World Academy of Science, Engineering and Technology
International Journal of Electronics and Communication Engineering
Vol:5, No:3, 2011

Novel SNC-NN-MRAS Based Speed Estimator for Sensor-Less Vector Controlled IM Drives

A.Venkadesan, S.Himavathi and A.Muthuramalingam

Abstract**—**Rotor Flux based Model Reference Adaptive System (RF-MRAS) is the most popularly used conventional speed estimation scheme for sensor-less IM drives. In this scheme, the voltage model equations are used for the reference model. This encounters major drawbacks at low frequencies/speed which leads to the poor performance of RF-MRAS. Replacing the reference model using Neural Network (NN) based flux estimator provides an alternate solution and addresses such drawbacks. This paper identifies an NN based flux estimator using Single Neuron Cascaded (SNC) Architecture. The proposed SNC-NN model replaces the conventional voltage model in RF-MRAS to form a novel MRAS scheme named as SNC-NN-MRAS. Through simulation the proposed SNC-NN-MRAS is shown to be promising in terms of all major issues and robustness to parameter variation. The suitability of the proposed SNC-NN-MRAS based speed estimator and its advantages over RF-MRAS for sensor-less induction motor drives is comprehensively presented through extensive simulations.

Keywords**—**Sensor-less operation, vector-controlled IM drives, SNC-NN-MRAS, single neuron cascaded architecture, RF-MRAS, artificial neural network

I. Introduction

ADVANCES in digital technology have made the vector control realizable by industries for high performance variable speed control applications. Various vector controlled techniques for induction motor drives have been proposed in the literature. In particular, sensor-less vector control is an emerging area. The speed sensor which is expensive, fragile, requires extra attention from failures under hostile environment and needs special enclosures and cabling is not needed for sensor-less closed loop control of Induction Motor (IM) drives. This leads to cheaper and more reliable control.The performance of sensor-less vector controlled IM drive depends to a large extent on the knowledge of motor speed. Various techniques for speed estimation have been suggested such as Model Reference Adaptive System (MRAS), Luenberger and Kalman filter Observers, Sliding Mode Observers. MRAS scheme offer simpler implementation and require less computational effort compared to other methods and therefore the most popular strategies used for sensor-less control [1]-[3]. Various MRAS schemes have been introduced in the literature based on rotor flux, back electromotive force, and reactive power [3]-[5]. However, rotor flux MRAS, first introduced by Schauder [3], is the most popular MRAS strategy. In this strategy, conventional voltage model equations for flux estimation are used as the reference model. Conventional voltage model suffers from the problems of pure integrator and variation of stator resistance especially at low frequencies/speed [6], [7]. Several techniques were proposed in the literature to overcome the problems of pure integrator [8]-[10]. Neural Network (NN**)** based estimators provide an alternate solution for flux estimation. It dispenses the direct use of complex mathematical model of the machine and hence overcomes the problems of integrator. The nonlinear dynamic system mapping capability of neural network was well proven in the literature [11]. Several Neural Network methods were reported for flux estimation. Programmable-cascaded low pass filter was realized as a recurrent NN whose weights were obtained through a polynomial-NN [12]. SLFF-NN trained using input/output data was proposed for rotor flux estimation [1]. It is shown to improve the performance of the drive at very low and near zero speed, provide immunity to motor parameter variations, remove low-pass filter/ integrator and reduce the error.

A compact NN model with desired accuracy assumes importance in real implementation of on-line flux estimator to ensure faster estimation for effective control. In [13], Single Neuron Cascaded (SNC) NN model is identified and shown to provide distinctly compact NN model for on-line flux estimation.

In this paper the application of SNC-NN model for MRAS is investigated. It replaces the conventional voltage model in the RF-MRAS to form a novel MRAS scheme named as 'SNC-NN-MRAS' which enhances the accuracy of speed estimation at low frequencies/speed as compared to RF-MRAS.

The paper is organized as follows. Section II details the sensor-less IM drives, RF-MRAS and its issues and SNC-NN based flux estimator. The performance comparison of RF-MRAS and SNC-NN-MRAS at low frequencies/speed are carried out, simulation results are presented and discussed in section III. Section IV concludes the paper.

A.Venkadesan, Research Scholar in the department of Electrical and Electronics Engineering, Pondicherry Engineering College, Puducherry-605014, India. (e-mail:a_venkyeee@yahoo.co.in).

Dr.S.Himavathi, Professor and Head in the department of Electrical and Electronics Engineering, Pondicherry Engineering College, Puducherry-605014, India. (e-mail: himavathi@pec.edu).

Dr.A.Muthuramalingam, Professor in the Department of Electrical and Electronics Engineering, Pondicherry Engineering College, Puducherry-605014, India. (e-mail:amrlingam@hotmail.com).

II. Speed-Sensor-less Vector Controlled IM Drives

The speed sensor-less vector control of induction motor drive presented was indirect rotor flux field oriented control. Fig. 1 shows the overall block diagram of the speed-sensor-less drive system of an induction motor. Generally through a PI controller, the speed error signal is processed and the torque command is generated. It is combined with the flux command corresponding to the flux error to generate the common reference to control the motor current. The reference is used to produce the PWM pulses to trigger the voltage source inverter and control the current and frequency applied to the IM drive.

The performance of sensor-less vector controlled IM drive to a large extent depends on the accuracy of speed estimation. There are many speed estimation schemes available in the literature. Out of which, Rotor Flux Model Reference Adaptive System (RF-MRAS) is the most popular MRAS strategy.

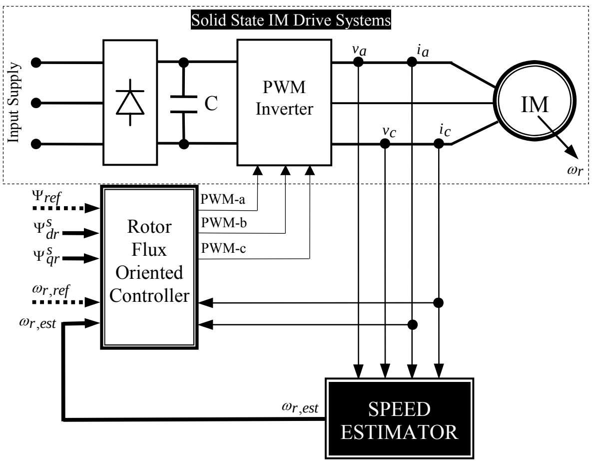


Fig. 1 Sensor-less Vector Controlled IM Drives showing the Speed Estimator

The general block diagram of MRAS scheme for speed estimation is shown in Fig. 2. The MRAS scheme 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 speed which is used to adjust the adaptive model. This process continues till the error between two outputs tends to zero.

A. RF-MRAS

In RF-MRAS, the state variable used is the rotor flux. Conventional voltage model equations for rotor flux estimation are used as the reference model because it is independent of the rotor speed. The voltage model equations are given from (1)-(4).

$$\Psi^s_{ds} = \int (v^s_{ds} - R_s i^s_{ds})dt \quad (1)$$

$$\Psi^s_{qs} = \int (v^s_{qs} - R_s i^s_{qs})dt \quad (2)$$

$$\Psi^s_{dr} = \frac{L_r}{L_m}(\Psi^s_{ds} - \sigma L_s i^s_{ds}) \quad (3)$$

$$\Psi^s_{qr} = \frac{L_r}{L_m}(\Psi^s_{qs} - \sigma L_s i^s_{qs}) \quad (4)$$

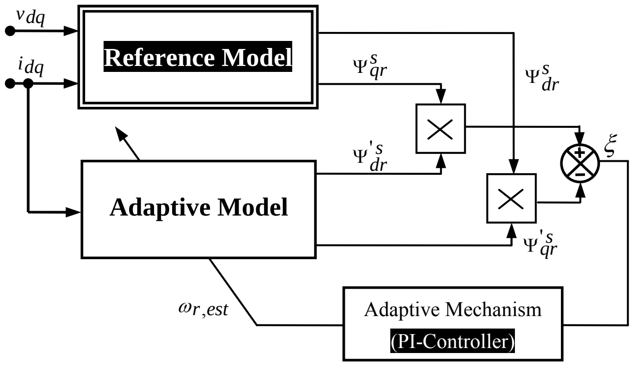


Fig. 2 MRAS Scheme for Speed Estimation

The current model equations for rotor flux estimation are used as the adaptive model because it is dependent on the rotor speed. The current model equations are given in (5) and (6).

$$\frac{\Psi^s_{dr}}{dt} = \frac{L_m}{T_r} i^s_{ds} - \omega_r \Psi^s_{qr} - \frac{1}{T_r}\Psi^s_{dr} \quad (5)$$

$$\frac{\Psi^s_{qr}}{dt} = \frac{L_m}{T_r} i^s_{qs} + \omega_r \Psi^s_{dr} - \frac{1}{T_r}\Psi^s_{qr} \quad (6)$$

Where,

$v^s_{ds}(v^s_{qs})$	- Stator voltages d axis (q axis)
$i^s_{ds}(i^s_{qs})$	- Stator currents d axis (q axis)
$\Psi^s_{ds}(\Psi^s_{qs})$	- Stator flux d axis (q axis)
$\Psi^s_{dr}(\Psi^s_{qr})$	- Rotor flux d axis (q axis)
$R_s(R_r)$	- Stator resistance (rotor)
$L_s(L_r)$	- Stator inductance (rotor)
L_m	- Magnetization inductance
$\sigma = 1 - \frac{L_m^2}{L_r L_s}$	-Leakage Co-Efficient
T_r	-Rotor Time Constant

With correct speed signal, ideally, the fluxes calculated from the reference model and those calculated from the adaptive model will match, that is, $\Psi^s_{dr} = \Psi'^s_{dr}$ and $\Psi^s_{qr} = \Psi'^s_{qr}$, where Ψ^s_{dr} and Ψ^s_{qr} are reference model outputs and Ψ'^s_{dr} and Ψ'^s_{qr} are the adaptive model outputs. An adaptation algorithm with PI controller, as indicated, can be used to tune the speed $(\omega_{r,est})$ so that the error $\xi = 0$.

In designing the adaptation algorithm for the MRAS, it is important to take account of the overall stability of the system and ensure that the estimated speed will converge to the desired value with satisfactory dynamic characteristics. Using popov's criteria for a globally asymptotically stable system, the following relation for speed estimation can be derived.

$$\omega_{r,est} = \xi\left(K_p + \frac{K_i}{S}\right)$$

$$\xi = \Psi'^{s}_{dr}\Psi^{s}_{qr} - \Psi^{s}_{dr}\Psi'^{s}_{qr}$$

In steady state, $\xi = 0$ balancing the fluxes; in other words,

$$\Psi^{s}_{dr} = \Psi'^{s}_{dr} \text{ and } \Psi^{s}_{qr} = \Psi'^{s}_{qr}$$

The reference model (voltage model) in the RF-MRAS encounters major drawbacks at low frequencies/speed which lead to the poor performance of RF-MRAS. This in turn affects the performance of the speed sensor-less operation.

(1) Integrator Drift Problem:

The application of pure integrator for flux estimation is difficult. This is because the dc bias in the measured signal for integration is inevitable, no matter how small it is, makes the estimated flux drift from the actual.

(2) Parameter Variation Problem:

The voltage model equations are dependent on resistance R_s and inductances L_s, L_m, L_r. The variation of these parameters tends to reduce the accuracy of the flux estimation. Particularly, temperature variation of R_s becomes more dominant. A small change in R_s would cause the voltage model based estimator to drift at low frequency. At higher frequency, the influence of R_s change on the estimator is negligible.

In this paper, Single Neuron Cascaded Neural Network based flux estimator is proposed to replace the conventional voltage model based flux estimator to form a novel MRAS scheme named as "SNC-NN-MRAS" to improve the MRAS performance at low frequencies/speed.

B. *SNC-NN based Flux Estimator used as a Reference Model in MRAS*

The block diagram of SNC-NN based flux estimator is shown in Fig.3.

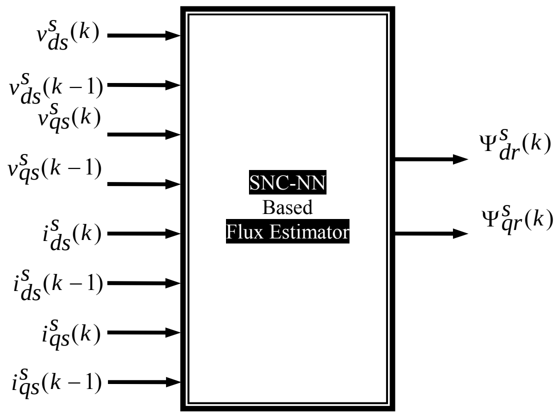


Fig. 3 The Inputs and Outputs of SNC-NN based Flux Estimator

The inputs to SNC-NN Model are direct and quadrature axis stator voltages $\{v^s_{ds}(k), v^s_{ds}(k-1), v^s_{qs}(k), v^s_{qs}(k-1)\}$ and stator currents $\{i^s_{ds}(k), i^s_{ds}(k-1), i^s_{qs}(k), i^s_{qs}(k-1)\}$ measured at k^{th} and $k\text{-}1^{th}$ sample. The outputs are the direct and quadrature axis rotor fluxes $\{\Psi^s_{dr}(k), \Psi^s_{qr}(k)\}$.

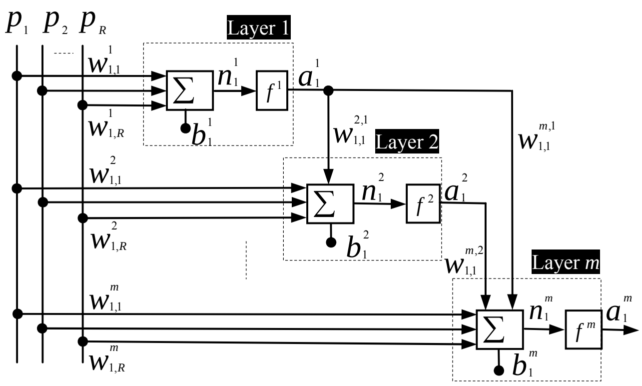


Fig. 4. SNC-NN with multiple inputs/single output

Where,

p	-	Input vector, $p = [1, 2, \ldots R]$
$w^{m,k}_{i,j}$	-	Link weight of neuron '*i*' of layer '*m*' for input from neuron '*j*' of layer '*k*'.
$w^{m}_{i,R}$	-	Input weight of neuron '*i*' of layer '*m*' for external input '*R*'.
b^{m}_{i}	-	bias for neuron '*i*' of layer '*m*'.
f^{m}	-	Activation functions of all neurons in a layer '*m*'.
a^{m}_{i}	-	Output of neuron '*i*' of layer '*m*'

The Single Neuron Cascaded (SNC) architecture [13] with multiple inputs/single output is shown in Fig. 4. SNC-NN architecture consists of an input layer, hidden layers and an output layer. The first hidden layer receives only external signals as inputs. Other layers (M) receive external inputs and outputs from all previous (M-1) 1ayers.

To create multilayer structure hidden layers are added one by one and the whole network trained repeatedly using the concept of moving weights so as to obtain compact network [13], [14]. This process continues, till the performance index is reached.

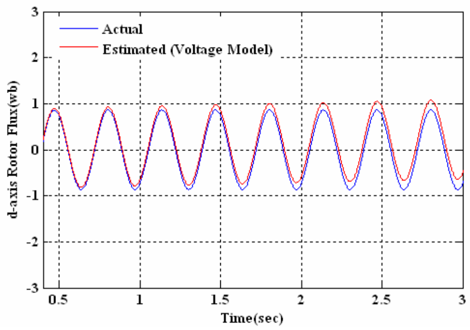
Around 13,200 data sets were obtained through simulation. To make SNC-NN model robust to R_s change, the training data is obtained with 25% change in R_s. The activation function for hidden and output layers is chosen as tan-sigmoid and pure linear function respectively. The SNC-NN is trained with input/output data using LM algorithm for the target mean square error (MSE) of 1×10^{-7}. The obtained SNC-NN model for on-line flux estimation has the structure 8-13(h)-2 (h-hidden layer with one neuron). The obtained SNC-NN model for flux estimation replaces the conventional voltage model in the RF-MRAS.

III. Comparison of RF-MRAS and SNC-NN-MRAS

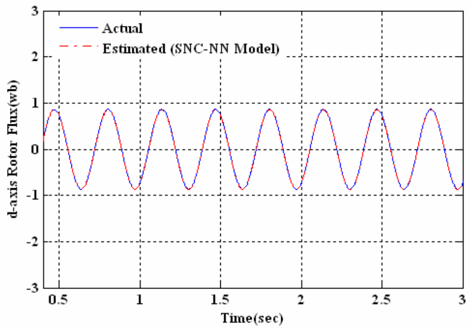
The performance of RF-MRAS and SNC-NN-MRAS are investigated for low frequency problems (Integrator drift and R_s variation problems) and compared. Both the problems are investigated under very low frequency of 3Hz at no load condition.

A. Integrator Drift Problem

The application of pure integrator for flux estimation is difficult. This is because the dc bias in the measured signal for integration is inevitable, no matter how small it is, makes the estimated flux drift from the actual. To investigate the dc drift problem, a dc bias of 2% of the peak current is added to the measured current.

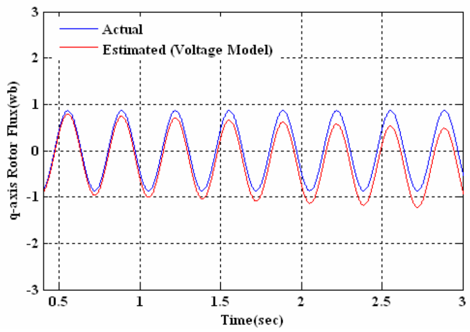


(a)

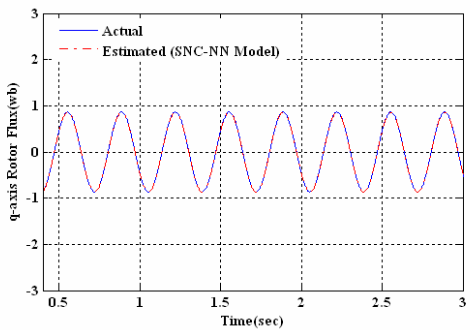


(b)

Fig. 5 d-axis Rotor Flux for integrator drift Problem: (a) Voltage Model (b) SNC-NN Model

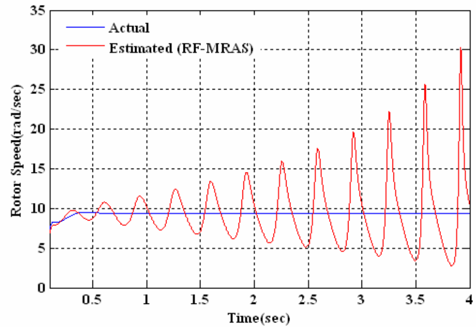


(a)



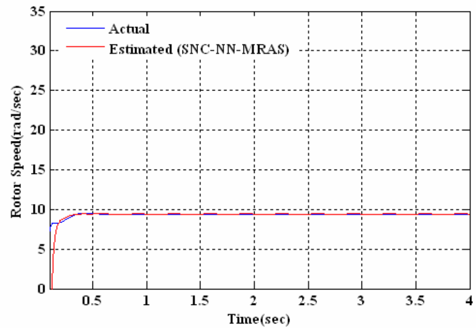
(b)

Fig. 6 q-axis Rotor Flux for integrator drift Problem:



(a)

(a) Voltage Model (b) SNC-NN Model



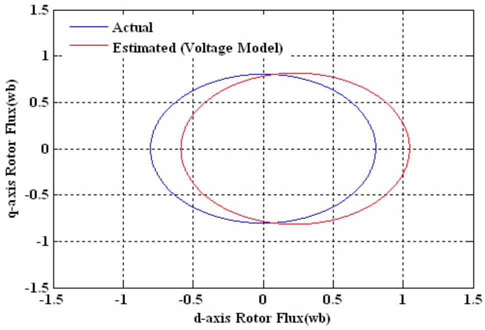
(b)

Fig. 7 Response of MRAS based speed estimator for integrator drift Problem
(a) RF-MRAS (b) SNC-NN-MRAS

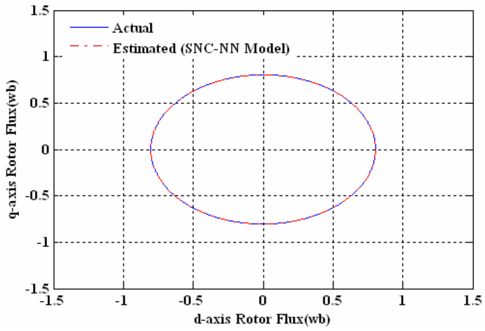
The d-axis rotor flux estimated from voltage model and SNC-NN Model is shown in Fig. 5. The q-axis rotor flux estimated from voltage model and SNC-NN Model is shown in Fig. 6. From the results obtained, it is clearly understood that d and q-axis rotor fluxes estimated from the SNC-NN tracks the actual flux very well even in the presence of dc bias with the d and q-axis rotor flux MSE of 4.50×10^{-5} and 2.60×10^{-5} respectively. Thus SNC-NN model based flux estimator is found to be less sensitive to dc bias problem. This is due to the inherent presence of saturating nonlinear activation function in the NN, where as d and q-axis rotor fluxes estimated from the voltage model gets deviated from the actual. It is also noted that the error in the d and q-axis rotor fluxes keeps on increasing with time. Thus, from the above analysis, it is understood that SNC-NN model exhibits stable performance where as voltage model shows unstable performance with the presence of small dc bias.The performance of SNC-NN-MRAS and RF-MRAS for dc drift problem is presented in Fig. 7. For the comparison, both the figures are shown with same scale. From the results obtained, it is seen that the SNC-NN-MRAS based speed estimation displays stable performance tracks the actual speed well whereas RF-MRAS becomes unstable and fails to estimate. The SNC-NN-MRAS based speed estimation is shown to overcome the drift problem.

B. Parameter Variation Problem

Another major problem of voltage model based flux estimation is stator resistance (R_s) variation problem. A small change in R_s would cause the estimator to drift at low frequency. At higher frequency the influence of R_s change on the estimator is negligible.

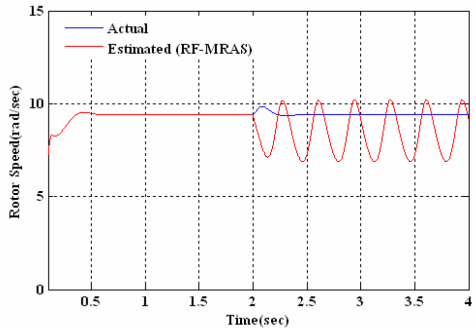


(a)

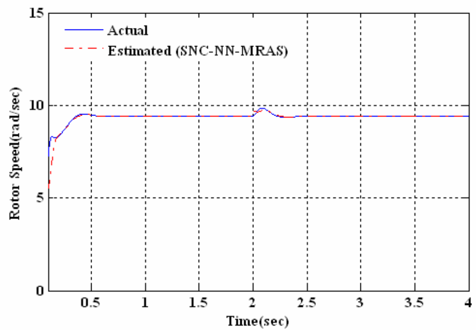


(b)

Fig. 8 Locus Diagram of Rotor Fluxes for R_s change:
(a) Voltage Model (b) SNC-NN Model



(a)



(b)

Fig. 9 Response of MRAS based Speed Estimator for R_s change:
(a) RF-MRAS (b) SNC-NN-MRAS

To investigate the R_s variation problem a 25% step change in R_s is applied at 2sec. The locus diagram of rotor fluxes is shown in Fig. 8. It is understood that the locus diagram of rotor fluxes of SNC-NN model closely tracks the locus of the actual flux and it is centered on the origin similar to the actual flux where as the locus diagram of rotor fluxes of voltage model is not centered on the origin and it is shifted away from the origin approximately 0.25wb. Hence, SNC-NN model is found to estimate the flux components very well even when there is change in the parameter. Thus SNC-NN model is robust to R_s variation as compared to voltage model.
The performance of SNC-NN-MRAS and RF-MRAS for R_s variation problem is shown in Fig. 9.From the results obtained, it is obvious that the speed estimated from the SNC-NN-MRAS tracks closely the actual speed even when there is a change in the parameter and the error in the speed estimation is almost negligible whereas RF-MRAS becomes unstable and fails to estimate. The SNC-NN-MRAS based speed estimation is shown to overcome the R_s variation problem. The voltage-based model can also be made robust to R_s variation with an additional on-line R_s estimator, which may increase the complexity of the drive system. The NN based estimator, trained for parameter variations, exhibits robust speed estimation even in the presence of parameter variation.

IV. Conclusion

The performance of sensor-less vector controlled IM drives to a large extent depends on the accuracy of speed estimation. RF-MRAS is the popularly used speed estimation scheme for sensor-less vector controlled IM drives. The reference model (conventional voltage model) in RF-MRAS encounters major drawbacks at low frequencies/speed which leads to poor performance of RF-MRAS. This paper proposes SNC-NN model based flux estimator which replaces the conventional voltage model in the RF-MRAS to form a novel MRAS scheme named as SNC-NN-MRAS. The proposed SNC-NN-MRAS based speed estimator is designed to be robust to parameter variations and its performance is compared with RF-MRAS for the various issues such as integrator drift and R_s variation problems at low frequencies/speed. Through extensive simulations, the proposed SNC-NN-MRAS is shown to improve the speed estimation at low frequencies/speed as compared to RF-MRAS and found to be promising alternative for sensor-less vector controlled IM drives.

APPENDIX

The parameters of the induction machine used for simulation are given in the table shown below.

INDUCTION MOTOR PARAMETERS

Parameters	*Values*	*Parameters*	*Values*
Rated Power	1.1kW	Stator Resistance (R_s)	6.03Ω
Rated voltage	415V	Rotor Resistance (R_r)	6.085Ω
Rated current	2.77A	Magnetizing Inductance (L_m)	0.4893H
Type	3 Ph	Stator Inductance (L_s)	0.5192H
Frequency	50Hz	Rotor Inductance (L_r)	0.5192H
Number of poles	4	Total Inertia (J_T)	0.011787Kgm^2
Rated Speed	1415RPM	Friction Coefficient (B)	0.0027Kgm^2/s

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