

# Fault Diagnosis of an Induction Motor based on Fuzzy Logic, Artificial Neural Network and Hybrid System

Alexandre Boum\*, Nyobe Yome Jean Maurice, Leandre Nneme Nneme, Laure Mafonang Mbumda

University of Buea, Cameroon / HTTTC Kumba

**Abstract** This paper presents the fault diagnosis of a three-phase induction motor using fuzzy logic, neural network and hybrid system. Detailed analysis during voltage unbalance, open phase, low voltage and overload motor fault using these strategies are presented. Stator currents were measured and their root mean square were derived. These values were used to train data. Each output of these diagnosis tools is used to determine the motor conditions whether it is in a healthy state or in a faulty one. A novel hybrid system is design and used in fault diagnosis. Simulation results show that hybrid systems give the best estimation of faults and can be therefore used in monitoring of induction motors with greater efficiency.

**Keywords** Fuzzy logic, Neural network, Hybrid system, Induction motor

## 1. Introduction

Diagnostic of industrial processes is a scientific discipline aimed at the detection of faults in industrial plants, their isolation, and their identification [9, 16]. Many scientific researches deal with the problem of induction motors faults detection and diagnosis and the major difficulty is the lack of accurate model that describes a fault motor [7, 9]. In fact, a fuzzy logic approach, neural networks and hybrid system may help to diagnose an induction motor faults. It is very important in this project to do analysis, comparison and data collection to acknowledge the behavior of the induction motor conditions and determine the causes of the faults occurrence using fuzzy logic, neural network and hybrid system. Moreover, this will be done throughout modeling of induction motor, estimation of the state of the faults that can occur on a such a motor, the use of fault diagnosis method by fuzzy logic, neural and the combination of both paradigm (hybrid system). This paper is organized as follow: in section 1, introduction is presented. Section 2 presents the modeling of an induction motor. In section 3, 4 and 5, fault detection of this machine is studied using the stated methods. And finally, results, discussions and conclusion are presented in section 6 and 7.

## 2. Modeling of Induction Motor

The model use is derived from [3, 8], and [6]. Modeling of asynchronous motor is based on many assumptions among which we have:

- Gap perfectly smooth;
- Negligible iron losses;
- Saturation is negligible in the magnetic circuit
- Negligible space harmonics; The winding of the stator and the rotor are sine distributed in such a way that mutual inductances between the stator and the rotor are sine functions of the mechanical position of the rotor with respect to the stator.

### 2.1. Electrical and Mechanical Equations in Three-phase System

Electrical diagram of an asynchronous motor is shown in Figure 1. Were  $U_s(abc)$ ,  $U_r(abc)$  are respectively voltages apply to the stator and the rotor.

From Figure 1, the following equations are derived:

- For the stator side

$$U_s = \begin{pmatrix} U_{sa} \\ U_{sb} \\ U_{sc} \end{pmatrix} = \begin{pmatrix} R_s & 0 & 0 \\ 0 & R_s & 0 \\ 0 & 0 & R_s \end{pmatrix} \begin{pmatrix} I_{sa} \\ I_{sb} \\ I_{sc} \end{pmatrix} + \frac{d}{dt} \begin{pmatrix} \Phi_{sa} \\ \Phi_{sb} \\ \Phi_{sc} \end{pmatrix} \quad (1)$$

- For the Rotor side

$$U_r = \begin{pmatrix} U_{ra} \\ U_{rb} \\ U_{rc} \end{pmatrix} = \begin{pmatrix} R_r & 0 & 0 \\ 0 & R_r & 0 \\ 0 & 0 & R_r \end{pmatrix} \begin{pmatrix} I_{ra} \\ I_{rb} \\ I_{rc} \end{pmatrix} + \frac{d}{dt} \begin{pmatrix} \Phi_{ra} \\ \Phi_{rb} \\ \Phi_{rc} \end{pmatrix} \quad (2)$$

Where  $U_s(abc)$ ,  $I_s(abc)$ ,  $\Phi_s(abc)$  represent respectively voltages, currents and fluxes for the stator side.

\* Corresponding author:

boumat2002@yahoo.fr (Alexandre Boum)

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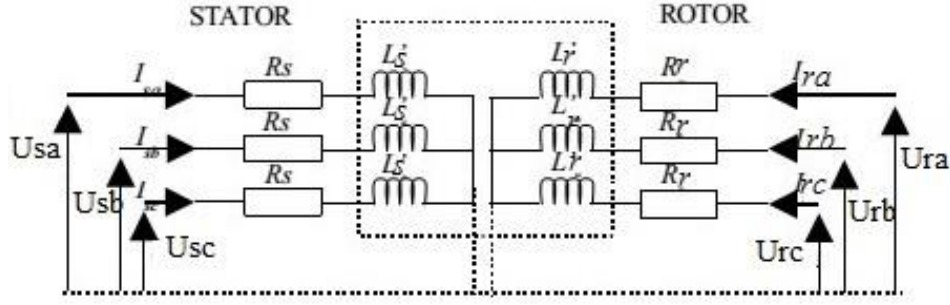


Figure 1. Electrical diagram of an asynchronous motor [3, 8]

Similarly,  
 $U_{r(abc)}$ ,  $I_{r(abc)}$ ,  $\Phi_{r(abc)}$  are respectively voltages, currents and fluxes for the rotor side.

For squirrel cage induction motor,

$$U_{ra} = U_{rb} = U_{rc} = 0.$$

Electromagnetic torque is

$$T_{em} = p \frac{1}{2} I^T \frac{dL}{d\theta} I \quad (3)$$

Where  $\theta$  denotes the electrical angle between a phase of the rotor and the corresponding phase of the stator [3, 8].

The mechanical equation is:

$$J \frac{d\omega_r}{dt} + f_v \cdot \omega_r = T_{em} - T_r \quad (4)$$

## 2.2. Electrical and Mechanical Equations in dq Reference Frame

After making Park transformation, equations below in dq reference frame are as follow:

**Stator side:**

➤ **Voltages**

$$U_{ds} = R_s i_{ds} + \frac{d\Phi_{ds}}{dt} \quad (5)$$

$$U_{qs} = R_s i_{qs} + \frac{d\Phi_{qs}}{dt} \quad (6)$$

➤ **Fluxes**

$$\Phi_{ds} = L_s i_{ds} + M i_{dr} \quad (7)$$

$$\Phi_{qs} = L_s i_{qs} + M i_{qr} \quad (8)$$

**Rotor side:**

➤ **Voltages**

$$0 = R_r i_{dr} + \frac{d\Phi_{dr}}{dt} + \omega_r \Phi_{qr} \quad (9)$$

$$0 = R_r i_{qr} + \frac{d\Phi_{qr}}{dt} - \omega_r \Phi_{dr} \quad (10)$$

➤ **Fluxes**

$$\Phi_{dr} = L_r i_{dr} + M i_{ds} \quad (11)$$

$$\Phi_{qr} = L_r i_{qr} + M i_{qs} \quad (12)$$

**Electromagnetic torque**

$$T_{em} = \frac{3}{2} p M (i_{qs} i_{dr} - i_{ds} i_{qr}) \quad (13)$$

**Angular velocity**

$$J \frac{d\omega_r}{dt} = T_{em} - T_r - f_v \cdot \omega_r \quad (14)$$

### Voltage apply to the stator

$U_a$ ,  $U_b$  and  $U_c$  are three phase balanced source. This system (abc) to dq transformation is given by:

$$U_{ds} = \sqrt{\frac{2}{3}} (U_{as} - \frac{1}{2} U_{bs} - \frac{1}{2} U_{cs}) \quad (15)$$

$$U_{qs} = \sqrt{\frac{2}{3}} (\frac{\sqrt{3}}{2} U_{bs} - \frac{\sqrt{3}}{2} U_{cs}) \quad (16)$$

All these set of equations were used for modeling of three phase squirrel cage motor with Matlab/Simulink software.

The parameters of this induction motor are shown on Table 1.

Table 1. Parameters of motor

Parameters	Values
Rated power P (kW)	2.2
Rated speed Nn (r.p.m)	1450
Rated torque Tn (N.m)	50
Stator resistance Rs (Ω)	0.63
Rotor resistance Rr (Ω)	0.4
Mutual inductance M (mH)	0.91
Stator inductance Ls (mH)	0.97
Rotor inductance Lr (mH)	0.91
Inertia J (kg.m <sup>2</sup> )	0.22
Friction factor f (N.m.s)	0.001
Pairs of pole p	2
Maximal voltage U (V)	380

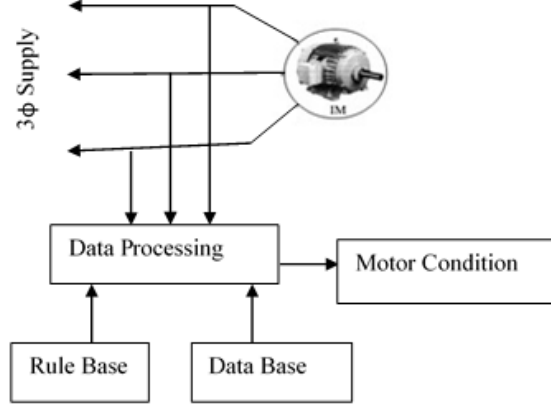
## 3. Fuzzy Logic in Fault Diagnosis of Induction Motor

### 3.1. Stator Current Monitoring System

Figure 2 shows how stator currents were used for diagnosis.

After measuring these currents, their Root Mean Square were transferred into the corresponding discourse universe as inputs [7]. The fuzzy logic inference engine evaluates the inputs using the knowledge base [15, 17, 5, 7] and then

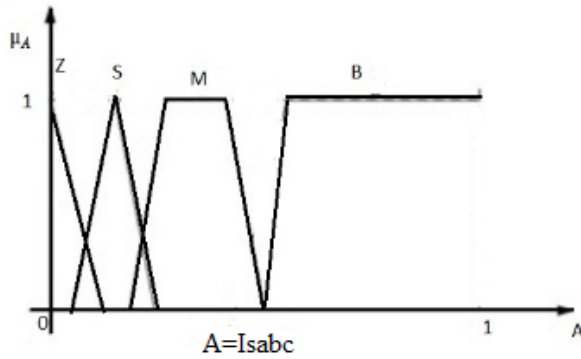
diagnoses the motor conditions. In this final step, where fuzzy actions are reconverted to crisp ones, the “center of area” method has been adopted. According to this method, first each affected output membership function is cut at the strength indicated by the previous max-rule, next the gravity center of the possible distribution is computed and it becomes the crisp output value [7, 17, 5].



**Figure 2.** Block diagram of induction motor condition monitoring system [7]

### 3.2. Creating If-Then Rule

Fourteen (14) rules have been created as shown on Table 2. These rules are optimized in such a way that the healthy and the faulty cases are covered.



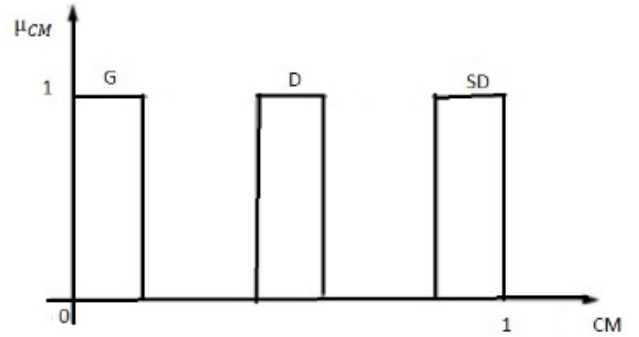
**Table 2.** If-then rule of stator monitoring [7]

Rules	Inputs			Outputs
	$I_{sa}$	$I_{sb}$	$I_{sc}$	$CM$
1	Z	—	—	SD
2	—	Z	—	SD
3	—	—	Z	SD
4	B	—	—	SD
5	—	B	—	SD
6	—	B	B	SD
7	S	S	M	D
8	S	M	M	D
9	S	S	S	G
10	S	M	S	D
11	M	S	S	D
12	M	M	S	D
13	M	M	M	G
14	M	S	M	D

For inputs membership functions,  $Z$ ,  $S$ ,  $M$ , and  $B$ , represent respectively the linguistic variables *Zero*, *Small*, *Medium* and *Big*.

For output membership functions  $G$ ,  $D$ , and  $SD$ , represent respectively the linguistic variables *Good*, *Damage* and *Seriously Damage*.

Figure 3 represents the membership functions of the inputs ( $I_{sa}$ ,  $I_{sb}$  and  $I_{sc}$ ) and the output ( $CM$ : Condition Monitoring) of the system.

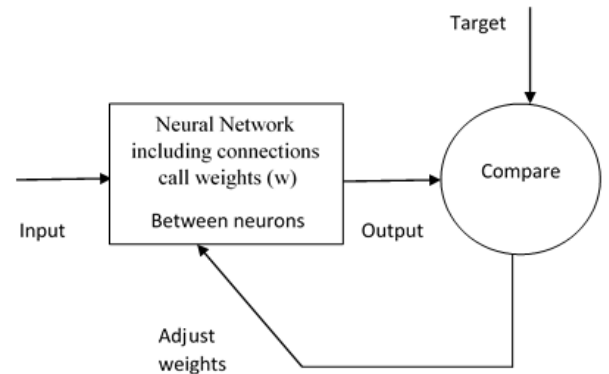


**Figure 3.** Input-Output membership function: input (left), output (right) [7]

## 4. Neural Network for Induction Motor Fault Identification

Data used here are generated from Root Mean Square values of three phase currents of asynchronous motor as shown on Figure 2. The entire neural network has the following parameters:

- \* Type of the network: Radial Basis Function neural network (RBF),
- \* supervised learning as shown on Figure 4
- \* Three inputs ( $I_{sa}$ ,  $I_{sb}$ , and  $I_{sc}$ )
- \* One output (Condition monitoring)
- \* Two (02) layers: one input layer and one output layer



**Figure 4.** Functional block diagram of ANN, [18]

The network was trained in such a way that healthy and faulty conditions are covered. Its output varies between zero (0) and one (1). When this output approaches zero (0) this means that the motor is healthy, and when it approaches one (1), this means that the motor is faulty. Block diagram of the entire neural network is shown on Figure 5.

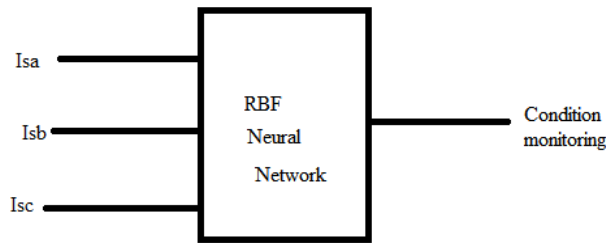


Figure 5. Block diagram of the neural network

## 5. Proposed Hybrid System

There are several ways to combine neural networks and fuzzy logic [5, 1]. These two technologies may be characterized by considering three main categories [5]

- \* Auxiliary hybrid system;
- \* Sequential Hybrid system;
- \* Embedded Systems.

The Adaptive Network based Fuzzy Inference System ANFIS implements a Takagi Sugeno fuzzy inference system [1]. It is a family of embedded system and it has five layers as shown in Figure 6 below [1].

The first hidden layer is responsible for the mapping of the inputs variables relatively to each membership functions [5]. The second hidden layer to calculate the antecedents of the rules. The third hidden layer normalizes the rules strengths followed by the fourth hidden layer where the consequents of the rules are determined. The output layer calculates the global output as the summation of all the signals that arrive to this layer [5].

A total of sixty numbers of data were used to train the system. The initial FIS Model used is the same FIS Model as used to create fuzzy logic. Figure 7 shows the training sequence (with 300 epochs) of the system with acceptable error and Figure 8 represents the proposed Hybrid system.

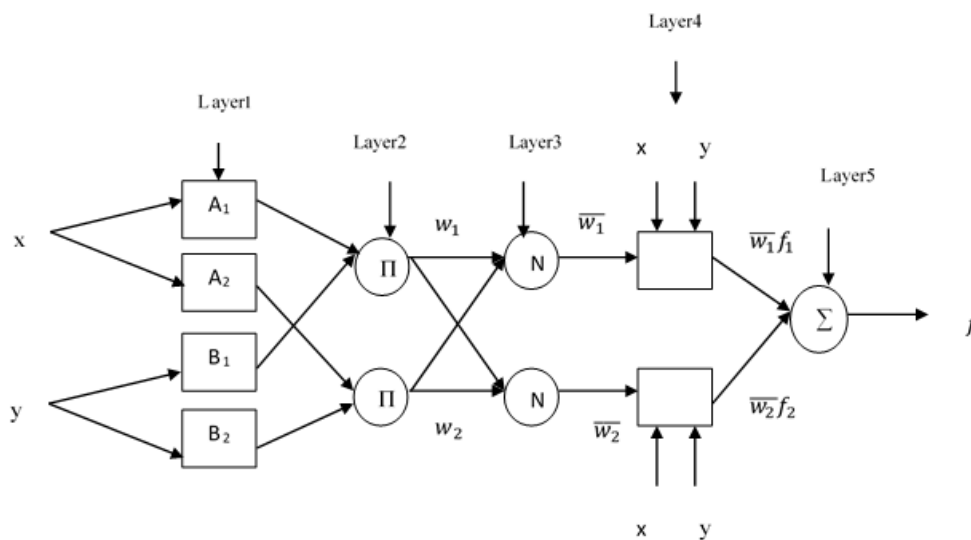


Figure 6. ANFIS system [5]

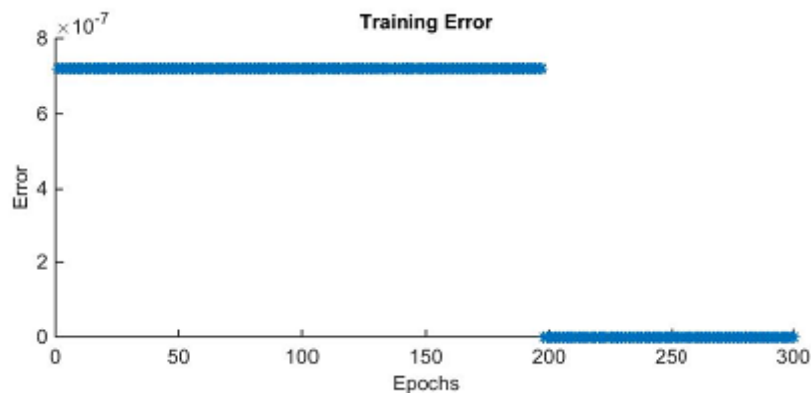


Figure 7. Training ANFIS

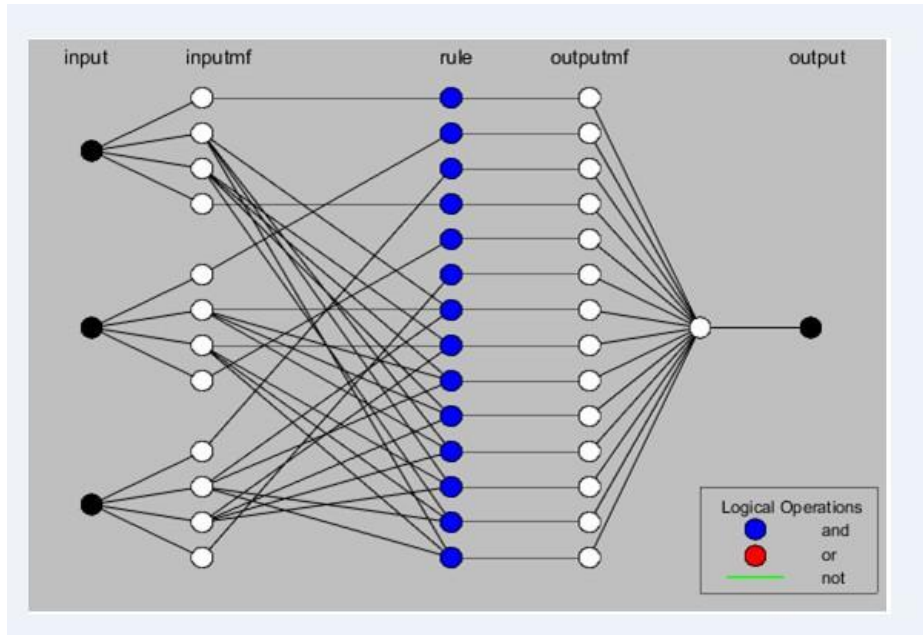


Figure 8. Proposed hybrid system

## 6. Results and Discussions

### 6.1. Healthy Motor

This simulation is done by applying a load torque of 50N.m at  $t=1s$ . When the motor starts, its current rises more than six times the rated current [12]. In this transient regime, that is between  $t=[0 \ 0.5]$ , diagnosis tools see this as a fault and their outputs vary according to the values of currents. In other hand, when the motor is running at its permanent regime, root mean square values of motor currents  $I_{sa}$ ,  $I_{sb}$  and  $I_{sc}$  are 19.22A. Figure 9 and Figure 10 present the motor response in healthy conditions:

### 6.2. Faulty Motor

This simulation is done by applying a load torque of 50N.m at  $t=1s$  when the motor is running. After load insertion, a fault is occurred at  $t=1.5s$ .

#### 6.2.1. Induction Motor under Phase Unbalance

When the motor starts normally, and runs at its permanent regime, load is inserted at  $t=1s$ , and then a fault is occurred at  $t=1.5s$ . Phase (c) is maintained at normal voltage  $U=380V$ , phases (a) and (b) are respectively 693.51V and 571.4V. In other hand, ripples are observed on motor torque and motor speed.

Figure 11 and Figure 12 present the motor response under phase unbalance.

#### 6.2.2. Induction Motor under a Low Voltage

The motor was running normally when low voltage occurred. In this case, its performances are reduced. The

process has to be stopped. If not, increase in current will increase an overheating [7-12] and the motor will burn.

Figure 13 and Figure 14 present the motor response under a low voltage.

#### 6.2.3. Induction Motor under a Critical Overload

This simulation is done by varying the load torque from zero (0) to  $3T_n$  ( $T_l=[0 \ 150]$  N.m). Increase in load increases motor currents and decreases speed. When the motor is overloaded, the motor torque increases and then decreases highly until the motor stops running, speed is equal to zero ( $N=0$ ) at  $t=2.2s$  and the motor attempts to turn in reverse.

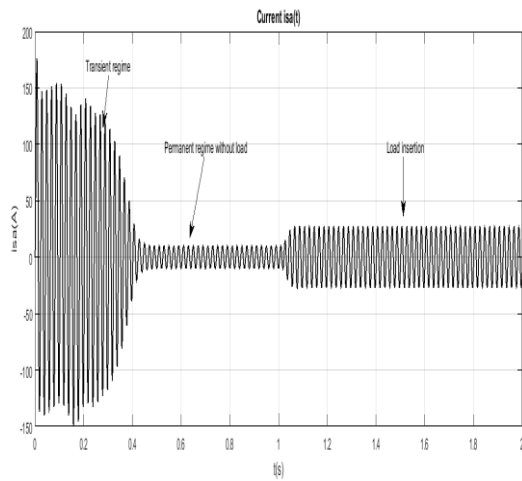
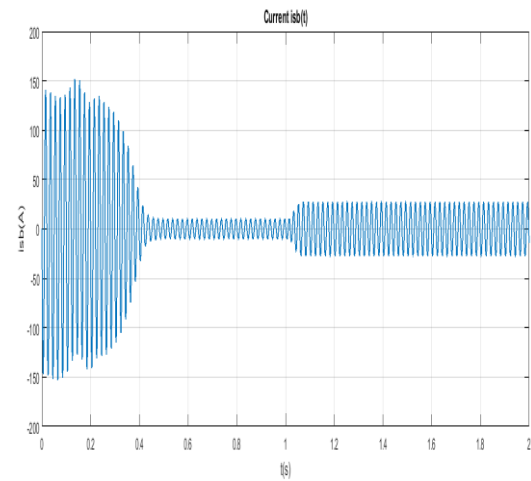
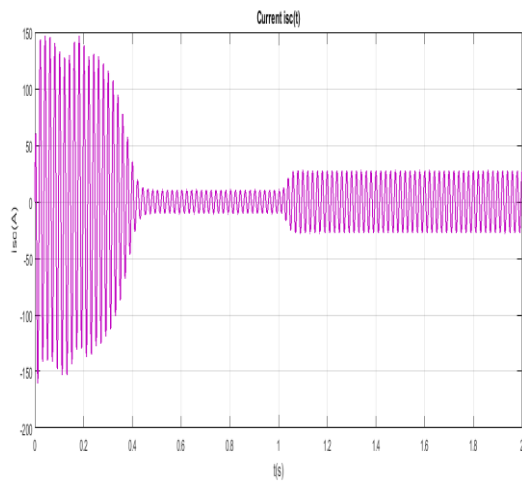
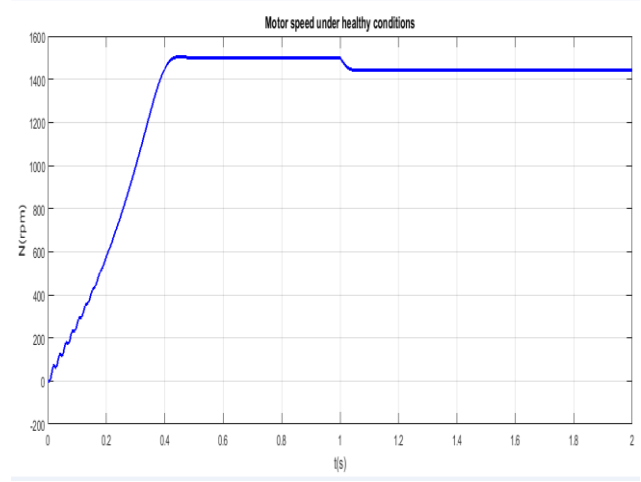
Figure 15 and Figure 16 present the motor response under a critical overload.

Table 3 shows the comparative study among different tools observers. This is about the rate of detecting fault when it is occurred.

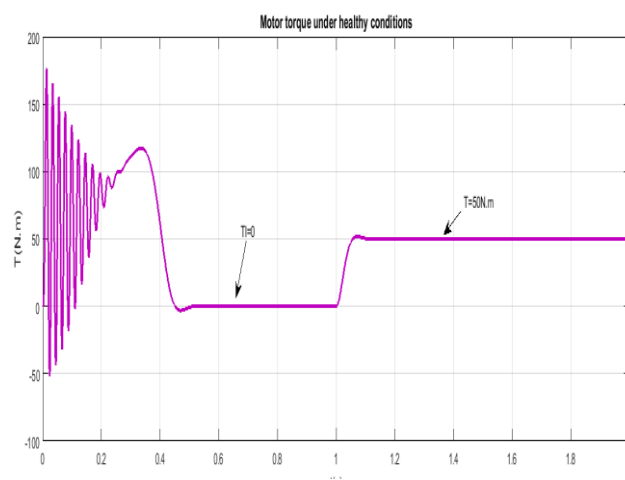
Table 3. Diagnosis accuracy

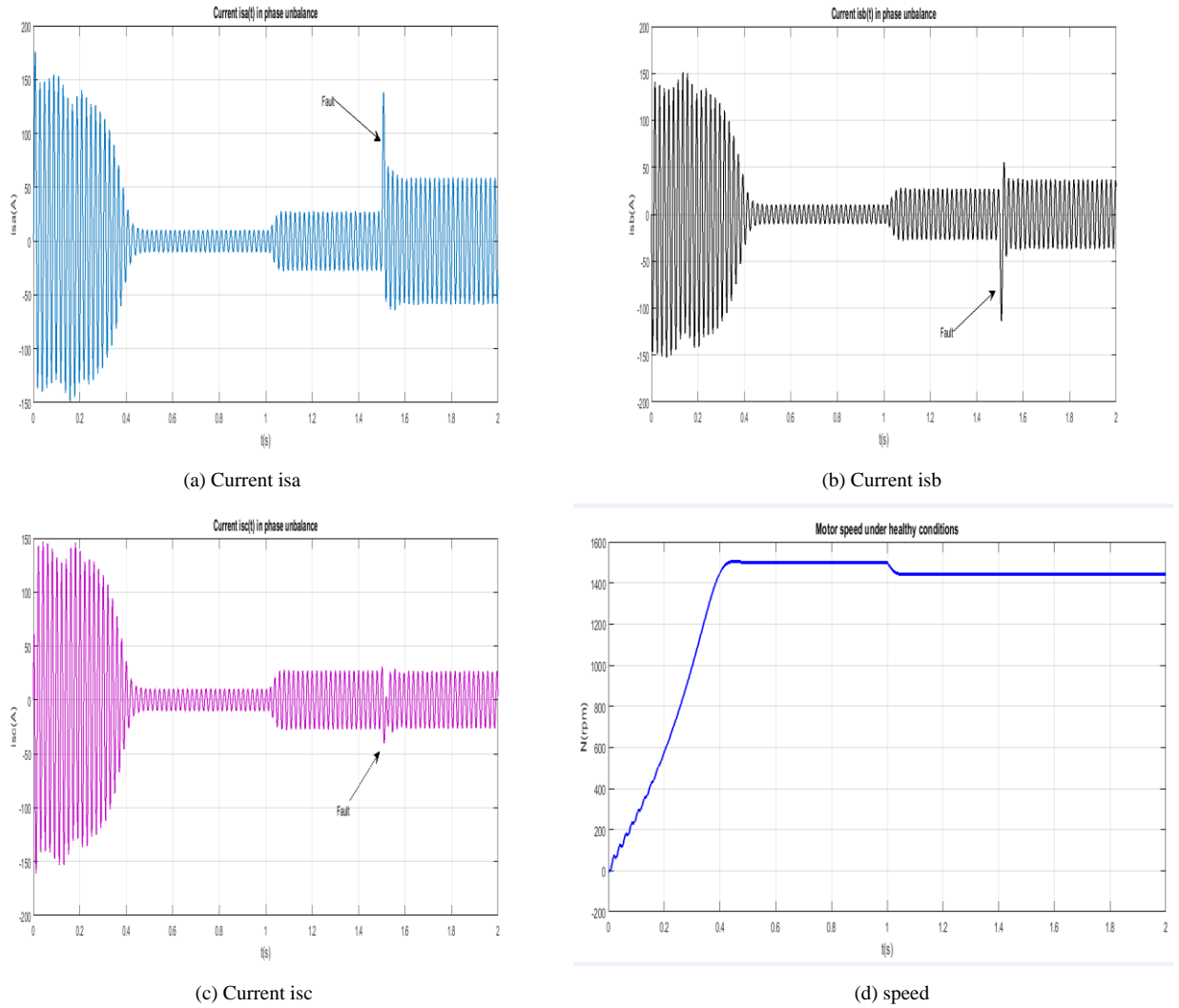
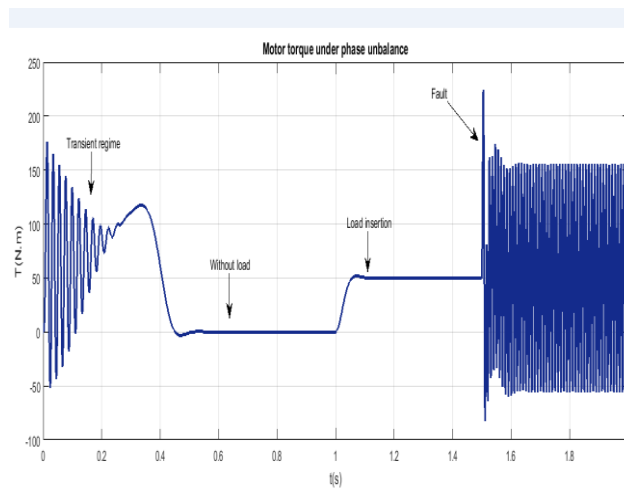
Fault detection	Diagnosis accuracy		
	Fuzzy logic	Neural network	Hybrid system
Good condition	94%	99%	100%
Voltage unbalance	95%	100%	100%
Overload	95%	100%	100%

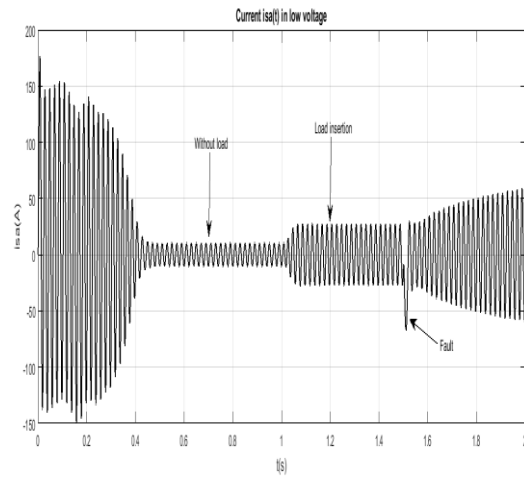
From Table 3, the following conclusion can be derived: Fuzzy logic detects the stated faults at 95 percents while Artificial neural network and hybrid system detect at 100 percents. This depends on how they are trained. Furthermore, combining the two methods is more advantageous than one method itself.

(a) Current  $i_{sa}$ (b) Current  $i_{sb}$ (c) Current  $i_{sc}$ 

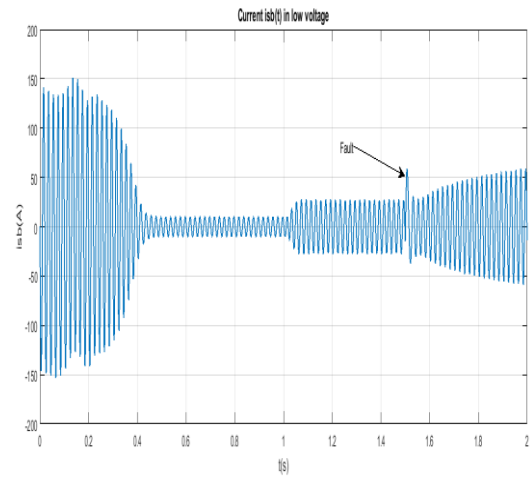
(d) speed

**Figure 9.** Motor response in healthy conditions**Figure 10.** Torque (Motor response in healthy conditions)

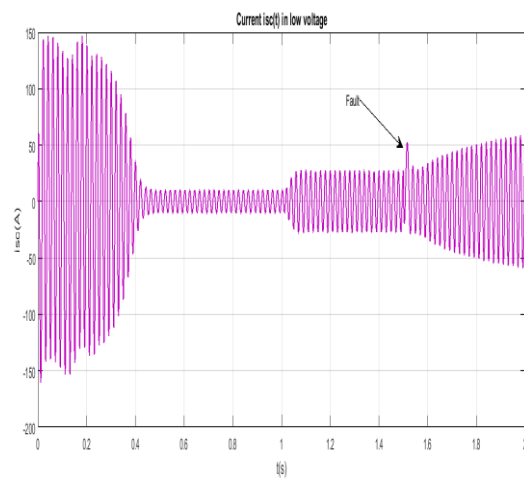

**Figure 11.** Motor response under phase unbalance

**Figure 12.** Torque (Motor response under phase unbalance)



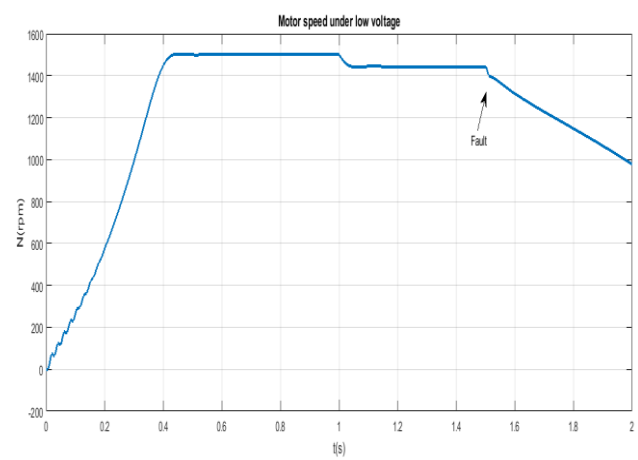
(a) Current isa



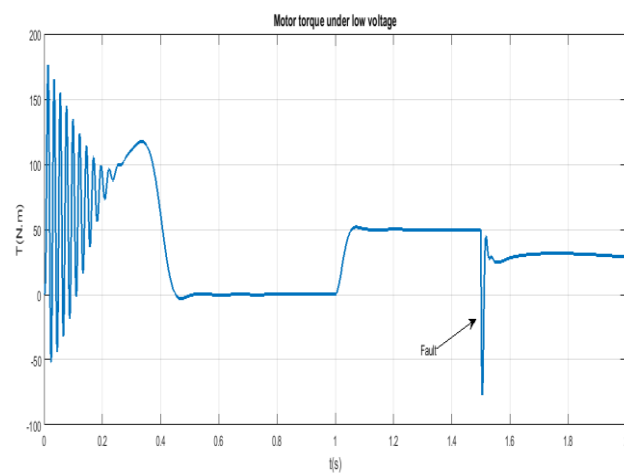
(b) Current isb



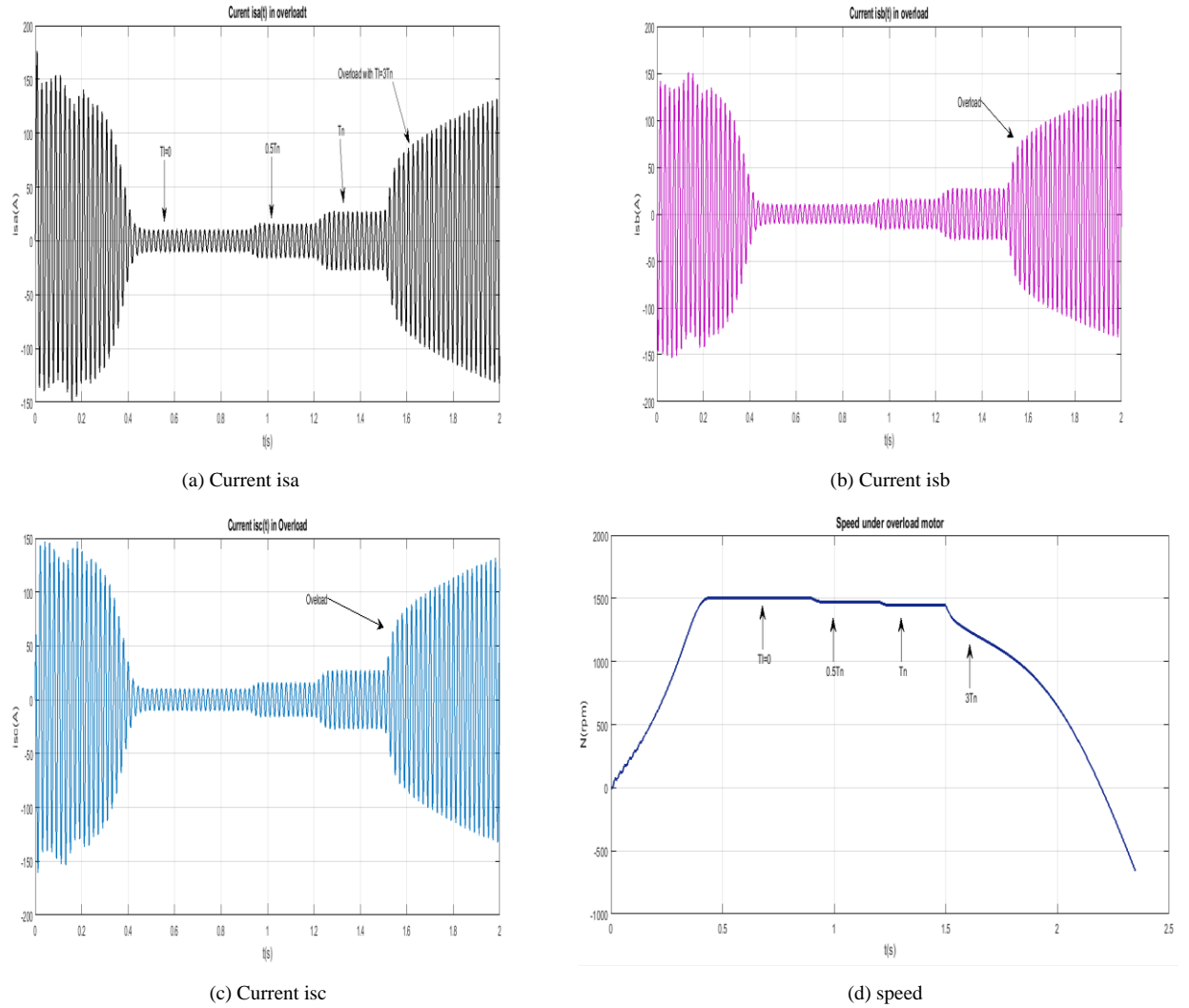
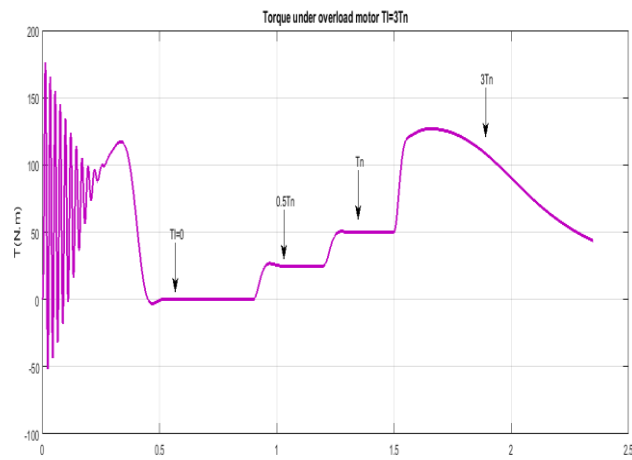
(c) Current isc



(d) speed

**Figure 13.** Motor response under a low voltage**Figure 14.** Torque (Motor response under a low voltage)




**Figure 15.** Motor response under a critical overload

**Figure 16.** Torque (Motor response under a critical overload)

## 7. Conclusions

This research work has successfully presented a fault diagnosis of an induction motor based on fuzzy logic and artificial neural network. Additionally, an hybrid system were proposed to combine both system. A method of using fuzzy logic, neural network and hybrid system to interpret root mean square currents of induction motor for its conditions was presented. Correctly processing theses root mean square currents and inputting them to a fuzzy decision, neural network and neuro-fuzzy system achieved high diagnosis accuracy. However, the exact architecture of designing artificial intelligence techniques is not known in advance. It is usually obtained after a trial-and-error procedure. The performances of a such a system depend on the quality of rule, training data and so on.

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