The Journal of CPRI,
Vol. 11, No. 2, June 2015 pp. 333-340

On line GNN based induction motor parameter estimation

Chaturvedi D K*, Mayank Pratap Singh*, Md. Sharif Iqbal* and Vikas Pratap Singh**

The induction motor is commonly used in industries due to its rugged construction and almost no maintenance. To precisely control the induction motor, accurate estimation of parameters is required. Artificial Neural Network (ANN) is used in the past for parameter estimation. The conventional ANN has its own problems such as learning issues, unknown size of ANN and its connections, etc. To overcome some of its problems generalized neural network is used in this paper. The GNN is trained to estimate parameters of three phase induction motor. Experimental setup is developed in DEI, which is consisting of a 415 V, 3Φ squirrel cage induction motor, data acquisition system and on-line parameter estimator.

Key Words: *Parameter estimation, three phase induction motor, ANN, generalized neuron.*

1.0 INTRODUCTION

Based on observed data from the systems [1], parameter estimation deals with the problem of building models of dynamical systems. The parameter estimation is the technique of building mathematical models of dynamic systems from observed input-output data [2, 13].With their merits and demerits [4-11], there are many techniques to estimate the induction motor parameters,such as:

1. Conventional techniques &
2. Soft computing techniques

Either directly or indirectly,there are many conventional techniques to estimate electrical parameters of induction motors by using motor current, line neutral voltage, instantaneous reactive power, stator current and motor efficiency, electromagnetic field monitoring etc.

The soft computing techniques are also used to estimate the parameters, such as artificial neural network (ANN)[9, 17] and generalized neural network (GNN).

To estimate parameters accurately, Artificial Neural Networks ANNs are very useful. It is shown in Figure 1.

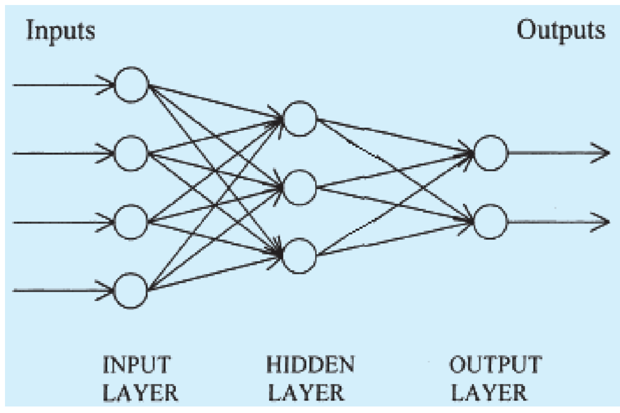


FIG. 1 ARTIFICIAL NEURAL NETWORK

Artificial Neural Network (ANN) is based on the operation of biological neural networks. It is an abstract simulation of a real nervous system. The Induction motor is a nonlinear multivariable

*Department of Electrical Engineering, Dayalbagh Educational Institute, Dayalbagh, Agra, U.P., India
E-mails: dkc.foe@gmail.com, mayankpratapsinghonline@yahoo.com, mdsharifiqbal@gmail.com
**Central Power Research Institute, Bangalore, India. E-mail: vpscpri@gmail.com

dynamic system with parameters that vary with temperature, frequency, saturation, and operating point [10]. The rotor parameters are the most important parameters for the control of the induction motor. The rotor resistance can change up to 150% over the entire operation [11-12]. As the temperature influences the fundamental frequency component of the terminal voltage for a given input current. The conventional ANN has some disadvantages such as learning rate, hidden layers of ANN and its connections, etc. To overcome some of its problems generalized neural network is used in this paper.

2.0 GENERALIZED NEURAL NETWORK

To overcome some of the limitations of ANN, GNN is proposed in this paper. The GNN has adopted two functions for developing the GNN algorithm. The one is Sigmoid function and the second is Gaussian function. The combination of both provides the ability to deal with the nonlinearity involved in the problem. The typical developed GNN model processes the output by summing up the output of Sigmoid function and Gaussian function, the proposed model is known as summation type neural model [17].

The final output of the GNN is a function of two outputs O_Σ and O_π, where Σ is summation function and π is aggregation function. The output of summation part is given by

$$O_\Sigma = \frac{1}{1+e^{-\lambda s * s\_net}} \quad ....(1)$$

where, $s\_net = \sum W_i X_i + X_{o\Sigma}$

The output of the product aggregation part can be represented as

$$O_\Pi = e^{-\lambda p \times pi\_net^2} \quad ....(2)$$

where, $p\_net = \prod W_i X_i \times X_{o\Pi}$ and the final output of the GNN is given by (2).

$$GNNoutput = O_\Sigma \times W + O_\Pi \times (1-W) \quad ....(3)$$

This GNN output is depending on weights factor (W). In this case the weights are W and (1-W) for summation function and aggregation function respectively.

a. *Error minimization*

The output of the GNN will contain error, and this error is calculated and minimized by comparing it with the desired output. The LM optimization technique is adopted to minimize this error using error function shown in equation (10). Basically the sum squared error for convergence of model is used. The sum squared error E_p is given by

$$E_p = \sum E_i^2 \quad ....(4)$$

where, $E_i^2 = (Y_i - O_i)$ between Desired output Y_i and GNN output O_i.

The new weights (W_Σ) for summation function and weights (W_Π) for product function are find out to minimize the error.

3.0 EQUIVALENT CIRCUIT OF INDUCTION MOTOR

The induction motor is similar to the transformer with the exception that its secondary windings are free to rotate (Shown in Figure 2).

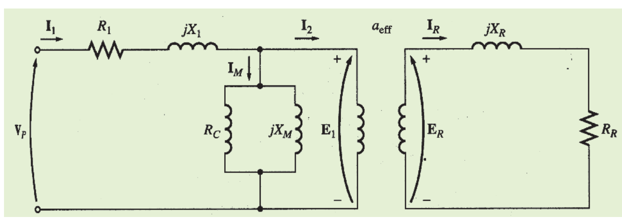


FIG. 2 EQUIVALENT CIRCUIT OF INDUCTION MOTOR

The same is true for the frequency, i.e. $fr=s*fs$

It is known that $X = \omega L = 2\pi f L$ so, as the frequency of the induced voltage in the rotor changes, the reactance of the rotor circuit also changes $X_R = s \times X_{R0}$, Where X_{R0} is the rotor reactance at the supply frequency (at blocked rotor). Then, we can draw the rotor equivalent circuit as follows (Shown in Figure 3).

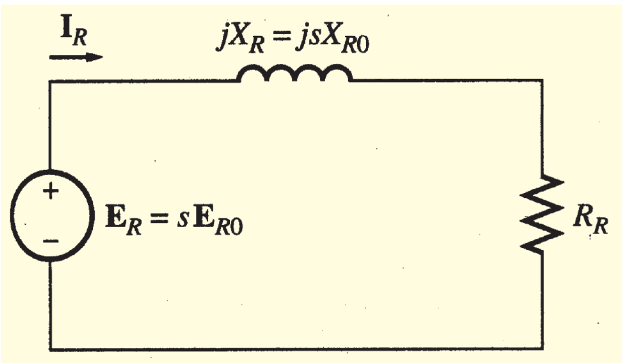


FIG. 3 ROTOR EQUIVALENT CIRCUIT

Where E_R is the induced voltage in the rotor and R_R is the rotor resistance.

Now we can calculate the rotor current as

$$I_R = \frac{E_R}{(R_R + jX_R)}$$

$$= \frac{sE_{R0}}{(R_R + jsX_{R0})} \quad ....(5)$$

Dividing both the numerator and denominator by s so nothing changes we get

$$I_R = \frac{E_{R0}}{\left(\frac{R_R}{s} + jX_{R0}\right)} \quad ....(6)$$

Where E_{R0} is the induced voltage and X_{R0} is the rotor reactance at blocked rotor condition ($s = 1$)

Now the rotor equivalent circuit may be redrawn as shown in Figure 4.

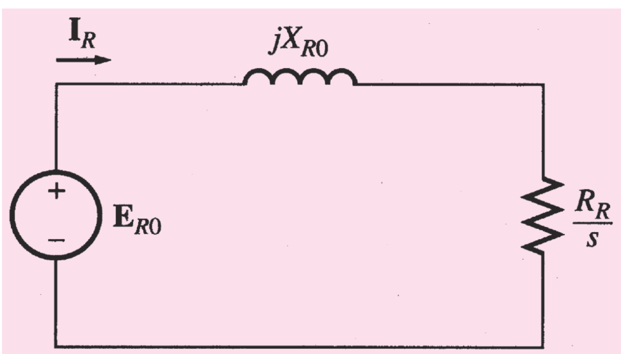


FIG. 4 MODIFIED ROTOR EQUIVALENT CIRCUIT

If we can combine the stator and rotor equivalent circuits in one equivalent circuit as shown in Figure 5.

Where

$$X_2 = a_{eff}^2 X_{R0}$$

$$R_2 = a_{eff}^2 R_R$$

$$I_2 = \frac{I_R}{a_{eff}}$$

$$E_1 = a_{eff} E_{R0}$$

$$a_{eff} = \frac{N_S}{N_R}$$

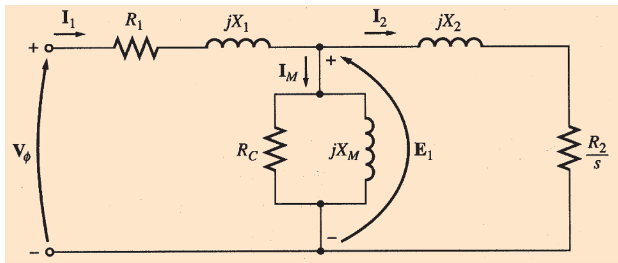
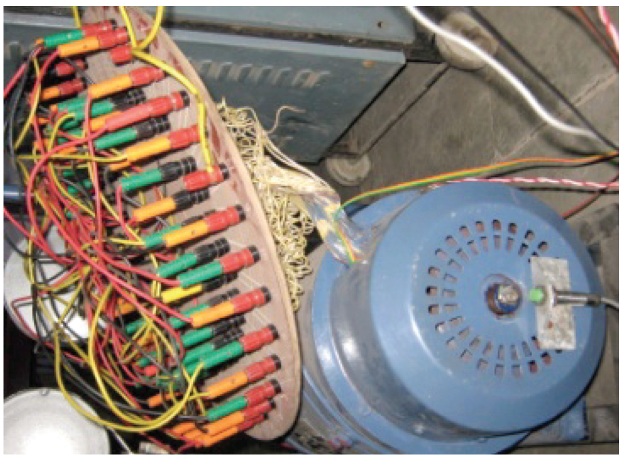
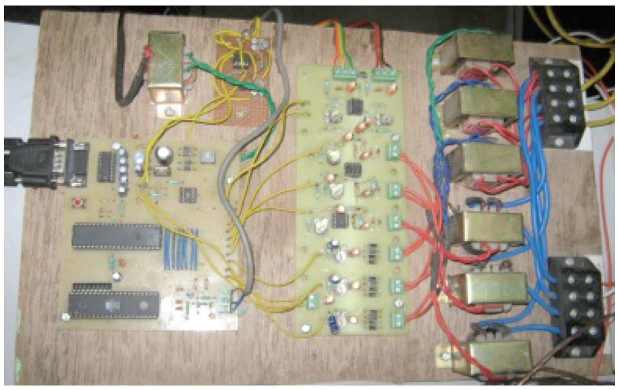


FIG. 5 EQUIVALENT CIRCUIT OF INDUCTION MOTOR REFERRED TO STATOR SIDE

4.0 EXPERIMENTAL SETUP





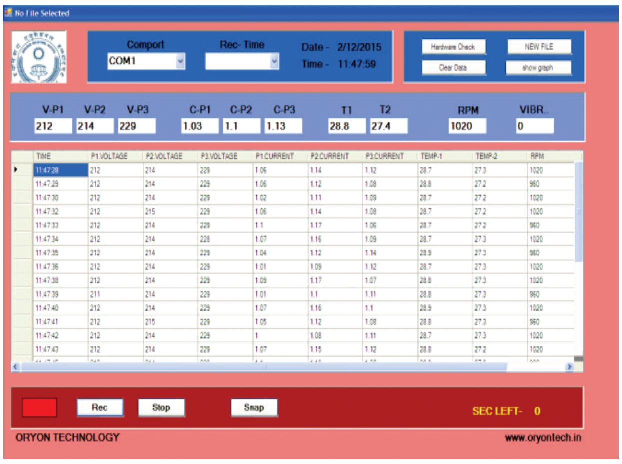


FIG. 6 EXPERIMENTAL SET UP

The experimentation is done in Electrical Power Research lab at Dayalbagh Educational Institute (Deemed University) Agra, India. The experiment setup is consisting of the 5 hp, three 3 Φ, 41 5V, 7.8 A, 50 Hz Squirrel cage induction motor, a voltage–current-frequency (VIF) meter, Data Acquisition System (DAS or DAQ).

The DAQ system is used to acquire the signals and interface with the computer. Voltage and Current signals are taken with the help of PT & CT and after that rectified and filtered. The temperature signal is taken with the help of LM35 after that filtered. Vibration sensor and Proximity sensor are used to take vibration and speed signals. Vibration and Speed signals are sent to AT89C51 Microcontroller. After that all the signals are sent to ATMEGA16 Microcontroller, which is connected to Max232 and then to PC. A thermal camera is connected to PC for capturing thermal images of induction motor at different operating conditions.

5.0 EXPERIMENTATION

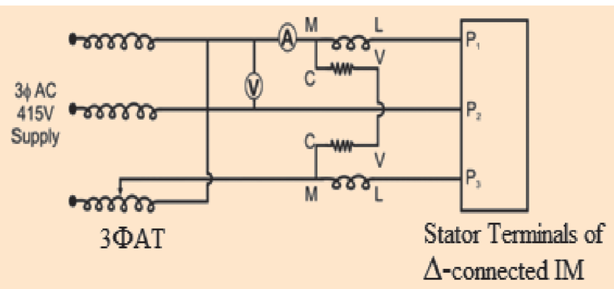


FIG. 7 CIRCUIT DIAGRAM FOR EXPERIMENT

5.1 No load test

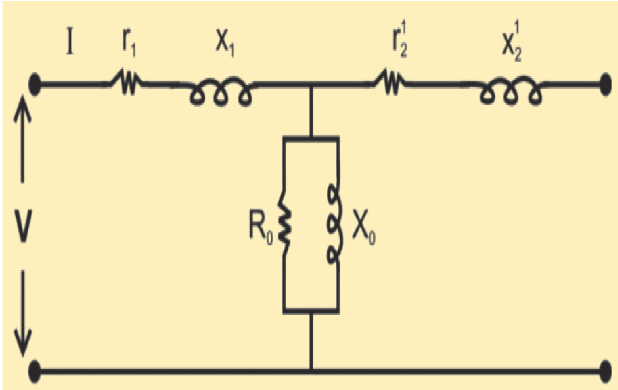


FIG. 8 CIRCUIT DIAGRAM FOR NO-LOAD TEST

The rotor is allowed to run freely under no-load condition at rated voltage and rated frequency. At no-load condition, the speed is very close to synchronous speed and the very small slip. Determine voltage, current and power. The shunt parameterscan determined as Z_o, R_o and X_o.

$$Z_o = V/(I/\sqrt{3}),$$

$$R_o = (P/3)/[(I/\sqrt{3})^2],$$

$$X_o = \sqrt{(Z_o^2 - R_o^2)}$$

Where V, I, P are called no load voltage, current and power and

Zo-no load impedance in ohms,

Ro-no load resistance in ohms,

X_o-no load reactance in ohms.

5.2 Blocked rotor test

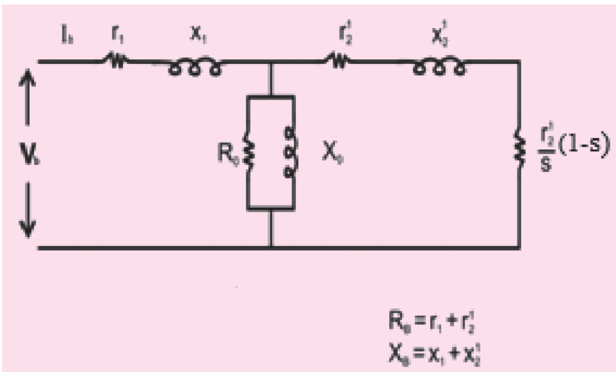


FIG. 9 CIRCUIT DIAGRAM FOR BLOCKED ROTOR TEST

Block the rotor so that it will not turn. Connect to a variable-voltage AC supply and adjust the supply voltage until the blocked-rotor current is equal to the rated current. Determine voltage, current and power. Now we determine equivalent resistance and equivalent reactance.

$Z_b=V_b/(I_b/\sqrt{3})$,

$R_b=(P_b/3)/ [(I_b/\sqrt{3})$^2],

X_b=√ (Z_b^2-R\b^2)

Where Vb, Ib, Pb are called blocked rotor voltage, current and power and

Z_b-equivalent impedance in ohms,

R_b-equivalent resistance in ohms,

X_b-equivalent reactance in ohms.

5.2.1 No load test at different voltages

V=[320, 340, 360, 380, 400, 420, 430, 440] Volts

I=[2.5,2.8, 3,3.2,3.4,3.7,4,4.2] A

P=[200, 220, 225, 240, 270, 290, 320, 340] Watts

5.2.1 Blocked rotor test at different currents

V_b=[174, 179, 184, 190, 196, 220, 225, 230] W

I_b=[6,6.25, 6.5,7, 7.35, 7.7, 7.75, 7.8] A

P_b=[780, 860, 940, 1100, 1200, 1220, 1300,1400] W

6.0 PARAMETER ESTIMATION USING ANN AND GNN

The above data is used as input for training of ANN and GNN, and estimate the values of Ro, Xo, equivalent resistance and equivalent reactance are output data (Shown in Table 1). The ANN used for on line parameter estimation is consisting of 2-10-4 structure (i.e. 2-input, 10-hidden neuron and 4-output neurons). The ***tansigmoidal*** and ***pure linear*** functions are considered at hidden and output layer respectively. On the other hand GNN is consisting of single neuron and giving good resultsare shown in Figure 10.

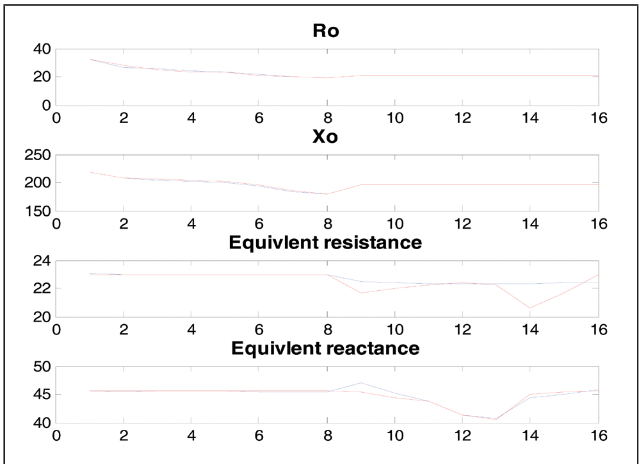


FIG. 10 ESTIMATED PARAMETERS VARIATIONS USING GNN

TABLE 1

COMPARISION OF EXPERIMENTAL & ESTIMATED VALUES

3Φ Induction Motor Parameters	Experimental Value (Ω)	Estimated Value by ANN (Ω)	Estimated Value by GNN (Ω)
R_O	21.18334	21.1833	21.18332
X_O	195.3894	195.4669	195.3994
R_b	23.01117	23.0112	23.01115
X_b	45.5996	45.5957	45.5997

By using ANNs we get the approximately same parameters.

7.0 ON LINE PARAMETER ESTIMATION

The voltage, current and power is acquired on-line and the IM parameters are estimated on-line using ANN and GNN. The results are tabulated in Table 2-3. The screen shot is also shown in Figure 11.

TABLE 2

ON LINE PARAMETER ESTIMATION UNDER DIFFERENT LOADING CONDITIONS USING ANN

Motor Parameters	No load	Quarter load	Half load	¾ of full load	Full load	Over load
R_o	11.55	12.05	14.07	18.9	19.6	20
X_o	182.4	185.8	190	196	202.1	209
R_b	22.61	22.78	22.88	22.9	23.18	23.9
X_b	44.84	45.22	46.62	48.8	49.11	50

TABLE 3

ON LINE PARAMETER ESTIMATION UNDER DIFFERENT LOADING CONDITIONS USING GNN

	No load	Quarter load	Half load	¾ of full load	Full load	Over load
R_o	11.75	12.15	14.47	19.1	19.5	20.1
X_o	183.1	186.4	190.8	197	202.5	210
R_b	22.71	22.98	23.18	23.2	23.38	23.9
X_b	45.14	45.52	46.82	48.9	49.31	51

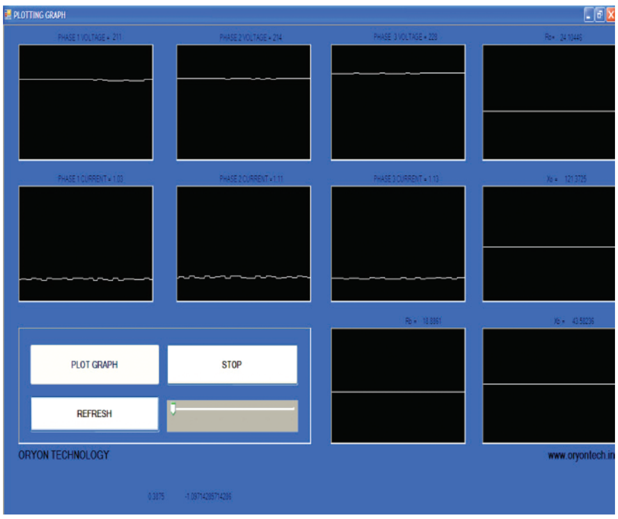


FIG. 11 ON-LINE PARAMETER ESTIMATION OF INDUCTION MOTOR USING GNN

8.0 CONCLUSIONS

The online parameter estimation is essential for improved performance used in wide range of applications. The methods for estimating the online shunt resistance, shunt reactance, equivalent resistance and equivalent reactance of induction motor are presented. GNN and ANN are trained for parameter estimation of induction motor under different operating conditions. The used to compute the parameterson line. From the results obtained, it is seen that the parameter estimation GNN is better.

ACRYNOMS

r_1 - series resistance of stator side

x_1 - series reactance of stator side

r_2 - effective series resistance of rotor side

x_2 - effective series reactance of rotor side

REFERENCES

[1] W Miroslaw, Krzeminski Zbigniew, and Toliyat Hamid A., IEEE transactions on industrial electronics Neural-Network-Based Parameter Estimations of Induction Motors, Vol. 55, No. 4, pp. 501-510, April, 2008.

[2] A Toliyat Hamid, Levi Emil, and Raina Mona, A Review of RFO Induction Motor Parameter Estimation Techniques, IEEE transactions on energy conversion, Vol. 18, No. 2, June, 2003.

[3] Bambang urwahyudi, Soebagio, and Ashari M., RNN Based Rotor Flux and Speed Estimation of Induction Motor, International Journal of Power Electronics and Drive System JPEDS), Vol. 1, No. 1, pp. 58-64 September, 2011.

[4] H A Toliyat and G H Hossein, “Parameter estimation algorithm using spectral analysis for vector controlled induction motor drives,” in Proc. IEEE Int. Symp. Ind. Electron, pp. 90-95.

[5] T Kataoka, S Toda, and Sato Y., “On-line estimation of induction motor parameters by extended Kalman filter”, Proc. Europe. Conf. Power Electron. Applicat., Vol. 4, pp. 325–329, 1993.

[6] L Umanand and S Bhat , “Online estimation of stator resistance of an induction motor for speed control applications”, IEE Proc. Electr. Power Appl., Vol. 142, pp. 97–103, March, 1995.

[7] K Yassine,,"Recursive identification of induction motor parameters", Simulation Modelling Practice and Theory 12 363–381, 2004.

[8] J Holtz, “Sensorless control of induction machines — With or without signal injection?” IEE Trans. Ind. Electron., Vol. 53, No. 1, pp. 0–30, Feb. 2006.

[9] D Telford, M W Dunnigam, and Williams, “Online identification of induction machine electrical parameters for vector control loop tuning”, IEEE Trans. Ind. Electron., Vol. 50, No. 2, pp. 253–261, Apr. 2003.

[10] H Nerkar Madhavi & B Kushare EITSI Transactions on Electrical and Electronics Engineering (ITSI-TEEE), Neural-Network-Based Parameter Estimations of Induction Motor. Vol. 1, Issue 2, pp. 2320-8945, 2013.

[11] D E Borgard, G Olsson, and R D Lorenz, “Accuracy issues for parameter estimation of field oriented induction machine drives”, IEEE Trans. Ind. Applicat., Vol. 31, pp. 795–801, July 1995.

[12] S N Vukosavic and M R Stojic, “On-line tuning of the rotor time constantfor vector-controlled induction motor in position control applications,” IEEE Trans. Ind. Electron., Vol. 40, pp. 130–138.,1993.

[13] S I Moonand and A Keyhani, “Estimation of induction machine parameters from standstill time-domain data”, IEEE Trans. Ind. Applicat., Vol. 30, pp. 1606–1615, Nov. / Dec.1994

[14] P S Bhimra, Gerneralized theory of Electrical Machine, Khanna Publishers, Delhi, chapter. No. 8, pp. 421-620

[15] P Vas , “Sensorless Vector and Direct Torque Control”. New York: Oxford Univ. Press, 1998.

[16] K Yassine, "Recursive identification of induction motor parameters", Simulation Modelling Practice and Theory 12 pp. 363–381, 2004.

[17] D K Chaturvedi, “Soft computing techniques and its applications to electrical engineering”, Springer Verlag, Germany, 2008.