2020 IEEE Students Conference on Engineering & Systems (SCES)
July 10-12, 2020
Prayagraj, India

Intelligent Speed Estimation in Induction Motor Drive Control using Feed - Forward Neural Network Assisted Model Reference Adaptive System

Arpit Bhushan Sharma, *Student Member IEEE*,
KIET Group of Institutions,
Delhi-NCR, Ghaziabad, Uttar Pradesh,
India – 201206
E-Mail: arpit3043@gmail.com

Sandeep Tiwari
KIET Group of Institutions,
Delhi-NCR, Ghaziabad, Uttar Pradesh,
India – 201206
E-Mail: sandeep.tiwariblp@gmail.com

Brijesh Singh, *Senior Member IEEE*
KIET Group of Institutions,
Delhi-NCR, Ghaziabad, Uttar Pradesh,
India – 201206
E-Mail: singhb1981@gmail.com
ORCID: 0000-0001-5340-6643

Abstract – Adjustable speed of induction motor (IM) is powered without a velocity sensor is one of the most alluring solutions with high energy efficiency, low cost, and compact size drives. The efficiency will increase enormously if these kinds of systems will come into existence through intelligent expert systems. However, the low speed of the rotor is a bit challenging in the case of an induction motor to get accurate speed estimation. The study is based on the estimation of the intensity of rotor flux using multilayered feed-forward neural network technology in a speed estimator. The proposed speed estimator replaces the conventional reference model of the Model Reference Adaptive System (MRAS). The execution of the energy with the projected estimator is tested on various operational conditions, particularly in low-speed situations. The IM speed is estimated and controlled by the Artificial Neural Network (ANN). In the proposed study 08, 20 and 02 neurons have been chosen in the input, hidden and output layers to model the ANN. The paper shows the full description of the estimation of the speed of induction Motor drive.

Index Terms -- Induction motor drive, neural networks, MRAS speed estimation

I. Introduction

Squirrel cage induction motors have been mostly used in many domestic, agricultural, and industrial applications for different purposes. These motors are more robust, economical and require low care. Further, the multifarious progress in the fields of power electronics and digital processing has increased its popularity. Adjustable speed induction motor (IM) drives are becoming more popular due to being energy efficient and being able to provide adjustable speed. Nowadays, a lot more importance is made on developing speed-sensor less adjustable speed drives (ASDs) as they offer a cost-effective and reliable choice to conventional drives [1]. Estimation of the speed, of induction motor is quite complex. Mostly, the model reference adaptive system (MRAS) method has been for estimating the speed of IMs. Multiple forms of MRAS have been proposed based on the key factors used for approximating the rotor speed. Among all, rotor flux based MRAS (RF-MRAS) is a more popular form due to hyper stability and less complexity. However, the speed evaluation in the low-speed zone with a RF-MRAS is still an accessible domain of research. The main reasons for poor performance in the low-speed region by speed estimators are the use of pure integrator, parameter sensitivity, and weakening of signal strengths.

The low pass filters can be used to overcome the problem of pure mixing. But they introduce a delay in the system [2],[3]. Variation in stator and rotor resistances due to uninterrupted procedure involves the drive performance primarily. The discrepancy in the resistance values used during the speed estimator designing and the actual value reduces the speed estimation efficiency. The effect of mismatch is more prominent in the zero speed and low speed condition. One of the ways to handle the resistance mismatch is to use additional loops for continuously updating the value of resistance in a speed estimator. Although, it improves the estimation but increases the complexity of the system and usually has DC drift problems [4],[5]. In recent years, researchers have explored the application of ANN in conventional MRAS strategies vary widely [19]. The main reasons behind the interest are its features like the capability to handle nonlinearity of different complexities, the capability to adapt the surrounding changes and capability to protect the system by predicting future values. The use of ANN makes the drive less sensitive to parameter variations and stable in regenerating mode [6]-[9]. ANN-based estimators have been used either as an integral component of MRAS or as supportive components. Considering the structure of MRAS, ANN has been proposed to replace either a reference model or an adaptive model. ANN-based flux observer has been proposed to replace the voltage model of RF-MRAS in [6]. ANN-based rotor flux observer in replacement of adaptive model in MRAS velocity approximation for induction motor drive has been proposed [7],[10]. The ANN based approximation for IM rotor speed has been discussed and resolve in sensor less vector-controlled method [11]. Simultaneous estimation and adaptation of stator resistance along with speed using neural networks are also explored [12],[13]. In addition to the speed estimators, two separate estimators based on neural networks, one for stator resistance and other for rotor resistance estimation are also proposed for improvement of vector-controlled induction motor drive performance [14],[20-21].
In developing ANN, training data plays a key role in its performance. ANN trained by the data set obtained from experimentation can give better results. Although the different structure of ANN has been used in MRAS based speed estimators, multilayer feed forward NN is more commonly used [15]. The LM algorithm trains the proposed neural network efficiently. The performance of the drive is extensively examined with a proposed speed estimator on various realistic operating conditions such as speed change, speed reversal, and load variations [16]. In this paper, an ANN used as a reference model for estimating the rotor flux values is proposed for an MRAS based speed estimator. A field-oriented indirect control scheme of speed control drive has been used to study the proposed estimator in this work. The performance of the drive with the proposed estimator is

978-1-7281-9339-7/20/$31.00 ©2020 IEEE

tested on various operating conditions, particularly in low-speed situation. The speed of IM is estimated and controlled by the feed-forward neural network. The paper shows the full description of the estimation of the speed of induction Motor drive. The classical approach using rotor flux estimation based MRAS speed estimation and ANN based estimation have been described in subsequent sections. The obtained results have been discussed in the third section of the paper.

II. SPEED ESTIMATOR USING ROTOR FLUX EVALUATION BASED MRAS MODEL

Nomenclature

R_s, R_r	Resistance of stator and rotor windings
L_s, L_r	Inductance of stator and rotor windings
L_m	Mutual inductance between stator and rotor windings
v_{ds}, v_{qs}	*d axis* and *q* axis stator voltages
v_{dr}, v_{qr}	*d axis* and *q* axis rotor voltages
i_{ds}, i_{qs}	*d axis* and *q* axis stator currents
i_{dr}, i_{qr}	*d axis* and *q* axis rotor currents
ψ_{ds}, ψ_{qs}	*d axis* and *q* axis stator flux
ψ_{dr}, ψ_{qr}	*d axis* and *q* axis rotor flux
T_e, T_L	Electromagnetic and load torque respectively.
ω_r, ω_{sl}, ω_e	Rotor, slip and synchronous speed respectively.
p	Differential operator

The block diagram representation of proposed model has been shown in Figure 1.

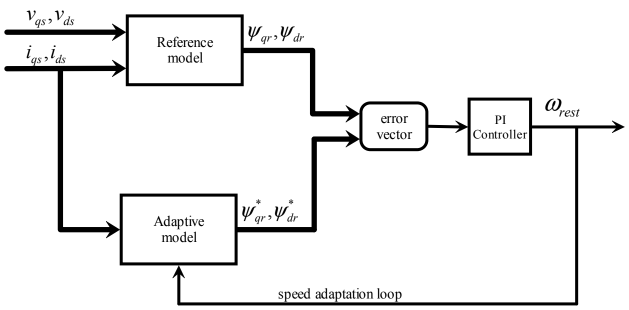


Figure 1 Block diagram of MRAS speed estimator

In this form, the speed estimator utilizes the instantaneous values of motor current and voltage for computing the instantaneous values of rotor fluxes of the reference model and adaptive model. It is shown that the equations used in the reference model are independent from speed value of motor. However, the adaptive model equations are speed-dependent and therefore require continuous updating. The equations (1) to (4) have been derived from the dynamic d-q model of IM. The stationary locus frame has been selected to design the reference and the adaptive models in conventional rotor flux based MRAS speed estimator.

$$\psi_{dr} = \frac{L_r}{L_m}\int(v_{ds} - R_s i_{ds} - \sigma L_s p i_{ds}) \quad (1)$$

$$\psi_{qr} = \frac{L_r}{L_m}\int(v_{qs} - R_s i_{qs} - \sigma L_s p i_{qs}) \quad (2)$$

$$\hat{\psi}_{dr} = \int(\frac{L_m}{T_r} i_{ds} - \frac{1}{T_r}\psi_{dr} - \omega_r \psi_{qr}) \quad (3)$$

$$\hat{\psi}_{qr} = \int(\frac{L_m}{T_r} i_{qs} - \frac{1}{T_r}\psi_{qr} - \omega_r \psi_{dr}) \quad (4)$$

where, the leakage factor is defined as $\sigma(= 1 - L_m{}^2/L_s L_r)$ and the rotor time constant is $T_r(= L_r/R_r)$.

The difference in the values, calculated using the reference model and the adaptive model is utilized for forming an error vector expressed as equation (5).

$$e = \psi_{qr}\psi^*_{dr} - \psi^*_{qr}\psi_{dr} \quad (5)$$

This error is usually passed on to the proportional-integral (PI) controller for generating the estimated speed. Gains of the PI controller in the speed estimator can be selected by hit and trial. Figure 1 shows the block diagram connection of the rotor flux estimator based on the MRAS. The speed is estimated by the model is up to 88.4% accurate and made easy to control it.

III. INTELLIGENT MRAS SPEED ESTIMATOR

The basic function of ANN is to think and learn like a network of biological neurons. In engineering applications, ANN is used where a mathematical model of the plant is either unknown or complex. The basic unit of ANN is a neuron, which has an activation function, weight, and bias. In comparison to other ANNs, a multilayer feed-forward (MLFF) neural network is more commonly applied in the speed estimation of motors. These networks do not have a backward connection between the layers and the output from the previous layer passed on to the next layer only. In this work, an MLFF type ANN is developed for replacing the reference model of a conventional MRAS estimator as shown in Figure 2.

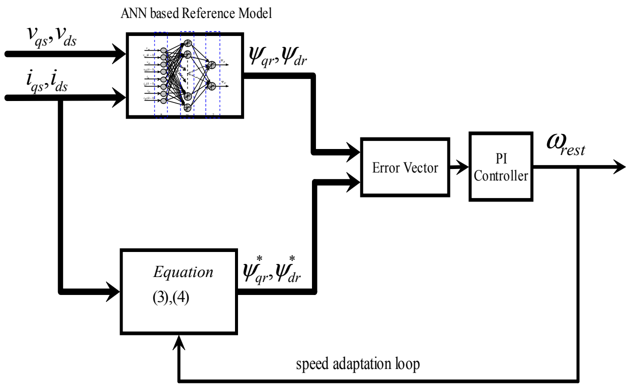


Figure 2 Structure of proposed ANN assisted MRAS speed estimator

The Figure 2 shows the circuit diagram of an estimator of wind speed with a self-assisted Artificial Neuron Network-based model. In proposed study, 5000 samples have been taken from speed encoder of IM drive using indirect vector-controlled model in the training process. In respect to the backpropagation training algorithm, the Levenberg-Marquardt (LM) algorithm is faster and hence is used in this work. In the hidden layer as well as in the output layer, the hyperbolic tangent sigmoid function is used as an activation function. Mathematically, a hyperbolic tangent sigmoid function can be expressed as [17]:

$$tan\square(b) = \frac{2}{1+e^{-2b}} - 1 \quad (6)$$

For stopping the training of the ANN, the decay of the mean of squared errors (MSE) to the value of $1\text{x}10^{-3}$ is selected as a stopping criterion [17]. The net output from the proposed ANN can be expressed as:

$$o_k = \xi \sum_{k=1,j=1}^{2,20} \square_j w_{jk}^2 \qquad (7)$$

where ξ is an activation function used to squash the output of the neuron and $\square_j$ is the output from the j^{th} neuron in the hidden layer of neural network.

To structure the ANN, 08, 20 and 02 neurons have been selected in input, hidden and output layers respectively in the proposed work as shown in Figure 3 [18]. This is an adaptive two layered artificial neural network model trained offline.

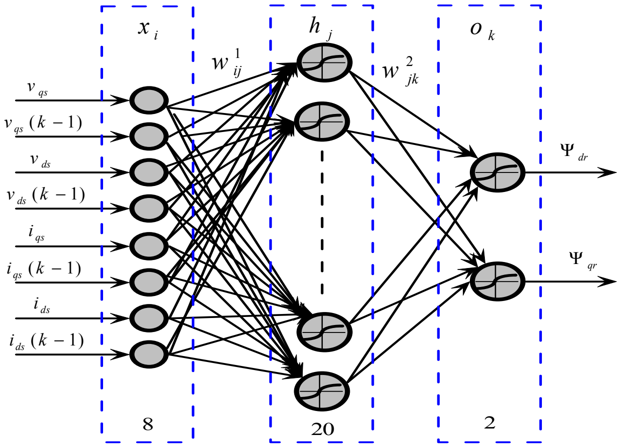


Figure 3 Structure of presented multilayer feed-forward network

The controlled drive orientation with speed encoder is run through the dataset of 5000 samples for the artificial neural network. The drive runs in a low region of speed ranging from (100 to -100) RPM with connecting load and without connecting load to it, to generate a training dataset for evaluation of results. The neural network is trained by the Levenberg Marquardt feed forward back propagation neural network algorithm. The paper presents recent and past values of stator current and estimated flux is taken as a feature for more accurate predictions of results. Here the dataset is divided in the random state of 2:3, where 2000 data values are taken for training from conventional model to test the data at different operating conditions and 3000 values are taken for testing and implementing the results. To estimate the rotor flux linkages of the adaptive model, an 8-20-2 multilayer feed-forward neural network is used in this work. We used more hidden layers for more epochs running which in turn gives us more accuracy for better prediction. The Figure 4 shows a MATLAB Simulink multi-layer feed-forward neural network model [18].

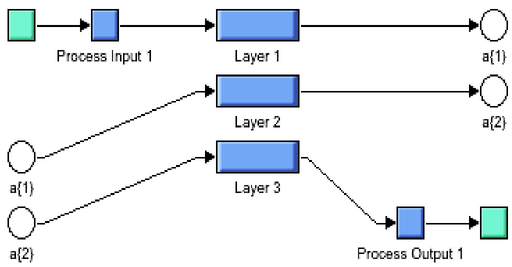


Figure 4 Feed Forward Neural Network – Simulink Mode

The data connections flow is in a single direction feeding forward i.e., from input to output. Layer 1 is an input layer; Layer 2 is the hidden layer and Layer 3 has the output layer followed by the target output. The Figure 5 shows the Simulink setup circuit of the multi-layer Feed-Forward Neural Network assisted Model Reference Adapted System (MRAS) [18]. To get high accuracy by balancing the rotor resistance variability, the model is trained online with feed backward neural network by adjusting the weights at low speed. The Simulink model demonstrates the possibility to use a feedforward neural network (static neural network) to estimate (more precisely to approximate) the mechanical speed of the induction motor.

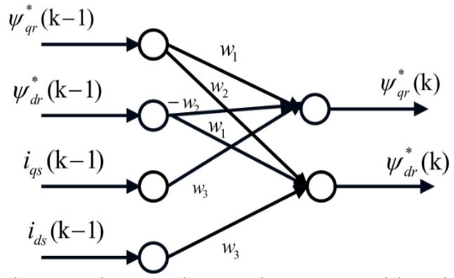


Figure 5 The neural network structure with weight estimation on the feed-forward multilayer neural network

IV. TEST RESULTS & DISCUSSIONS

Indirect vector-controlled drive with polyphase squirrel cage induction motor of 4 kW, 400 V, 50 Hz, 4 pole and 1430 RPM is modeled and simulated in MATLAB software. The parameters of the induction motors are shown in Table 1 and Simulink model of induction motor drive with ANN is represented in Figure 6 and The Drive is run with a speed encoder while estimators are run in an open loop to estimate the actual running speed of the motor. The results obtained on some important operating conditions are illustrated and discussed in subsequent sections.

Table 1: The Parameters of Induction Motor

Parameter	**Value**
Stator Resistance (R_s)	14.85 mΩ
Rotor Resistance (R_r)	9.295 mΩ
Stator Inductance (L_s)	0.302 mH
Rotor Inductance (L_r)	0.302 mH
Mutual Inductance (L_m)	10.46 mH
Inertia (J)	0.0131 Kg.m^2
Pole Pair (P)	2
Friction Factor (F)	0.002985 Nm-sec

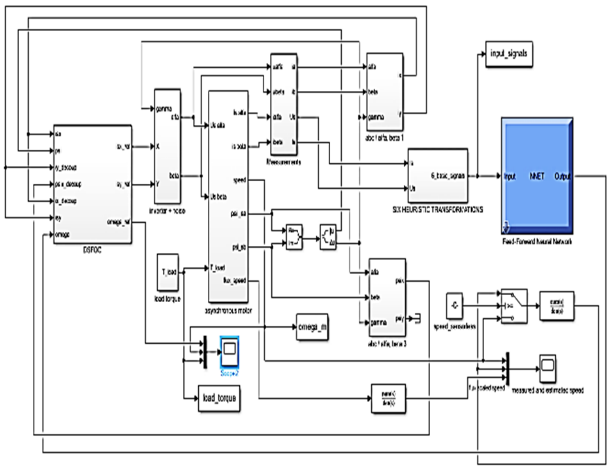


Figure 6 Simulink Model of induction motor drive using feed forward artificial neural network

The ANN tool gives us the estimation of different parameters and the torque value after implementation of 8-20-2 neural network for getting the results of load torque, estimated torque, and modelled torque of the induction motor for better accuracy.

A. *Setpoint tracking with a nominal resistance value*

For The Duration Of this test, the effort is operated with no load torque and the value of resistances in the speed estimator is considered the same as of motor. In the first test, the drive is operated to acquire the speed of 120 rad/s to verify the performance of the speed estimator in the high-speed region. The responses obtained are illustrated in Figure 7. In Figure 7, it is shows that the response time graph for the rotor speed of 120 rad/sec of speed tracking for conventional model reference assisted system and Neural network-based model reference assisted system. The motor torque is shown regarding time with more harmonic distortions. The Figure 7(a) illustrates the routine of the conventional speed approximation. Whereas, the performance of the proposed neural network speed approximation is illustrated in Figure 7 (b). The response of the motor torque is shown in Figure 7 (c). As no external load is applied the steady-state torque developed is almost zero. The performance of both speed estimators is also tested for very low-speed value. In this test, the drive without any load is run to acquire the reference speed of 5 rad/s. The responses obtained are shown in Figure 8. It is observed that both the speed estimators effectively estimate the motor speed in the low-speed region also. The obtained results shows that the conventional MRAS speed estimator is sensitive towards the stator resistance variations.

B. *Setpoint tracking with 50% difference in stator resistance*

To test the sensitivity towards stator resistance variations the values in the speed estimators are taken different from the actual values. The difference is 50% of the actual value. The performance of the speed estimator is again tested for both high and low-speed regions. The drive is operated without load. In starting, the drive is operated to achieve the reference speed of 120 rad/s. The responses obtained are shown in Figure 9.

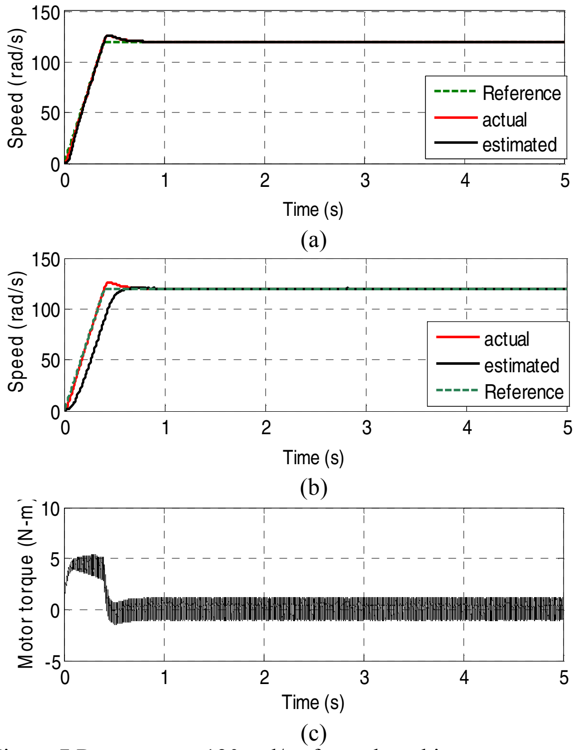


Figure 7 Response on 120 rad/s of speed tracking
(a) conventional-MRAS (b) NN-MRAS (c) motor torque

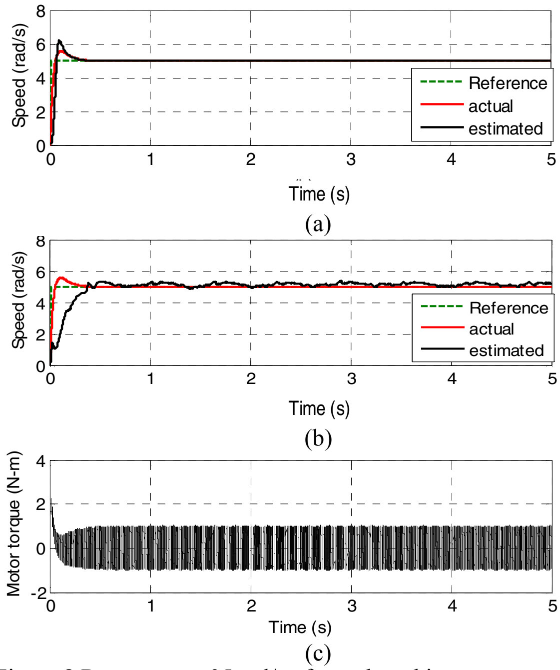


Figure 8 Response on 05 rad/s of speed tracking:
(a) conventional-MRAS (b) NN-MRAS (c) motor torque

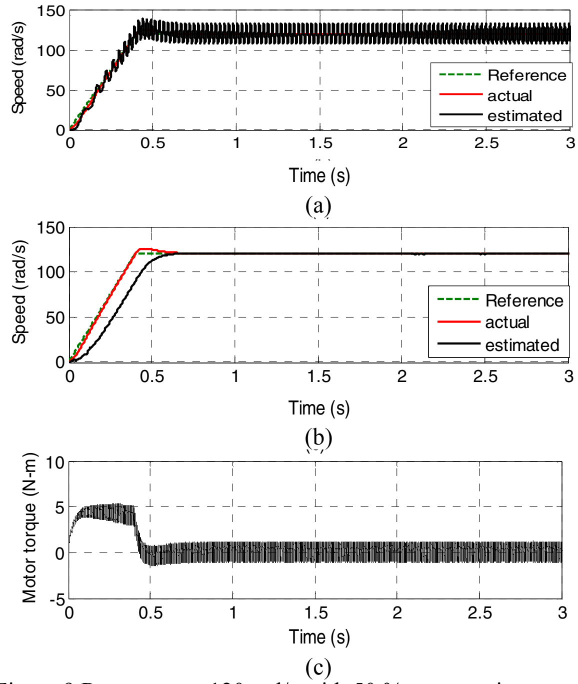
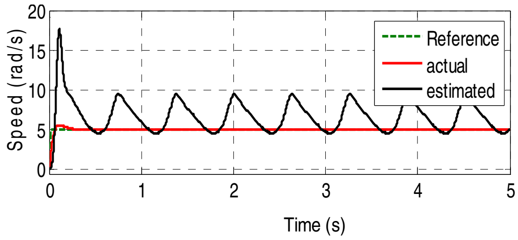
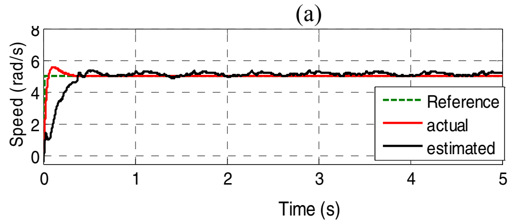


Figure 9 Response on 120 rad/s with 50 % stator resistance mismatch: (a) conventional-MRAS (b) NN-MRAS (c) motor torque

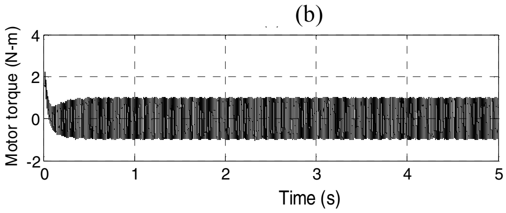
It is observed from Figure 10 (a) that the conventional MRAS speed estimator is sensitive towards the stator resistance variations. However, NN-MRAS seems insensitive to the variations. figure 10 illustrates the performance of the speed estimators at a low speed of 5 rad/s. As can be observed from Figure 10 (a) and 10 (b) the conventional speed estimator is sensitive towards the stator variations and the impact is more in the low-speed region whereas NN-MRAS is unaffected by the variations.



(a)



(b)

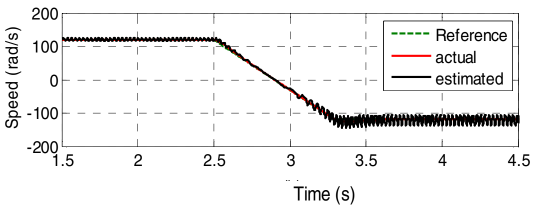


(c)

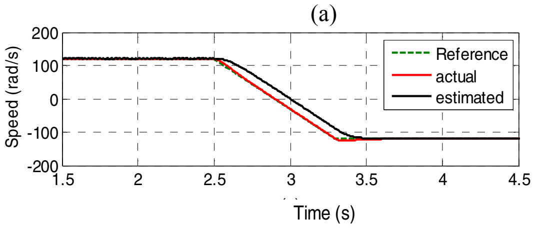
Figure 10 Response on 0.5 rad/s with 50 % stator resistance mismatch: (a) conventional-MRAS (b) NN-MRAS (c) motor torque

C. *Speed reversal with 25% change in stator resistance*

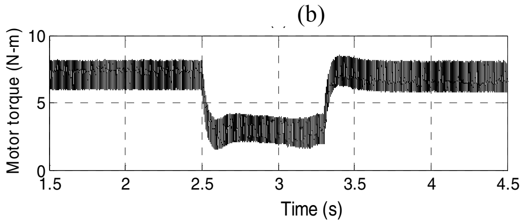
The speed estimator performance is also tested for speed reversal. To make it more realistic the mismatch of 25% in stator resistance from the actual value is given to the speed estimators. The performance is tested in low and high-speed regions both. The response obtained during the speed reversal of 120 rad/s to -120 rad/s with 25 % of the rated load is shown in Figure 11.



(a)



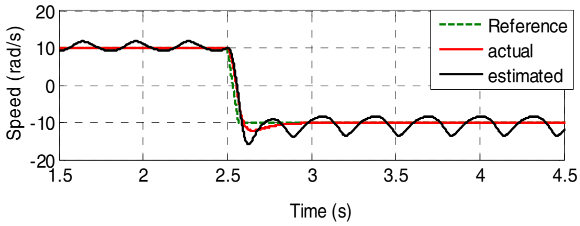
(b)



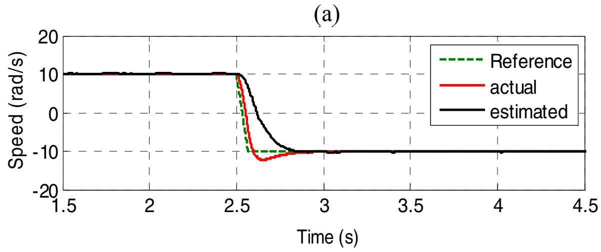
(c)

Figure 11 Response on speed reversal (120 to -120 rad/s) with 25 % stator resistance mismatch: (a) conventional-MRAS (b) NN-MRAS (c) motor torque

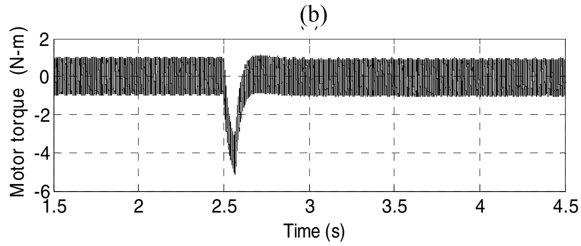
The performance of NN-MRAS is superior as it is insensitive to the mismatch. The same can be observed from Figure 12 in the low-speed zone with the speed reversal of ± 10 rad/s. The load is thrown off for the period of speed reversal in the zone of low speed.



(a)



(b)



(c)

Figure 12 Response on speed reversal (10 to -10 rad/s) with 25 % stator resistance mismatch: (a) conventional-MRAS (b) NN-MRAS (c) motor torque

In this study, it has been observed that the response of speed reversal (±120 rad/sec) with 25 % stator resistance mismatched with conventional MRAS. The results show the reference changes in the plot. The Neural Network-based Model Reference Adaptive System shows a little dip at the actual and estimated velocity of induction motor. The motor torque shows the Total harmonic distortions in the plot from 2.5 seconds to 3.5 seconds. In the present work, a comparative study has been shown for analyzing the performance of ANN based MRAS speed estimator. The test results have been obtained by implementing the proposed idea in MATLAB/ Simulink platform. The results shown at low speeds are relevant and should be more emphasized. The response of reversal of rotor velocity (±10 RPM) has been shown in Figure 12 (b). In this result, the efficiency of induction motor (IM) has been shown with change in initial and final conditions of velocity ((±10 red/sec).

The Figure 13 shows the measured speed plot and estimated speed plot show a little difference in the scope plots at some points due to the model selection of Neural Network. The system is accurately made by LM-algorithm which is used to train the proposed neural network. These deviations show that the modeled and estimated speed is shown in the given plot. The estimated speed and modeled speed are congruent to each other with a minute deviation in their graph. The torque curve deviates between (-10 Nm to 10 Nm) which in robust conditions show the reversal in the graph values. The limitations of the given solution are if it is controlled at 0 Hz frequency, then the above-given technique is not applicable. This shows the scope graph between load torque, modeled speed, and estimated speed of induction motor after running the ANN model and we can see the predicted estimated output overlaps the modelled output which shows the accuracy of the 8-20-2 Model of ANN.

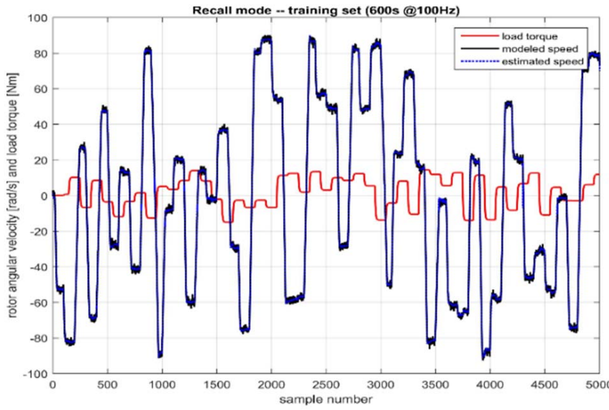


Figure 13 Load torque, modeled speed, and estimated speed of induction motor after running the ANN model

V. CONCLUSION

This paper presented a speed estimator based on the MRAS scheme assisted by an artificial neural network for sensor less operation of induction motor drive. The controlled drive orientation with speed encoder is run through the dataset of 5000 samples for the artificial neural network. The drive runs in a low region of speed ranging from (100 to -100) RPM with connecting load and without connecting load to it, to generate a training dataset for evaluation of results. The paper presents recent and past values of stator current and estimated flux is taken as a feature for more accurate predictions of results. Here the dataset is divided in the random state of 2:3, where 2000 data values are taken for training from conventional model to test the data at different operating conditions and 3000 values are taken for testing and implementing the results. The Artificial neural network of (8-20-2) structure is proposed to replace the numerical reference model with more hidden layers to get the better accuracy of output. The Levenberg-Marquardt algorithm is used to train the proposed neural network. The performance of the drive is extensively examined with a proposed speed estimator on various realistic functioning environments such as speed change, speed reversal, and load variations. The simulation result verifies the superiority of the proposed speed estimator.

VI. REFERENCES

[1] D. Mitronikas and A. N. Safaris, "An improved sensorless vector-control method for an Induction motor drive," *IEEE Trans. Indust. Elect.*, vol. 52, no. 6, pp. 1660-1668, Dec. 2005.

[2] M. Rashed and A. F. Stronach, "A stable back-EMF MRAS-based sensorless low-speed Induction motor drive insensitive to stator resistance variation," *IEE Proceedings - Electric Power Applications*, vol. 151, no. 6, pp. 685-693, 7 Nov. 2004.

[3] E. Levi and Mingyu Wang, "A speed estimator for high-performance sensorless control of Induction motors in the field weakening region," *IEEE Trans. Power Electr.*, vol. 17, no. 3, pp. 365-378, May 2002.

[4] V. Arunachalam, H. Srinivasan, and A. Muthuramalingam, "A novel NN based rotor flux MRAS to overcome low-speed problems for rotor resistance estimation in vector-controlled IM drives," Front Energy, vol. 10, no. 4, pp 382–392, 2016.

[5] Y. B. Zebedee, S. M. Gadoue and D. J. Atkinson, "Model Predictive MRAS Estimator for Sensorless Induction Motor Drives," *IEEE Trans. Indust. Elect.*, vol. 63, no. 6, pp. 3511-3521, June 2016.

[6] V. Vasic, S. N. Vukosavic, and E. Levi, "A stator resistance estimation scheme for speed sensorless rotor flux-oriented Induction motor drives," *IEEE Trans. Ener. Conver.* vol. 18, no. 4, pp. 476-483, Dec. 2003.

[7] A. Iqbal and M. R. Khan, "Sensorless control of a vector controlled three-phase Induction motor drive using artificial neural network," *2010 Joint International Conference on Power Electronics, Drives and Energy Systems & 2010 Power India*, New Delhi, 2010, pp. 1-5.

[8] S. M. Gadoue, D. Giaouris, and J. W. Finch, "Sensorless Control of Induction Motor Drive at Very Low and Zero Speed Using Neural Network Flux Observers," *IEEE Trans. Indust. Elect.*, vol. 56, no. 8, pp. 3029-3039, Aug. 2009.

[9] S. M. Gadoue, D. Giaouris, and J. W. Finch, "A neural network-based stator current MRAS observer for speed sensorless Induction motor drives," *IEEE International Symposium on Industrial Electronics*, Cambridge, 2008, pp. 650-655.

[10] R. Ajabi Farshbaf, M.R. Azizian, and A. Ebrahimi "NN-MRAS based speed estimator VS. RF-MRAS one: design and comparison," *IEEE Conference Proceeding on Power Electronics and Drive Systems Technology*, pp. 223-228, 2012.

[11] S. M. Gadoue, D. Giaouris, and J. W. Finch, "Low-speed operation improvement of MRAS sensorless vector control Induction motor drive using neural network flux observers," *IECON 2006 - 32nd Annual Conference on IEEE Industrial Electronics*, pp. 1212-1217, 2006.

[12] S. Maiti, V. Verma, C. Chakraborty, and Y. Hori, "An Adaptive Speed Sensorless Induction Motor Drive with Artificial Neural Network for Stability Enhancement," *IEEE Trans. Indust. Inform.*, vol. 8, no. 4, pp. 757-766, Nov. 2012.

[13] Giribabu Dyanamina, Mukesh Kumar Pathak, and Satya Prakesh Srivastava, "Parallel Stator Resistance Estimator Using Neural Networks for Rotor Flux Based Model Reference Adaptive System Speed Observer" Electric Power Components and Systems, Vol. 44, No. 6, pp. 658-672, 2016.

[14] M. E. Elbuluk, Liu Tong, and I. Husain, "Neural-network-based model reference adaptive systems for high-performance motor drives and motion controls," *IEEE Trans. Indust. Application.*, vol. 38, no. 3, pp. 879-886, May-June 2002.

[15] Baburaj Karanayil, Muhammed Fazlur Rahman, and Colin Grantham "Online Stator and Rotor Resistance Estimation Scheme Using Artificial Neural Networks for Vector Controlled Speed Sensorless Induction Motor Drive" *IEEE Trans. Indust. Elect.*, pp.167- 176, vol. 54, no. 1, 2007.

[16] Manolis I.A. Lourski, "A brief description of Levenberg-Marquardt Algorithm", Institute of Computer Science Foundation for research and technology (ICSRT) -Hellas (FORTH), Vassilika Vouton, Greece, February 2011

[17] A. Tiwari, B. Kumar, and Y.K. Chauhan, "ANN-based RF-MRAS speed estimation of Induction motor drive at low speed", International Conference on Electronics, Communication and Aerospace Technology, ICECA 2017.

[18] MathsWork, "MATLAB 2015," MathsWork, october 2015. Available: https://in.mathworks.com/. [Accessed February 2020]

[19] A. Kerboua, A. Metatla, R. Kelailia, and M. Batouche, "Fault Diagnosis in Induction Motor using Pattern Recognition and Neural Networks," *2018 International Conference on Signal, Image, Vision and their Applications, SIVA 2018*, pp. 1–7, 2019, doi: 10.1109/SIVA.2018.8660995.

[20] A. Venkadesan, S. Himavathi, A. Muthuramalingam, and K. Sedhuraman, "ANN based Flux Estimator for Rotor Resistance Estimation in Vector Controlled im Drives," *2018 IEEE International Conference on System, Computation, Automation and Networking, ICSCA 2018*, no. 1, pp. 1–5, 2018, doi: 10.1109/ICSCAN.2018.8541240.

[21] P. M. Menghal and A. J. Laxmi, "Real time control of Induction motor using neural network," *Proceedings - 2018 International Conference on Communication, Information and Computing Technology, ICCICT 2018*, vol. 2018-Janua, pp. 1–6, 2018, doi: 10.1109/ICCICT.2018.8325873.