Modeling and Experimental Verification of ANN Based Online Stator Resistance Estimation in DTC-IM Drive

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Abstract – Direct Torque controlled induction motor (DTC-IM) drives use stator resistance of the motor for stator flux estimation. So, stator resistance estimation properly is very important for a stable and effective operation of the induction motor. Stator resistance variations because of changing in temperature make DTC operation difficult mainly at low speed. A method based on artificial neural network (ANN) to estimate the stator resistance online of IM for DTC drive is modeled and verified in this paper. To train the neural network a back propagation algorithm is used. Weight adjustment of neural network is done by back propagating the error signal between measured and estimated stator current. An extensive simulation has been carried out in MATLAB/SIMULINK to prove the efficacy of the proposed stator resistance estimator. The simulation & experimental result reveals that proposed method is able to obtain precise torque and flux control at low speed.

Keywords: ANN, Stator resistance estimator, DTC, IM, Motor drive, Temperature.

1. Introduction

Direct torque control (DTC) induction motor (IM) drive is becoming more popular day by day [1, 2] due to its robustness and fast dynamic response [3-6]. Implementation of this control strategy is very simple and also coordinate transformation is not required. Albeit DTC scheme is robust to motor parameter variation but stator resistance is only parameter which is required. Due to the temperature variation throughout the operation of the motor stator resistance varies continuously [7, 8]. Stator resistance variation introduces error in estimated stator flux position and magnitude which deteriorates the DTC-IM drive performance. The effect of error in estimation is very important mainly at low speed [7]. However a common shortcoming of the conventional DTC is high torque ripple. To reduce the torque ripple proper estimation of stator flux is necessary which depends greatly on stator resistance of motor. For this reason many stator resistance estimation scheme when motor operates in DTC drives have been addressed recently.

Stator resistance estimation schemes developed to date can be broadly classified under some distinct categories. Generally all of the methods depend on stator voltage (reconstructed or measured) and measured stator current.

All schemes which uses steady state induction motor model and some measured quantities to calculate explicitly the stator resistance [9-13] can be categorized as the first group. In [9] reactive power is evaluated using measured terminal variables, rotor and stator flux is evaluated next and then drive torque is evaluated. Finally an expression is derived to calculate stator resistance as a function of the previously evaluated quantities. The scheme addressed in [10] is mainly based on back electromagnetic force (BEMF) detector. In this strategy the stator resistance calculation has been carried out in reference frame which aligned with stator current vector. In [11] stator voltage model has been used to calculate stator resistance. Stator resistance is evaluated from active power balance of machine in [12].

The second category of the stator resistance estimation schemes is the most frequently used which includes estimators where value of stator resistance is updated through the adaptive mechanism [14-24]. For this purpose integral (I) or proportional-integral (PI) controllers are being used. In principle, different two subgroups exist. In the observer based system [16, 17, 22, 23, 25] error quantity worked as input to the adaptation mechanism of the stator resistance determination using difference between the measured and observed current signal. In this field extended kalman filter is mostly used because of its robustness and also it requires less number of PI controllers [26, 27]. In model reference adaptive system (MRAS) [14, 15, 18, 21, 24, 28] error quantity selection is more diverse. The method addressed in [14] operates in the rotating coordinate system and error determination is accomplished with difference between d-axis rotor flux obtained from voltage and current models. The method proposed in [15] is almost same but it uses rotor flux reference and one model is used to determine d-axis component of rotor flux to form the error. Error signal in [24] is mainly based on the active power but in [18] it is

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found as the sum of the products of rotor flux and rotor current d and q-axis components. Error signal of [21] uses an error in d-axis stator current component as input of integral controller, while error signal of [22] is obtained in such a way that identification of stator resistance is totally independent of leakage inductance. The model reference adaptive controller (MRAC) proposed in [28] is formed with the use of steady state and instantaneous values of a fictitious quantity which has no physical significance. The third group of the stator resistance identification techniques depends on the utilization of the artificial intelligence schemes in the adaptation mechanism of stator resistance [29-34].Fuzzy logic control (FLC) [31, 33], artificial neural network(ANN) [29, 34], or neuro-fuzzy control can be applied for this goal. One of the main advantage of neural network is the capability of approximating nonlinear function relationship. In this paper effect of the change in stator resistance is discussed and an online neural network stator resistance estimator is modeled and verified at different operating conditions.

This paper has been organized in five sections. DTC principle is presented in the following section. Proposed stator resistance estimation technique is given in section 3. Simulation results are described in section 4. Finally conclusion is presented in section 5.

2. DTC Principle

Basic DTC scheme is presented in Fig. 1. Here, errors of the electromechanical torque and stator flux status are detected then passed through the hysteresis comparator (two and three level) for digitization. Then a predetermined switching table (Table 1) determines the status of the inverter switches which will be used to determine voltage vector (V_s) location which is selected according to flux angle of the stator. Voltage vectors used in DTC drive are shown in Fig. 2. The stator flux is given by the following equation
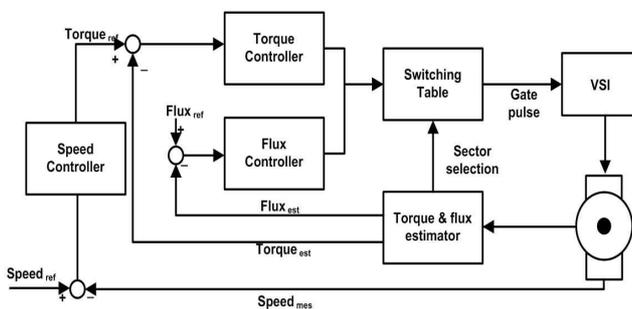
$$\omega_s = \int (v_s - R_s i_s) \, dt \tag{1}$$

Fig. 1. Basic IM-DTC drive

Table 1. Switching table

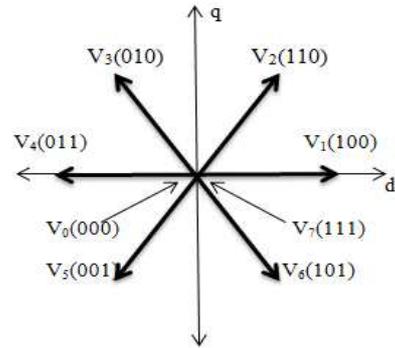| $\Delta\Psi_s$	ΔT	S_1	S_2	S_3	S_4	S_5	S_6
	1	V_2	V_3	V_4	V_5	V_6	V_1
1	0	V_7	V_0	V_7	V_0	V_7	V_0
	-1	V_6	V_1	V_2	V_3	V_4	V_5
	1	V_3	V_4	V_5	V_6	V_1	V_2
0	0	V_0	V_7	V_0	V_7	V_0	V_7
	-1	V_5	V_6	V_1	V_2	V_3	V_4

Fig. 2. Voltage vectors obtained from voltage source inverter (VSI)

So d and q axis stator flux can be given as

$$\omega_{ds} = \int (v_{ds} - R_s i_{ds}) \, dt \tag{2}$$

$$\omega_{qs} = \int (v_{qs} - R_s i_{qs}) \, dt \tag{3}$$

Electromagnetic Torque is given by

$$T = \frac{3}{2} p \, (\omega_{ds} i_{qs} - \omega_{qs} i_{ds}) \tag{4}$$

If we neglect the stator resistance then stator flux will become as follows

$$\omega_s = \int v_s \, dt \tag{5}$$

According to the basic DTC strategy stator flux is estimated by integrating the back emf as stated in Eq. (1) and electromagnetic torque estimation can be done by (4). From (1) it has been seen that stator resistance variation will cause to change the stator flux which will in turn effect the estimated torque, which will deteriorate the effectiveness of the robustness and faster response of the DTC, which is described in Fig. 3.
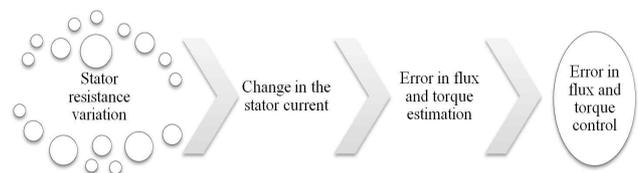

Fig.3. Effect stator resistance variation on the DTC drive

3. Stator Resistance Estimation Using ANN

Machine model used in the DTC is not dependent on all machine parameters except stator resistance. So the current is only affected by the variations of stator resistance not by others parameter. Flux and torque commands are used to determine current vector. It means for constant torque and flux command, stator current is dependent only on the stator resistance of the motor. So any variation in stator current indicates the variation in stator resistance [31, 35] and also there is a nonlinear relationship between stator current and stator resistance [31, 34]. The basic structure for stator resistance adaptation described by Fig. 4 is expanded for estimation of stator resistance of induction motor as presented in Fig. 5 Two distinct observers are used for estimating stator current vectors of IM.

Eqs. (6) and (7) is known as voltage model of induction motor which based on currents and voltages and Eqs. (8) and (9) is known as induction motor current model which based on rotor speed and currents.

Voltage model:

$$\frac{d\omega_{rd^s}^{vm}}{dt} = \frac{L_r}{L_m}(v_{sd^s} - R_s i_{sd^s} - \sigma L_s \frac{di_{sd^s}}{dt}) \tag{6}$$

$$\frac{d\omega_{rq^s}^{vm}}{dt} = \frac{L_r}{L_m}(v_{sq^s} - R_s i_{sq^s} - \sigma L_s \frac{di_{sq^s}}{dt}) \tag{7}$$

Current model:

$$\frac{d\omega_{rd^s}^{im}}{dt} = \frac{1}{T_r}(L_m i_{sd^s} - \omega_{rd^s}^{im} - \omega_r T_r \omega_{rq^s}^{im}) \tag{8}$$

$$\frac{d\omega_{rq^s}^{im}}{dt} = \frac{1}{T_r}(L_m i_{sq^s} - \omega_{rq^s}^{im} + \omega r T_r \omega_{rd^s}^{im}) \tag{9}$$

From eqn. (6) and (8)

$$\frac{1}{T_r}(L_m i_{sd^s} - \omega_{rd^s}^{im} - \omega r T r \omega_{rq^s}^{im}) = \frac{L_r}{L_m}$$
$$(v_{sd^s} - R s i_{sd^s} - \sigma L_s \frac{di_{sd^s}}{dt}) \tag{10}$$

$$\sigma L_s \frac{di_{sd^s}}{dt} = v_{sd^s} - R_s i_{sd^s} - \frac{L_m}{L_r T_r}$$
$$(L_m i_{sd^s} - \omega_{rd^s}^{im} - \omega r T r \omega_{rq^s}^{im}) \tag{11}$$

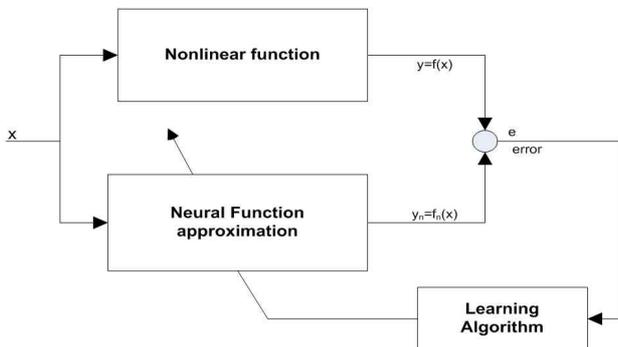**Fig. 4.** Training process of the neural approximator

Eq. (11) can be written in the discrete form as follows

$$\sigma Ls \frac{i_{sd^s}(k) - i_{sd^s}(k-1)}{T_s}$$
$$= v_{sd^s}(k-1) - Rs i_{sd^s}(k-1) - \frac{L_m^2}{L_r T_r} i_{sd^s}(k-1) \tag{12}$$
$$+ \frac{L_m}{L_r T_r}\omega_{rd^s}(k-1) + \frac{L_m}{L_r}\omega r\omega_{rq^s}^{im}(k-1)$$

$$i_{sd^s}^r(k) = (\frac{T_s}{\sigma L_s}) v_{sd^s}(k-1) + [(\frac{T_s}{\sigma L_s})\frac{L_m}{L_r T_r}]\omega_{rd^s}(k-1)$$
$$+ [(\frac{T_s}{\sigma L_s})(\frac{L_m}{L_r}\omega r)]\omega_{rq^s}(k-1) \tag{13}$$
$$+ [1 - (\frac{T_s}{\sigma L_s})R_s - (\frac{T_s}{\sigma L_s})\frac{L_m^2}{L_r T_r}]i_{sd^s}(k-1)$$

$$i_{ds}^r(k) = W_1 \omega_{rd^s}(k-1) + W_2 \omega_{rq^s}(k-1)$$
$$+ W_3 v_{sd^s}(k-1) + W_4 i_{sd^s}(k-1) \tag{14}$$

Here,

$$\begin{matrix} W_1 = \left[\left(\frac{T_s}{\sigma L_s}\right)\left(\frac{L_m}{L_r T_r}\right)\right] \\ W_2 = \left[\left(\frac{T_s}{\sigma L_s}\right)\left(\frac{L_m}{L_r}\omega_r\right)\right] \\ W_3 = \left(\frac{T_s}{\sigma L_s}\right) \\ W_4 = [1 - (\frac{T_s}{\sigma L_s})R_s - (\frac{T_s}{\sigma L_s})\frac{L_m^2}{L_r T_r}] \end{matrix} \Bigg\} \tag{15}$$

Eq. (14) can be illustrated by a single layer recurrent neural network which is demonstrated in Fig. 6. There are four inputs and one output node. Weights W_1, W_2, W_3 are directly calculated from the motor speed (ω_r), motor parameters and sampling time (T_s). Considered that motor parameters are constant except stator resistance (R_s).

To train the neural network Back propagation is used as learning algorithm. Adjustment of weight W_4 is done for minimizing the cost function (E) error given below.
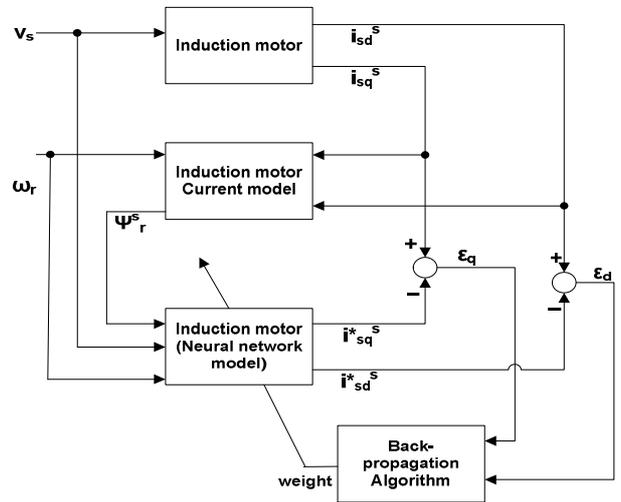

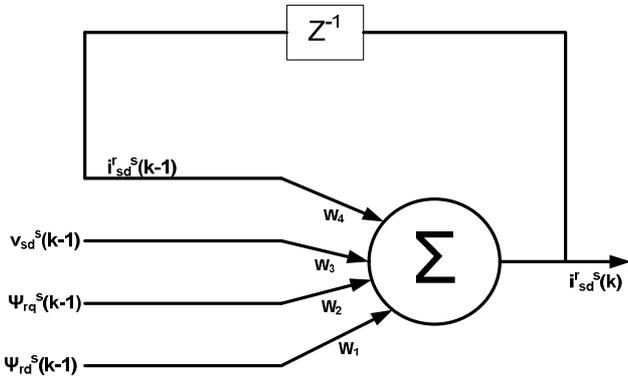**Fig. 5.** Model of neural network for stator resistance estimation

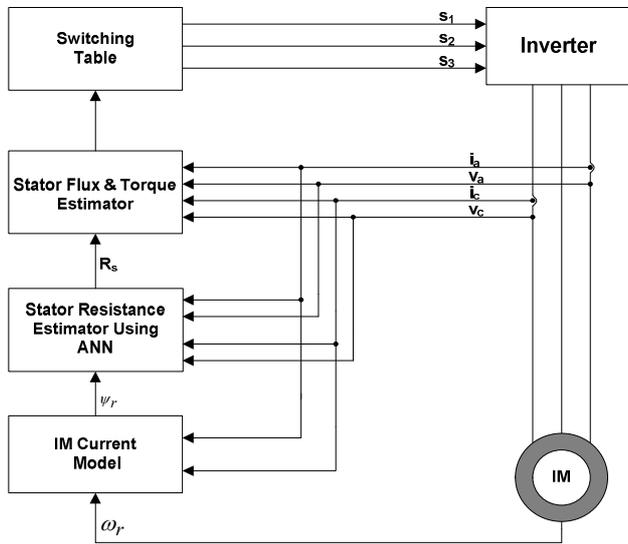**Fig. 6.** Recurrent neural network scheme to estimate the d axis stator current

Fig. 7. Block diagram of DTC-IM drive with online stator resistance tracking

$$E= \frac{1}{2}\ \varepsilon^2 = \frac{1}{2}\ \{i_{sd}{}^s\ (k) - i_{sd}^r{}^s(k)\} \qquad (16)$$

Weight (W4) adjustment is done according to the Eq. (17)

$$W_4\ (k) = W_4\ (k-1) + \eta\ \Delta\ W_4(k) + \alpha\ W_4(k-1) \quad (17)$$

Where η= training coefficient & α=positive momentum constant.

Similarly we can get

$$i_{qs}^r(k) = W_1\ \omega_{qr}(k-1) - W_2\ \omega_{dr}(k-1)$$
$$+ W_3\ V_{ds}(k-1) + W_4\ i_{qs}(k-1) \qquad (18)$$

Eq. (18) can also be illustrated by a recurrent neural network as like as Eq. (14)

Block diagram of the DTC-IM drive with stator resistance estimator is presented in Fig. 7.

4. Simulation & Experimental Results

With the aim of investigating the estimator performance, IM drive system, including the IM, inverter, and direct torque controller is modeled. The efficacy of the proposed neural network stator resistance estimator is validated in MATLAB/Simulink at different operating conditions. Nominal Parameters of IM are given in Table 2. A PI speed controller is used which gives corresponding reference torque and reference stator flux used for the drive is 0.96Wb. An IGBT inverter is being used to drive the IM. The coefficients used to train the network are η=.009 and α=1e-6. In the simulation run, the response of the system with and without the estimator of stator resistance is compared shown in Figs. 8 and 9 respectively where a step change in stator resistance is introduced at 1.0 s. During the operation of the motor stator resistance may vary up to 50%. So, stator resistance of the motor has been increased 20% of the rated value shown in Fig. 8(a) to verify and investigate the effectiveness of the proposed estimator at 1sec.

In the conventional system fixed value of the stator resistance is used. Therefore more ripples introduced in the output torque when changing of the stator resistance take place as illustrated in Fig. 8(b). Zoomed view of torque ripple is presented in Fig. 8(c). From stator flux locus it has been seen that more ripples are introduced around the expected stator flux shown in Fig. 8(e). It has been seen from Fig. 8(d) that there is also small variation in speed.

From Fig. 9(a) it can be seen that estimated value of the proposed estimator can track the actual value of the stator resistance within 50 ms which is shown in the zoomed view of the stator resistance tracking given in Fig. 9(b). Torque and flux ripples are reduced after using the proposed estimator albeit the stator resistance has been changed as presented in Figs. 9(c) and Fig. 9(f) respectively.

From zoomed view of torque given in Fig. 9(d) it has been seen that ripple is reduced after using the stator resistance estimator and also speed becomes stable which is shown in Fig. 9(e) after introducing the stator resistance

Table 2. Induction motor parameter

Parameter	Simulation	Experimental
Rated Power (kW)	3.7	0.9
Rated Voltage (V)	460	400
Rated Frequency (Hz)	60	50
Pole Pair	2	2
Stator resistance(Ω)	1.115	21
Rotor resistance(Ω)	1.083	22.63
Stator inductance(H)	0.209674	0.0563
Rotor inductance (H)	0.209674	0.0846
Magnetizing inductance(H)	0.2037	0.9963
Rated speed(rpm)	1750	1400

estimator.

The control procedure has been carried out using the rapid prototyping and real-time interface system dSPACE with DS1104 control card which consist of Texas Instruments TMS320F240 sub processor and the PowerPC 603e/250 MHz main processor. This card permits the user to build the system in MATLAB/Simulink® and then to transform the model files to real-time codes by the use of MATLAB/Simulink® Real-Time Workshop and control card's Real-Time Interface (RTI). A control-monitor interface is constructed using Control Desk software, which is dSPACE's experiment software, which provides
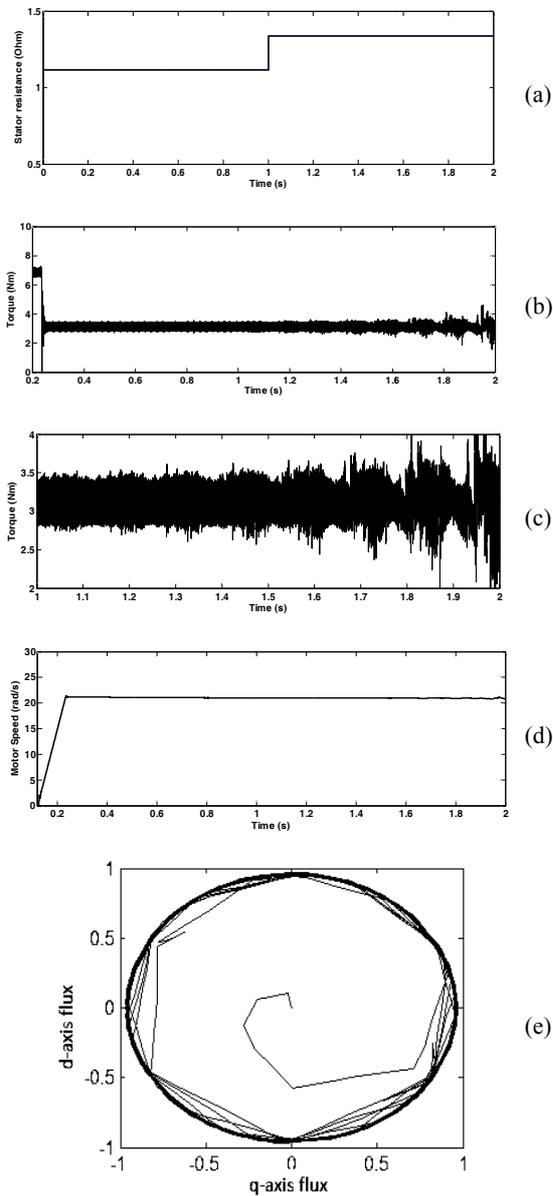
all the functions to control, monitor and automate the experiments and make the controllers development more effective. Total experimental layout and experimental setup is given in Figs. 10 and Fig. 11 respectively.
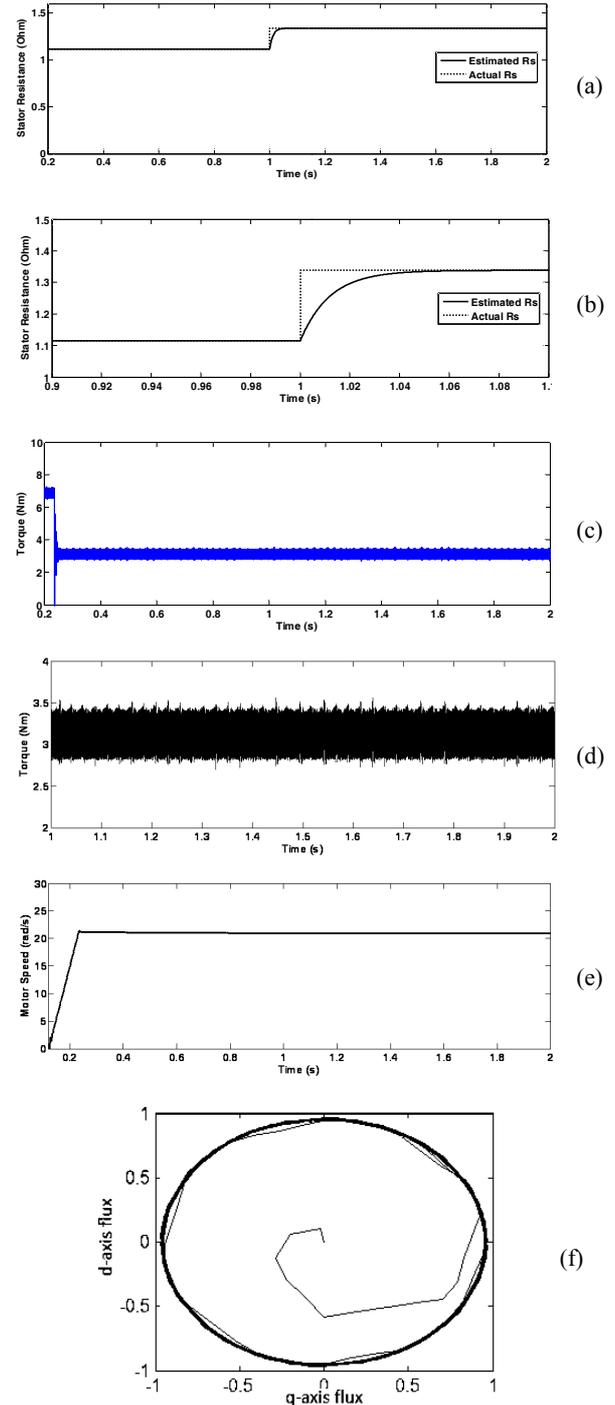

Fig. 8. Stator resistance variation effect: (a) step variation of the stator resistance; (b) electromagnetic torque (N-m); (c) zoomed view of electromagnetic torque (N-m); (d) speed (rad/s); (e) Stator flux locus

Fig. 9. Compansation of the Stator resistance variation effect: (a) step variation of the stator resistance; (b) zoomed view of stator resistance tracking; (c) electromagnetic torque(N-m); (d) zoomed view of electromagnetic torque(N-m); (e) motor speed (rad/s); (f) Stator flux locus
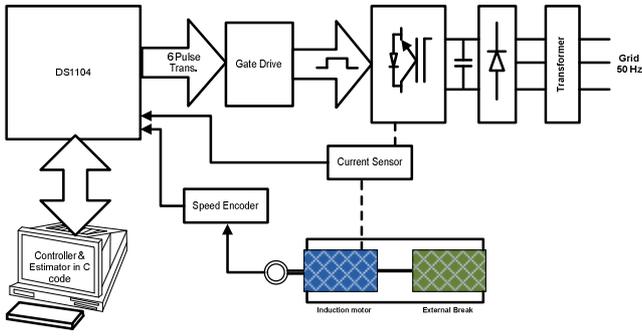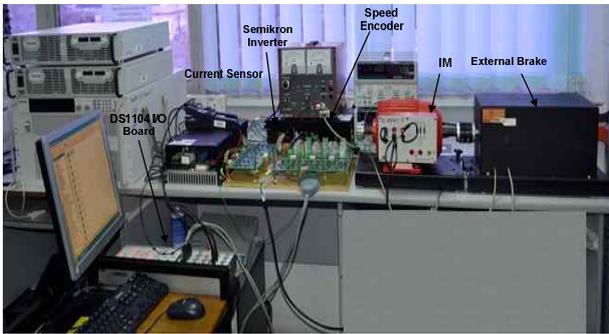
Fig. 10. Experimental layout


Fig. 11: Experimental setup

Table 3. Comparison between proposed estimator and [27, 36-38]

| Indicators Estimators	Oversho- ot	Steady state error	Settling Time(s)
PI [36]	25.33%	Zero	.16
Neuro-fuzzy [36]	2.5%	.0004	.35
Adaptive observer [37]	No overshoot	Tends to zero	1
Stator resistance adaptation [38]	Present	Present	1
Reduced order EKF [27]	No	0.3	3
Proposed ANN	No	Zero	.05

The experimental results found under a load torque of 1.0 Nm which is shown in Fig. 12(a). Estimated stator resistance is illustrated in Fig. 12(c) and also rotor speed and stator flux locus is presented in Figs. 12(b) and Fig. 12(d) respectively.

5. Conclusion

A neural network to estimate online stator resistance of the IM is modeled in this paper. To train the neural network back propagation algorithm is used. It is revealed that the proposed estimator can track changes in stator resistance and also it can converge to steady state value of the stator resistance within around 50 ms. From Table 3 it has been confirmed that proposed estimator is better than the estimators proposed previously as there is no overshoot
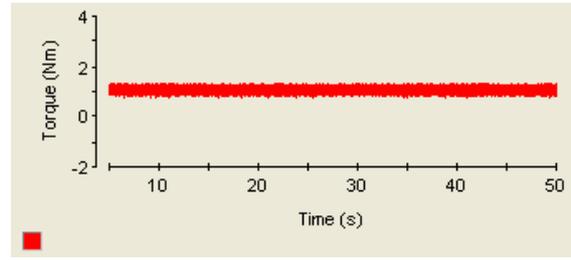
(a)
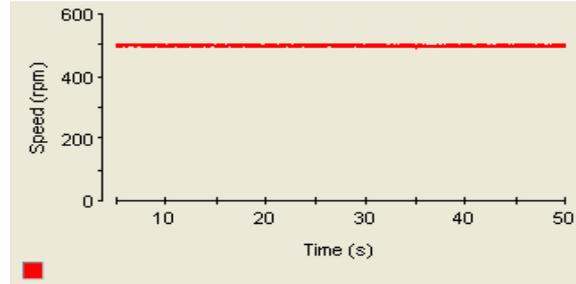
(b)
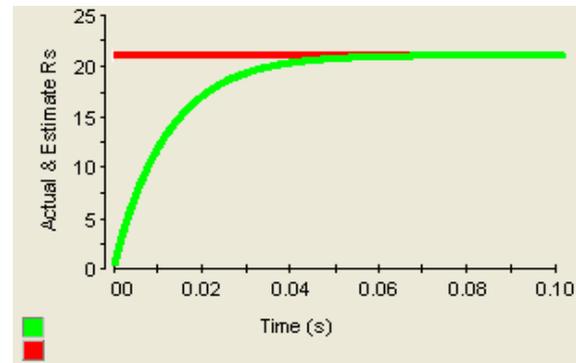
(c)

(d)

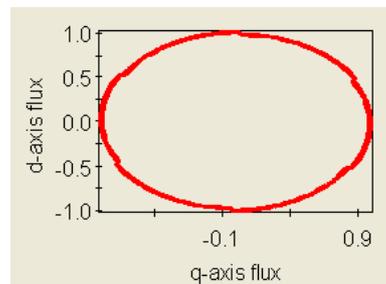**Fig. 12.** Experimental Results; a.Laod torque (Nm) b. rotor speed (rpm) c.estimated resistance (ohm) d. stator flux locus

and also zero steady state error. Experimental results also show the efficacy of the proposed estimator. Utilization of this estimator facilitates the development of a DTC-IM drive system with reduced torque and flux ripple at different operating condition of the motor.

Acknowledgement

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