Fault Detection using ANFIS for the Magnetically Saturated Induction Motor

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Abstract: The problem of fault detection of the *π-model* induction motor with magnetic saturation is considered in this paper. In this paper we use a new technique which is the Adaptive Neuro Fuzzy Inference Systems (ANFIS) technique for online identification of the different motor fault conditions. A simulation study is illustrated using MATLAB simulink depending on stator currents measurement only for online detection of the motor faults. The proposed technique shows promising results using the simulation model.
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1. Introduction:

In the last decade, a tremendous development in the theory of nonlinear control has been achieved. The common assumption made in the development of these control laws is the linearity of the magnetic circuit of the machine. This assumption is usually justified by including the flux magnitude in the outputs to be regulated by the controller and keeping this magnitude regulated at a value far from the saturation region. However there are no guarantees that the flux magnitude remains in the linear magnetic region during machine transients. Moreover in many variable torque applications, it is desirable to operate the machine in the magnetic saturation region to allow the machine to develop higher torque [1] and [2]. Saturation effects are also known to be pronounced in drives operating in the field weakening region, or in drives that operate with varying flux levels to achieve optimally in a specified sense [3]. However, the operation of the motor at various magnetization levels makes the nominal inductance a bad approximation. Recently, researchers have been attracted to induction motor control with magnetic saturation. Feedback input-output linearization schemes for induction motors with magnetic saturation were proposed in a fixed stator frame [4] and in a synchronously rotating frame [5]. While in [4] the control signal is the stator voltage, but in [5] it is the stator current. Both papers treat the *T-model* of an induction motor. Unfortunately, due to the complicated nature of the *T-model*, drastic simplifications are required to facilitate the use of this model in nonlinear control synthesis. The major drawback in [4] (also present in the optimal flux reference selection of [5]) is the assumption that the stator and rotor leakage parameters σs and σr, as defined by W. Leonard in [6], are *equal* and *constant*. This assumption has the indirect effect of neglecting any cross-saturation effect that might appear in the dynamics of the motor. On the other hand, the model in [5] is obtained by firstly simplifying the motor equations assuming a linear magnetic circuit and then including a mutual inductance that varies with mutual current. This approach does not include derivatives of the saturation function that should appear in a complete model which was driven by Gokdere in [7]. A similar modeling approach can also be found in [8] for incorporating magnetic saturation in the passivity-based control design methodology appears in the work of H. A. Abdel Fattah and K. A. Loparo that was proposed in [9]. It is worth pointing out that the work published in [8] similar to [5] that stator currents are used as the control signal. All the work presented so far is based on a *T-model* of the induction motor, contrary to the *π-model* proposed in [1]. The *π-model* differs from the conventional *T-model* in that it is more closely related to the physical structure of the machine, since its derivation is primarily based on the stator-rotor tooth pair magnetic circuit. Even though the work in [1] is based on a wound rotor motor, it is shown in the same paper how the modeling approach can be applied to a squirrel cage motor. It is not difficult to show that both models are equivalent when a linear magnetic circuit is assumed, this equivalence does not hold when main flux saturation is included. In the published work of H. A. Abdel Fattah and K. A. Loparo as in [10]. It was shown that considering magnetic saturation explicitly in nonlinear control synthesis is of foremost importance especially when the machine is voltage actuated. Because the π-model was experimentally found in [1] to be better suited to capture the nonlinear magnetic effects. E Levi have designed a simplified saturated model of induction motor that was proposed in [11].

Many techniques are performed for detection of the motor faults [12] to [29]. The previous procedure are deal with the linear model of the induction motor and deal with the online diagnostics of the motor fault detection , from the previous work we find that many factors are lead to motor faults such that bearing faults induce 40% of the motor faults , 38% are due to the stator winding , 10% are due to rotor faults and 12% other faults ,the new in this paper that the saturated model of induction motor is considered and the fault conditions are performed using simulation model in matlab simulink.

2. Induction Motor Saturated Model

The main results of the dissertation on induction motor control under magnetic saturation will be based on the π- model. The π-model for the complete motor, at zero speed, is shown in Figure (1). The two phase electrical equations for an induction machine in an arbitrary frame rotating with speed (ω0) are given by:

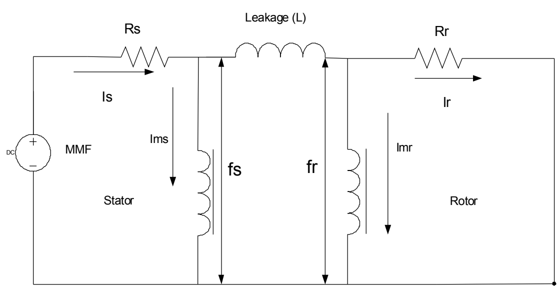

Figure (1): Induction Motor π- Model

$$V_s = R_s I_s + \frac{d\psi_s}{dt} + \omega_0 J_2 \psi_s$$
$$0 = R_r I_r + \frac{d\psi_r}{dt} + (\omega_0 - \omega_e) J_2 \psi_r \quad (1)$$

Where; Vs is the stator phase voltage vector, Is is the stator phase current vector, Ir is the rotor phase current vector, p is t he number of pole pair s, ω is the rotor speed, Rs is the stator phase resistance, Rr is the rotor phase resistance, Ψs and Ψr are the stator and rotor flux linkage vector s respectively.

Equation (1) holds whether the induction motor magnetic circuit is considered linear or saturated and J2 is the 2 × 2 rotating matrix defined by;

$$J_2 = [0 -1; 1 0] \quad (2)$$

The mechanical equation can be expressed as:

$$J\frac{d\omega}{dt} + b\omega = T - T_L \quad (3)$$

Where J is the motor inertia, b is the viscous damping, T_L is the load torque and T is the generated torque. The relationship between the currents and the fluxes for the π model at d-q frame rotating with speed (ω0) are given by:

$$\begin{bmatrix} I_s \\ I_r \end{bmatrix} = \begin{bmatrix} G_s(\|\psi_s\|) \\ G_r(\|\psi_r\|) \end{bmatrix} + \begin{bmatrix} g_l I_2 & -g_l I_2 \\ -g_l I_2 & g_l I_2 \end{bmatrix} \begin{bmatrix} \psi_s \\ \psi_r \end{bmatrix} \quad (4)$$

Where gl is defined as:

$$g_l = \frac{1}{L_l} \quad (5)$$

Where Gs and Gr are the stator and rotor vector-valued nonlinear functions and defined as:

$$G_X(\psi_X) = G_X\left(\begin{bmatrix} \psi_{xd} \\ \psi_{xq} \end{bmatrix}\right) = \begin{bmatrix} I_{mxd} \\ I_{mxq} \end{bmatrix} = I_{mx} \quad (6)$$

Where; Im and Ψm are the mutual current and flux vector, respectively, and subscript (x) can be (s) for stator and (r) for rotor. The relationship between the currents and the fluxes for the π model can be compactly written as:

$$\begin{bmatrix} I_s \\ I_r \end{bmatrix} = \begin{bmatrix} (g_s(\|\psi_s\|)+g_l)I2 & -g_l I2 \\ -g_l I2 & (g_r(\|\psi_s\|)+g_l)I2 \end{bmatrix} \begin{bmatrix} \psi_s \\ \psi_r \end{bmatrix} \quad (7)$$

Where; I2 is the 2 × 2 identity matrix, gl is defined as the reciprocal of the leakage inductance (Ll), gs and gr are the stator and rotor vector-valued nonlinear saturation functions. The scalar saturation functions gs and gr only affect the magnitude, while keeping the directions of the fluxes and currents the same. These functions are monotone increasing and are non zero at the origin. The saturation functions gs(x) and gr(x) have to be identified experimentally for each motor as shown in the next section.

Finally, the generated torque (T) and p is the poles number is given by;

$$T = P g_l(\psi_s)^T J_2(\psi_r) \quad (8)$$

3. Fault Detection Using Anfis

The new in this paper is the online detection of the motor fault conditions using ANFIS technique. The induction motor monitoring diagnosis techniques such that magnetic flux, vibration, stator currents, induced voltage, power and surge testing are used for detection of the motor faults.

Stator current signal are contains potential fault information and is the most suitable measurements for diagnosing the faults under consideration, in term of easy accessibility, reliability, and sensitivity. A simple construction using stator current for motor fault detection is indicated in figure1, the linguistic variables of the induction motor stator conditions are shown in figure 2.

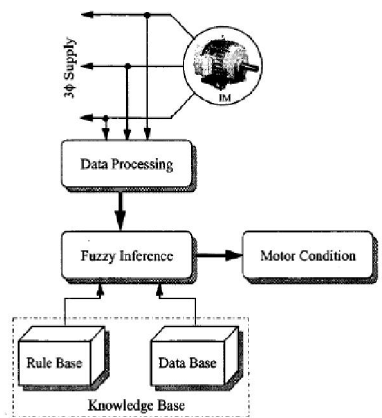

Fig 1 Block diagram of induction motor condition monitoring system

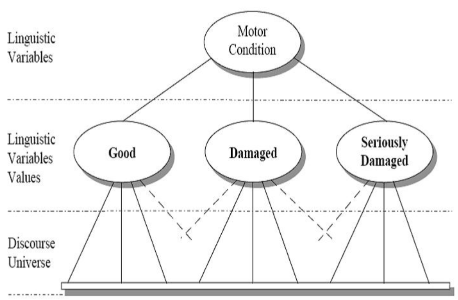

Fig2 Linguistic variables of the induction motor stator condition.

The fault condition that taken in consideration using stator current measurement in this paper will be

1- Line to ground fault of the motor supply voltage
2- Line to line fault of the motor supply voltage
3- One phase is lost of the motor supply voltage
4- Short circuit occur in the stator winding of the induction motor (Rs=0)
5- Short circuit occur in the rotor winding (Rr=0)

A. Neuro Fuzzy Controller

During the past three decades, fuzzy logic has been an area of heated debate and much controversy. The first implementation of Zadeh's idea was accomplished in 1975 by Mamdani, which demonstrated the viability of fuzzy logic control (FLC) for a small model steam engine. After this pioneer work, many consumer products as well as other high technical applications have been developed using fuzzy technology.

A list of industrial applications and home appliances based on FLC can be found in several recent references [30] to [36]. However, the design of a FLC relies on two important factors: the appropriate selection of knowledge acquisition techniques, and the availability of human experts. These two factors subsequently restrict the application domains of FLC. In this paper, the application of Adaptive Neuro Fuzzy Inference Systems (ANFIS) is presented to overcome such restrictions.

An adaptive neuro -Fuzzy Inference System (ANFIS) is a cross between an Artificial Neural Network (ANN) and a fuzzy inference system (FIS). An artificial neural network is designed to simulate the characteristics of the human brain and consists of a collection of artificial neurons. An adaptive network is a multi-layer feed-forward network in which each node (neuron) performs a particular function on incoming signals. The form of the node functions may vary from node to node. In an adaptive network, there are two types of nodes, adaptive and fixed. The function and the grouping of the neurons are dependent on the overall function of the network. Based on the ability of an ANFIS to learn from training data, it is possible to create an ANFIS structure from an extremely limited mathematical representation of the system. In sequel, the ANFIS architecture can identify the near-optimal membership functions of FLC for achieving desired input-output mappings. The network applies a combination of the least squares method and the back propagation gradient descent method for training FIS membership function parameters to emulate a given training data set. The system converges when the training and checking errors are within an acceptable bound. The ANFIS system generated by the fuzzy toolbox available in MATLAB allows for the generation of a standard Sugeno style fuzzy inference system or a fuzzy inference system based on sub-clustering of the data. Figure 2 shows a simple two-input ANFIS architecture. The above ANFIS architecture is based on a Sugeno fuzzy inference system. The Sugeno FIS is similar to Mamadani format except the output memberships are singleton spikes rather than a distributed fuzzy set. Using singleton output simplifies the defuzzification step.

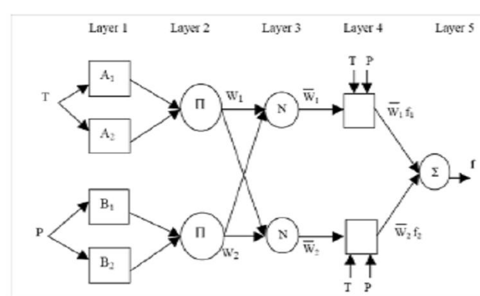

Figure (2): ANFIS Architecture for a Two-Input System

The ANFIS network shown in Figure (2) is composed of five layers. Each node in the first layer is a square (adaptive) node with a node function. The basic diagram computation in ANFIS is sown in Figure (3). This structure contains the same components as the FIS, expect for the NNblock. The structure of the network is composed of a set of units (and connections) arranged into five connected network layers, via., l1 to l5 as shown in the Figure (4).

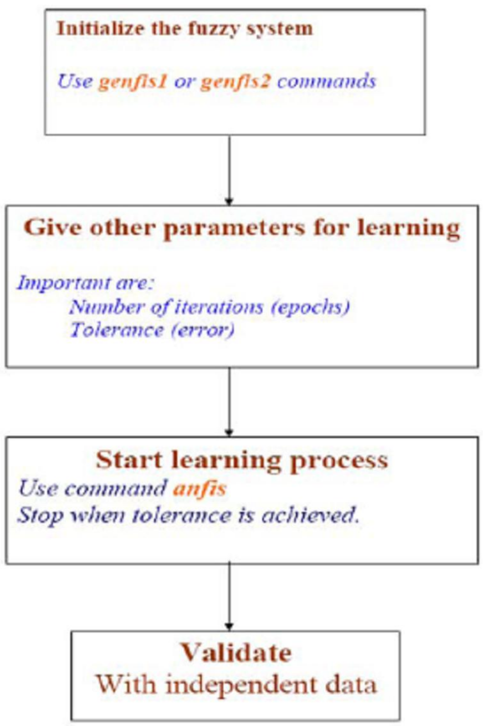

Figure (3): Basic Diagram Of ANFIS Computation

Layer 1: This layer consists of input variables (membership functions), via., input 1 & input 2. Here, triangular or bell shaped MF can be used. This layer just supplies the input values x to the next layer, where i= 1 to n.

Layer 2 : This layer (membership layer) checks for the weights of each MFs. It receives the input values x from the 1st layer and act as MFs to represent the fuzzy sets of the respective input variables. Further, it computes the membership values which specify the degree to which the input value x belongs to the fuzzy set, which acts as the inputs to the next layer.

Layer 3 : This layer is called as the rule layer. Each node (each neuron) in this layer performs the pre-condition matching of the fuzzy rules, i.e., they compute the activation level of each rule, the number of layers being equal to the number of fuzzy rules. Each node of these layers calculates the weights which are normalized.

Layer 4 : This layer is called as the defuzzification layer and provides the output values y resulting from the inference of rules. Connections between the layers l3 and l4 are weighted by the fuzzy singletons that represent another set of parameters for the neuro fuzzy network.

Layer 5 : This layer is called as the output layer which sums up all the inputs coming from the layer 4 and transforms the fuzzy classification results into a crisp (binary). The ANFIS structure is tuned automatically by least-square estimation as well as the back propagation algorithm. The algorithm shown above is used in the next section to develop the ANFIS technique to control the various parameters of the induction motor. Because of its flexibility, the ANFIS strategy can be used for a wide range of control applications.

B. ANFIS Design for motor fault detection conditions

The main purpose of using ANFIS controller in this paper is for identification of the fault occurrence in the saturated model of induction motor. The ANFIS controller structure is shown in Figure (4) . The fuzzy logic membership functions for the input and output are turned using neural network method which is well known in MATLAB program as ANFIS structure. The parameters are selected such that, optimization method is hybrid, the membership function is gbellmf , the membership function output is linear , error tolerance was chosen to be 0. 01 , the no of epochs are 1000 , grid partitions , the inputs of the grid partitions are the number MFS are 3 , MF type is gbellmf , the outputs is MF type defined to be constant . The motor parameters that used in simulation are shown in table 1.

Table 1 motor parameters

parameters	π − model	unit
R_s	8	Ω
R_r	6	Ω
$L_{\sigma s}$	N/A	H
$L_{\sigma r}$	N/A	H
L_m	N/A	H
L_I	0.062	H
J	0.06	Kgm^2
b	0.04	N_s/rad

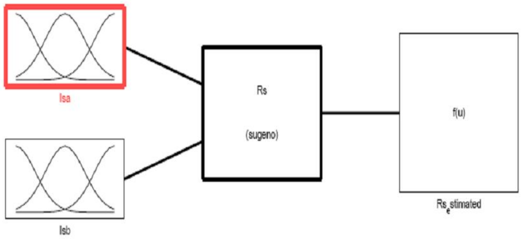

Fig 4 Fault detection controller using ANFIS

I. SIMULATION RESULTS

Using the saturated model of induction motor with the parameters in table 1 , the applied supply voltage are :U_a =380 sin (2π 50 t) , U_b= 380 sin (2π 50 t - 2π/3) , U_c= 380 sin (2π 50 t + 2π/3) the simulation duration is 20 second .

The fault conditions are performed using simulation and by using the ANFIS programming, the controller will detect that there is a fault occurrence to the motor during the operation. The controller will also state which type of fault in each case.

Simulation1

Start the simulation of the motor by performing the different fault conditions stated before and plotting the effect of the faults on the measured signals of the stator currents. The result of the simulation is indicated in figures (5) to (12).

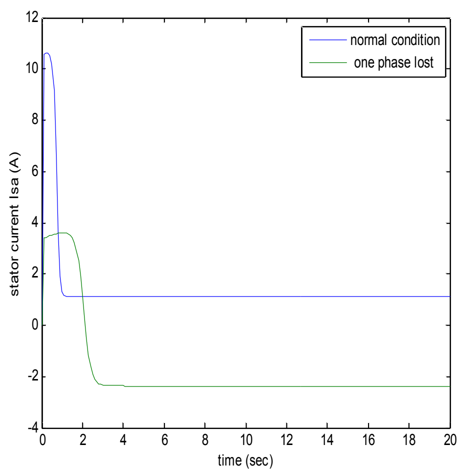

Fig 5 Stator current Isa in case of one phase is lost or line to ground fault of the motor supply

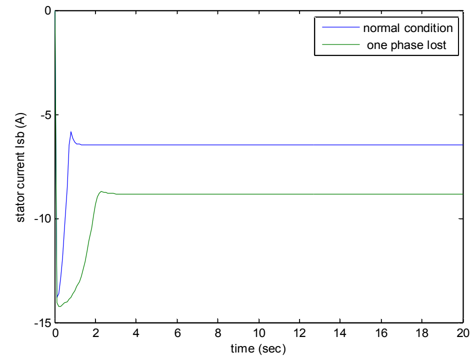

Fig 6 Stator current Isb in case of one phase is lost or line to ground fault of the motor supply

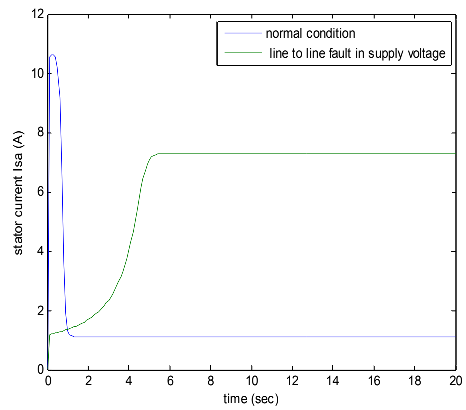

Fig 7 Stator current Isa in case of line to line fault of the motor supply

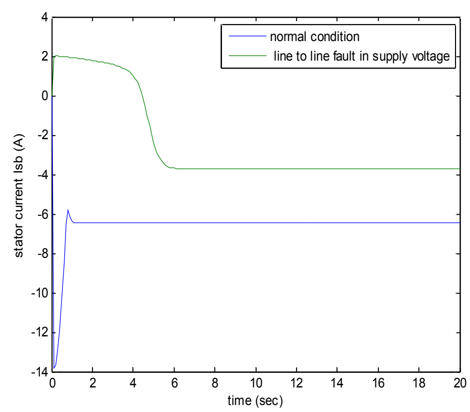

Fig 8 Stator current Isb in case of line to line fault of the motor supply

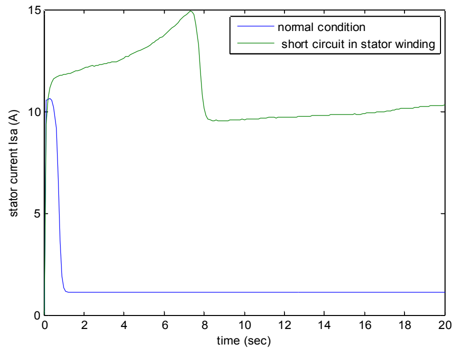

Fig 9 Stator current Isa in case short circuit in the stator windings

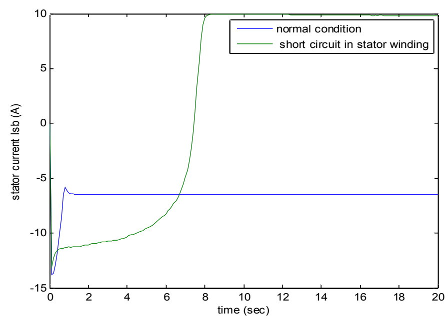

Fig 10 Stator current Isb in case short circuit in the stator windings

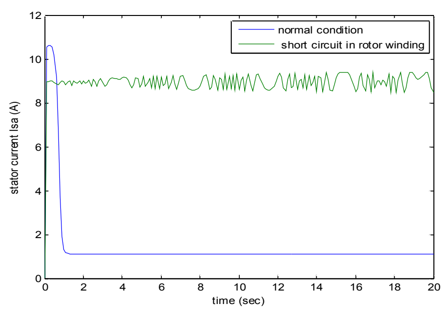

Fig 11 Stator current Isa in case short circuit in the rotor windings

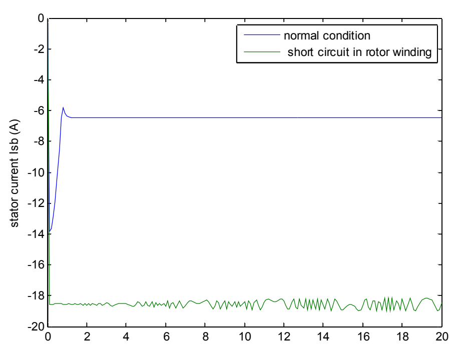

Fig 12 Stator current Isb in case short circuit in the rotor windings

Simulation 2

Using ANFIS controller to detect online the type of fault that occur to the induction motor as follows:

Item	Type of fault	ANFIS output
1	One phase loss or line to ground fault	0-0.5
2	Line to line fault	1-1.5
3	Short circuit in the stator winding	2-2.5
4	Short circuit in the rotor winding	3-3.5

We start the simulation in normal conditions with line voltage 380V then and reducing the voltage magnitude of the supply voltage at 5 second to 220 V then at 10 second the supply voltage will be 110V then we perform a line to ground fault at 15 seconds and the result of the ANFIS controller is shown in figure (13)

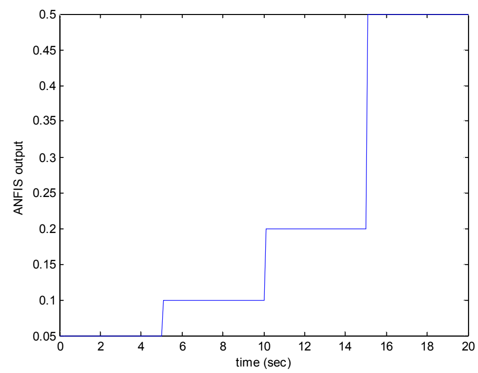

Fig 13 ANFIS output in case line to ground fault

Next we start the simulation in normal conditions with line voltage 380V then and we perform a line to line fault at 10 seconds and the result of the ANFIS controller is shown in figure (14)

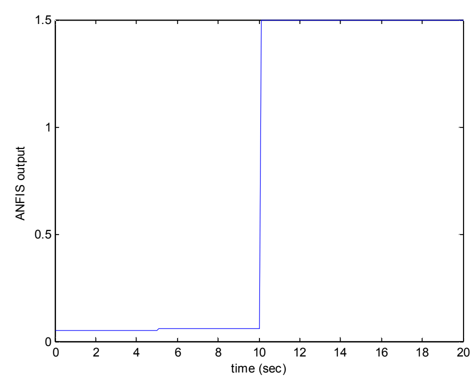

Fig 14 ANFIS output in case line to line fault

Next we start the simulation in normal conditions and the stator resistance is reduced from 8 ohm to 4 ohm at 5 seconds and to 3 ohm at 10 second then we perform a short circuit in stator winding at 15 seconds and the result of the ANFIS controller is shown in figure (15)

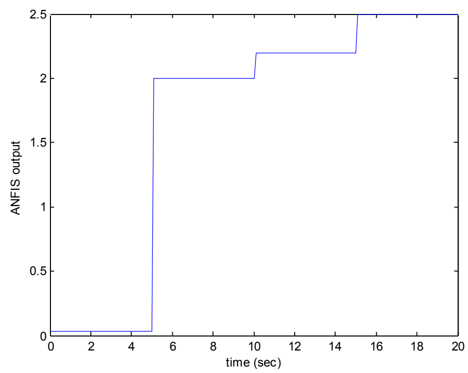

Fig 15 ANFIS output in case of stator winding short circuit

Finally we start the simulation in normal conditions and the rotor resistance is reduced from 6 ohm to 3 ohm at 5 seconds and to 2 ohm at 10 second then we perform a short circuit in rotor winding at 15 seconds and the result of the ANFIS controller is shown in figure (16)

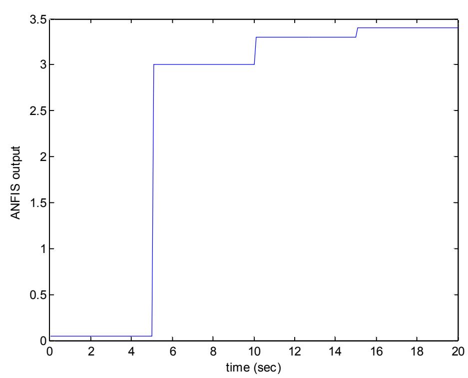

Fig 16 ANFIS output in case of rotor winding short circuit

4. Conclusion

The new in this paper is using ANFIS technique for detection of the induction motor different fault conditions. This paper is different from the previous work that we are using ANFIS controller for detection of the supply voltage faults as well as any short circuit appears in the motor windings. The percentage of the fault is appear in the ANFIS controller output so we can early detect any failure start in the motor winding for predictive maintenance

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