NEURAL NETWORK BASED MRAS FOR SENSORLESS INDUCTION MOTOR DRIVES TO IMPROVE PERFORMANCE AT LOW SPEEDS

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Abstract: *This paper proposes a new Neural Network based MRAS speed observer for sensorless vector controlled induction motor drive. This neural network replaces reference model (voltage model) in conventional MRAS. In conventional MRAS, reference model equations depends on stator resistance that changes with temperature during running condition. This change in stator resistance is predominant in low and zero speed operation. In proposed MRAS, all drive non-linearities are included. Hence need for separate stator resistance estimator and integrator problem are eliminated in the proposed neural network based MRAS. Simulation work is done in various operating conditions using MATLAB/Simulink software. Better steady state and dynamic performances are achieved with proposed neural network based MRAS.*

Keywords*: Sensorless, Model Reference Adaptive System (MRAS), Neural Network (NN).*

1. Introduction

Sensorless vector control is the most popular control in induction motor Drives [1]-[6]. Drive cost, size, maintenance requirements are reduced with the help of sensorless control. Hence, in sensorless drives, robustness and reliability are increased. However it has some problems like parameter sensitivity, stability at low and zero speed and high computational effort [1],[2],[5],[10],[14].Various techniques like MRAS, luenberger observer, Kalman filter observer, sliding mode observer and artificial intelligence are proposed in various literatures for flux and speed estimation. Among these techniques, MRAS is the most popular strategy because of its less computational effort and simpler implementation [5], [10]. MRAS observers are of different types, they are rotor flux based, reactive power based and back emf based [5]. The rotor flux MRAS observer introduced by schauder is the widely used scheme [14]. Inverter non-linearity, pure integration problem and parameter sensitivity are the drawbacks of this scheme. These drawbacks affect the low speed operation of the drive [1], [14].

At low speed region, the performance of the MRAS system can be improved by online stator resistance estimation. However, it increases the complexity of the drive system [1], [5]. Pure integrator can be replaced by LPF with low cut-off frequency but phase and gain errors are introduced. Hence dynamic performance of the drive may be affected [1]. In [1], 8-25-2 neural network is used for rotor flux estimation. In [18], a programmable cascaded LPF is introduced to replace pure integration. Several neural network methods are discussed for flux estimation in research literatures[1],[5],[7],[9],[12],[13],[17].

In [5], Artificial neural network is used in adjustable model of the QMRAS to estimate speed. In [12], a two layer neural network is used to represent the adaptive model (CM) in which simple forward Euler integration method is used. Advancement of the previous work is done in [13], [17] in which total least square algorithm is used. In [19], predictive control using Dspace is discussed for permanent magnet synchronous generator. Backpropagation and Radial Basis Function (RBF) neural networks are used in [20]. In this paper, a novel neural network based MRAS is used. A multilayer feed forward neural network is used to replace reference model in the conventional MRAS. Present and past samples of terminal voltage and current are used as input values to the neural network. Flux values from current model is used as target values. This method does not use LPF for flux estimation since, the neural network does not use pure integration.

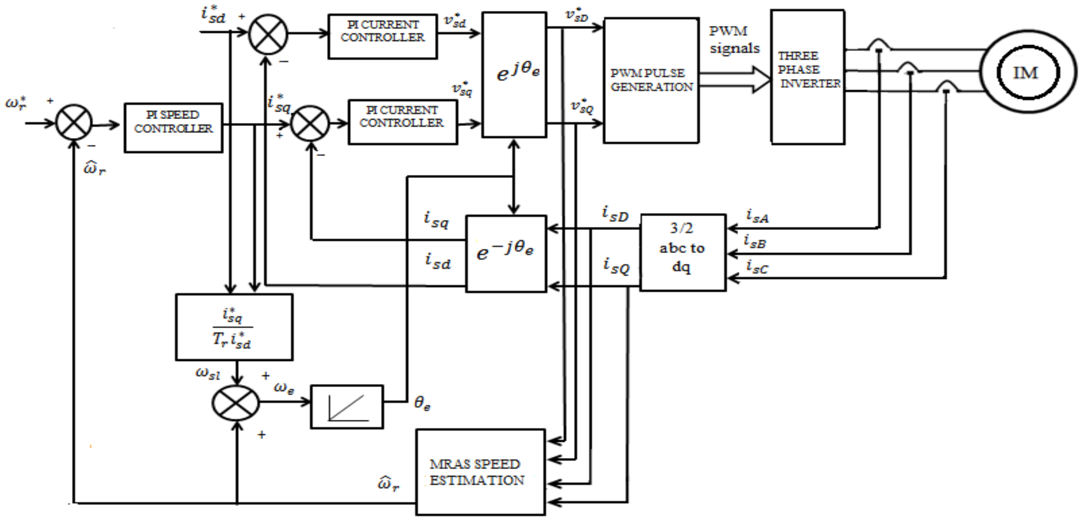

Fig.1. Block diagram of Sensorless Induction Motor Drive with MRAS

In this paper, a sincere attempt is made to eliminate the need of separate stator resistance estimator and pure integrator. The proposed neural network flux estimator is trained with input /target data set including stator resistance R_s changes. Hence separate stator resistance R_s estimator is not needed. MATLAB /Simulink software is used for simulation work. Comparison between proposed neural network based MRAS and conventional rotor flux MRAS is carried out. In low and zero speed operating regions, superior performance is achieved with proposed neural network based MRAS. It dispenses the direct use of complex mathematical model of the system. Hence integrator problem is also eliminated.

2. Conventional rotor flux MRAS

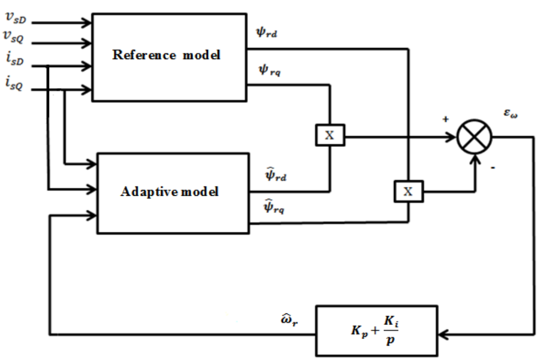

Fig.2. Block diagram of Conventional MRAS

Block diagram of indirect vector control for sensorless induction motor drive is shown in Fig.1, in which MRAS is used to estimate induction motor speed.

MRAS is used to estimate induction motor speed. Conventional MRAS block diagram is shown in Fig.2.It consists of reference model, adaptive model and an adaptive mechanism. Voltage model equations represents reference model of the MRAS. Current model equations represents adaptive model of the MRAS. Adaptive model is dependent on rotor speed, whereas reference model is independent of rotor speed. Reference model equations are written as [2], [10]

$$p\psi_{rd} = \frac{L_r}{L_m}\{v_{sD} - R_s i_{sD} - \sigma L_s p i_{sD}\} \tag{1}$$

$$p\psi_{rq} = \frac{L_r}{L_m}\{v_{sQ} - R_s i_{sQ} - \sigma L_s p i_{sQ}\} \tag{2}$$

Adaptive model equations are represented as follows [2], [10]

$$p\hat{\psi}_{rd} = \frac{L_m}{T_r} i_{sD} - \frac{1}{T_r}\hat{\psi}_{rd} - \hat{\omega}_r \hat{\psi}_{rq} \tag{3}$$

$$p\hat{\psi}_{rq} = \frac{L_m}{T_r} i_{sQ} - \frac{1}{T_r}\hat{\psi}_{rq} + \hat{\omega}_r \hat{\psi}_{rd} \tag{4}$$

where

v_{sD},v_{sQ} Stator voltage components in the stator frame.

i_{sD},i_{sQ} Stator current components in the stator frame.

ψ_{rd}, ψ_{rq} Components of the rotor flux linkage vector

T_r Rotor time constant.

L_m Mutual inductance.

L_r	Self-inductance at the rotor side.
L_s	Self-inductance at the stator side.
σ	Total leakage factor.
$\widehat{\omega}_r$	Estimated rotor speed.
ω_r	Rotor speed.
R_s	Stator resistance.
R_r	Rotor resistance.
p	Differential operator.

Popov's hyper stability theory is used to design adaptation mechanism.
An adaptation law is defined as [2]

$$\widehat{\omega}_r = \varphi_2(\varepsilon) + \int_0^t \varphi_1(\varepsilon)d\tau \quad (5)$$

Popov's integral inequality [2] is defined as

$$\int_0^t \varepsilon^T \boldsymbol{W} dt \geq -\gamma_0^2 \quad (6)$$

Using Popov's criteria for globally asymptotically stable system, the estimated speed can be written as[2]

$$\widehat{\omega}_r = \left(k_p + \frac{k_i}{p}\right) \mathcal{E}_\omega \quad (7)$$

where
$\mathcal{E}_\omega$ isSpeed tuning signal which is defined as

$$\mathcal{E}_\omega = \psi_{rq}\widehat{\psi}_{rd} - \psi_{rd}\widehat{\psi}_{rq} \quad (8)$$

when$\widehat{\psi}_{rd}$=ψ_{rd} and $\widehat{\psi}_{rq}$=ψ_{rq},the speed tuning signal will be zero i.e. in steady state.

3. Proposed Neural Network based MRAS

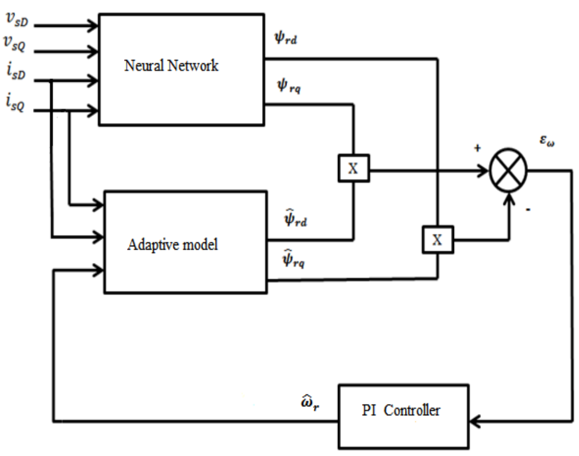

Fig. 3. Proposed NN based MRAS

Fig 3 shows the block diagram of proposed NN based MRAS. Parameter sensitivity, inverter non-linearity, pure integration problems are the problems associated with conventional rotor flux MRAS scheme. In order to overcome these problems, Neural Network is used to replace (voltage model) reference model. This method greatly improves the overall performance of the drive system. Basic unit of artificial Neural Network is neuron which consists of summer and activation function.

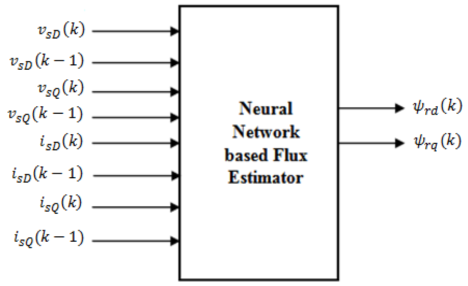

Fig. 4. Inputs and outputs of NN based Flux Estimator

In this work,a multilayer feed forward NN is used. It consists of an input layer, hidden layer and output layer. Each layer consists of neurons. Fig. 4.shows block diagram of NN based flux estimator with 8 inputs and 2 target values. In this work 8-20-2 multilayer feed forward NN is used to estimate the rotor flux. The present and past samples of d-q components of stator voltages $\{v_{sD}(k), v_{sD}(k-1), v_{sQ}(k), v_{sQ}(k-1)\}$and stator currents $\{i_{sD}(k), i_{sD}(k-1), i_{sQ}(k), i_{sQ}(k-1)\}$ are used as input to the NN. Direct and quadrature axis rotor fluxes $\{\psi_{rd}(k),\ \psi_{rq}(k)\}$ are used as target values. Around 7500 input/output data set for various operating conditions is used for training the NN. Stator resistance variations are included in the training data set. Hence separate stator resistance estimator is not needed. Tansigmoid activation function is used for hidden layer. Purelin is used for output layer. The number of hidden layer neuron is selected by trial and error method. Hence duration for training the data is increased. This is the major drawback of NN design. Levenberg-Marquardt (LM) training algorithm is used. After training, mean square error (MSE) between target and NN output reaches to $1.203\text{x}10^{-3}$. This offline trained NN is used to replace Voltage Model of conventional MRAS.

4. Simulation Results and Discussion

The induction motor drive is tested under low and at or around zero speed operating regions. The motor rating and its parameters values are listed in the Table II. Computer simulation is carried out using MATLAB/Simulink Software. Some of the simulation results of the tests are discussed below.

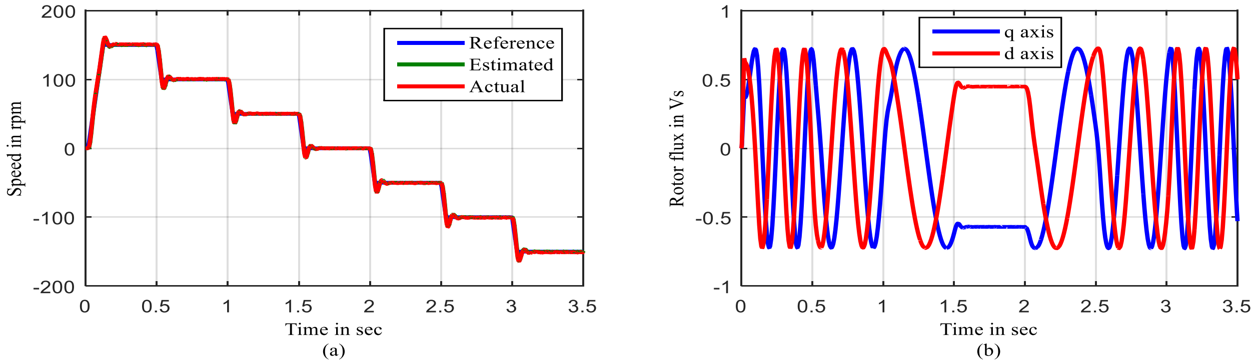

Fig.5. Performances of Conventional MRAS under Test 1 (a) Rotor speed (b) Rotor flux

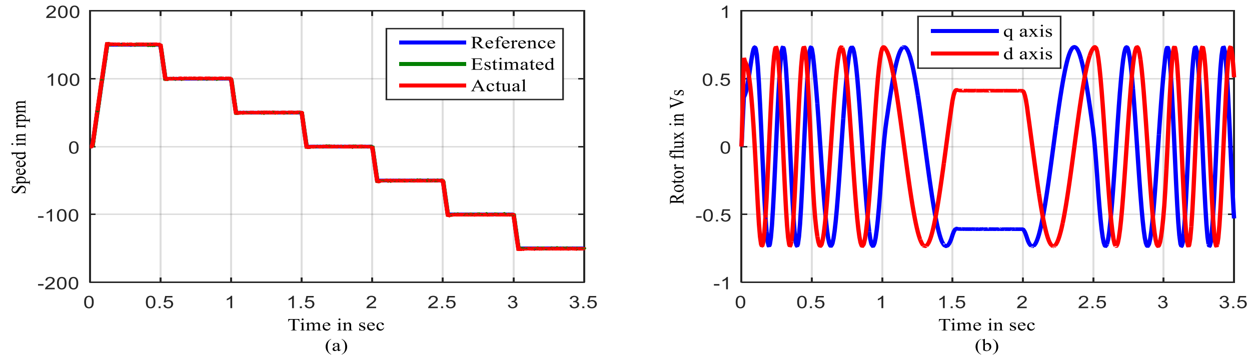

Fig.6. Performances of NN based MRAS for under Test 1 (a) Rotor speed (b) Rotor flux

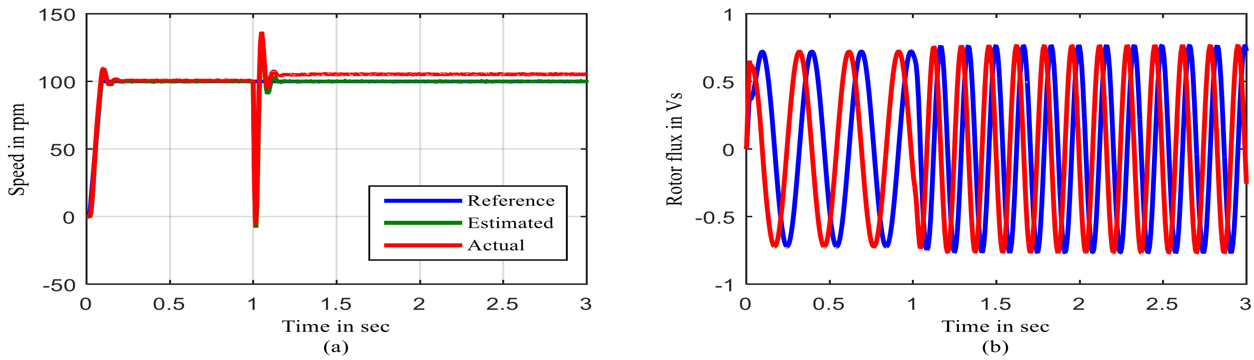

Fig.7. Performances of conventional MRAS under Test 2 (a) Rotor speed (b) Rotor flux

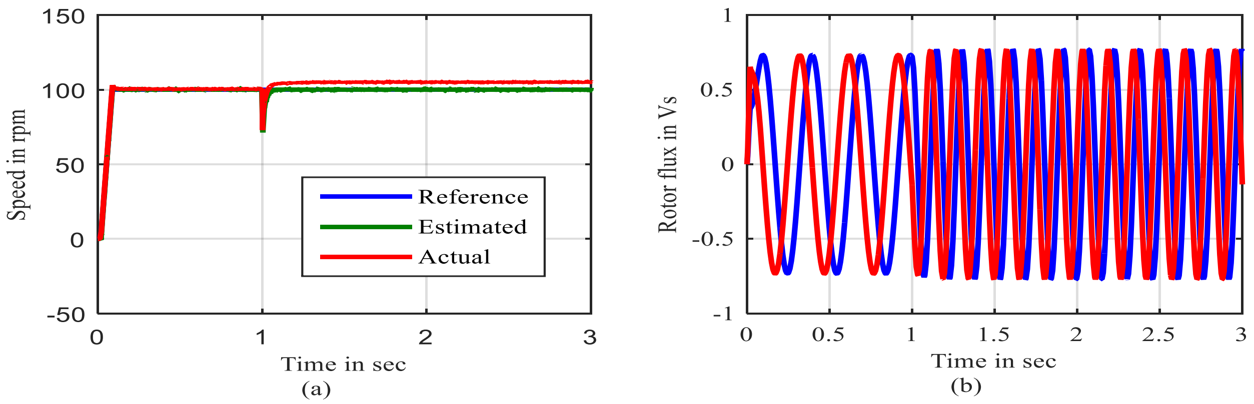

Fig.8. Performances of NN based MRAS under Test 2 (a) Rotor speed (b) Rotor flux

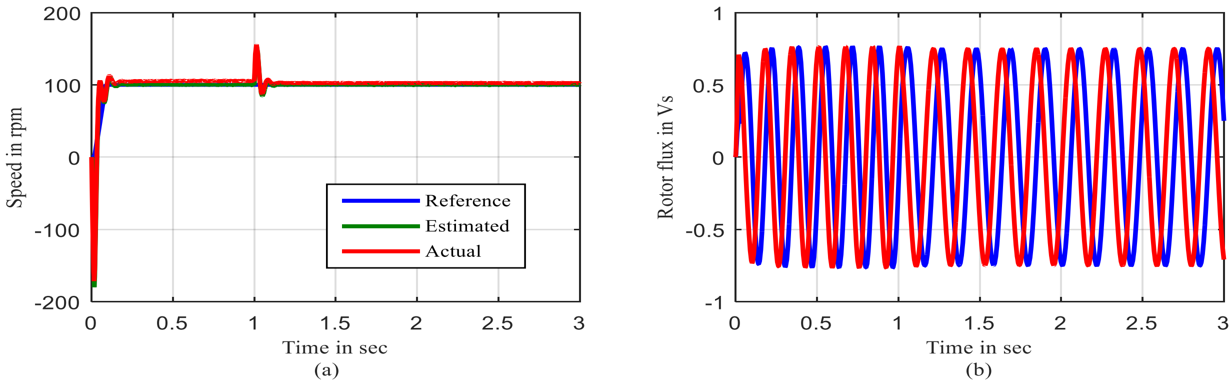

Fig.9. Performances of conventional MRAS under Test 3 (a) Rotor speed (b) Rotor flux

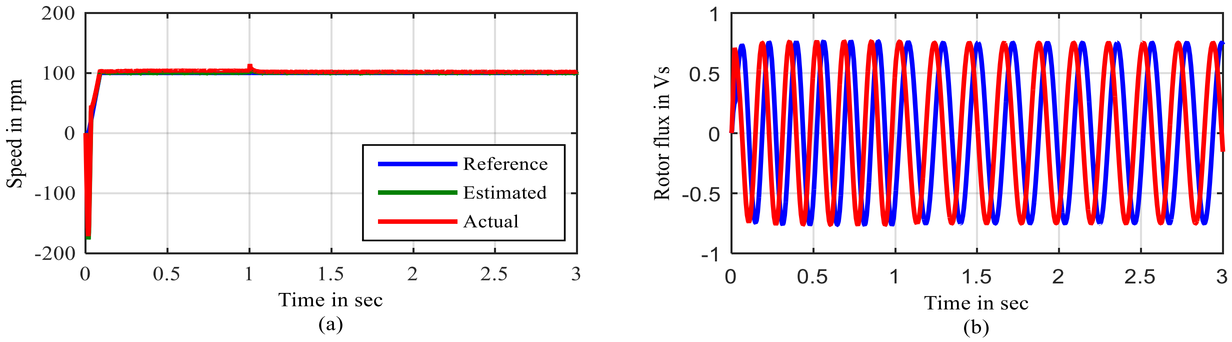

Fig.10. Performances of NN based MRAS under Test 3 (a) Rotor speed (b) Rotor flux

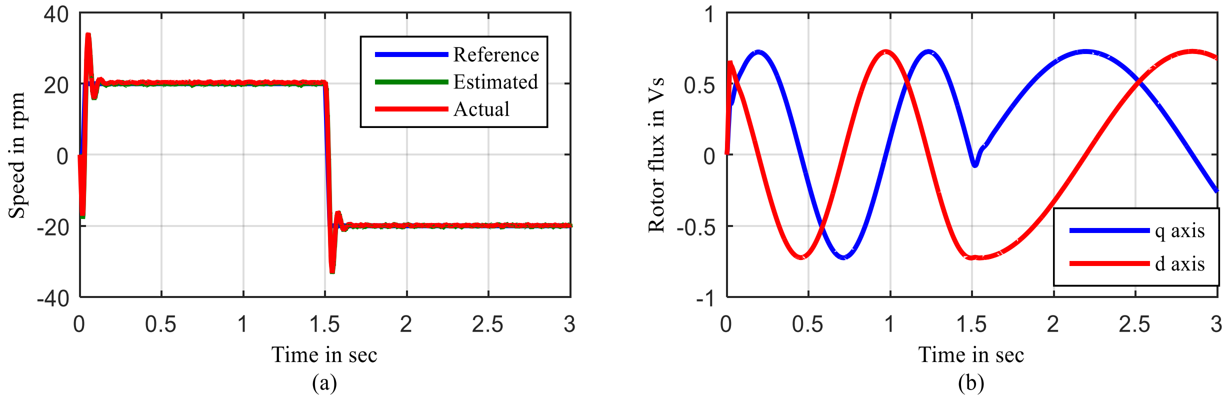

Fig.11. Performances of conventional MRAS under Test 4 (a) Rotor speed (b) Rotor flux

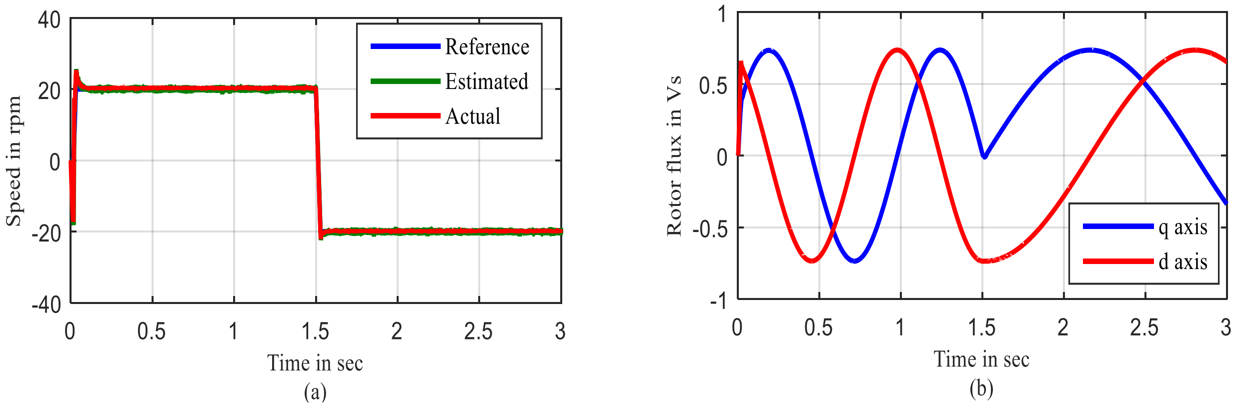

Fig.12. Performances of NN based MRAS under Test 4 (a) Rotor speed (b) Rotor flux

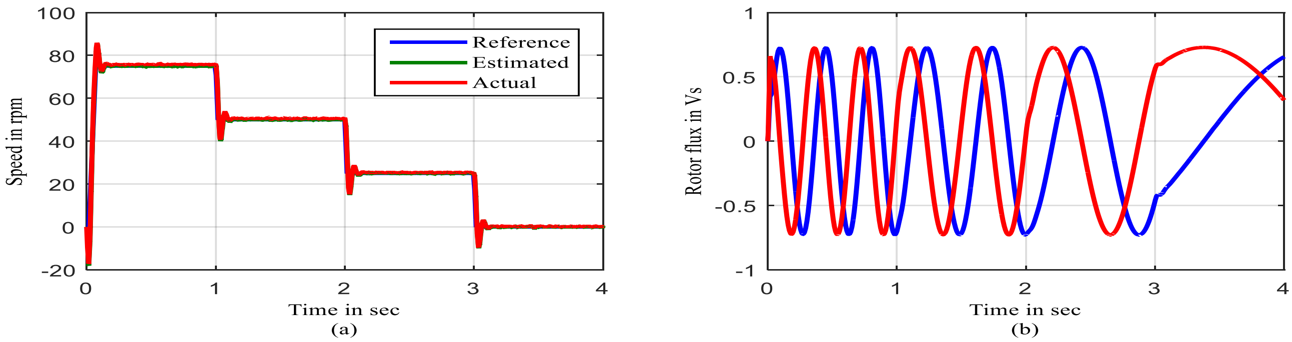

Fig.13. Performances of conventional MRAS under Test 5 (a) Rotor speed (b) Rotor flux

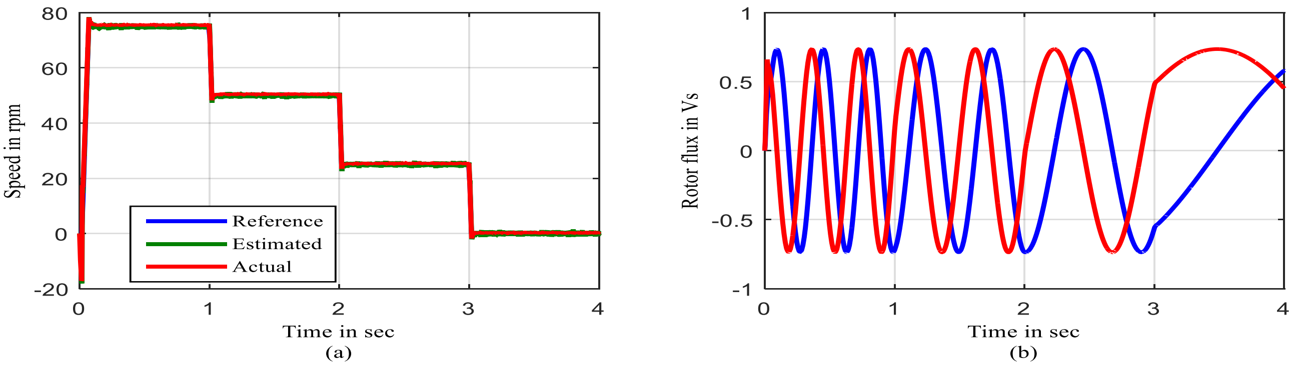

Fig.14. Performances of NN based MRAS under Test 5 (a) Rotor speed (b) Rotor flux

4.1. Test1-Staircase speed Transients from +150 rpm to 0 to -150 rpm at No load:

In this test, the induction motor is subjected to staircase speed command from +150 rpm to 0 rpm and then continuing to -150 rpm at no load. The performances of both conventional MRAS and proposed NN-MRAS are shown in Fig.5 and 6. In NN-MRAS, the estimated speed closely tracks the actual speed with negligible error. Stable operation is ensured with proposed estimator. Fig. 5(a) and 5(b) shows rotor speed and rotor flux for the conventional MRAS speed estimator. Fig. 6(a) and 6(b) shows rotor speed and rotor flux for the proposed NN based MRAS speed estimator.

4.2. Test2-Load torque change from 0 to 20 Nm at 100 rpm:

This test is used to test the load disturbance capability of the induction motor drive. Load torque 20 Nmis applied at 1 sec. The proposed NN based MRAS estimator shows better dynamic performance than the conventional one. At 1 sec, the estimated speed undershoots like the actual speed. Fig. 7 and 8 shows the performances of both conventional and proposed estimator.Fig. 8(a) and 8(b) shows rotor speed and rotor flux for the proposed NN based MRAS speed estimator.

4.3.Test3-Load torque change from 20 Nm to 10 Nm at 100 rpm:

This test also proves the load disturbance capability of the drive. Initially load torque of 20 Nm is applied and it is reduced to 10 Nm at 1sec. Fig. 9 and 10 shows the performance of the drive under test 3. At 1 sec, the estimated speed overshoots like actual speed. Minimum tracking error is observed in NN-MRAS scheme.

4.4. Test4-±20 rpm at 2Nm load torque:

The performance for very low speed reversal under load condition is examined in this test. ±20 rpm speed command is given when working under 2Nm load.Fig.11. shows the performance of the conventional method.Fig.12. shows that the proposed estimator has better performance with minimum steady state error.

4.5. Test5-Speed step down from 75 rpm to 0 rpm in four steps each of 25 rpm at 2 Nm load torque:

Performance under low and zero speed with load is examined in this test. Fig.13. shows the performance of the conventional MRAS. Fig.14. shows that the NN-MRAS provides negligible steady state error and better performance. Stable operation is achieved with proposed estimator. Summary of the test results are given in Table I.

TABLE I
PERFORMANCE COMPARISON BETWEEN CONVENTIONAL AND PROPOSED NN BASED SPEED ESTIMATOR

	Test 1	Test 2	Test 3	Test 4	Test 5
Conventional MRAS	Overshoot=10rpm	At t=1 sec overshoot=36 rpm undershoot=100 rpm	At t=1 sec overshoot=55 rpm undershoot=15 rpm	Overshoot=15 rpm	Overshoot=10 rpm
NNbased MRAS	Stable operation	At t=1 sec undershoot=30 rpm	At t=1 sec overshoot=15 rpm	Stable operation	Stable operation

TABLE II
INDUCTION MACHINE RATING AND PARAMETERS

Symbol	Parameter	Values
-	Rated shaft power	4 kW
-	Line to line voltage	400V
-	Rated speed	1430 rpm
P	Pole pair	2
f	Frequency	50 Hz
L_{ls}	Stator Leakage inductance	0.005839 H
L_{lr}	Rotor Leakage inductance	0.005839 H
L_m	Mutual inductance	0.1772 H
R_s	Stator resistance	1.405 ohm
R_r	Rotor resistance	1.395 ohm
J	Machine inertia	0.0131 kg m^2

5. Conclusion

Thus, the proposed Neural Network based MRAS eliminates integrator problems which occurs in conventional rotor flux MRAS. It performs well in low speeds including zero speed. It eliminates the need for separate stator resistance Estimator. It is less rigorous when compared to the integral equation, which are present in the reference model of the conventional MRAS. It is evident from the simulation results that the proposed neural network based MRAS performs well in low speed and zero speed operating regions than the conventional estimator. Hence this proposed controller is used to improve the performance of the drive in low speeds without separate stator resistance estimator and pure integrator.

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