fault effect on the three phase currents.

Fig. 2 shows that before 0.5 sec the current in all phases are equal in magnitude but after that the currents are unequal in the three phases. If a fault occurs in A-phase, the current in the phase increases to its peak value as compared to that of B-phase and C-phase. Consequently, the phase angle between the phase voltage and line current will change. This phase angle information is used to train and test the ANFISs to be described in sec. 4.

## 4. Detection of faulty phase location

A training database for the ANFISs in this work comprises of input and output data sets and have been prepared by using the procedure described in sec 3. The input data are collected through the simulation by MATLAB, using the model shown in Fig. 1. Fig. 3 shows the input data set which is composed with a successive range of the three phase shifts. All the phase shifts are presented to the ANFISs under different load torque conditions such as $T = 7$, 5, 3 [Nm]. In this work, the total 8 numbers of shorted stator turns are taken as $n = 1, 3, 5, 7, 9, 11, 13, 15$. Thus, for three load torque conditions we have $(3 \times 8 = 24)$ numbers of inputs are considered. For three phases a total of $(24 \times 3) + 3$ (for healthy condition) $= 75$ training and testing data patterns have been generated. As the number of short circuit inter-turn and the load torque changes the induction motor parameters such as stator resistance $R_s$, global leakage inductance $L_f$, and magnetizing inductance $L_m$ are change. Thus, using the model equation (3) we can calculate the phase shifts $\theta_a$, $\theta_b$ and $\theta_c$ between the phase voltage and line current

$$\tan\theta = \frac{x_s}{R_s} \tag{3}$$

where $R_s$ is the stator resistance and $x_s$ is the stator reactance. Thus, the simulated training input data to the Neural Network (three phase shifts $\theta_a$, $\theta_b$ and $\theta_c$) are obtained and are shown in Fig. 3.

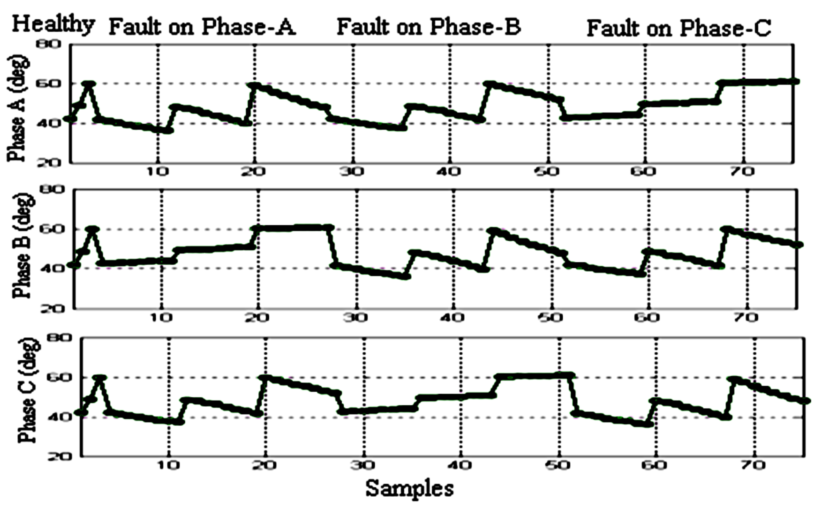


Figure 3. Simulated training input data set.

## 5. NN fault detection system

In this paper, we consider a feed forward MLP network trained by back propagation training algorithm (Fig. 4). The number of inputs and outputs are chosen as the number of fault indicators, which are the three phase shifts of the induction motor, but the number of neurons in the hidden layer is selected by trial and error as follows.

If the number of neurons in the hidden layer are too few, the NN cannot learn properly, and if this number is too large, the NN may simply memorize the training set. To avoid this, we start with two neurons, then we add other ones until an appropriate number that provides the low training mean square error is reached. In this paper we have used five neurons in the hidden layer. The activation functions of the hidden and output layers are "logsig" and "tansig" respectively.

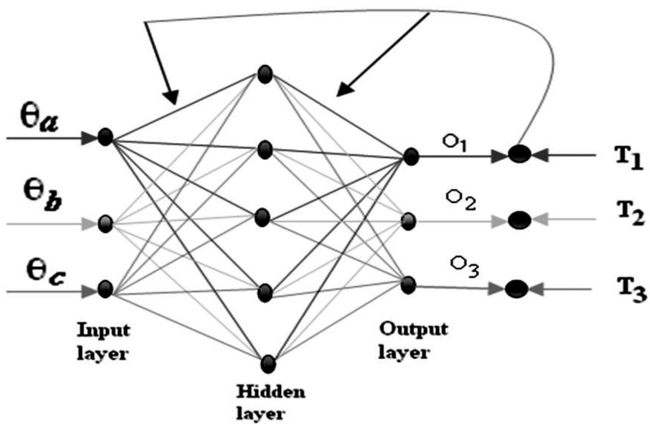


Figure 4. NN fault detector.

## 6. ANFIS fault detection system

The neural-fuzzy architecture takes into account both ANN and fuzzy logic technologies. The system is a neural network structured upon fuzzy logic principles, which enables the neural-fuzzy system to provide qualitative description of the motor condition and fault detection process. This knowledge is provided by the fuzzy parameters of membership functions and fuzzy rules. The fault detector bases on ANFIS, which is a fuzzy inference system implemented on five layers feed-forward network.

The ANFIS is implemented for the fault detection process due to its knowledge extraction feasibility, domain partitioning, rule structuring, and modifications [20]. Extracted knowledge is the knowledge acquired from the system after training. It is in terms of membership functions and Takagi-Sugeno type fuzzy if-then rules. The training procedure is an unsupervised learning scheme. It provides the partitioning for each and every input and output domain parameter. This is called domain partitioning. By using a hybrid learning procedure, ANFIS can construct an input-output mapping in the form of Takagi-Sugeno type if-then rules. The membership functions that correspond to the fuzzy antecedents as well as functions that form the consequence parts are parameterized. The hybrid learning proposed is composed of a forward pass and a backward pass. In forward pass, by keeping the antecedent parameters fixed, consequence parameters are optimized by a least square estimation. A fuzzy logic control/decision network is constructed automatically by learning from the training data.

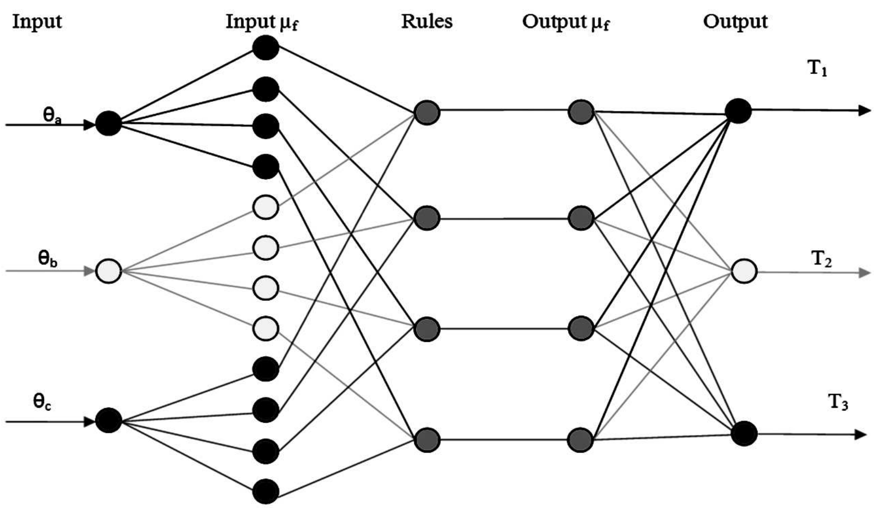


Figure 5. ANFIS fault detector.

The ANFIS architecture enables a change in rule structure during the evaluation of fuzzy inference system. The ANFIS optimizes itself in given number of iterations by providing a change in rules, by discarding unnecessary rules, and by changing shapes of membership functions, which is called modifications. It is an inherent characteristic of ANFIS architecture. The use of least square estimation follows from the fact that the network output is linear function of the consequence parameters [20]. Once the system is trained for specific data over a wide range, it can be applicable to similar types of motor used in plants, and thus there is no need to train the model for each motor.

In this paper we have written a suitable ANFIS program in the MATLAB environment which is used for fault detection purposes. The detection system is trained and tested by using the above simulated data as shown in Fig. 3. The detector is developed with three input parameters (three phase shifts $\theta_a$, $\theta_b$ and $\theta_c$). The ANFIS motor fault detector is trained to learn inter-turn short circuit fault in the stator winding of an induction motor. Fig. 5 shows the three inputs training data (three phase shifts $\theta_a$, $\theta_b$ and $\theta_c$)

which are applied for training the inter-turn short circuit fault in the stator winding of an induction motor. All the four membership functions for inputs are chosen as functions.

## 7. Results and discussions

Training data of all the three input parameters (three phase shifts $\theta_a$, $\theta_b$ and $\theta_c$) are applied to both of the fault detector to obtain the optimized architecture for the detection of inter-turn short circuit fault in the stator winding of an induction motor.

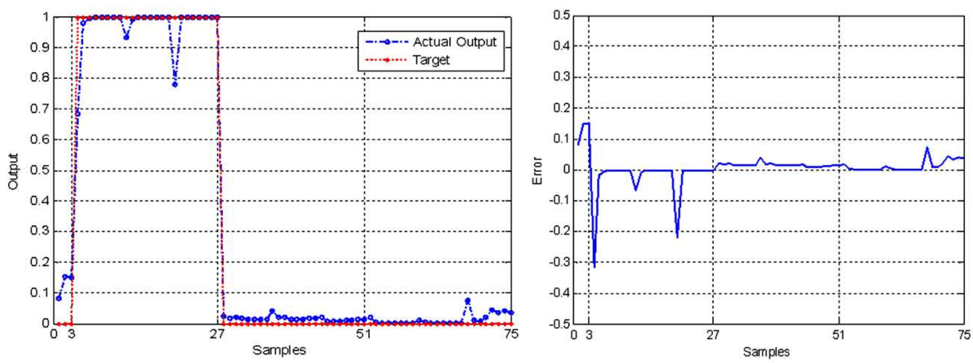


Figure 6. NN output and error for fault on phase A.

Fig. 6 shows the NN output and error when a fault will occur on phase A. Left part of the figure shows the output of the NN: star one represents the target value, the circle one is the actual output. When a fault will occur on phase A then the output of the phase A should equal be to one and others are zero. The result clearly shows that there is greater deviation between the target and the actual output. So the error which is the difference between the target value and the actual output is greater than 0.003 which is shown in the right part of Fig. 6.

Fig. 7 shows the ANFIS output and error when a fault will occur on phase A. Left part of the figure shows the output of the ANFIS: star one represents the target value and the circle one is the actual output. When a fault will occur on phase A then the output of the phase A should be equal to one and others are zero. The result clearly shows that the deviation between the target and the actual output is very little. So the error which is the difference between the target value and the actual output is $9.9016 \times 10^{-9}$ which is shown in the right part of the second figure.

Fig. 8 shows the NN output and error when a fault occurs on phase B. Some deviation between the target and the actual output can be observed. The error is $1.3832 \times 10^{-4}$.

Fig. 9 shows the ANFIS output and error when a fault occurs on phase B. The deviation between the target and the actual output is very little. The error is $1.1236 \times 10^{-8}$.

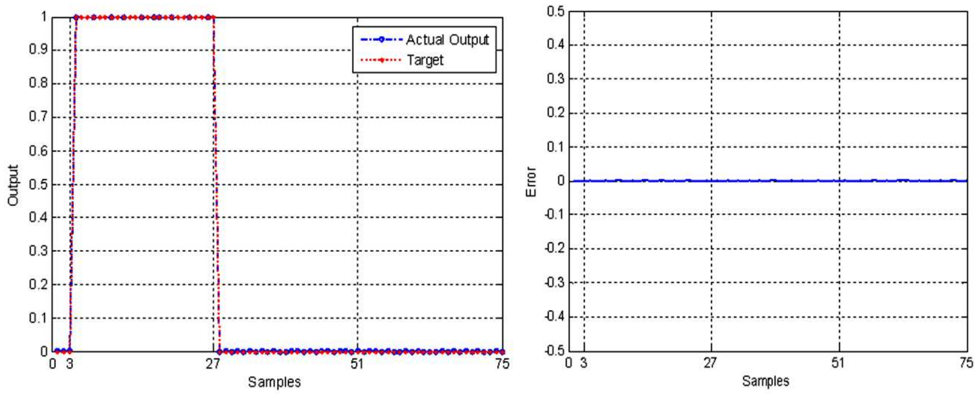


Figure 7. ANFIS output and error for fault on phase A.

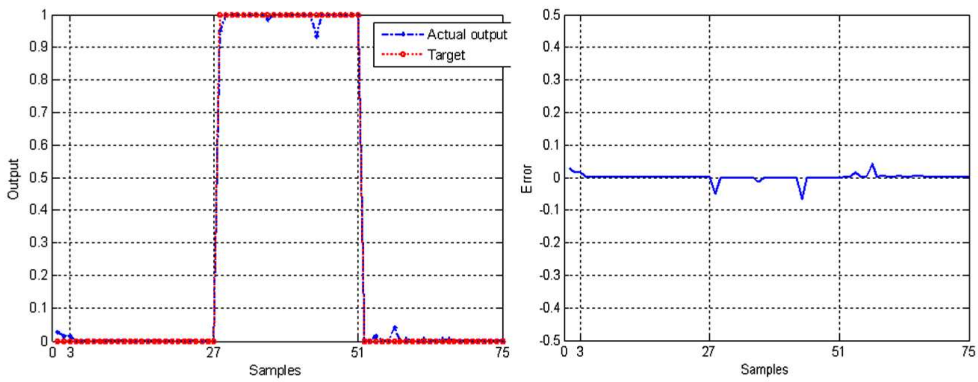


Figure 8. NN output and error for fault on phase B.

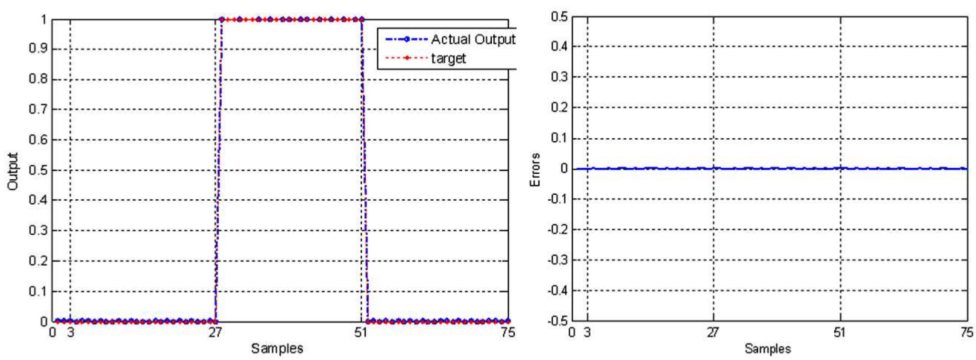


Figure 9. ANFIS output and error for fault on phase B.

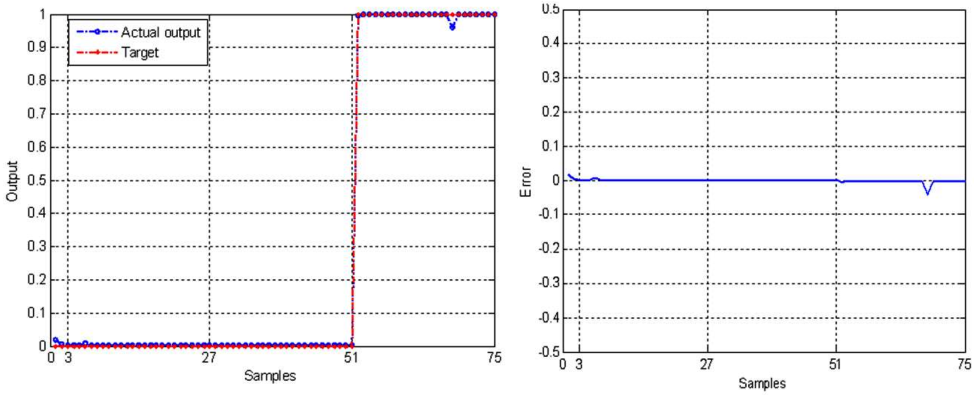


Figure 10. NN output and error for fault on phase C.

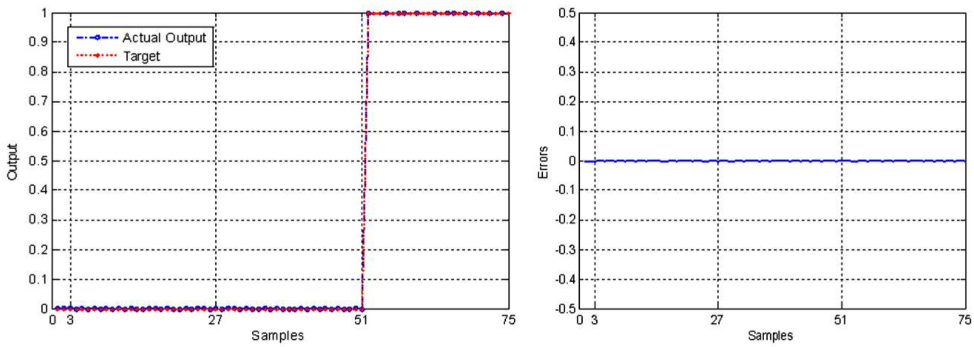


Figure 11. ANFIS output and error for fault on phase C.

Fig. 10 shows the NN output and error when a fault occurs on phase C. Again some deviation between the target and the actual output can be seen. The error is $2.8240 \times 10^{-5}$.

Fig. 11 shows the ANFIS output and error when a fault occurs on phase C. The deviation between the target and the actual output is very little. The error is $1.0744 \times 10^{-8}$.

Fig. 12 shows the training performance curve of the NN. The performance of the NN is detected by its mean square error. After learning with 500 epochs, the NN reaches a low training mean square error that is equal to 0.0503.

Fig. 13 shows the training performance curve of the ANFIS. The performance of the ANFIS is detected also by its MSE. After learning with 500 epochs, the ANFIS reaches a low training MSE that is equal to $7.1328 \times 10^{-6}$.

Table 1 shows the error comparison between the neural network (NN) and adaptive neural fuzzy inference system (ANFIS). It is observed that the errors in ANFIS are sig-

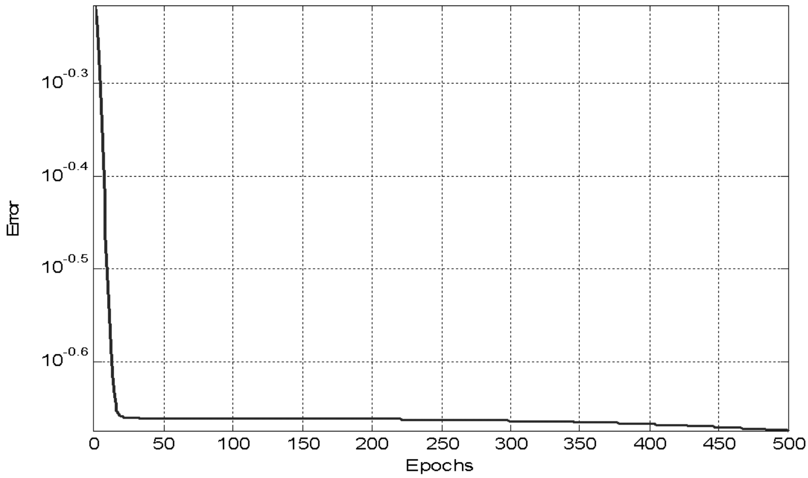


Figure 12. Training performance curve of the NN.

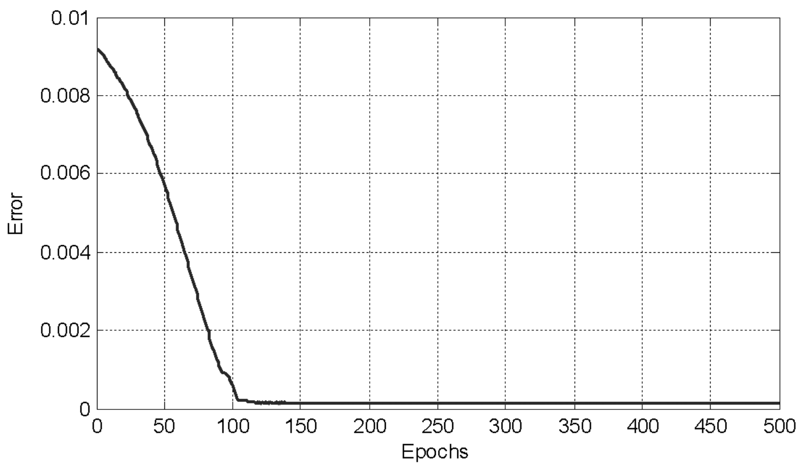


Figure 13. Training performance curve of the ANFIS.

nificantly smaller as compared with the NN. Hence, the accuracy of the system using ANFIS as the fault detector is much better than the system using NN.

## 8. Conclusions

This paper presents a comparison of stator inter-turn fault detection techniques applied to a three phase induction motor by using a multi layer perceptron neural network

Table 3. Comparison between NN and ANFIS

| | Error in NN | Error in ANFIS |
|---|---|---|
| Fault on phase A | 0.003 | $9.9016 \times 10^{-9}$ |
| Fault on phase B | $1.3831 \times 10^{-4}$ | $1.1236 \times 10^{-8}$ |
| Fault on phase C | $2.8240 \times 10^{-5}$ | $1.0744 \times 10^{-8}$ |
| MSE | 0.0503 | $7.1328 \times 10^{-6}$ |

(MLP NN) and an adaptive neural fuzzy inference system (ANFIS). The data base is obtained for the inter-turn fault by simulation of the induction motor model. Three inputs have been used (three phase shifts $\theta_a$, $\theta_b$ and $\theta_c$) to both the NN and ANFIS detector and the performance is tested. From the Table 1 it is observed that the errors in ANFIS are significantly smaller as compared with the NN. Hence, the accuracy of the system using ANFIS as the fault detector is better then the system which uses NN.

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