# Neural-Network-Based Parameter Estimations of Induction Motors

Madhavi H. Nerkar & B. E. Kushare

*Department of electrical engg., K.K.W.I.E.E.R, Nashik, Maharashtra State, India*
E-mail : madhavi.nerkar@gmail.com & be_kushare@rediffmail.com

***Abstract*** **– Accurate estimation of parameters during transient and steady state is required for controlling of Induction motor. Artificial neural networks (ANNs) based online identification of induction motor parameters are presented. ANNs such as feed forward network is used to develop an ANN as a memory for remembering the estimated parameters and for computing the parameters during transients. Simulations and experimental results are presented for induction motors.**

***Index Terms—Artificial neural networks (ANNs), Induction motor, Mutual inductance, Observer system, Parameter estimation***

## I. INTRODUCTION

The Induction motor is a nonlinear multivariable dynamic system with parameters that vary with temperature, frequency, saturation, and operating point. Considering that induction motors are widely used in industrial applications, these parameters have a significant effect on the accuracy and efficiency of the motors and, ultimately, the overall system performance. Therefore, it is essential to develop algorithms for online parameter estimation of the induction motor. Such algorithms can be performed in real time because of the progress in the use of digital signal processors (DSPs) and microelectronics. In this paper ANN based parametric estimation method is developed. The Luenberger observer system is implemented for flux estimation, and the speed observer system is utilized for rotor-speed estimation. The rotor parameters are the most important parameters for the control of the induction motor drives. The rotor resistance can change up to 150% over the entire operation. A number of methods that are both for the detection of the rotor parameter and the prevention of its variation have been discussed.In the rotor parameter estimation is proposed by estimating the rotor temperature. This is based on the fact that the temperature influences the fundamental frequency component of the terminal voltage for a given input current. This is a tedious process because the temperature of the rotor windings has to be measured every time. Many published research papers have shown the effect of motor parameters on the quality of flux and speed estimation in vector control of rotation systems[3]. In this paper, the online identification of the rotor resistance and mutual inductance techniques based on ANN is presented. Artificial neural networks (ANNs) can be used to identify and control the nonlinear dynamic systems because they can approximate a wide range of nonlinear functions to any desired degree of accuracy. Moreover, they can be implemented in parallel and, therefore, shorter computational time can be achieved. In addition, they have immunity to harmonic ripples and have fault-tolerant capabilities. Since the 1990s, several investigations into the applications of neural networks in the field of electrical machines and power electronics have appeared. In recent years, the use of ANN in modulation systems, in breakdown detection, in control, in the estimation of state variables, and in the identification of induction-motor parameters. The use of ANN has been tried for estimating the rotor angular speed. Among the methods used, it is possible to note two types of ANN designs. One is based on the machine model, and the other one uses stator currents and voltages for direct speed estimation. In the proposed solution, the neural networks are used to develop an associated system for remembering the calculated values and for computing these values during the transients. Therefore, this paper considers the online identification of machine parameters in a sensor less control system.

## II. MATHEMATICAL MODEL AND NONLINEAR CONTROL SYSTEM OF INDUCTION MOTOR

The model of a squirrel-cage induction motor expressed as a set of differential equations for the stator-current and rotor-flux vector components presented in a stationary coordinate system are as follows

$$\frac{di_{sx}}{d\tau} = a_1 i_{sx} + a_2\Psi_{rx} - a_3\omega r\Psi_{ry} + a_4 u_{sx} \qquad (1)$$

$$\frac{di_{sy}}{d\tau} = a_1 i_{sy} + a_2\Psi_{ry} - a_3\omega r\Psi_{rx} + a_4 u_{sy} \qquad (2)$$

$$\frac{d\Psi_{rx}}{d\tau} = a_5\Psi_{rx} - \omega_r\Psi_{ry} + a_6 i_{sx} \qquad (3)$$

$$\frac{d\Psi_{ry}}{d\tau} = a_5\Psi_{ry} + \omega_r\Psi_{rx} + a6 i_{sy} \qquad (4)$$

$$\frac{d\omega_r}{d\tau} = L_m/ L_r J(\Psi_{rx} i_{sy} - \Psi_{ry} i_{sx}) - (1/ J) m_o \qquad (5)$$

where $usx$, $usy$, $isx$, $isy$, $\Psi rx$, and $\Psi ry$ are the stator-voltage, the stator-current, and rotor-flux vector components in the stationary coordinate system $xy$, respectively. $\omega r$ is the angular speed of the rotor shaft, $Lm$ is the mutual inductance, $J$ is the moment of inertia, $mo$ is the load torque, and, furthermore

$$a_1 = -\frac{R_s L_r^2 + R_r L_m^2}{L_r w_\sigma}$$

$$a_2 = \frac{R_r L_m}{L_r w_\sigma}$$

$$a_3 = \frac{L_m}{w_\sigma}$$

$$a_4 = \frac{L_r}{w_\sigma}$$

$$a_5 = -\frac{R_r}{L_r}$$

$$a_6 = \frac{R_r L_m}{L_r}$$

$$w_\sigma = L_r\ L_s - L_2$$

$Rs$, $Rr$, $Ls$, $Lr$, and $Lm$ are the rotor and stator resistances and inductances, respectively. $\tau$ is the time in per unit (p.u.).

## III. FEEDBACK LINEARIZATION OF THE INDUCTION MOTOR FED BY VSIS

In induction-motor drives fed by voltage-source inverters (VSIs), the control signals are the voltage vector components. Four novel state variables have been proposed to describe the motor model[6]. The new variables may be interpreted as the rotor angular speed, scalar and vector

$$x_{11} = \omega_r \qquad (6)$$

$$x_{12} = \Psi_{rx} i_{sy} - \Psi_{ry} i_{sx} \qquad (7)$$

$$x_{21} = \Psi^2_{rx} + \Psi^2_{ry} \qquad (8)$$

$$x_{22} = \Psi rx isx + \Psi ry isy \qquad (9)$$

After taking the differential equations for the new state Variables into account, the new model of the motor is obtained .

$$\frac{dx_{11}}{dt} = \frac{L_m}{JL_r} x_{12} - \frac{1}{J} m_o \qquad (10)$$

$$\frac{dx_{12}}{dt} = -\frac{1}{T_v} x_{12} - x_{11}\left(x_{12} + \frac{L_m}{w_\delta}\right) + \frac{L_r}{w_\delta} u_1 \qquad (11)$$

$$\frac{dx_{21}}{dt} = -2\frac{R_r}{L_r} x_{21} + 2R_r\frac{L_m}{L_r} x_{22} \qquad (12)$$

$$\frac{dx_{22}}{dt} = \frac{1}{T_v} x_{22} + x_{11}x_{12} + \frac{R_r L_m}{L_r w_\delta} x_{21} + R_r\frac{L_m}{L_r}\frac{x_{12}^2 + x_{22}^2}{x_{21}} + \frac{L_r}{w_\delta} u_2 \qquad (13)$$

products of the rotor flux vectors and stator current, and the square of the rotor-flux linkages.

Where,

$$\frac{1}{T_v} = \frac{R_r w_\delta + R_s L_r^2 + R_r L_m^2}{w_\delta L_r}$$

$$u_1 = \Psi_{rx} u_{sy} - \Psi_{ry} u_{sx} \qquad (14)$$

$$u_2 = \Psi_{rx} u_{sy} + \Psi_{ry} u_{sx} \qquad (15)$$

The compensation for nonlinearities in (11) and (13), using the nonlinear feedback, leads to the following expressions with the new input variables $m_1$ and $m_2$:

$$u_1 = \frac{w_\delta}{l_r}\left[x_{11}\left(x_{22} + \frac{L_m}{w_\delta} x_{21}\right) + m_1\right] \qquad (16)$$

$$u_1 = \frac{w_\delta}{l_r}\left(-x_{11}x_{12} - \frac{R_r L_m}{L_r w_\delta} x_{21} - \frac{R_r L_m}{L_r}\frac{x_{12}^2 + x_{22}^2}{x_{21}} + m_2\right) (17)$$

The sensorless nonlinear control system for the induction motors with speed observer system, where the ˆ symbol denotes the variables estimated by the speed observer.

A novel speed observer system was recently proposed in. This speed observer is used for the rotor-speed estimation. The rotor-flux linkages of the induction motor may be estimated by using the modified Luenberger observer system.

## IV. ROTOR-RESISTANCE IDENTIFICATION

The accuracy of the rotor-speed estimation using the observer system depends on the value of the rotor resistance used in the observer. A simple algorithm for the identification of the rotor resistance provides large errors which should be eliminated by using extra procedures. The estimation of the rotor resistance using the presented modified algorithm was tested by computer simulation and experiments. The experimental results of the nonlinear control system confirmed the necessity of using feed forward neural networks for remembering the identified resistance. For the small estimation errors of the stator-current components in the Luenberger observer, it is possible to assume that

$$i_{sx} \approx \hat{\imath}_{sx} \quad (18)$$

$$i_{sy} \approx \hat{\imath}_{sy} \quad (19)$$

$$\frac{di_{sx}}{d\tau} \approx \frac{d\hat{\imath}_{sx}}{d\tau} \quad (20)$$

$$\frac{di_{sy}}{d\tau} \approx \frac{d\hat{\imath}_{sy}}{d\tau} \quad (21)$$

Therefore, taking these relations from the motor model and observer system into account yields

$$-R_r L^2_m i_{sx} + R_r L_m \psi_{rx} + \omega_r\, \omega_\sigma \psi_{ry} =$$

$$-R^*_r L^2_m \hat{\imath}_{sx} + R^*_r L_m \widehat{\psi_{rx}} + \omega^*_r \omega_\sigma \widehat{\psi_{ry}} \quad (22)$$

$$-R_r L^2_m i_{sy} + R_r L_m \psi_{ry} - \omega_r\, \omega_\sigma \psi_{rx} =$$

$$-R^*_r L^2_m \hat{\imath}_{sy} + R^*_r L_m \widehat{\psi_{ry}} - \omega^*_r \omega_\sigma \widehat{\psi_{rx}} \quad (23)$$

Where *R*r is the rotor resistance and the variables with the superscript * denote the estimated parameters. The left sides of the aforementioned equations are derived from the motor model, and the right sides are obtained from the observer system. The rotor angular speed varies slowly and could be assumed as a constant parameter in the variable-estimation system. Equations (22) and (23) are valid at steady state, particularly for the instants $\tau_1$ and $\tau_2$. The instantaneous values of the rotor-flux components are not accessed for direct measurement. However, it is possible to determine the difference between the values of the rotor-flux components for the instants $\tau_1$ and $\tau_2$. This makes it possible to determine the values of rotor resistance from the following equations, assuming that the rotor angular speed is constant and known:

$$R_r L_m( -L_m \Delta i_{sx} + \Delta \psi_{rx}) + \omega_r \omega_\sigma \psi_{ry} = \Delta_{zx} \quad (24)$$

$$R_r L_m( -L_m \Delta i_{sy} + \Delta \psi_{ry}) + \omega_r \omega_\sigma \psi_{rx} = \Delta_{zy} \quad (25)$$

$$\Delta i_{sx} = i_{sx}(\tau_2) - i_{sx}(\tau_1) \quad (26)$$

$$\Delta i_{sy} = i_{sy}(\tau_2) - i_{sy}(\tau_1) \quad (27)$$

$$\Delta \psi_{rx} = \psi_{rx}(\tau_2) - \psi_{rx}(\tau_1) \quad (28)$$

$$\Delta \psi_{ry} = \psi_{ry}(\tau_2) - \psi_{ry}(\tau_1) \quad (29)$$

$$\Delta_{zx} = -R^*_r L^2_m (\hat{\imath}_{sx}(\tau_1) - \hat{\imath}_{sx}(\tau_2)) + R^*_r L_m (\widehat{\psi_{rx}}(\tau_2) - \widehat{\psi_{rx}}(\tau_1)) + \omega_r\, \omega_\sigma(\widehat{\psi_{ry}}(\tau_2) - \widehat{\psi_{ry}}(\tau_1)) \quad (30)$$

$$\Delta_{zy} = -R^*_r L^2_m (\hat{\imath}_{sy}(\tau_2) - \hat{\imath}_{sy}(\tau_1)) + R^*_r L_m (\widehat{\psi_{ry}}(\tau_2) - \widehat{\psi_{ry}}(\tau_1)) - \omega_r\, \omega_\sigma(\widehat{\psi_{rx}}(\tau_2) - \widehat{\psi_{rx}}(\tau_1)) \quad (31)$$

Using the motor equations, the next relations could be obtained

$$\Delta \psi_{rx} = \frac{L_r}{L_m} \Delta \psi_{sx} - \frac{\omega_\sigma}{L_m} \Delta i_{sx} \quad (32)$$

$$\Delta \psi_{ry} = \frac{L_r}{L_m} \Delta \psi_{sy} - \frac{\omega_\sigma}{L_m} \Delta i_{sy} \quad (33)$$

The instantaneous values of the stator-flux linkage components, such as the rotor flux, cannot be directly measured. The stator-flux estimation by the voltage integration provides an error that resulted from the disturbances in the voltage and current signals. Without this error, it is possible to estimate the difference of the stator-flux vector components at instants $\tau_1$ and $\tau_2$ as

$$\Delta \psi_{sx} = \int_{\tau 1}^{\tau 2} (-R_s i_{sx} + u_{sx})\, d\tau \quad (34)$$

$$\Delta \psi_{sy} = \int_{\tau 1}^{\tau 2} (-R_s i_{sy} + u_{sy})\, d\tau \quad (35)$$

Two additional integrators introduced to the estimation system should be connected at a specified time with zero initial values. The outputs of these integrators at instant $\tau 2$ will be the incremental value of the stator-current vector components. The rotor resistance may be calculated from (35) or (36) as follows:

$$R_{rx} = \frac{\Delta z_x - \omega r\, L^2{}_r\, \Delta \psi_{ry}}{L_m ( -L_m\ \Delta i_{sx} + \Delta \psi_{rx})} \quad (36)$$

$$R_{ry} = \frac{\Delta z_y - \omega r\, L^2{}_r\, \Delta \psi_{rx}}{L_m ( -L_m\ \Delta i_{sy} + \Delta \psi_{ry})} \quad (37)$$

Where *R*r*x* and *R*r*y* are, respectively, the rotor-resistance *x*- and *y*-axis components in the stationary reference frame. In the following investigations, the next calculation algorithm for resistances *Rrx* and *Rry* is assumed. At instant $\tau_1$, when integrators are running, the values of the flux and current calculated in the Luenberger observer system are registered. The integration period equal to 50 periods of transistor switching (about 7.5 ms) has been assumed. At instant $\tau_2$, the flux calculation using the voltage model (34) and (35) is completed. At instant $\tau 2$, the values of the flux increments are computed by using the voltage models (32) and (33), and the flux increments are also computed from the Luenberger observer. Additionally, Δ*zx*, Δ*zy*, and resistances *R*rx and *R*ry are computed. The computed resistance is filtered and once again used in the Luenberger and the speed observer systems. For the next 50–100 switching periods, the variables estimated in the observers were stabilized. Then, at instant $\tau 1$, the integrators were again zeroed, and the process started from the beginning. Equations (36) and (37) were obtained by using approximated relationships, and these equations make it possible to identify the rotor resistance *R*r, with the error depending on the value of the rotor resistance *R**r assumed in the variable estimation algorithm. Relationships (36) and (37) may contain division by zero or by small values. In such situations, the rotor resistance *R*r is calculated with a large error. This results from the periodic character of the variables, whose increments are calculated. In special situations, the values of the periodic variable measured at different instances could be the same, and then, the increment of the variable would be zero. If the rotor resistance calculated from (36) and (37) exceeds the assumed limit, such value will be rejected. The effect of the mentioned errors may be decreased by calculating the averaged rotor resistance *R*r_s from the calculation for the two phases

$$R_{rav} = 0.5 \times (R_{rx} + R_{ry}) \tag{38}$$

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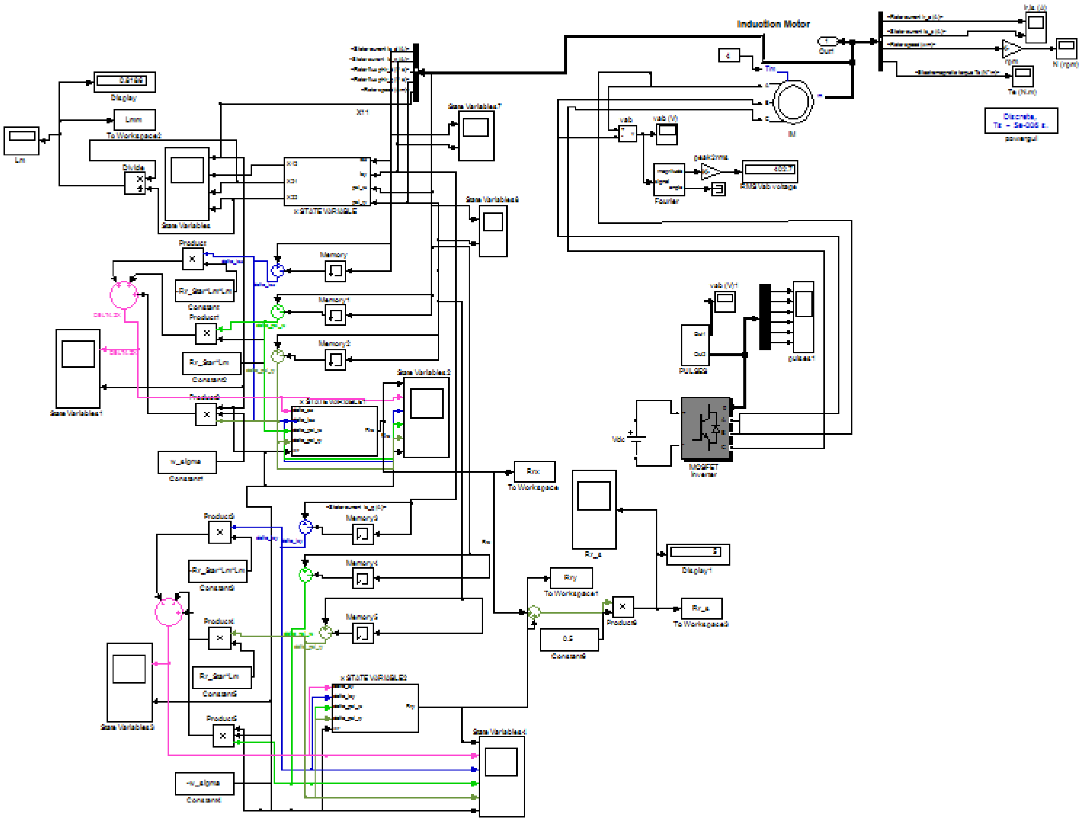


Fig.1 Simulink model of Induction motor in discerte mode

## . V. ANALYSIS OF SPEED OBSERVER ERRORS DURING ROTOR-RESISTANCE IDENTIFICATION

For an exact description of the effect of rotor-resistance identification on the operation of the speed control system of the induction motor, the mean-square averaged error *E* of speed estimation was calculated. The integral of the summation or the square of difference between the measured and the estimated speeds is assumed as a criterion. Assuming Euler's integration method, the criterion may be defined as

$$E=\int_{t=0}^{t=tN}[(\omega r - \hat{\omega} r)^2]dt= \frac{\sum_{i=1}^{N}(\omega r - \hat{\omega} r)^2}{N} \tag{39}$$

During the investigations, the rotor speed was estimated without using and by using the ANN correction. It is seen that the speed estimation error decreased by about 50% when the proposed resistance estimation method was used

## VI. MUTUAL-INDUCTANCE IDENTIFICATION OF THE INDUCTION MOTOR.

For the synthesis of the control system for the induction motor, it is essential to compute the mutual inductance for any operating point. This parameter could be calculated by using the Luenberger observer system and a multiscalar motor model. The method depends on the iterative identification of this parameter using, which has the following form after substituting the measured values with the estimated ones from the Luenberger observer system:

$$\frac{d\hat{x}_{21}}{dr} = -2\frac{R_r}{L_r}\hat{x}_{21} + 2\frac{R_r\hat{L}_m}{L_r}\hat{x}_{22} \quad (40)$$

the steady state, at the *k*th step of the observer sampling, (18) has the following form:

$$0 = -2\frac{R_r}{L_r}\hat{x}_{21}(k) + 2\frac{R_r\hat{L}_m(k)}{L_r}\hat{x}_{22}. \quad (41)$$

Where $\hat{x}_{21}(k)$ and $\hat{x}_{22}(k)$ are the estimated values at the *k*th step of the observer sampling. A simple relationship for the calculation of the mutual inductance ˆ*L*m using the estimated current and rotor flux has been developed

$$\hat{L}_m(k) = \frac{\hat{x}_{21}(k)}{\hat{x}_{22}(k)}. \quad (42)$$

It is proved that the iterative method for mutual inductance identification gives a result that is close to the real value. An acceleration of the identification process was used, by getting the new value from the following relationship using the acceleration factor.

Where $\hat{L}_{ma}$ the value is obtained from (5.20), and is the previous value used in the observer system. The acceleration factor *k* depends on the variables $\hat{x}_{21}$ and $\hat{x}_{22}$ the estimation of the mutual inductance at the steady state and during transients using ANNs with a recurrent-network structure is proposed in this paper.

$$\hat{L}_m = + \hat{L}_{mp} + k.(-\hat{L}_{mp}). \quad (43)$$

## VII. MODELLING AND SIMULATION OF INDUCTION MOTOR.

### *a) Induction Motor Working In Discrete Mode*

The basic SVPWM based vector control block diagram of the proposed drive system of the Induction motor is shown in fig.1.The system comprises of the following modules:

- SVPWM based voltage source inverter (VSI) module.
- Three phase Induction motor module.
- Computation of mathematical equations to estimate Rr_s &Lm module.

### *b) Simulation of motor in discrete mode.*

Simulation of Induction motor during load condition has been observed. The simulation results are given in the form of following Figures:

a. Rotor Resistance in X axis Rr_x.

b. Rotor Resistance in X axis Rr_y.

c. Average Rotor Resistance Rr_s.

d. Angular speed Wr.

e. Mutual inductance Lm.

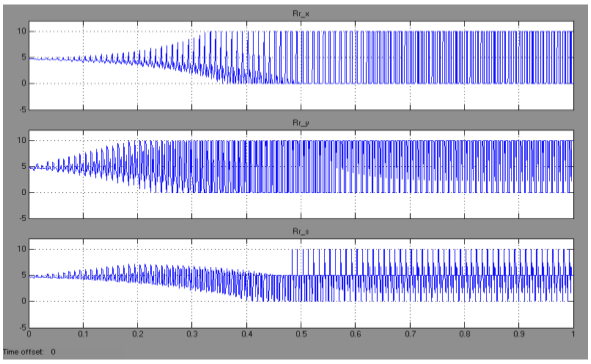


Fig.2: Graph of Wr, Rr_x, Rr_y,& Rr_s.

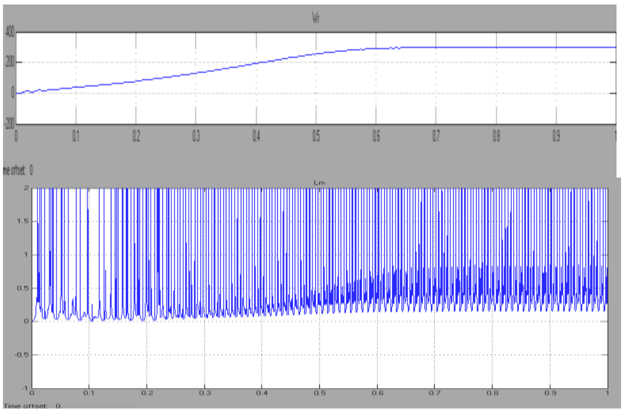


Fig.3: Graph of ωr &Lm

*c) Estimation of Rotor Resistance And Mutual Inductance with Ann.*

*i) Estimation of Rotor Resistance with ANN*

The rotor resistance as mathematical parameter of the machine model is not constant and changes with the time, temperature, and speed. During transients, which is when the speed changes, the resistance estimation algorithm shows a large estimation error (30%) although filtering is used. Artificial Neural Network (ANN) can be used for remembering the rotor resistance at the steady states and is determined during transients

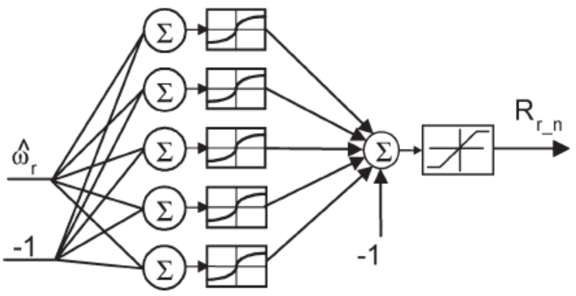


Fig. 4: ANN architecture for remembering the rotor resistance: feed forward ANN.

*ii) Rr_n estimation results using ANN.*

Training input data of Induction motor using ANN has been observed. The simulation results are given in the form of following Figures:

a) Rotor speed ωr
b) Estimated Rotor Resistance Rr_s.
c) Rotor resistance calculated by ANN Rr_n.

Due to the use of an ANN,Rotor resistance Rr_n in the steady-state error was decreased nearly to zero. After nearly zeroing the error, small oscillations are observed. However, as a result of using the ANN corrector, it does not exceed 2.5%.

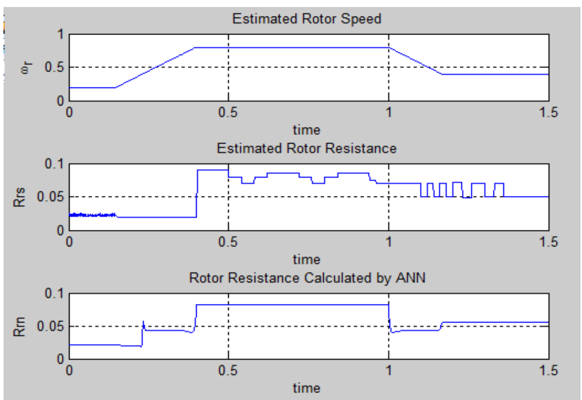


Fig.5: Graph of ωr, Rr_s &Rr_n Vs Time

The some oscillations observed during the estimated value Rr_s shown in Fig.5.during steady state condition

*ii) Estimation of Mutual inductance with Ann*

Artificial Neural Network (ANN) can be used for remembering the mutual inductance at the steady states and is determined during transients. The structure of the mutual inductance estimation using ANN for remembering the mutual inductance. ANN is trained online on the basis of the mutual inductance calculated from the simulation of simulink model for the induction motor.

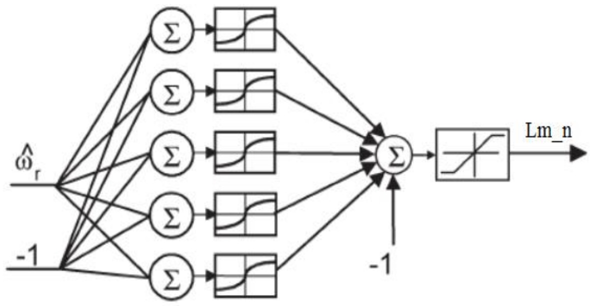


Fig. 6: ANN architecture for remembering the mutual inductance feed forward ANN.

*ii) Lm_n estimation results using ANN.*

Training input data of Induction motor using ANN has been observed. The simulation results are given in the form of following Figures:

a) Rotor speed ωr.
b) Estimated mutual inductance Lm.
c) mutual inductance calculated by ANN Lm_n.

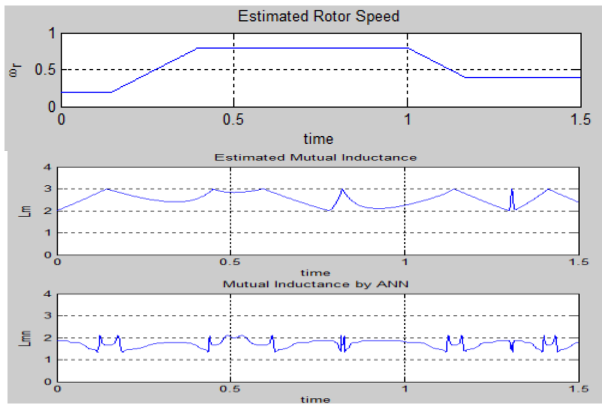


Fig.7: Graph of ωr, &Lm_n Vs Time

Due to the use of an ANN, mutual inductance Lm_n in the steady-state error was decreased nearly to zero. After nearly zeroing the error, small oscillations are observed. However, as a result of using the ANN corrector, it does not exceed 2.5%. The some oscillations observed during the estimated value Lm shown in Fig. 7.during steady state condition.

*d) Rotor resistance Rr_s under no load and load condition.*

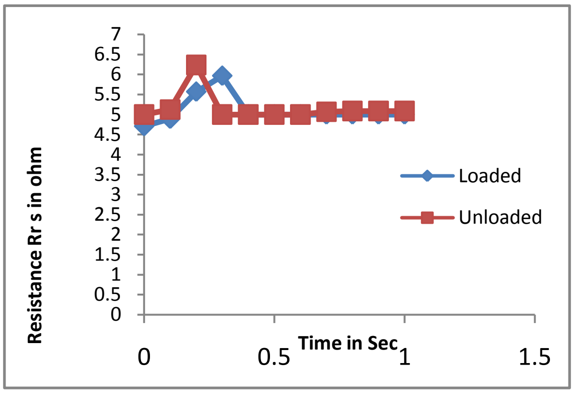


Fig.8: Graph of Rr_s Vs Time.

*e) Mutual inductance Lm under no load and load condition.*

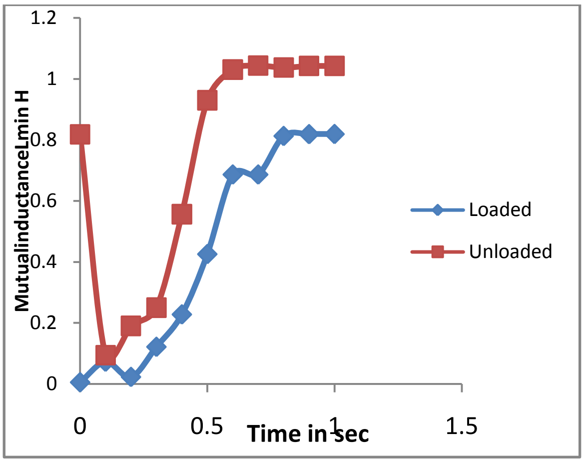


Fig.9: Graph of Lm Vs Time.

## VIII. CONCLUSION

The online parameter estimation is essential for improved static and dynamic performance for drives used in wide speed range applications, such as those in electric and hybrid vehicles. The methods for estimating the online rotor resistance and mutual inductance of induction motor are presented. ANNs for remembering the estimated parameters and computing the parameters during transients are used. These methods are applied to the closed-loop sensorless nonlinear control of induction motors. From the results obtained, it is seen that the speed estimation process was significantly improved and error in estimation is within limit. The proposed system is useful for high performance applications.

## APPENDIX I

INDUCTION-MACHINE DATA

| | | |
|---|---|---|
| HP rating | 3 | HP |
| Rated Voltage ($V_1$) | 400 | V |
| Frequency (f) | 50 | Hz |
| Pole pairs (P) | 2 | |
| Stator resistance (Rs) | 3.1485 | Ohm |
| Stator self inductance ( Ls) | 0.0197 | H |
| Rotor resistance ( Rr) | 4.6977 | Ohm |
| Rotor self inductance ( Lr) | 0.0197 | H |
| Mutual Inductance (Lm) | 0.8091 | H |
| Inertia of rotor (J) | 0.022 | Kg.m$^2$ |
| Rotor speed (Nr) | 2990 | rpm |

## IX. REFERENCES

[1] Dr P.S. Bhimra," Gerneralized theory of Electrical Machine",ch.no.8,pp-421-620.

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

[3] "Neural-Network-Based Parameter Estimations of Induction Motors" Miroslaw Wlas, Zbigniew Krzemi´nski, and Hamid A. Toliyat, Senior Member, IEEE transactions on industrial electronics, vol. 55, no. 4, april 2008.

[4] A Review of RFO Induction Motor Parameter Estimation Techniques" Hamid A. Toliyat, Senior Member, IEEE, Emil Levi, Senior Member, IEEE, and Mona Raina, Student Member, IEEE transactions on energy conversion, vol. 18, no. 2, june 2003.

[5] Neural Network Applications in Power Electronics and Motor Drives—An Introduction and Perspective Bimal K. Bose, Life Fellow, IEEE

.[6]. "Artificial-Neural-Network-Based Sensorless Nonlinear Control of Induction Motors" Miroslaw Wlas, Zbigniew Krzemin´ski, Jarosław Guzin´ski, Haithem Abu-Rub, Member, IEEE, and Hamid A. Toliyat, Senior Member, IEEE

[7] "Rotor Resistance Identification Using Neural Networks For Induction Motor Drives In The Case Of Insensitivity To Load Variations" M. Ebrahimi**, E. Rezaei, B. Vaseghi And M. Danesh

[8] "Speed Observer System for Advanced Sensorless Control of Induction Motor" Haithem Abu-Rub, Member, IEEE, Jaroslaw Guzinski,

Zbigniew Krzeminski, and Hamid A. Toliyat, Senior Member, IEEE.

[9] **"**On Nonlinear Control of Induction Motors Comparison of two Approaches" Afef Fekih and Fahmida. N. Chowdhury.

[10] "RNN Based Rotor Flux and Speed Estimation of Induction Motor" Bambang urwahyudi1, 2, Soebagio1, and M. Ashari1 International Journal of Power Electronics and Drive System JPEDS) Vol.1, No.1, September 2011, pp. 58~64 ISSN: 2088-8694

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