New Model Reference Adaptive System Speed Observer for Field-Oriented Control Induction Motor Drives Using Neural Networks

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Abstract

One of the primary advantages of field-oriented controlled induction motor for high performance application is the capability for easy field weakening and the full utilization of voltage and current rating of the inverter to obtain a wide dynamic speed rangeThis paper describes a Model Reference Adaptive System (MRAS) based scheme using Artificial Neural Network (ANN) for online speed estimation of sensorless vector controlled induction motor drive. The proposed MRAS speed observer uses the current model as an adaptive model. The neural network has been then designed and trained online by employing a back propagation network (BPN) algorithm. The estimator was designed and simulated in Matlab/Simulink. Simulation result shows a good performance of speed estimator. The simulation results show good performance in various operating conditions. Also Performance analysis of speed estimator with the change in resistances of stator is presented. Simulation results show this estimator robust to parameter variations especially resistances of stator.

***Keywords**: Field Oriented Control (FOC), Induction motor (IM), Sensorless Control, Artificial Neural Network (ANN), Model Reference Adaptive System (MRAS)*

1. Introduction

Induction motors are electromechanical systems suitable for a large spectrum of industrial applications, due to its high reliability, relatively low cost, and modest maintenance requirements [1]. Control of the Induction motors can be done using various techniques. Most common techniques are: (a) constant voltage/frequency control (V/F), (b) field orientation control (FOC), and (c) direct torque control (DTC). The first one is considered as scalar control since it adjusts only magnitude and frequency of the voltage or current with no concern about the instantaneous values of motor quantities. It does not require knowledge of parameters of the motor, and it is an open-loop control. Thus, it is a low cost simple solution for low-performance applications such as fans and pumps. The other two methods are in the space vector control category because they utilize both magnitude and angular position of space vectors of motor variables, such as the voltage and flux. They are employed in high performance applications, such as positioning drives or electric vehicles. Especial, the formulation of Field Orientated Control (FOC) has lead to the induction motor replacing the DC motor as the main source of energy conversion in industrial applications. Along with the increasing in technology and the rapid improvement in power devices, it is possible to apply the induction motor drives for high performance applications [2, 3]. It is necessary to be able to control the speed of these motor drives and the most common way of doing this is by using Vector Control or Direct Torque Control, which need feedback of motor speed. So they require a speed sensor which is usually placed on the rotor shaft of the machine. These sensors are sources of trouble, mainly in hostile environments. Thus sensorless control is taken into consideration. The main reasons for the development of sensorless drives are [4]:

- reduction of hardware complexity and cost
- increased mechanical robustness
- higher reliability
- working in hostile environments

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- decreased maintenance requirements
- unaffected moment of inertia

Since the late 1980s, speed-sensorless control methods of induction motors using the estimated speed instead of the measured speed have been reported. They have estimated speed from the instantaneous values of stator voltages and currents using induction motor model. Other approaches to estimate speed use Rotor Slot Harmonic [5] Extended Kalman Filter (EKF), Extended Luenbergern Observer (ELO) [6] Saliency Techniques [7] and Model Reference Adaptive System (MRAS) [8], [9]. The saliency techniques attempt to be parameter independent, but secondary magnetic effects do lead to complications in their implementation. Rotor slot harmonic speed estimation will work successfully if the rotor is about a minimum speed. The problems related to EKF or ELO are the large memory requirement, computational intricacy, and the constraint such as treating all inductances to be constant in the machine model. MRAS schemes are also direct dependent on motor parameters. However, an induction motor is highly coupled, non-linear dynamic plant, and its parameters vary with time and operating conditions. Therefore, it is very difficult to obtain good performance for the entire speed range using previous methods.

Recently, the use of Artificial Neural Network (ANN) to identify and control nonlinear dynamic systems has been proposed because they can approximate a wide range of nonlinear functions to any desired degree of accuracy [10]-[14]. Artificial Neural Network advantages such as:

- ability to approximate arbitrary nonlinear mappings
- learning from the real system or the approximate
- intelligence and self-organizing capability
- possibility of parallel computing
- robustness
- ability to generalize and fault tolerance

It is a major advantage of ANN based techniques that they do not require any mathematical model of the motor under consideration and the drive development time can be substantially reduced [4]. In the paper, speed estimator, based on ANN based Model Reference Adaptive System (MRAS) has been studied and analysed. In ANN the back propagation network (BPN) algorithm is used for online training of neural network to estimate the motor speed.

2. Model of Induction Motor

Neglecting the motor core loss, the saturation, the slot effect, etc, the equivalent circuit of the IM in stationary reference frame is shown in Figure 1. The mathematical model in this frame then can be derived from the equivalent circuit, that is

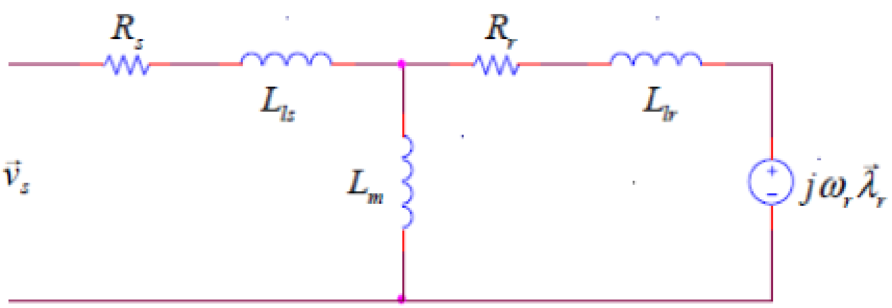

Figure 1. The equivalent circuit of IMs (T-model) in the stationary reference frame

$$\vec{V}_s = R_s\vec{I}_s + \frac{d\vec{\lambda}_s}{dt} \quad (1)$$

$$\vec{0} = R_r\vec{i}_r + \frac{d\vec{\lambda}_r}{dt} - j\omega_r\vec{\lambda}_r \quad (2)$$

Where

$$L_s = L_{ls} + L_m \quad (3)$$

$$L_r = L_{lr} + L_m \quad (4)$$

And

$$\vec{\lambda}_s = L_s\vec{i}_s + L_m\vec{i}_r \quad (5)$$

$$\vec{\lambda}_r = L_r\vec{i}_r + L_m\vec{i}_s \quad (6)$$

The electromagnetic torque produced in the motor is

$$T_e = \frac{2}{3}p\mathrm{Im}(\vec{i}_s\vec{\lambda}_s^{\,*}) \quad (7)$$

The induction motor model in the α −β fixed reference frame can be described by the following equations

$$\begin{bmatrix} u_{\alpha s} \\ u_{\beta s} \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} R_s + L_s p & 0 & L_m p & 0 \\ 0 & R_s + L_s p & 0 & L_m p \\ L_m p & \omega_r L & R_r + L_r p & \omega_r L \\ -\omega_r L & L_m p & -\omega_r L & R_r + L_r p \end{bmatrix} \begin{bmatrix} i_{\alpha s} \\ i_{\beta s} \\ i_{\alpha r} \\ i_{\beta r} \end{bmatrix} \quad (8)$$

$$\begin{bmatrix} \Psi_{\alpha s} \\ \Psi_{\beta s} \\ \Psi_{\alpha r} \\ \Psi_{\beta r} \end{bmatrix} = \begin{bmatrix} L_s & 0 & L_m & 0 \\ 0 & L_s & 0 & L_m \\ L_m & 0 & L_r & 0 \\ 0 & L_m & 0 & L_r \end{bmatrix} \begin{bmatrix} i_{\alpha s} \\ i_{\beta s} \\ i_{\alpha r} \\ i_{\beta r} \end{bmatrix} \quad (9)$$

Where the subscripts s and r stand for stator and rotor quantities; u and i denotes voltage and current respectively; R denotes resistance and ω_r is the rotor speed; ψ denotes flux linkage.

3. FOC Principles

According to the above equation

$$T = p\frac{L_m}{\sigma L_s L_r}(\lambda_s.j\lambda_r) \quad (10)$$

Where p is the pole pair number and

$$\sigma = 1 - \frac{L_m^2}{L_s L_r} \quad (11)$$

Assuming a rotor flux reference frame, and developing the previous equations with respect to the d axis and q axis components, leads to

$$\frac{d\lambda_{dr}}{dt} + \frac{1}{\tau_r}\lambda_{dr} = \frac{L_m}{\tau_r}i_{ds} \quad (12)$$

$$T = \frac{3}{2}p\frac{L_m}{L_r}\lambda_{dr}i_{qs} \quad (13)$$

These equations represent the basic principle of the FOC: in the rotor flux reference frame, a decoupled control of torque and rotor flux magnitude can be achieved acting on the q and d axis stator current components, respectively. A block diagram of a basic FOC scheme is presented in Figure 2.

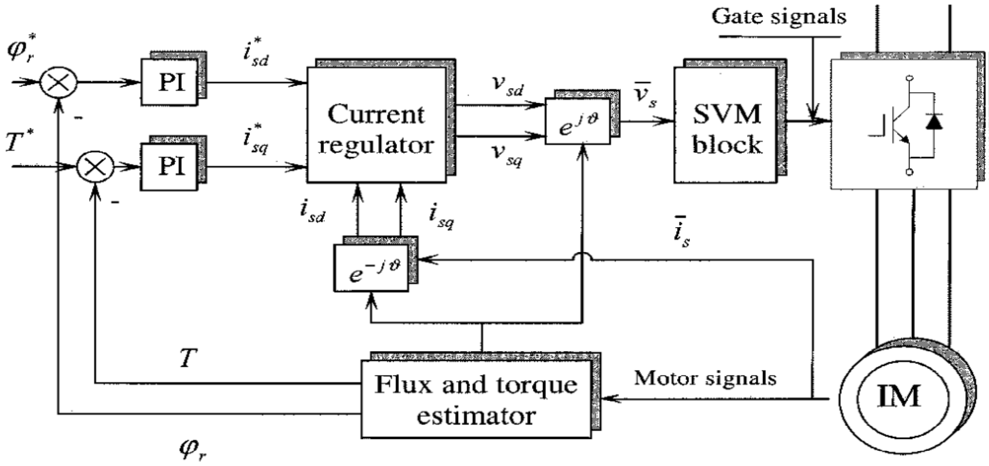

Figure 2. Basic FOC scheme

4. Speed Estimation using Neural Network

In MRAS technique, some state variables, X_d, X_q (e.g. rotor flux-linkage components, Ψ_{dr}, Ψ_{dr}, or back-emf components, e_d, e_q, etc.) of the induction machine (which are obtained by using measured quantities, e.g. stator voltages and currents) are estimated in a reference model and are then compared with state variables $\widehat{X}_d$, $\widehat{X}_q$ estimated by using an adaptive model. The difference between these state variables is then formulated into a speed tuning signal (ε), which is then an input into an adaptation mechanism, which outputs the estimated rotor speed ($\widehat{\omega}$).

Speed estimator using ANN is a part of a Model Reference Adaptive System (MRAS), where ANN takesthe role of the adaptive model. ANN contains the adjustable and constant weights and the adjustable weightsare proportional to the rotor speed. The adjustable weights are changed by using the error between the outputs of the reference and adaptive model. Figure 3 shows the MRAS-based speed estimation scheme, which contains an ANN with BPN adaptation technique [4].

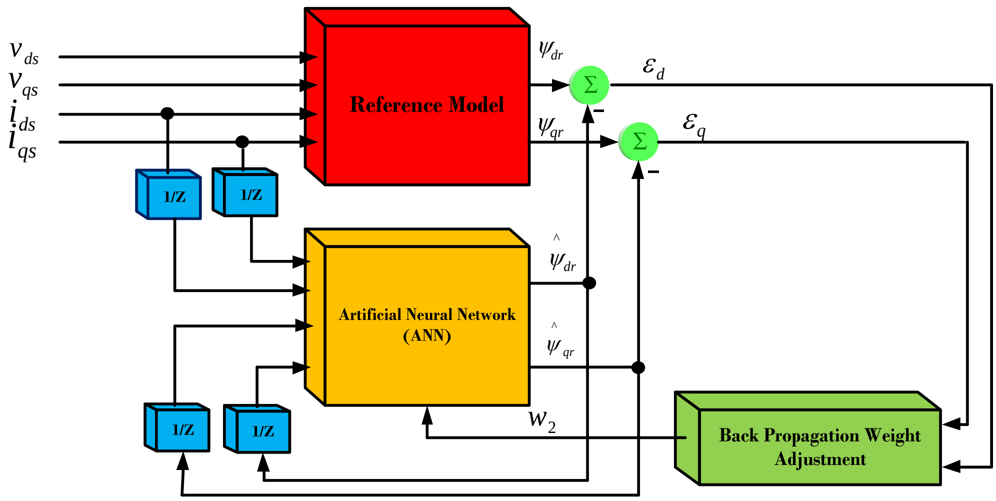

Figure 3. MRAS-based rotor speed estimator containing an ANN

The outputs of the reference model are the rotor flux linkage components in stationary reference frame, aregiven by

$$\psi_{dr} = \frac{L_r}{L_m}\left[\int \left(v_{ds} - R_S i_{ds}\right) dt - L_s' i_{ds}\right] \tag{14}$$

$$\psi_{qr} = \frac{L_r}{L_m}\left[\int \left(v_{qs} - R_S i_{qs}\right) dt - L_s' i_{qs}\right] \tag{15}$$

These two equations do not contain the rotor speed anddescribe the reference model. The equations of adaptivemodel are given by

(16)

$$\hat{\psi}_{qr} = \frac{1}{T}\int L_m\, i_{qs} - \hat{\psi}_{qr} - \omega_r T_r \hat{\psi}_{dr})dt \tag{17}$$

It is possible to implement equations (16) and (17) by a two layer ANN containing weights, W_1 (= 1-C), W_2 (= $\omega_r T_r$C), W_3 (=Cl_m). Where C=$\frac{T}{T_r}$, T, $T_r$are sampling time and rotor time constant. The variable ANN weight W_2 is proportional to the rotorspeed. By using the backward difference method, theequation of adaptive model is given below.

$$\hat{\psi}_{dr}(k) = W_1\hat{\psi}_{dr}(k-1) - W_2\hat{\psi}_{qr}(k-1) + W_3 i_{ds}(k-1) \tag{18}$$

$$\hat{\psi}_{qr}(k) = W_1\hat{\psi}_{qr}(k-1) - W_2\hat{\psi}_{dr}(k-1) + W_3 i_{qs}(k-1) \tag{19}$$

which gives the value of rotor flux at K^{th} sampling instant. These equations can be visualized by the very simple two layer ANN shown in Figure 4.

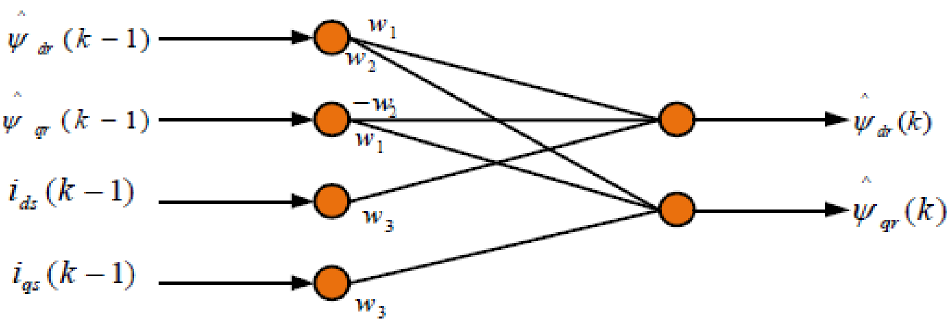

Figure 4. ANN model for the estimation of rotor flux linkage

After taking learning factor ηand momentum term α into account, the estimated rotor speed is given below.

$$\hat{\omega}_r(k) = \hat{\omega}_r(k-1) + \frac{\eta}{T}\begin{Bmatrix} -[\psi_{dr}(k) - \hat{\psi}_{dr}(k)]\hat{\psi}_{qr}(k-1) \\ +[\psi_{qr}(k) - \hat{\psi}_{qr}(k)]\hat{\psi}_{dr}(k-1) \end{Bmatrix} + \frac{\alpha}{T}\Delta w_2(k-1) \tag{20}$$

The learning rate (η) has to be selected to be large, but this can lead to oscillations in the outputs of the ANN. Usually α is in the range between 0.1 and 0.8. The inclusion of the momentum term into the weight adjustment mechanism can significantly crease the convergence, which is extremely useful when the ANN shown in figure 4 is used to estimate in real-time the speed of the induction machine [13].

5. Simulation Results

In this section, the performance of the proposed control strategy in a variety of operating conditions was evaluated through simulations. For this purpose, a three- phase, four-pole induction motor was selected and, accompanied by the suggested ANN based speed estimator, were implemented in Matlab/Simulink, as shown in Figure 5. The response of ANN based speed estimator is compared with actual machine, as shown in Figure 6. Block diagram of ANN-MRAS based sensorless vector control of a induction motor drive in Matlab/Simulink is shown in Figure 6. Here, three case studies were considered to verify the proposed drive under different conditions. Shown in the figures are motor speed, electromagnetic torque and stator current.

Case I. Nominal Load Condition: In this case, the IM was operating with the nominal load at 0.2 sec. and the circumstances below were considered:

- The speed stepped up to 1200 rpm and then slowly reduced to zero. The simulation results are shown in Figure 7.
- The speed stepped up to 1400 rpm and maintained at constant. Figure 8 shows the simulation results.
- The same as the first part of this case, the speed rose to 1000 rpm and then slowed down to zero. The results are shown in Figure 9.

Case II. No Load Condition: The performance of the proposed drive at low speed and no load condition was assessed in this case. The attention, in this case, was given to the operating of the IM in the following conditions:

- The speed rose to 500 rpm and thereafter, reduced rapidly to zero. Figure 10 shows the simulation results.
- The speed stepped up to 500 rpm and maintained at constant. Figure 11 shows the simulation results.
- The speed stepped up to 1000 rpm and maintained at constant. Figure 12 shows the simulation results.

The results of these cases show the effectiveness of the suggested drive in tracking the reference speed in both of no load and full load conditions.

Case III. Effects of Stator Resistance (R_s): It is important to see the performance of the drive in case of variation in rotor resistance. Here, the stator resistance is changed from its actual value to 1.5 times the actual value in the form of step (see Figure13). The load torque, as shown in Figure 13, went to positive and negative values in a step manner. Reference speed is changed from 0 to 300 rpm as shown in Figure 15. It is clear that the estimated speed is again matching with the reference speed. Thus, the robustness of proposed drive to the variation of the stator resistance is confirmed.

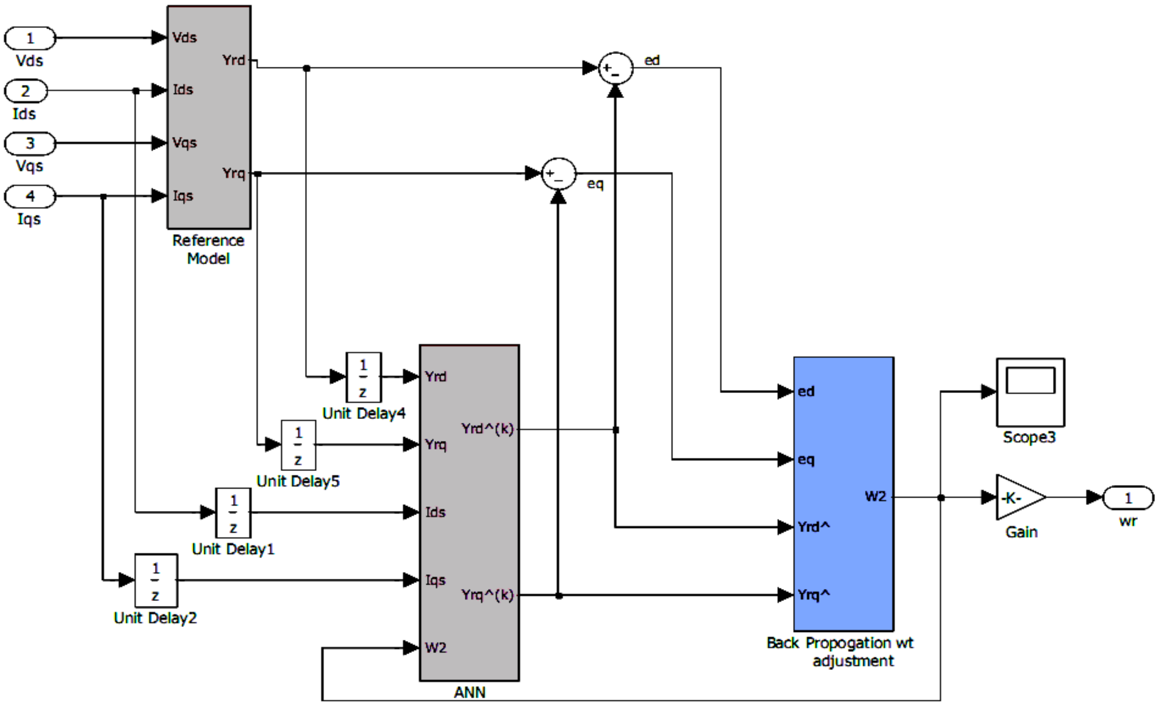

Figure 5. ANN based model of speed estimation

The response of ANN based speed estimator is comparedwith actual machine, as shown in Figure 6.

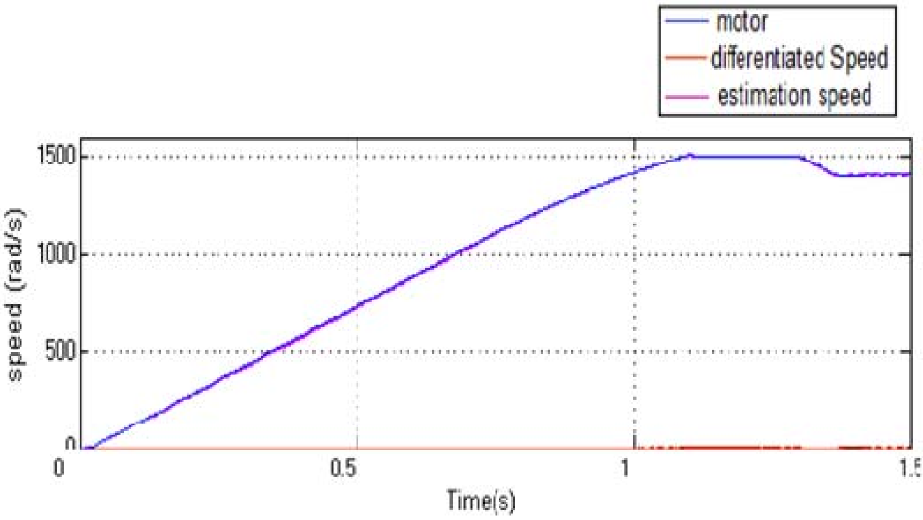

Figure 6. Response comparison of actual machine and ANN based speed estimator with error

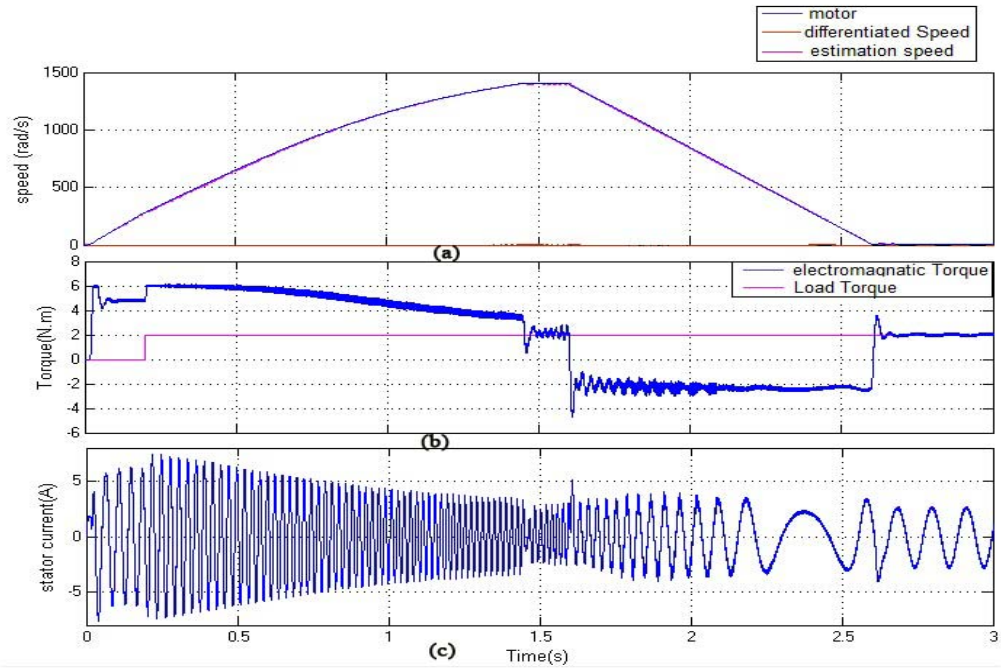

Figure 7. Case I. Nominal load at 0.2 seconds and speed-up to 1400 rpm, and then slow down to zero: (a) motor speed, (b) electromagnetic torque, (c) stator current

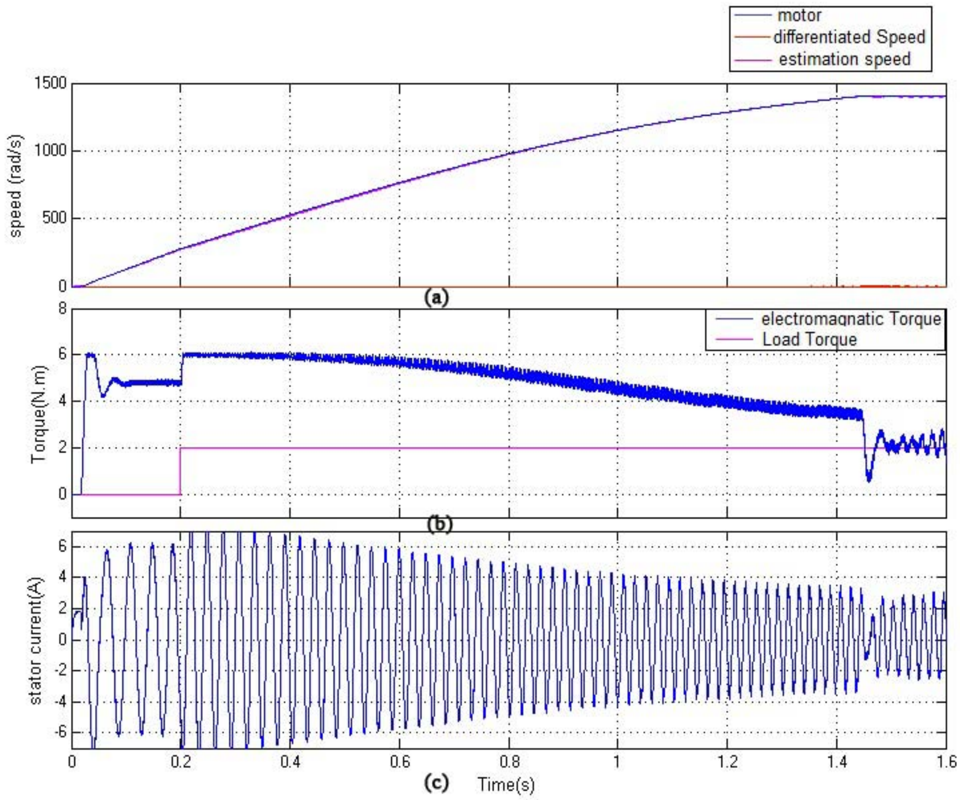

Figure 8. Case I. Nominal load at 0.2 seconds and speed-up to 1400 rpm: (a) motor speed, (b) electromagnetic torque, (c) stator current

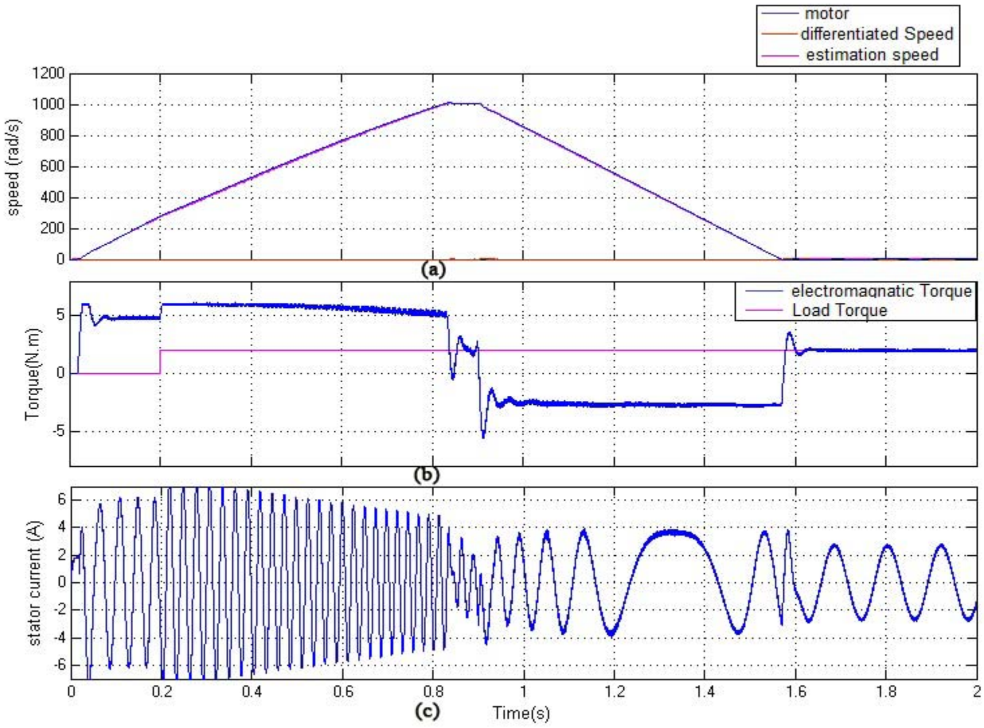

Figure 9. Case I. Nominal load at 0.2 seconds and speed-up to 1000 rpm, and then slow down to zero: (a) motor speed, (b) electromagnetic torque, (c) stator current

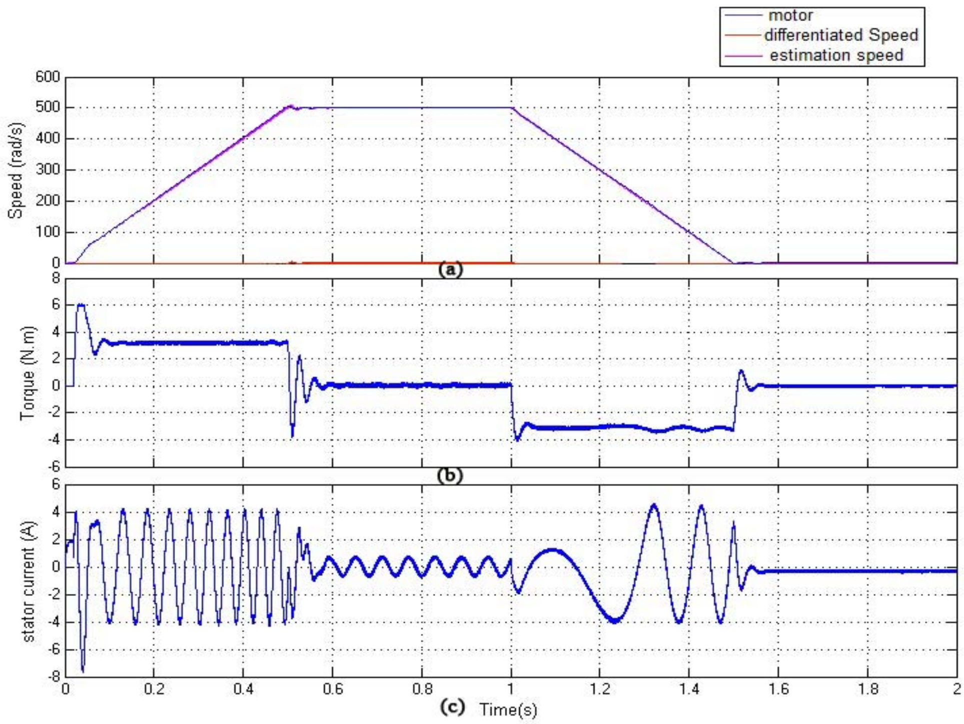

Figure 10. Case II. No load, speed-up to 500 r.p.m and subsequently, decreased rapidly from 500 to zero: (a) motor speed, (b): electromagnetic torque, (c) stator current

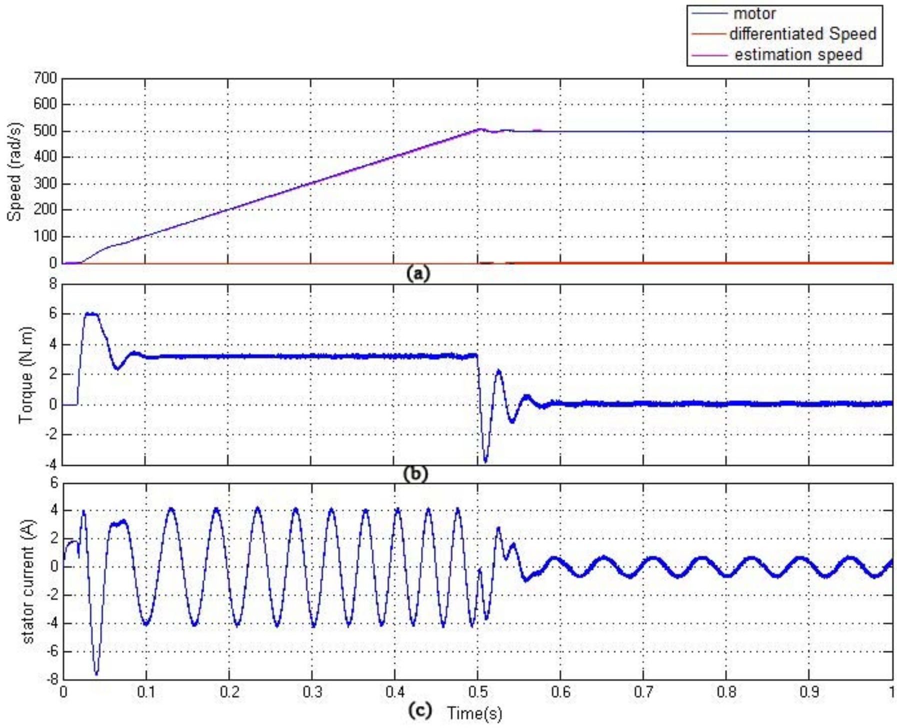

Figure 11. Case II. No load, speed-up to 500 rpm: (a) motor speed, (b) electromagnetic torque, (c) stator current

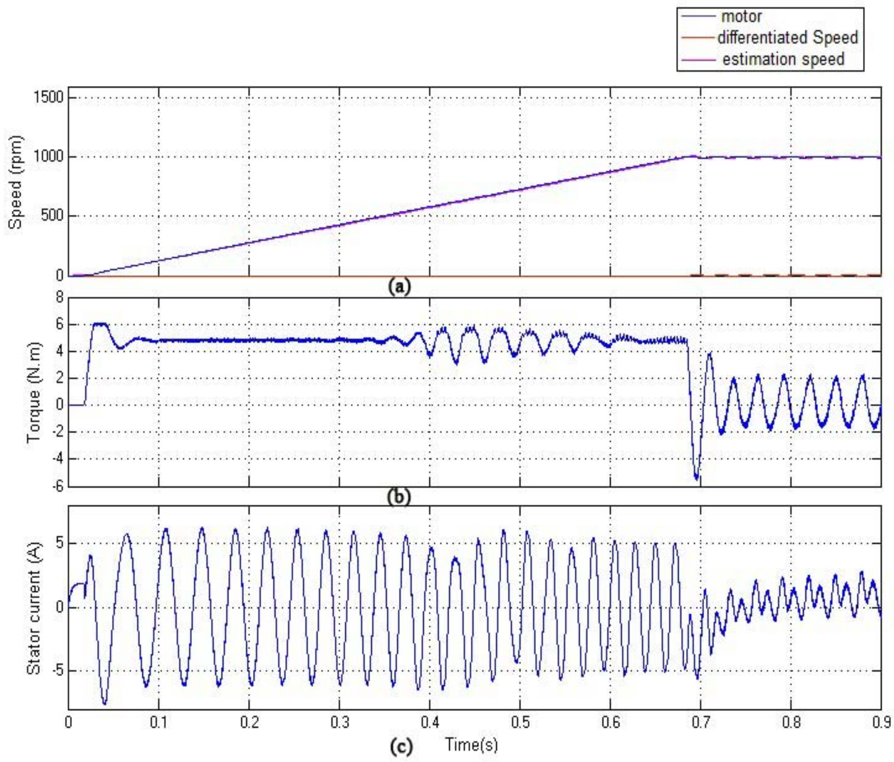

Figure 12. Case II. No load, speed-up to 1000 rpm: (a) motor speed, (b) electromagnetic torque, (c) stator current

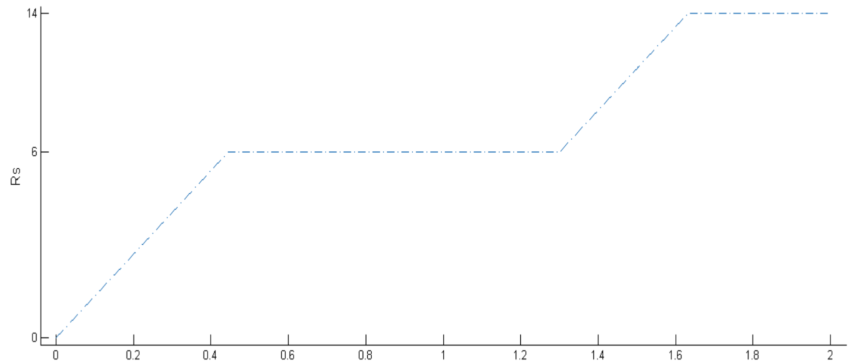

Figure 13. Case III. Effects of Stator Resistance (R_s), the stator resistance changes

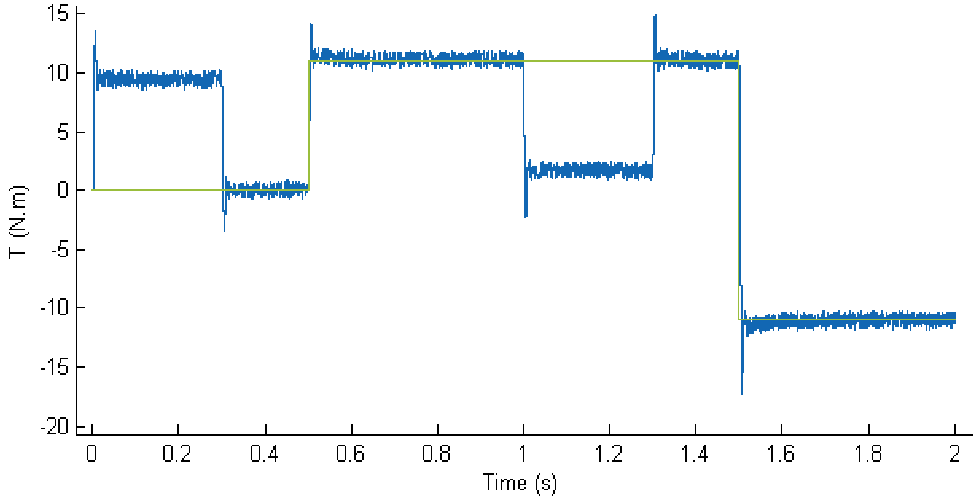

Figure 14. Case III. Effects of Stator Resistance (R_s), Electromagnetic torque and reference torque

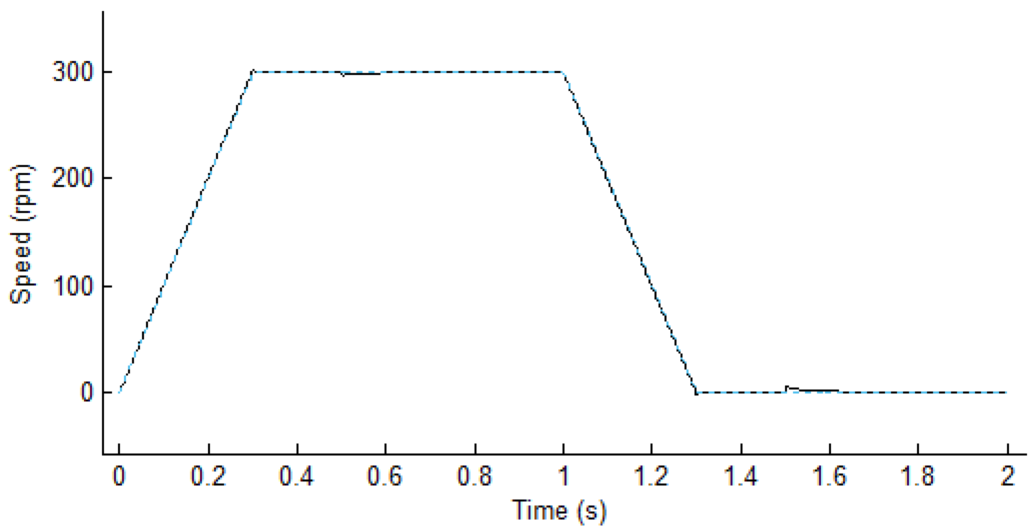

Figure 15. Case III. Effects of Stator Resistance (R_s), Motor speed and speed reference

6. Conclusion

This paper proposed a new MRAS speed observer for high-performance vector controlled of induction motor drives using a novel neural networks based speed estimator. Structure and algorithm were simple. The simulation showed that proposed control strategy could identify and track the motor speed accurately during the whole operating region. Overall, the dynamic response of this scheme of speed estimation showed a good performance. Also the results indicated the tracking of the speed references by the motor was good in terms of different conditions. Finally, analysis of the performance of the speed estimator during the changes of the stator resistance was presented which showed the speed estimator was robust to changes in motor parameters.

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