

Induction Motor Rotor Fault Detection using Artificial Neural Network

Rakeshkumar A. Patel
Department of Electrical Engineering
UVPCE, Ganpat University
Kherva, India
rap01@ganpatuniversity.ac.in

Dr. B.R. Bhalja
Department of Electrical Engineering
Indian Institute of Technology
Roorkee, India
bhaveshbhalja@gmail.com

Abstract — The present paper deals with the detection of broken rotor bar of an induction motor. The problem is approached through mathematical modeling of induction motor. Both the models, for healthy as well as faulty motor, are developed using MATLAB simulink. The model is used to simulate different conditions of fault with varying number of broken bars. Parameters like three-phase voltage, three-phase current and THD of all voltages and currents are acquired from the simulated model. The data thus generated is used to train Artificial Neural Network which diagnoses the condition of motor. The results obtained prove the effectiveness of proposed method.

Keywords—Condition Monitoring; Induction motor; Analytical model, Artificial Intelligence, Artificial Neural Network

I. INTRODUCTION

The induction motor is a very important production tool used universally in all the industries. The correct assessment of its health is crucial in order to avoid unexpected and catastrophic breakdowns. Therefore, in order to minimize production loss, repair cost and unscheduled maintenance, it is the need of time to have a system of reliable monitoring and non-invasive diagnostic methods [1]. The induction motor may be subjected to various types of faults including stator turns fault, rotor eccentricity, bearing damage and broken rotor bar. By condition monitoring we mean the continuous evaluation of the health of plant and equipment throughout its serviceable life. Earlier, time based maintenance had been the mainly used maintenance strategy for a long time. Implementation of condition monitoring on electrical equipments has been made easier by the fast development of computer technologies, transducer technologies, and signal processing techniques together with AI techniques. They would make CM systems more reliable, more intelligent and cheaper, in order to be widely employed in power systems [2].

A significant percentage of motor failures occur because of rotor cage problems, as indicated in surveys by the Electrical Power Research Institute and IEEE. In order to reduce motor damage and repair costs, early detection

of a broken rotor bar is desirable. In some cases, the broken bar condition begins with a fracture at a junction between the rotor bar and the end ring due to thermal and mechanical stresses. These stresses are more dominant when motors are started with high inertia loads. Changes in temperature also sometimes cause the fracture of bar due to bending stress. The breakage of one bar leads adjacent bars to carry more currents than their rated values, which further deteriorates the situation. Hence detection of broken bar condition is essential [3].

Among the varieties of techniques for induction machine diagnosis, two important categories are signal based and model based; signal based being the most widely used technique. In this method, better known as Motor Current Signature Analysis, the failure is detected by the appearance of additional components and /or the increase of the amplitude of some components in the spectrum of the stator current, flux, instantaneous electrical power or the induced voltage. The breakage of one or more bars is reflected by upper and lower sidebands appearing in frequency spectrum of stator current at $(1 \pm 2s)f_0$, where s is the motor slip and f_0 is the supply frequency. When number of broken bars increases the magnitude of these sidebands also increases [3].

The authors in [3] give information about simulations of a motor with broken bars. Use of multiple coupled circuit model has been demonstrated to analyze the harmonic content of the stator currents when a motor has broken bars. The rotor cage portion of the model for a healthy motor is represented by n identical and equally spaced current loops formed by rotor bars and two end ring segments. The authors have modelled a motor with 1, 2 and 3 broken bars to analyze the harmonic content of the stator currents for different operating conditions.

Motor current signature analysis of one phase of an induction motor with broken bar has also been represented in [4]. The classifier used in the paper is implemented by support vector machine and claimed to have good robustness and generalized performances. The proposed method is based on frequency and time domain analysis of one phase steady state and transient current signal, which are the only physical value to be measured.

The rotor bar fault identification using Support Vector Machine has also been demonstrated in [5]. The features extraction is performed by choosing the most significant component in the stator current spectrum. The basic idea is to find a line or hyper-plane which separates the data perfectly into its two classes. However, many such lines exist, but there is only one that maximises the margin. The nearest data points are used to define the margins and are known as support vectors.

Use of SVM for broken bar detection in induction motors at very low slip has been proposed in [6]. The proposed method consists of extracting reliable discriminative feature from a steady state one phase current signal and design of optimal classifier via a support vector machine. The fault related features are extracted from frequency spectra of a modulus of a motor phase current Hilbert transform series. The features are fed to the support vector machine input and the output indicates the rotor condition in respect of broken bar.

The present paper discusses the mathematical modelling of induction motor and prediction of broken rotor bar fault by ANN technique using the simulation of mathematical model.

This paper is organized as follows. Section II describes the mathematical modelling of induction motor in healthy as well as in rotor fault condition. Section III represents the simulation of the induction motor with rotor fault condition developed in MATLAB simulink. Simulation results are discussed in section IV. In section V a method is proposed for detection of broken bar and testing and training of neural network.

II. MATHEMATICAL MODELLING OF INDUCTION MOTOR

To carry out a dynamic modeling of induction motor, we need to concentrate on the basic equations of induction motor. As mentioned in various literatures, dynamic equations in a three-phase induction motor with a healthy status may be represented as given in appendix I [7, 8].

A. Modelling of induction motor with broken rotor bar fault

Rotor faults represent broken rotor bar, damage in end ring, etc. The focus here is on broken rotor bars. In the condition of broken rotor bar fault all the equations of healthy motor would remain as it is except the rotor impedance. When fault occurs, the rotor impedance will increase. But, as the change in reactance is very small, hence is being neglected here. So the equation of rotor resistance will be modified as derived below [9]:

Let r_r = rotor resistance referred to stator

N = total number of rotor bars

n = number of broken rotor bars

R_b = per bar rotor resistance

$$\text{Therefore now } r_r = \frac{R_b}{N/3} \frac{1}{k^2}$$

where, k is the transformation ratio.

The rotor resistance, after considering n number of broken bars, becomes

$$r_{r1} = \frac{R_b}{\left(\frac{N}{3} - n\right)} \frac{1}{k^2}$$

Now, change in rotor resistance

$$\Delta r = \frac{3n}{N - 3n} r_r$$

The end rings and the magnetizing current are not taken into account [10]. So, the equations for rotor becomes

$$\frac{d\lambda_{qr}}{dt} = -(r_r + \Delta r)i_{qr} - (\omega - \omega_r)\lambda_{dr}$$

$$\frac{d\lambda_{dr}}{dt} = -(r_r + \Delta r)i_{dr} - (\omega - \omega_r)\lambda_{qr}$$

III. SIMULATION OF MATHEMATICAL MODEL

A. Simulation of Induction Motor With Rotor Fault:

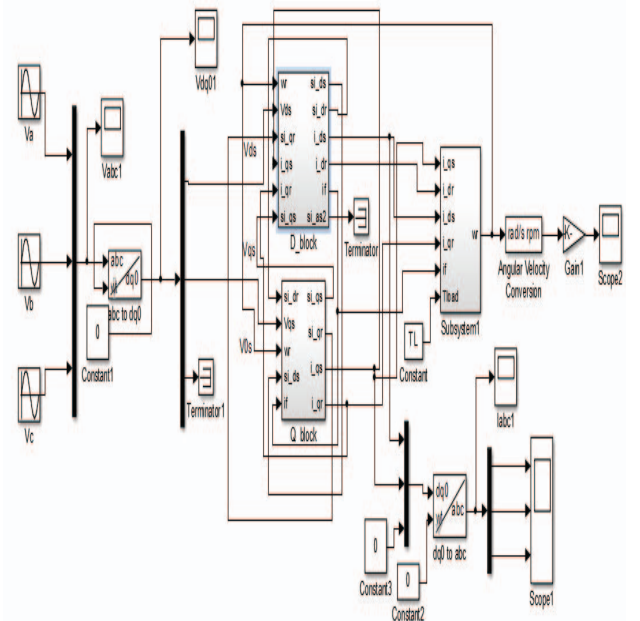


Fig. 1. Mathematical model of induction motor with rotor fault

The above model is composed by five blocks and a MATLAB code is composed to initialize induction parameters and process simulated data. Three phase voltage is generated and is transferred from abc to dq axis.

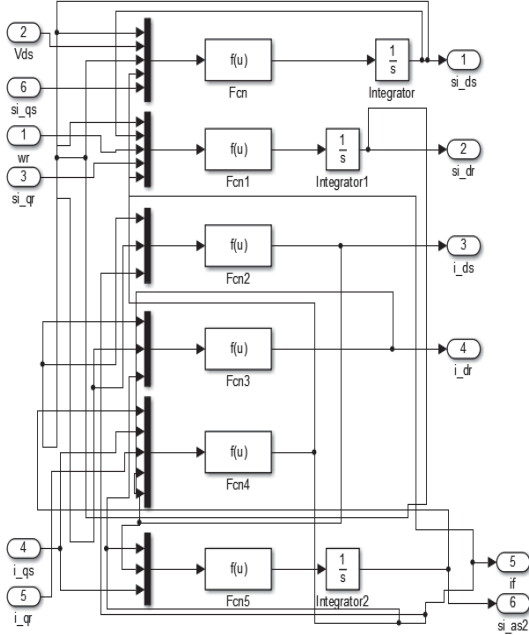


Fig. 2. Subsystem of d axis block

The inside diagrams of two major blocks, dq axis of stator and rotor are shown here. Equations of rotor circuit are solved in d-axis and q axis blocks. Rotor speed and torque are calculated in rotor block. Finally, the simulated current is transferred from dq to abc axis in dq to abc block.

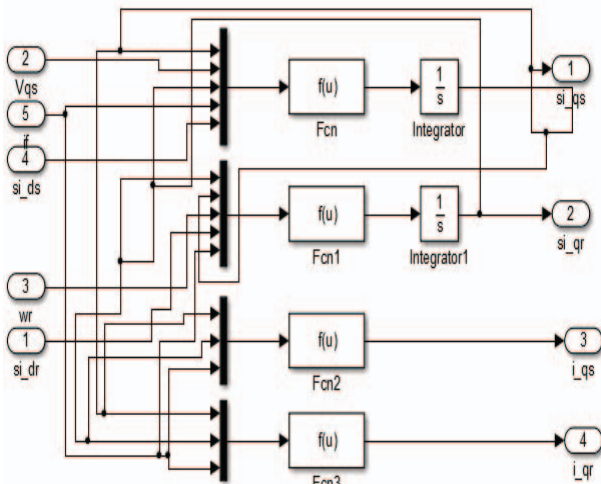


Fig. 3. Subsystem of q axis block

Fig. 2 and fig. 3 shows the subsystem used in the calculation of d axis and q axis block respectively. Fig. 4 shows the subsystem for rotor block.

Simulation is carried out at different load condition i.e. 0% load (no load), 20% load, 40% load, 80% load and 100% load (full load).

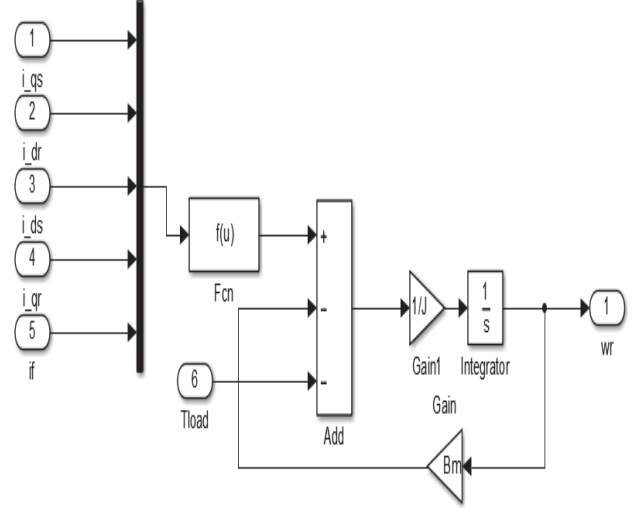


Fig. 4. Subsystem of rotor block

IV. SIMULATION RESULTS

The motor is simulated for healthy condition at 0% load (no load), 20% load, 40% load, 80% load and at 100% load (full load). The motor is also simulated for rotor fault with 2 broken bars, 3 broken bars, 4 broken bars and 5 broken bars. The parameters of the motor are given in appendix II.

In total 16 parameters are monitored and captured for the diagnosis purpose. Total 12500 samples are taken at five different load conditions for healthy and faulty motors. The samples are taken for different parameters like three phase stator current, active power, reactive power, THD in stator current, THD in voltage, and speed. These samples are then used to train the Artificial Neural Network.

The results for healthy condition and faulty condition are shown as under.

Fig. 5 and fig. 6 show the stator current of motor for healthy and rotor fault with 5 broken rotor bars at full load condition.

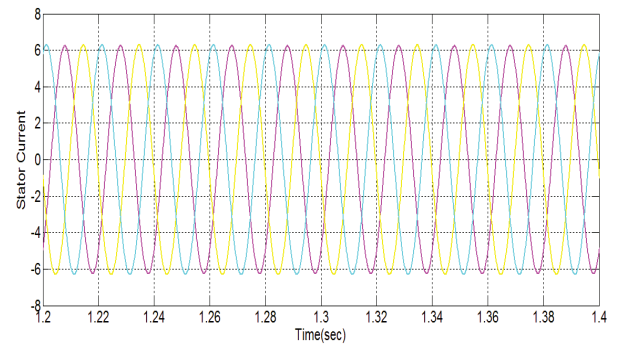


Fig. 5. Three phase stator current of healthy motor at full load

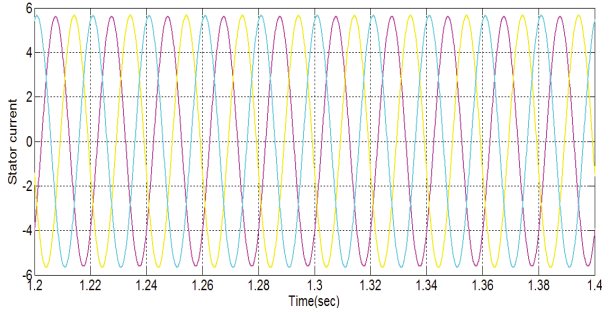


Fig. 6. Three phase stator current of faulty motor at full load with 5 broken rotor bars

Fig. 7 and fig. 8 show the torque of motor for healthy and rotor fault with 5 broken rotor bars at full load condition. Under the fault condition the oscillations are increased in the waveform of the torque.

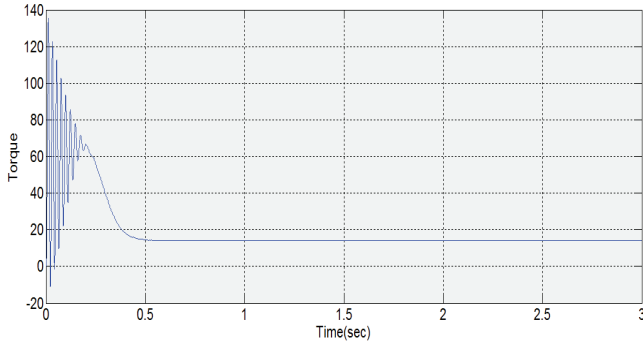


Fig. 7. Torque of healthy motor at full load

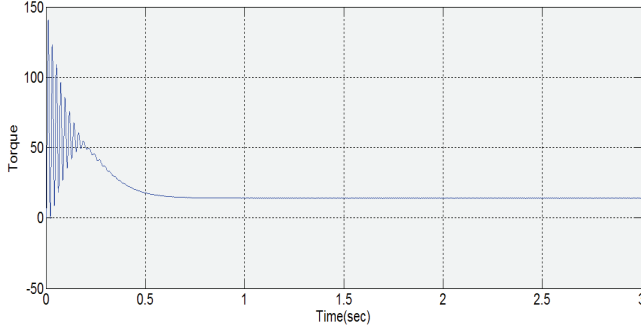


Fig. 8. Torque of faulty motor at full load with 5 broken rotor bars

Fig. 9 and fig. 10 show the speed of motor for healthy condition and faulty motor with 5 broken rotor bars at full load.

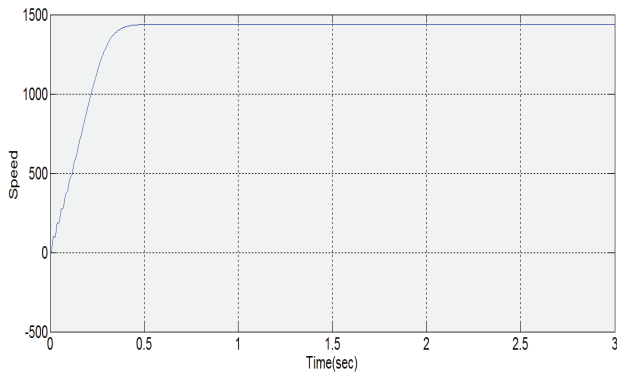


Fig. 9. Speed of healthy motor at full load

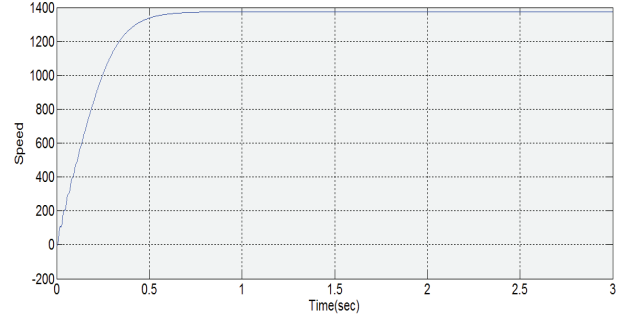


Fig. 10. Speed of faulty motor at full load with 5 broken rotor bars

From the simulation results we can conclude that when broken rotor bar fault occurs in motor the speed decreases and the effect increases if the number of broken rotor bars increases. Also, when 2 rotor bars are damaged the harmonics are increased in the waveform of the stator current as compared to 1 broken bar and similarly with increase in the number of damaged rotor bars amplitude of harmonics increases.

V. ARTIFICIAL NEURAL NETWORK FOR ROTOR FAULT DETECTION

Artificial neural network is trained by the samples which are taken from the simulation of healthy as well as faulty (for broken rotor bar fault) motor.

To achieve the above objective feed forward neural network is used. 12500 samples are used for training and testing purpose. From the total number of samples, 30% samples i.e. 3750 samples are used to train the neural network and 70% i.e. 8750 samples are used to test the neural network. MATLAB function is used for random selection of training samples and testing samples. The ANN indicates 0 in the output in healthy condition, and 1 for faulty condition.

Mean squared error is selected for the performance evaluation of proposed technique. Fig.11 shows the graph of the mean squared error when the number of neurons are 10 for hidden layer.

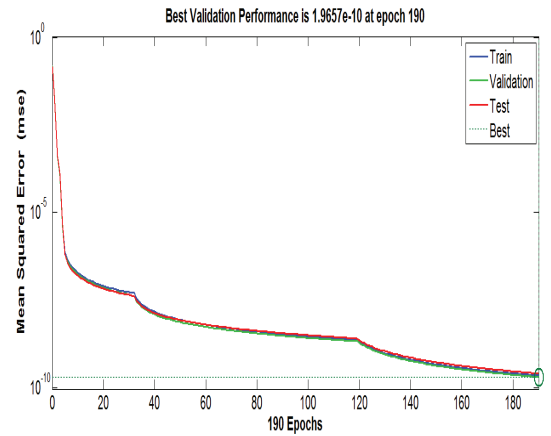


Fig.11. Mean squared error plot

When the neural network was not trained, it was not able to detect the condition of the induction motor. Once

the neural network is trained, it predicts the condition of motor.

Fig.12 shows plot of the actual output of ANN to predict the condition of the motor. Output shows that ANN predicts the condition of motor with least error.

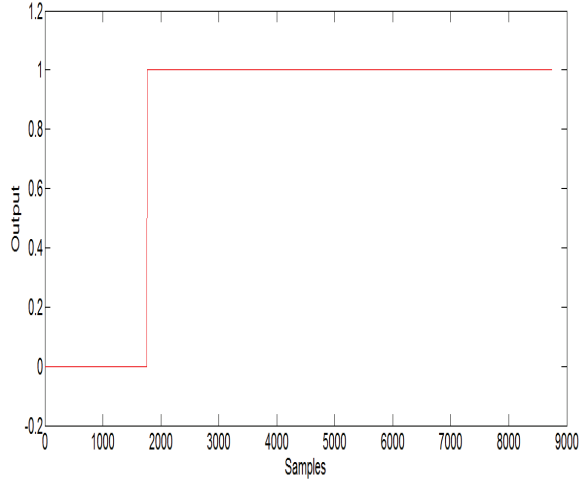


Fig.12. Actual output of ANN

VI. CONCLUSION

Detection of broken rotor bar of induction motor with the help of ANN was the focus of the paper. The mathematical models of induction motor in both healthy as well as fault condition were developed in order to simulate the faults of varying intensity at different load conditions. Various parameters of induction motor are recorded in all the different conditions. These recorded parameters are used to train the Artificial Neural Network. The output of the ANN shows that proposed technique successfully detects the presence of broken rotor fault of induction motor.

APPENDIX I

- *Equations of Stator:*

$$\frac{d\lambda_{qs}}{dt} = v_{qs} - r_s i_{qs} - \omega \lambda_{ds}$$

$$\frac{d\lambda_{ds}}{dt} = v_{ds} - r_s i_{ds} + \omega \lambda_{qs}$$

- *Equations of Rotor:*

$$\frac{d\lambda_{qr}}{dt} = -r_r i_{qr} - (\omega - \omega_r) \lambda_{dr}$$

$$\frac{d\lambda_{dr}}{dt} = -r_r i_{dr} - (\omega - \omega_r) \lambda_{qr}$$

- *Equations of Current:*

$$i_{qs} = \lambda_{qs} a_0 - \lambda_{qr} a_1$$

$$i_{ds} = \lambda_{ds} a_0 - \lambda_{dr} a_1$$

$$i_{qr} = \lambda_{qr} a_3 - \lambda_{qs} a_1$$

$$i_{dr} = \lambda_{dr} a_3 - \lambda_{ds} a_1$$

Constant coefficients are used in above equations are as follows.

$$a_0 = \frac{L_r}{a_0}, \quad a_1 = \frac{L_m}{a_0}, \quad a_3 = \frac{L_s}{a_0}$$

- *Equations of Torque:*

$$T_e = \frac{3}{2} \frac{p}{2} (\lambda_{ds} i_{qs} - \lambda_{qs} i_{ds})$$

- *Equation of Speed:*

$$\frac{d\omega_r}{dt} = \frac{T_e - B_m \omega_r - T_l}{J}$$

APPENDIX II

Specifications of motor

Output power	2.2 kW
Rated frequency	50 Hz
Rated current	4.9 A
Line Voltage	415 V
Number of Poles	4
Stator Resistance	2.60 Ω
Rotor Resistance	2.66 Ω
Stator leakage Inductance	0.000560 H
Rotor leakage Inductance	0.000875 H
Magnetizing Inductance	0.455 H
Rotor Inertia	0.05 kg.m ²

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