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NEURAL LEARNING ALGORITHM BASED MRAS ROTOR RESISTANCE ESTIMATOR USING REACTIVE POWER TECHNIQUE FOR VECTOR CONTROLLED INDUCTION MOTOR DRIVE

[1]Ms.M.NANDHINI GAYATHRI, [2]Dr.S.HIMAVATHI, [3]Dr.R.SANKARAN

[1]Assistant Professor-II, EEE Department/SEEE,SASTRA University, Thanjavur, India.

[2]Professor, EEE Department, Pondicherry Engineering College, Pondicherry, India.

[3]Professor, EEE Department/SEEE, SASTRA University, Thanjavur, India.

E-mail: [1]nandhini.gayathri@gmail.com , [2]hima_pondy@yahoo.co.in , [3]r_shankaran43@hotmail.com

ABSTRACT

This paper presents a new method for estimating the rotor resistance of an induction motor. The rotor resistance changes significantly with temperature and frequency. This variation has a major influence on the field oriented control performance of an induction motor due to the deviation of slip frequency from the set value. In conventional MRAS, the adaptation is done using a PI-controller. The MRAS approach using reactive power as a functional candidate for rotor resistance estimation makes MRAS computationally simpler and easy to design. This paper proposes the role of neural learning algorithm for adaptation in a MRAS based rotor resistance estimator. The proposed scheme combines the advantages of reactive power technique and the capability of neural network to form a scheme named "Neural Learning-Reactive Power Model Reference (NL-RPMR) based rotor resistance estimator" for Induction Motor Drives. In the NL-RPMR scheme, the error between neural network model and reference model is back propagated to adjust the weights of the neural network of the estimator. The performance of NL-RPMR based rotor resistance estimator is extensively simulated and compared with the conventional MRAS method. The promising results obtained are presented.

Keywords: *Induction Motor, MRAS, Rotor Resistance Estimator, Neural Network, Back Propagation Algorithm, Reactive Power.*

1. INTRODUCTION

During the past three decades, adjustable speed ac drive technology has gained lot of momentum. It is well recognized that ac motor drives account for more than 50% of all electrical energy consumed worldwide. Induction motor is very popular in drive applications due to its well known advantages of simple construction, ruggedness and low cost [1]. A major revolution in the area of induction motor based drives was the invention of field oriented or vector control in the late 1960's [2]. The variable speed control method is basically classified into two types: Scalar based control and Vector based control [3]. In scalar control, only the magnitude and frequency of voltage, current and flux linkage variables are controlled and hence suitable for steady state conditions. In vector control, the magnitude, frequency and instantaneous position of voltage, current and flux linkage vectors are controlled and are valid for both steady state and transient conditions. Thus, the vector control method is a better option than the scalar control to obtain the desired dynamic performance. High performance control requires an accurate estimate of the machine parameters at all operating points; it should be done continuously on-line to obtain a reliable estimate of machine variables [4]. The successful implementation of the indirect field oriented control require an accurate calculation of field angle and slip frequency. The errors in the model parameters

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can cause incomplete decoupling between flux and torque. This results in a mismatch between the torque command and the motor torque in the steady state mode on the one hand, and an oscillatory response of the transient torque on the other. Detuning of the rotor parameters renders implementation of an indirect rotor flux oriented control scheme unsatisfactory, and dependent on temperature, frequency and the saturation level of the machine [13].

In Indirect Field Oriented control, the major problem is determining rotor resistance which is sensitive to temperature. The practical temperature excursion of the rotor is approximately 130^{O}C above ambient temperature [5], [13]. This increases the rotor resistance by 50 percent over its ambient or nominal value. With variations in R_r, the calculated slip frequency is incorrect and the flux angle is no longer appropriate for field orientation. This results in instantaneous error in both flux and torque. Various schemes have been proposed for rotor resistance adaptation such as the Model Reference Adaptive Control technique, Extended Kalman filter and Spectral Analysis method [6-16]. Artificial neural network methods for the estimation of rotor resistance were also investigated. MRAS schemes offer simpler implementation and require less computational effort compared to other methods. MRAS observers are based on rotor flux and reactive power. In rotor flux based MRAS, the rotor flux error between reference and adjustable model is used by the adaptive mechanism (PI-controller) for rotor resistance estimation. Whereas, the reactive power based MRAS uses reactive power error instead of rotor flux. The selection of reactive power as a candidate for MRAS based rotor resistance estimator results in a simpler system model which is easier to design and implement and become advantageous on real time applications. Both MRAS schemes have used PI controller as a part of the adaptive mechanism for rotor resistance estimation. Recently, the use of Neural Networks (NNs) for identification and control of nonlinear dynamic systems in power electronics and drives have been proposed as they are capable of approximating wide range of nonlinear functions to a desired degree of accuracy [6]-[8].

In this paper, the capability of a Neural Learning for adaptive mechanism and advantages of Reactive Power Model Reference are combined to form a scheme named "Neural Learning – Reactive Power Model Reference (NL-RPMR) based rotor resistance estimator". This is proposed for a Space Vector PWM Inverter fed induction motor drive system. In the proposed NL-RPMR based rotor resistance estimator, the reactive power error between reference model and neural network model is back propagated to adjust the weights of neural network model to estimate the rotor resistance.

2. SCHEMATIC DIAGRAM OF SPACE VECTOR PWM INVERTER FED INDUCTION MOTOR DRIVE WITH ROTOR RESISTANCE ESTIMATOR

The block diagram of vector controlled scheme is shown in Fig.1.The calculation of slip speed depends on the rotor resistance. The vector control presented here is indirect field oriented control (rotor flux oriented control). Fig.1 shows the overall block diagram of Space Vector PWM Inverter fed Induction Motor drive system using an NL-RPMR rotor resistance estimator. The system consists of a solid state Induction Motor drive system, rotor flux oriented control, along with flux and NL-RPMR rotor resistance estimator. Rotor flux oriented control consists of a PI speed controller, a current controller, and PWM generator.

2.1 MRAS Based Rotor Resistance Estimation

The MRAS scheme shown in fig.2 consists of a reference model which determines the desired states and adaptive (adjustable) model which generates the estimated values of the states. The error between these states is fed to an adaptation mechanism to generate an estimated value of the rotor resistance which is used to adjust the adaptive model. This process continues till the error between two outputs tends to zero.

2.2 Neural Learning Algorithm Based Rotor Resistance Estimation Using Reactive Power Technique

In conventional MRAS, the PI-controller is used for adaptation mechanism. In this paper neural network learning algorithm is proposed and employed for adaptation mechanism. The proposed neural learning algorithm is based on powerful steepest descent method. In this method, the weights of Neural Network are adjusted in steps to minimize performance index, mean squared error. The learning rate employed in the algorithm determines the step size. Larger value of learning

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rate means faster learning of Neural Network. But, this would lead to oscillations in the output. To overcome this difficulty or to reduce oscillations in the output, a momentum term is added to smoothen the oscillations and accelerate the convergence.

In the proposed NL-RPMR (Fig.3), the reference model and neural network adjustable model computes instantaneous reactive power (Q_{ref}) and neural based estimated reactive power (Q_{nm}). The reference model is independent of slip speed (ω_{sl}) whereas the adjustable model depends on ω_{sl}. The error signal ($\varepsilon = Q_{ref} - Q_{nm}$) is fed to the adaptation mechanism block (adaptation mechanism is done using powerful steep descent neural network learning algorithm), which yields ω_e. The Slip speed (ω_{sl}) is computed from estimated ω_e shown. The rotor resistance (R_r) is then computed from ω_{sl}. The equations defining the induction motor reference model and adjustable model based on reactive power are given below.

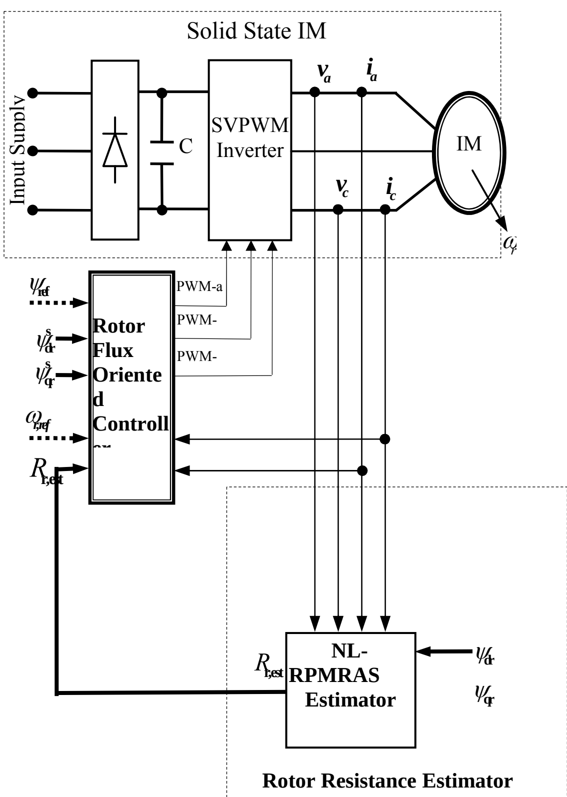

Fig.1 Vector Controlled IM Drives Showing The NL-RPMR Rotor Resistance Estimator

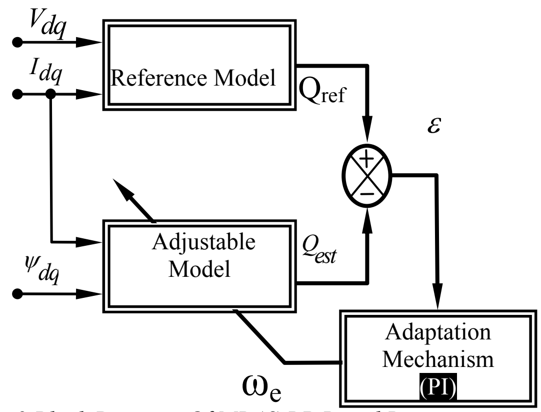

Fig.2 Block Diagram Of MRAS-RP Based Rotor Resistance Estimation

The d and q axis stator voltages of an induction motor can be expressed on synchronously rotating (ω_e) reference frame [17] as given in equations (1) and (2).

$$V_{ds} = R_s i_{ds} + \sigma L_s \frac{d}{dt} i_{ds} + \frac{L_m}{L_r}\frac{d}{dt}\psi_{dr} - \sigma L_s \omega_e i_{qs} - \omega_e \frac{L_m}{L_r}\psi_{qr} \quad \text{... (1)}$$

$$V_{qs} = R_s i_{qs} + \sigma L_s \frac{d}{dt} i_{qs} + \frac{L_m}{L_r}\frac{d}{dt}\psi_{qr} + \sigma L_s \omega_e i_{ds} + \omega_e \frac{L_m}{L_r}\psi_{dr} \quad \text{... (2)}$$

The Reactive Power equation for reference model is given as

$$Q_{ref} = V_{qs} i_{ds} - V_{ds} i_{qs} \quad \text{... (3)}$$

The neural network based estimated reactive power is given as

$$Q_{nm} = w_1 * P \quad \text{... (4)}$$

Where, $w_1 = \omega_e$ and

$$P = \sigma L_s (i_{ds}^2 + i_{qs}^2) + \frac{L_m}{L_r}(\psi_{qr} i_{qs} + \psi_{dr} i_{ds}) \quad \text{...(5)}$$

The neural network model is represented by the equation (4), where w_1 represents the weight of the network and P is the input to the neural network model. The standard Back-propagation learning rule is employed to train the network. In order to estimate Q_{nm}, w_1 needs to be updated, so as to minimize the energy function E which is given in equation (6). The energy function is minimized by using steepest descent method. The change in weight is given in (7) with the chosen learning rate (α). The weight is updated using momentum

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constant (η) and using (8). The slip speed (ω_{sl}) can be calculated from w_1 and rotor resistance (R_r) is then computed from the slip speed (ω_{sl}).

$$E = \frac{1}{2}\left(Q_{ref} - Q_{nm}\right)^2 \quad \dots (6)$$

$$\Delta w_1(k) = \alpha\,[E * P] \quad \dots (7)$$

$$w_1(k) = w_1(k-1) + \Delta w_1(k) + \eta \Delta w_1(k-1) \quad \dots (8)$$

The Slip speed is given as

$$\omega_{sl} = w_1 - \omega_r \quad \dots (9)$$

The slip speed is given as

$$\omega_{sl} = \frac{R_r\left(L_m i_{ds} - \psi_{qr}\right)}{\psi_{dr} L_r} \quad \dots (10)$$

The rotor resistance is given as

$$R_r = \frac{\omega_{sl}\psi_{dr}L_r}{L_m i_{ds} - \psi_{qr}}$$

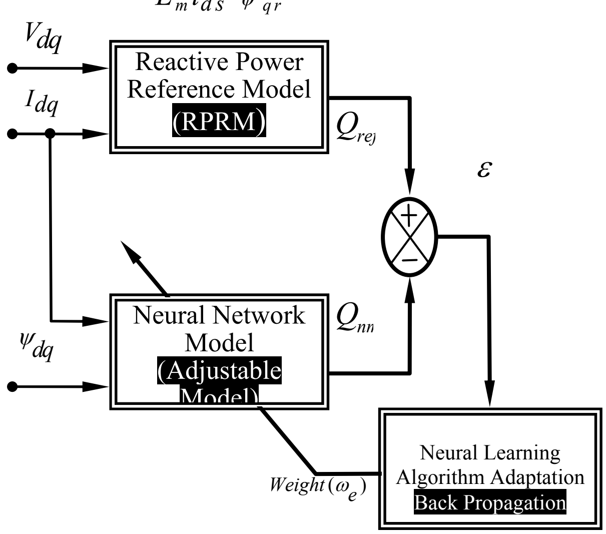

Fig.3 Block Diagram Of NL-RPMR Based Rotor Resistance Estimation

3. SIMULATION RESULTS

In order to verify the effectiveness and feasibility of estimating rotor resistance using MRAS-RP method and NL-RPMR method, a simulation model has been developed in MATLAB/SIMULINK platform. The space vector PWM based vector controlled drive is subjected to changes in rotor resistance and the tracking capability of both MRAS-RP and NL-RPMR method are compared. Simulations have been done for various changes in R_r for the operating condition of 415V/50Hz and rated load of 7.5Nm and the performance of Rotor Resistance Estimator has been analysed.

- With 100% step change in Rotor Resistance
- With 100% ramp change in Rotor Resistance

The rotor resistance of 6.085 is step change to 12.17 (100% change in R_r) at 1sec. Fig.4 shows that the NL-RPMR based rotor resistance estimation for step change in rotor resistance. Fig.5 shows that the NL-RPMR based rotor resistance estimation for ramp change in rotor resistance. The rotor resistance is rising in ramp manner gradually from 0.5sec to 1.7sec and reaches the value from 6.085 to 12.17(100% change in R_r).

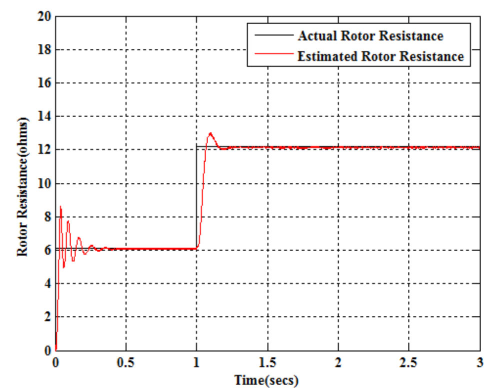

Fig.4 Actual and Estimated Rotor Resistance for 100% step change using NL-RPMR

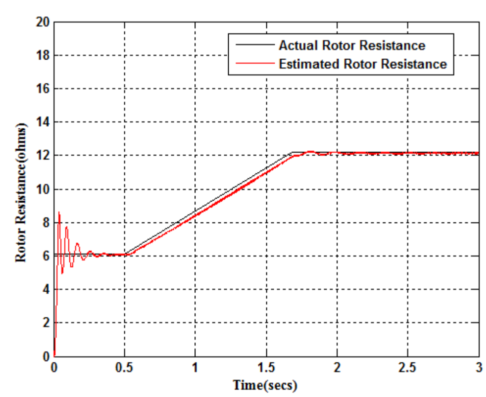

Fig.5 Actual and Estimated Rotor Resistance for 100% Ramp change using NL-RPMR

The table.1 shows that the error between actual rotor resistance and estimated rotor resistance and settling time for various changes in rotor resistance using MRAS-RP method and table.2 shows the

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performance of MRAS-RP based rotor resistance estimator for various voltages with rated load condition. From the result obtained, it is observed that the error between the actual and estimated R_r is always within 1.1% and settling time is found to be approximately 0.05sec.The table.3 shows that the error between actual rotor resistance and estimated rotor resistance and settling time for various changes in rotor resistance using NL-RPMR method and table.4 shows the performance of NL-RPMR for various voltages with rated load condition. From the result obtained, it is observed that the error between the actual and estimated R_r is always within 0.2% and settling time is found to be approximately 0.02sec. The maximum estimation error and maximum settling time for MRAS-RP and NL-RPMR based rotor resistance estimator is discussed in table 5.

Table.1 Estimator Error And Settling Time For Various Changes In Rotor Resistance Using MRAS – Reactive Power Method

Change in R_r (%)	Actual R_r(ohms)	Estimated R_r(ohms)	Settling Time(sec)	Error (%)
10	6.694	6.774	0.05	1.181
20	7.302	7.386	0.05	1.137
30	7.910	7.998	0.04	1.100
40	8.519	8.609	0.04	1.045
50	9.127	9.221	0.04	1.019
60	9.736	9.833	0.03	0.986
70	10.34	10.44	0.03	0.957
80	10.95	11.06	0.03	0.995
90	11.56	11.67	0.03	0.943
100	12.17	12.28	0.03	0.896

Table. 2 MRAS-RP Based Rotor Resistance Estimation For Various Voltages With Rated Load

S.no.	Voltage (V)	Actual R_r\ (Ohms)	Estimated R_r (ohms)	Error (%)	Settling Time (sec)
1	415	10.95	11.06	0.995	0.03
2	300	10.95	11.06	0.995	0.03
3	200	10.95	11.06	0.995	0.03
4	100	10.95	11.06	0.995	0.03
5	10	10.95	11.06	0.995	0.03

Table.3 Estimator Error And Settling Time For Various Changes In Rotor Resistance Using Neural Learning - Reactive Power MRAS Method (NL-RPMR)

Change in R_r (%)	Actual R_r (ohms)	Estimated R_r (ohms)	Settling Time(sec)	Error (%)
10	6.694	6.71	0.02	0.238
20	7.302	7.32	0.02	0.245
30	7.910	7.93	0.02	0.252
40	8.519	8.541	0.02	0.257
50	9.127	9.151	0.02	0.262
60	9.736	9.761	0.02	0.256
70	10.34	10.37	0.02	0.289
80	10.95	10.98	0.02	0.273
90	11.56	11.59	0.02	0.259
100	12.17	12.2	0.02	0.246

Table.4 NL-RPMR Based Rotor Resistance Estimation For Various Voltages With Rated Load

S.no.	Voltage (V)	Actual R_r Ohms	Estimated R_r ohms	Error (%)	Settling Time (sec)
1	415	10.95	10.98	0.273	0.02
2	300	10.95	10.98	0.273	0.02
3	200	10.95	10.98	0.273	0.02
4	100	10.95	10.98	0.273	0.02
5	10	10.95	10.98	0.273	0.02

Table.5 Comparison Of Estimator Error And Settling Time Between MRAS-RP and NL-RPMR Based Methods

Methods	Error (%)	Settling Time (sec)
MRAS-RP	1.1	0.05
NL-RPMR	0.2	0.02

From the table.5, it is observed that the estimation error and settling time of NL-RPMR method is found to be less compared to MRAS-RP based method.

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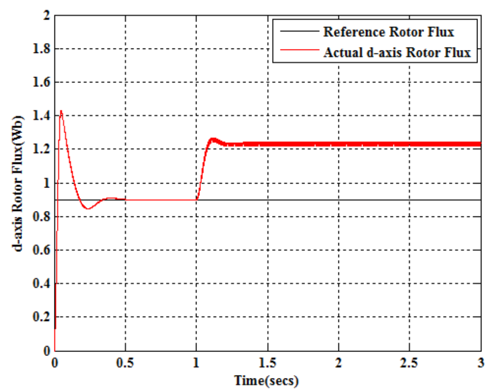
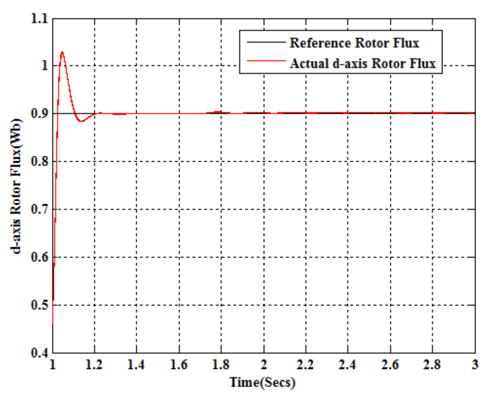
4. ANALYSIS OF VECTOR CONTROLLED INDUCTION MOTOR DRIVE PERFORMANCE WITH AND WITHOUT ROTOR RESISTANCE ESTIMATOR

The performance of vector controlled induction motor drives is analyzed without and with rotor resistance estimator for following operating condition.

- Reference speed = 100 rad/sec
- Reference rotor flux = 0.9wb
- Load torque =7.5 Nm
- 100% step change in rotor resistance is given at 1 second.

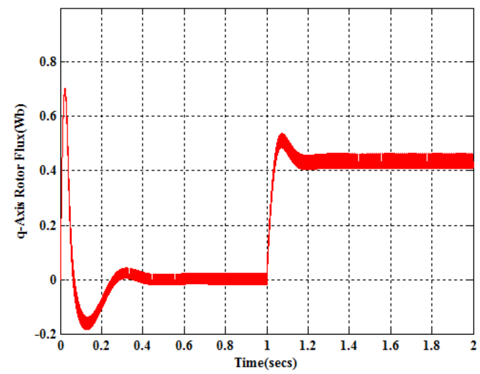


(a)

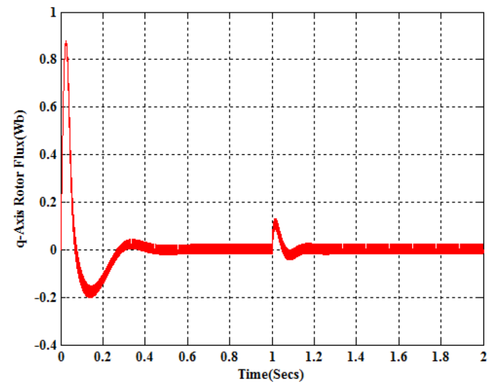


(b)

Fig.6 Actual and Reference d-axis rotor flux for (a) Without R_r Estimator (b) With R_r Estimator

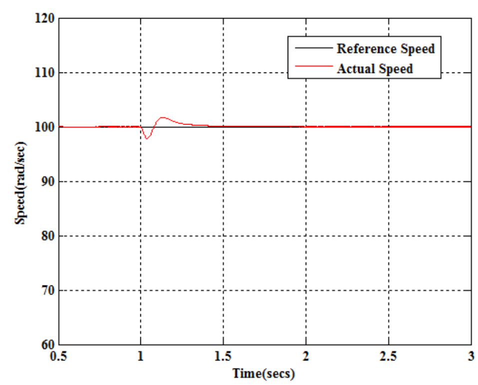


(a)



(b)

Fig.7 Actual and Reference q-axis rotor flux for (a) Without R_r Estimator (b) With R_r Estimator



(a)

Journal of Theoretical and Applied Information Technology
15th November 2012. Vol. 45 No.1

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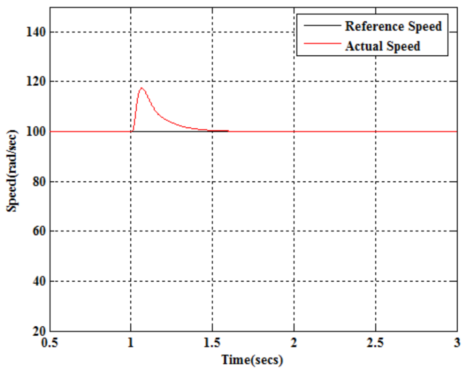
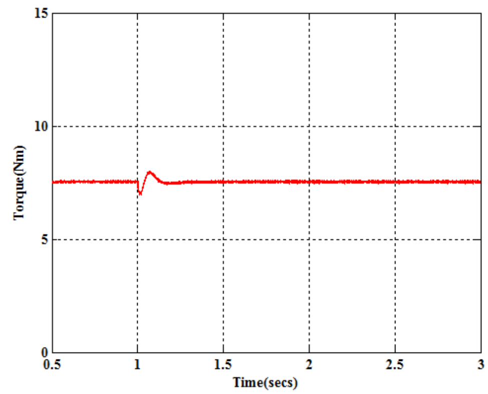


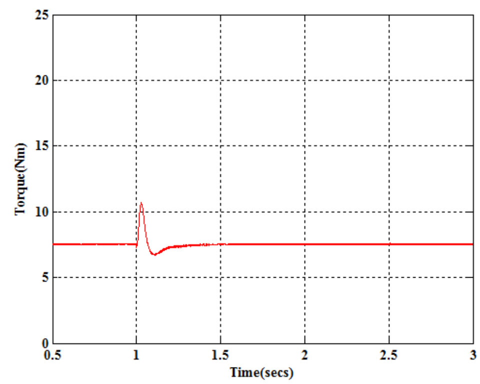
(b)

Fig.8 Actual and Reference Speed for (a) Without R_r Estimator (b) With R_r Estimator

Fig.6 shows the actual and reference flux without and with Neural Learning Algorithm based MRAS rotor resistance estimator using reactive power. From the result it is observed that without rotor resistance estimator, the actual rotor flux deviates from the reference flux for a step change in rotor resistance at 1sec. Whereas, with Neural Learning Algorithm based MRAS rotor resistance estimator, the actual rotor flux is tracking reference rotor flux. Fig.7 shows the q-axis rotor flux, without and with Neural Learning Algorithm based MRAS rotor resistance estimator using reactive power. From the result it is observed that with Neural Learning Algorithm based MRAS rotor resistance estimator, the q-axis rotor flux is zero indicating field orientation. Fig.8 shows the actual and reference speed for without and with Neural Learning Algorithm based MRAS rotor resistance estimator using reactive power. From the result it is observed that without rotor resistance estimator, the actual speed deviates from the reference speed (negative value) and takes a long time to track the reference speed for a step change in rotor resistance at 1sec. Whereas with Neural Learning Algorithm based MRAS rotor resistance estimator, the actual speed is tracking the reference rotor speed within a short period. Fig.9 shows the actual and reference torque without and with Neural Learning Algorithm based MRAS rotor resistance estimator using reactive power. From the result it is observed that without rotor resistance estimator, the controller is slightly failed to control the torque for a step change in rotor resistance at 1 sec. Whereas with Neural Learning Algorithm based MRAS rotor resistance estimator, the instantaneous torque control is achieved. Fig.10 shows the q-axis stator current without and with Neural Learning Algorithm based MRAS rotor resistance estimator using reactive power.

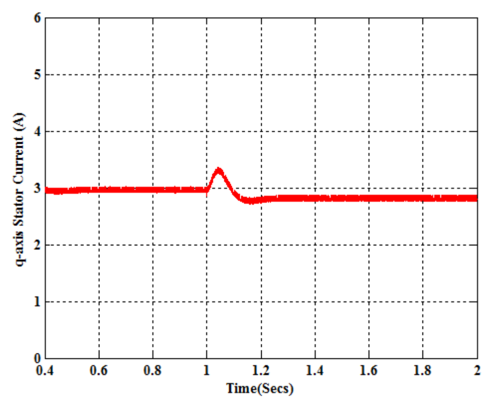


(a)



(b)

Fig.9 *Electromagnetic Torque for (a) Without R_r Estimator (b) With R_r Estimator*



(a)

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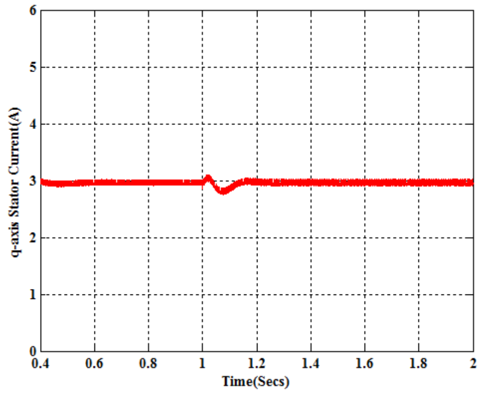

(b)

Fig.10 q-axis Stator Current for (a) Without R_r Estimator (b) With R_r Estimator

5. CONCLUSION

This paper proposes a NL-RPMR based rotor resistance estimator which combines the advantages of reactive power technique and capability of Neural Network. The choice of reactive power as a functional candidate in MRAS based rotor resistance estimation makes the system model equations simpler and easier to design. The nonlinear mapping capability of Neural Network and the powerful learning algorithms is adopted for rotor resistance estimation. The MRAS-RP and NL-RPMR based Rotor Resistance estimator is studied and designed for vector controlled induction motor drives. The performance of MRAS-RP and NL-RPMR based Rotor Resistance Estimator is analyzed for various operating conditions. In the NL-RPMR, the adaptive mechanism is done using powerful steep descent neural network learning algorithm and works well for various voltages with rated load torque conditions. The maximum error between actual and estimated rotor resistance for MRAS-RP and NL-RPMR method is found to be 1.1% and 0.2% respectively. The maximum settling time for MRAS-RP and NL-RPMR estimators is found to be approximately 0.05sec and 0.02sec respectively. The NL-RPMR based Rotor Resistance estimator has lesser estimation error compared to estimation error in MRAS-RP and the settling time is found to be similar. Hence from the above analysis, it is concluded that the NL-RPMR based rotor resistance estimator is found to be suitable for vector controlled induction motor drives. This method has the following advantages:

- No flux computation is required and hence free from integrator related problems.
- The Reference Model is free from machine parameters.
- Independent of stator resistance.

6. APPENDIX

Squirrel Cage Induction Motor Specifications:
3-phase, 1.1kw, 415V, 2.7A, 50Hz, 4-pole, 7.5Nm, $R_s = 6.03\Omega$, $R_r = 6.085\Omega$, $L_m = 0.4893$H, $L_s = L_r = 0.5192$H, J= 0.01178Kgm^2 , B = 0.0027Kgm

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