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Stator resistance estimation using ANN in DTC IM drives

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Abstract

Torque control of induction motors (IM) requires accurate estimation of the flux in the motor. But the flux estimate, when estimated from the stator circuit variables, is highly dependent on the stator resistance of the IM. As a result, the flux estimate is prone to errors due to variation in the stator resistance, especially at low stator frequencies. In this paper, an Artificial Neural Network (ANN) is used to adjust the stator resistance of an IM. A back propagation training algorithm was used in training the neural network for the simulation. The proposed ANN resistance estimator has shown good performance in both the transient and steady states. The system is first simulated with computer software and tested by hardware in the loop. Then, it is implemented using a TMS320C6711, 32-bit fixed point Digital Signal Processor (DSP). Experimental and simulated results prove the usefulness and feasibility of the proposed strategy as compared with conventional methods.

Key Words: *Induction machine, direct torque control (DTC), artificial neural network, stator resistance estimation.*

1. Introduction

Recent advances in power semiconductor and microprocessor technology have made possible the application of advanced control techniques to alternating current (AC) motor drive systems. Direct Torque Control (DTC) has become a popular technique for the control of induction motor (IM) drives as it provides a fast dynamic torque response and is robust to machine parameter variations without the use of current regulators [1-10]. The technique can be implemented easily using two hysteresis controllers and a switching table to select the switching voltage vector.

Stator resistance varies with the operating conditions of the motor. At low speeds, stator resistance is the most important factor in determining the accuracy of speed estimation using DTC. This is because of the fact that the stator resistance voltage drop ($I_s R_s$) is no longer negligible when compared to the applied voltage.

The variations in stator resistance are non-linear and are a function of the amount of current flowing through the stator windings and the speed of the motor shaft. Other factors that contribute to heating the stator are core losses and harmonic motor currents. Thus, compensating for the effect of variation in the stator resistance then becomes necessary [11-14].

This paper presents a model reference adaptive system based ANN estimator to estimate the stator resistance of an IM. Neural networks have yielded improved results in the estimation and control of nonlinear systems. A back propagation training algorithm was used in training the neural network. This work was motivated by the recent use of neural networks in a variety of industry applications, and their demonstrated advantages over conventional controllers, in particular stability, reliability, speed and robustness [15-18].

2. General description of DTC

In general, for a symmetrical three-phase IM, the instantaneous electromagnetic torque is a cross product of the stator and rotor flux linkage space vector, or, in other terms, the stator current space vector and stator flux linkage space vector.

$$T_e = \frac{3}{2} P \bar{\Psi}_s \times \bar{I}_s, \tag{1}$$

where $\bar{\Psi}_s$ is the stator flux linkage space vector and $\bar{I}_s$ is the stator space vector. In Eq. (1), both space vectors are expressed in the stationary reference frame. Considering that $\bar{\Psi}_s = L_s \bar{I}_s + L_m \bar{I}'_r$ and $\bar{\Psi}'_r = L_r \bar{I}_r + L_m \bar{I}_s$ where the primed rotor quantities are expressed in the stationary reference frame, it follows that $\bar{I}_s = \bar{\Psi}_s / L'_s - [L_m/(L_r L'_s)]\ \bar{\Psi}'_r$. Thus, Eq. (1) takes the following form:

$$T_e = \frac{3}{2} P \frac{L_m}{L'_s L_r} \left|\bar{\Psi}'_r\right| \left|\bar{\Psi}_s\right| \sin\gamma. \tag{2}$$

The electromagnetic torque given by Eq. (2) is a sinusoidal function of γ, the angle between the stator and rotor flux linkage space vectors. The magnitude of the stator flux is normally kept constant, and the motor torque is controlled by means of the angle γ. The rotor time constant of the standard IM is typically larger than 100 ms, thus the rotor flux is stable and its variation is slow in comparison to the stator flux. It is therefore possible to effectively achieve the required torque by rotating the stator flux vector directly in a given direction as fast as possible.

Figure 1 shows the stator flux behaviour as compared to the rotor flux after pulsating the stator with a step variation, $\omega_{s0} = \omega_{s0} + \Delta\omega_s$, where ω_{s0} is the initial pulsation and $\Delta\omega_s$ is the step variation. The electromagnetic torque can be quickly changed by controlling the stator flux linkage space vector, which in turn can be changed using appropriate stator voltages. It can be seen that there is direct stator flux and electromagnetic torque control that is achieved by applying appropriate stator voltages. Choosing suitable voltage vectors, which increase or decrease γ, causes the electromagnetic torque to increase or decrease, respectively.

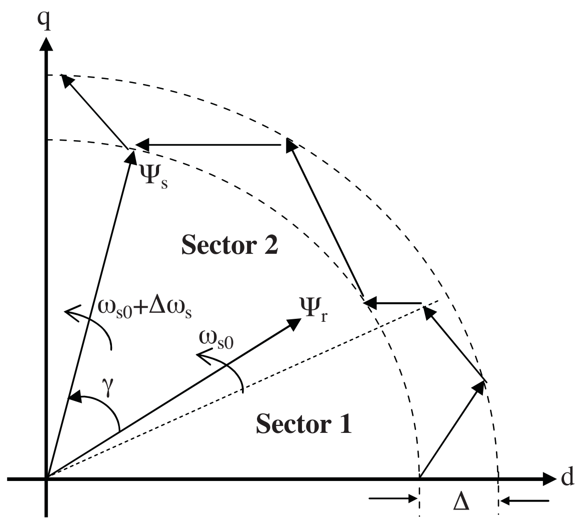


Figure 1. Optimum voltage vector for torque control.

Conventional DTC is presented in Figure 2. In a DTC drive, the stator flux and the electromagnetic torque are controlled directly and independently by the selection of suitable voltage vectors.

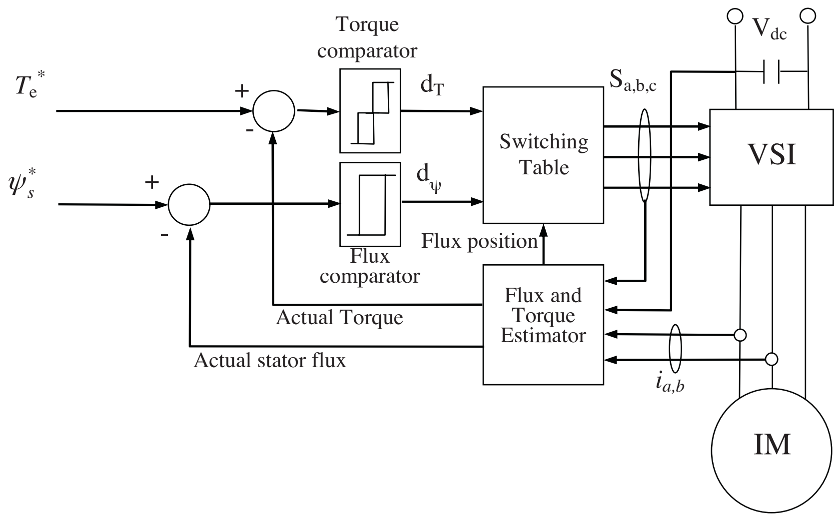


Figure 2. DTC induction motor drive system.

This selection is made based on the output of the torque and flux hysteresis comparators, as well as the stator flux position, so that the stator flux and the torque errors are limited to prescribed hysteresis bands. The required optimum switching-voltage vectors can be selected by using an optimum switching table. This can be obtained by simple physical considerations, including the position of the stator flux, the available switching vectors for a two-level inverter, and the required torque and flux [5].

The outputs of the flux and torque hysteresis comparators are used in the inverter optimal switching table, which also uses knowledge of the stator flux-linkage based on the stator voltage model. The angle of the stator flux space vector is also calculated to determine the sector in which the stator flux space vector is located. It should be noted that inaccurate stator flux estimation results in incorrect voltage vector selection. At low speeds, the open-loop voltage model estimator has large errors due to the variation of the stator resistance, pure integrator drift and noise. In this paper, an improved stator flux estimator that uses neural networks is proposed to overcome these problems.

The true stator flux and torque is estimated using two measured motor stator phase currents: the dc voltage, and the states of the power switches. The torque and flux references are compared with the actual values and a two-level (for flux) and a three-level (for torque) hysteresis controller method produces the control signals.

3. Artificial neural networks

Interest in ANN has grown remarkably over the last two decades. This is due to its novel approach of using the human brain as a model for parallel computation devices, resulting in a very different model than that of a traditional serial computer. The potential benefits of neural networks extend beyond the high computation rates provided by massive parallelism of the networks. Neural networks are commonly classified by their network topology, node characteristics, learning, or training algorithms. Additionally, adaptative and continual learning processes are integral components of an ANN. These properties are especially beneficial in areas where the training data sets are limited or the processes are highly nonlinear. Furthermore, studying real biological networks to design ANNs and solve otherwise intractible problems may also change the way. We think about these problems, leading us to gain new insights and improvements in algorithms [17, 18].

3.1. Back propagation algorithm

The back propagation algorithm is one of the most popular algorithms for training a network due to its success from both the simplicity and applicability viewpoint. The algorithm consists of two phases: the training phase and the recall phase. In the training phase, first, the weights of the network are randomly initialized. Then, the output of the network is calculated and compared to the desired value. Next, the error of the network is calculated and used to adjust the weights of the output layer. Similarly, the network error is also propagated backwards and used to update the weights of the previous layers. Figure 3 shows how the error values are generated and propagated to adjust the weights of the network. In the recall phase, only the feedforward computations using assigned weights from the training phase and input patterns occur. The feedforward process is used in both the recall and training phases [17].

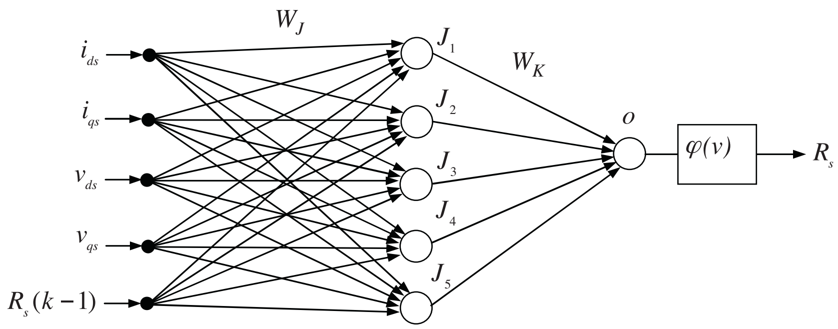


Figure 3. Back propagation in a two layer NN.

Back propagation of error is only utilized during the training phase. First, the weight matrix is first randomly initialised. Then, the output of each layer is calculated starting from the input layer and moving forward toward the output layer. The error at the output layer is calculated by comparing the actual output and to the desired value and updating the weights of the output and hidden layers accordingly.

There are two different methods of updating the weights: the weights can be updated for each of the input patterns using an iteration method, or, an overall error for all the input and output patterns of training sets can be calculated. In other words, either each of the input patterns, or all of the patterns together, can be used for updating the weights. The training phase will be terminated when the error value is less than the minimum set value provided by the designer. One disadvantage of the back propagation algorithm is that the training phase is very time consuming.

During the recall phase, the network with the final weights resulting from the training process is employed. Therefore, for every input pattern in this phase, the output will be calculated using both the linear calculation and the nonlinear activation functions. An important advantage of this process is that it yields a very fast network in the recall phase [17-21].

3.2. Delta training rule

As discussed in the previous section,the back propagation algorithm is an extension of the perception structure that uses multiple adaptive layers. The training of the network is based on the delta training rule method. The relations among the input, activity level and output of the system can be shown as follows:

$$a = w_0 + w_1 i_1 + w_2 i_2 + ... + w_n i_n, \tag{3}$$

or, in matrix form:

$$a = w_0 + W^T I \tag{4}$$

$$o = f(a) \tag{5}$$

where W and I are the weight and input vectors of the neuron, $a$is the activity level of the neuron, $o$is the output of the neuron $(o = \log sig(a))$, and w_0 is the bias value [19]. Suppose the desired value of the output is equal to d.The error e can be defined as follows:

$$e = \frac{1}{2}(d - o)^2 \tag{6}$$

Substituting Eqs. (4) and (5) into Eq. (6), the following relation may be obtained:

$$e = \frac{1}{2}\left[d - f(w_0 + W^T I)\right]^2 \tag{7}$$

The error gradient vector can be calculated as follows:

$$\nabla e = -(d - o) f'(w_0 + W^T I) I \tag{8}$$

The components of gradient vector are equal to:

$$\frac{\partial e}{\partial w_j} = -(d - o) f'(w_0 + W^T I) I_j \tag{9}$$

where $f'(.)$ is the derivative of the activation function. To minimize error, the weight changes should be in the negative gradient direction. Therefore,

$$\Delta W = -\eta \nabla e, \tag{10}$$

where η is a positive constant called the learning factor. From Eqs. (8) and (9), ΔW is calculated as follows:

$$\Delta W = -\eta (d - o) f'(a) I \tag{11}$$

$$\Delta w_j = -\eta (d - o) f'(a) I_j \quad j = 0, 1, 2, ..., n \tag{12}$$

Therefore, we update the weights of the network as

$$w_j(new) = w_j(old) + \Delta w_j \quad j = 0, 1, 2, ..., n. \tag{13}$$

4. Proposed stator resistance estimation

Generally, in DTC drive systems the stator flux is estimated using a voltage model that is dependent on stator resistance only. The DTC motor drive system can become unstable when the set value of the stator resistance used in the controller differs from the actual value in the machine. In order to overcome this problem, the stator resistance value used in the controller must be adapted to follow changes in the actual stator resistance.

To improve flux control at low speeds and select the optimum stator voltage vector, a technique that corrects for the effects of the $I_s R_s$ voltage drop and variation in the value of the actual stator resistance must be utilized. To compensate for the $I_s R_s$ voltage drop at low speed, a measurement of the stator winding resistance voltage drop, which is a function of the stator current, is incorporated into the flux estimator.

In this study, a Model Reference Adaptive System (MRAS) with an ANN adaptation is used to estimate the stator resistance in DTC controlled IM drives. In this scheme, the stator resistance is estimated using the error of active power as the reference input to the adaptation mechanism [15,16,18,19]. Here, the aim is to estimate the stator resistance so the stationary reference frame is used. The MRAS scheme is simple and does not require additional transducer. With this method, the stator resistance is estimated using only stator current and voltages without interrupting the controller or motor operation.

$$\bar{V}_s = R_s \bar{I}_s + p\bar{\Psi}_s \tag{14}$$

$$v_{sd} = R_s i_{sd} + p\psi_{sd} \tag{15}$$

$$v_{sq} = R_s i_{sq} + p\psi_{sq} \tag{16}$$

$$P_a = v_{sd} i_{sd} + v_{sq} i_{sq} \tag{17}$$

The active power can be rewritten using Eq. (15) and Eq. (16) as follows:

$$P_a = R_s (i_{sd}^2 + i_{sq}^2) + i_{sd} p\psi_{sd} + i_{sq}\psi_{sq} \tag{18}$$

$$P_a = R_s (i_{sd}^2 + i_{sq}^2) + i_{sd} L_s p i_{sd} + i_{sq} \sigma L_s p i_{sq} \tag{19}$$

According to the theory of MRAS, Eq. (17) and Eq. (19) can be used as the reference for adjustable models to estimate the stator resistance. The block diagram for the stator resistance estimation scheme is shown in Figure 4.

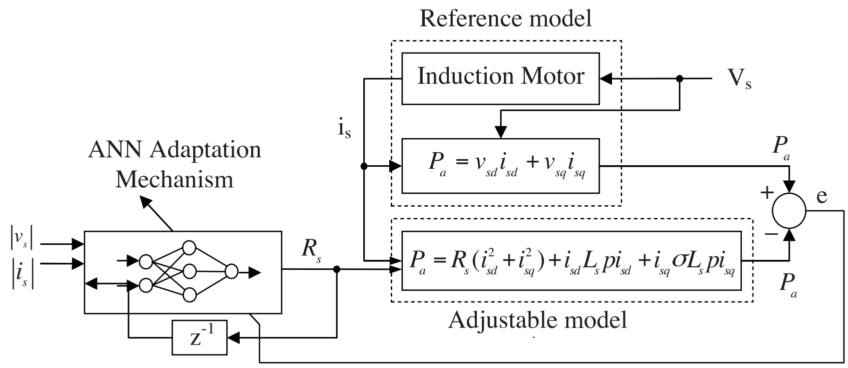


Figure 4. Proposed MRAS based stator resistance estimator with ANN.

In the experimental and simulation studies, the weights related to the stator resistance estimation algorithm based on MRAS using the adaptive mechanism are determined as follows:

1. $[W_J]_{5\times5}$ and $[W_K]_{5\times1}$ weights are chosen between (-1,+1) randomly.
2. The activation function (sigmoid) for neurons is chosen.
3. The input values of the line are the stator resistance as found in the former experiment, and the components of the stator currency and voltage.
4. The input vector I is applied into the line entry.
5. The stator resistance, the output established by the first set of weights, is calculated.
6. The active power error is calculated by giving the stator resistance as an input to MRAS.
7. The back propagation algorithm and the error expand at the same time to decrease the negativeness and the weights belonging to all layers.
8. Until the active power error value taken from the MRAS is lower than a reference value, steps 6 through 8 are repeated for each vector in training process.
9. When the error value is lower than the reference value, the training process ends. In that case, the ANN and the stator resistance are taken out of the process.
10. The present timing of the stator resistance on the trained network is calculated. If the active power error value coming from MRAS is bigger than a reference value, the fourth step is repeated to train the process again. Otherwise, the trained process values are kept as is.

The full block diagram of the algorithm to compute the resistance estimate based on an MRAS that uses the proposed ANN adaptation mechanism is shown in Figure 4. In Figure 5, the full block diagram of the IM drive system controlled by the DTC, which uses the proposed stator resistance estimator, is presented. Here, the Proportional Integral (PI) controller is used to transfer the speed feedback into the torque reference value. So, the process is able to perform speed control. Thus, not only the torque, but also the speed can be controlled.

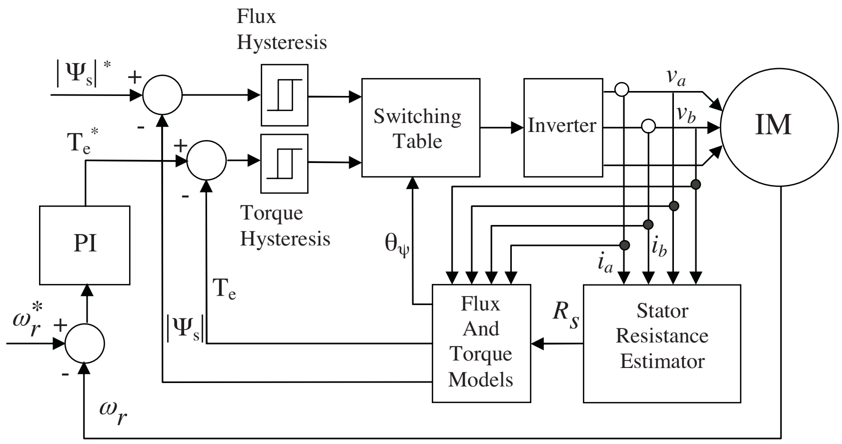


Figure 5. Block diagram of the dtc induction motor drive system.

5. Simulation and experimental results

A simulation of the proposed stator resistance estimator for the DTC IM drive has been carried out using a commercial software package. A simulation has also been performed using a PI regulator as the adaptation mechanism in the MRAS estimator. In both estimators 36.1 Ω is used as the initial stator resistance value. The motor parameters used in the simulations are given in Table 2.

Table 1. Switching table.

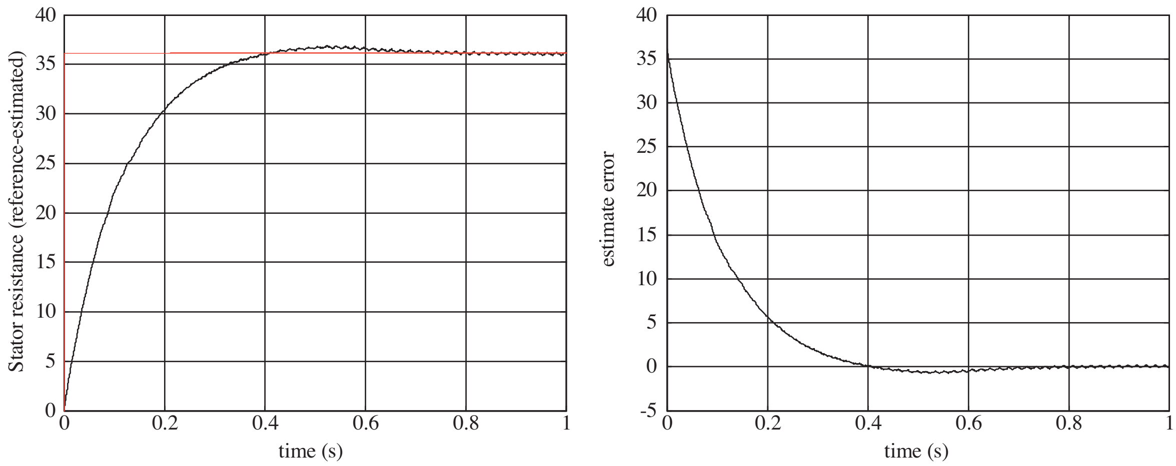
d_ψ	dt_e	sector 1	sector 2	sector 3	sector 4	sector 5	sector 6
1	1	V_2	V_3	V_4	V_5	V_6	V_1
	0	V_7	V_0	V_7	V_0	V_7	V_0
	-1	V_6	V_1	V_2	V_3	V_4	V_5
0	1	V_3	V_4	V_5	V_6	V_1	V_2
	0	V_7	V_0	V_7	V_0	V_7	V_0
	-1	V_5	V_6	V_1	V_2	V_3	V_4

Table 2. Parameters of induction motor and settings.

Power, P_N	0.37 kW
Frequency, f_N	50 Hz.
Supply Voltage (Delta/Star cont.) CCCon	0-240/380-415 V
Line current, I_N (Delta/Star cont.)	1.9/1.1 A
Pole pairs, P	2
Stator resistance, R_s	36.1 Ω
Rotor resistance, R_r	23.5 Ω
Stator self inductance, L_s	0.8 H
Rotor self inductance, L_r	0.8 H
Mutual inductance, M	0.53 H
Inertia, J	0.002 kg-m^2

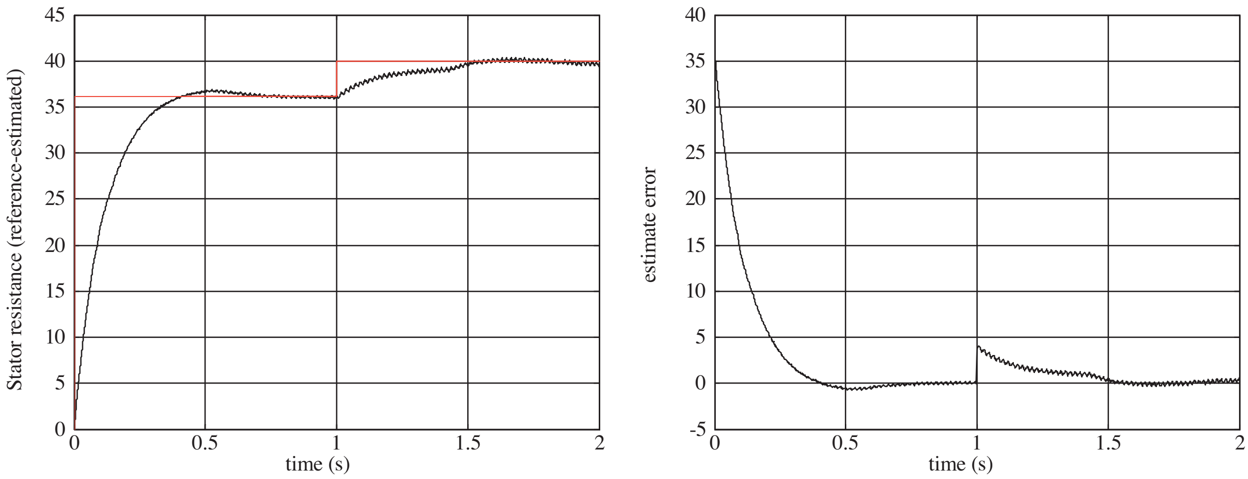
In the simulation, the proposed DTC drive is operated in speed control mode with a stator flux reference of 0.8 Wb. Figures 6 and 7 show the simulation results of the stator resistance as estimated using the classical

PI regulator. In Figure 8, the simulation results of the stator resistance estimated using the ANN are shown. The simulation results of the estimate errors of the stator resistance are also presented in Figures 6-8.



(a) (b)

Figure 6. Stator resistance estimation results with PI; (a) Estimated resistance, and (b) Estimation error.



(a) (b)

Figure 7. Step change stator resistance estimation results with PI; (a) Estimated resistance, and (b) Estimation error.

The experimental set-up of the proposed DTC motor drive system is shown in Figure 9. The setup consists of a 0.37 kW cage-rotor IM, an Insulated Gate Bipolar Transistor (IGBT) inverter, a 200 MHz TMS320C6711 DSP from Texas Instruments, and an 8 channel, 200 kHz, ADS8364 Evaluation Module (EVM) Analog-to-Digital Converter (ADC) board. Additionally, in Figure 9, the success of the proposed estimation method under possible changes in resistance is presented. In Figure 10, the results of stator resistance estimation achieved in experiments are shown. Here, it is observed that the simulation and experimental results support

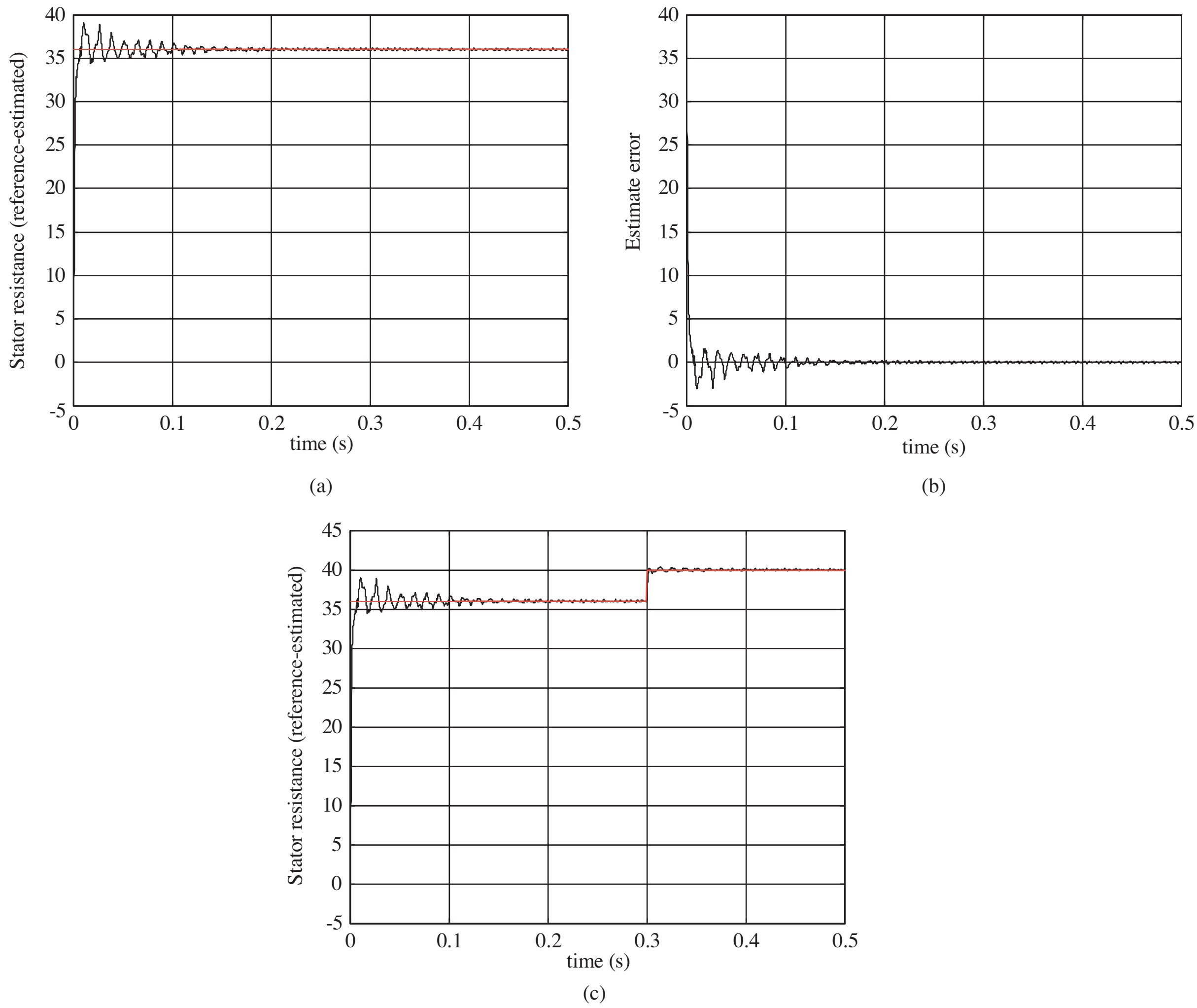


Figure 8. Simulation results; (a) Reference and estimated stator resistance, (b) Estimation error, and (c) Step change reference and estimated stator resistance.

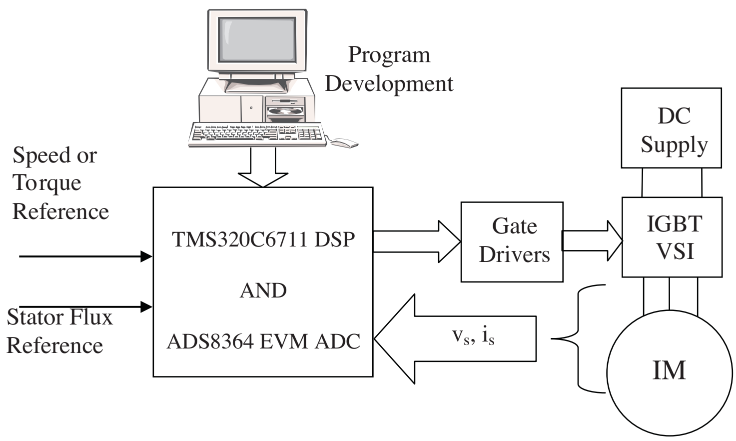


Figure 9. Experimental set-up.

each other. The experimental results obtained under no load for the active power error, i.e. the ANN training signal, using the MRAS-based ANN resistance estimate, are shown in Figure 11. The experimental results obtained under a load of 0.5 Nm for the torque, actual rotor speed and stator d-axis current using the MRAS-based ANN resistance estimate are shown in Figure 12. Finally, in Figure 13 and Figure 14 the experimental stator currents and stator voltages of two phases received from the oscilloscope are shown, respectively.

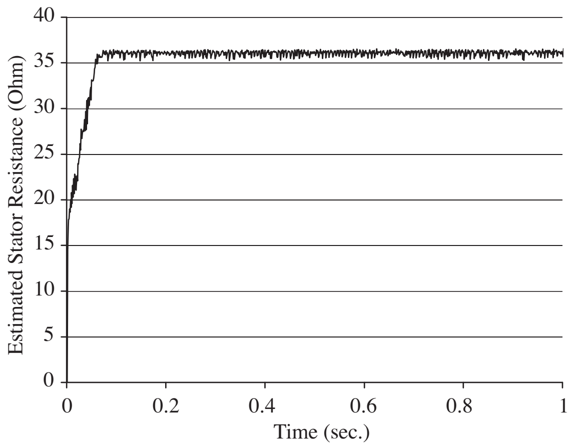


Figure 10. Estimated stator resistance (experimental).

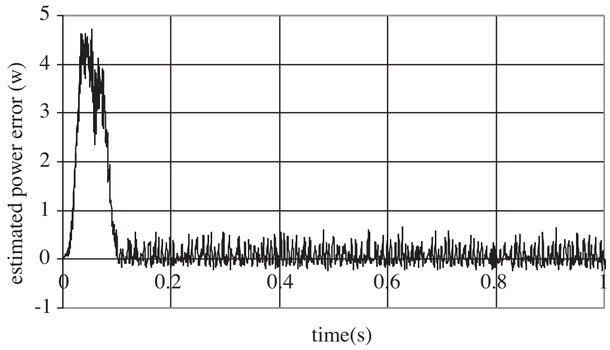


Figure 11. Experimental active power estimation error or training signal (w).

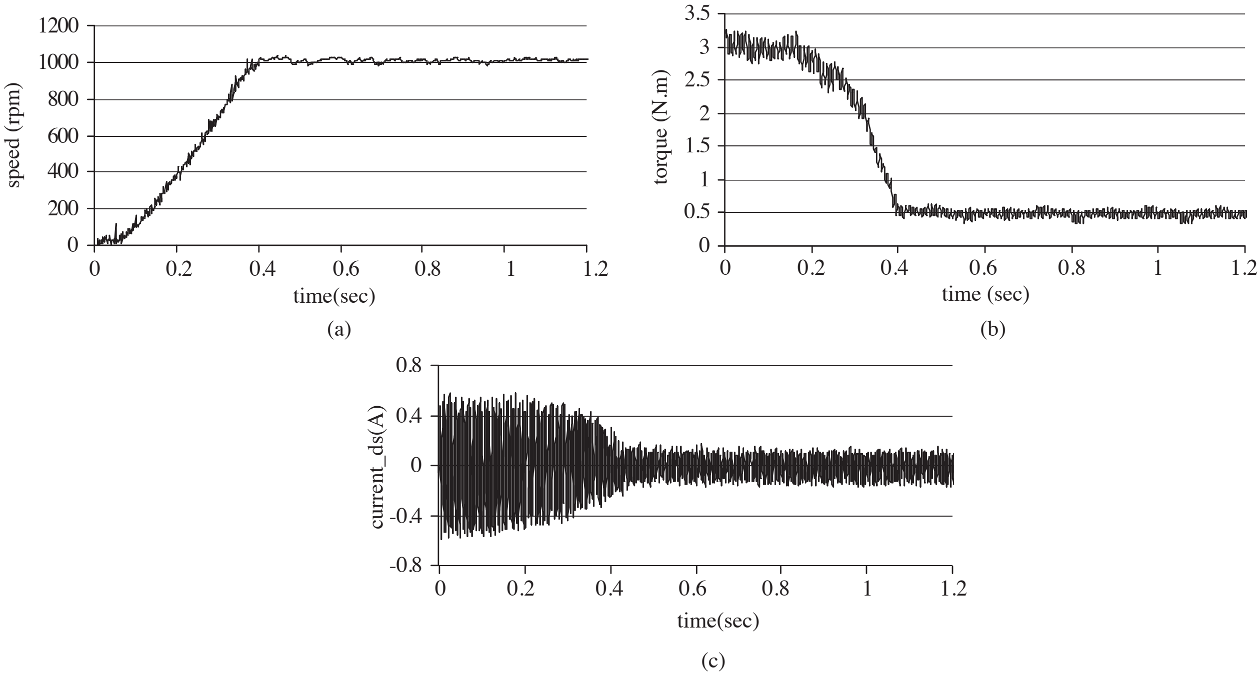


Figure 12. Experimental results in load (T_L =0,5 Nm); a) Rotor speed, b) lectromagnetic torque, and c) Stator current d-axis.

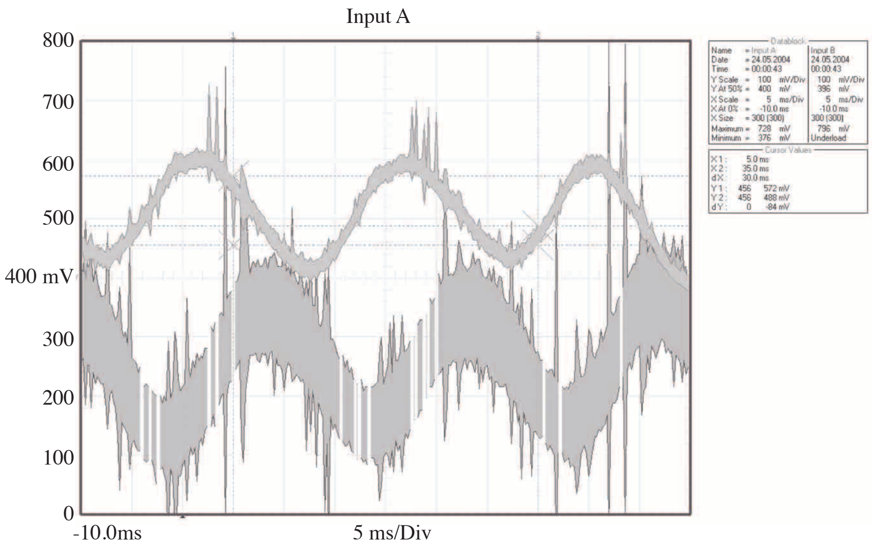


Figure 13. Experimental stator currents: a-phase and b-phase.

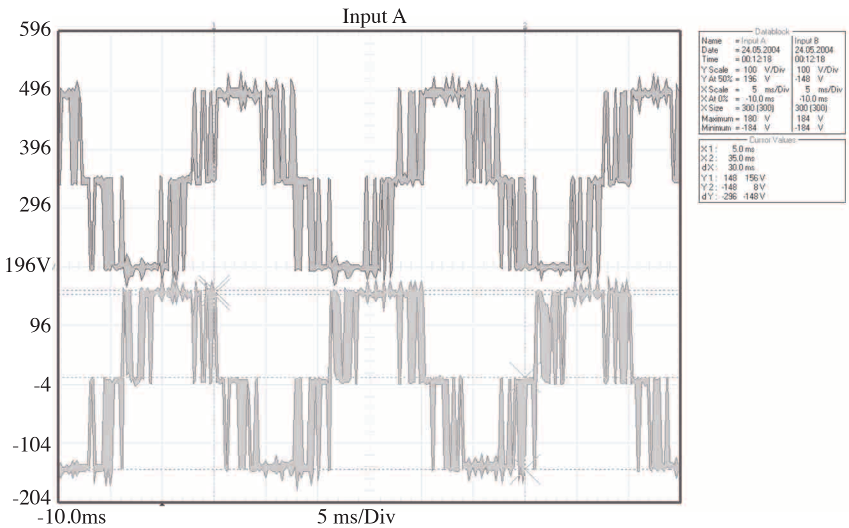


Figure 14. Experimental stator voltages: a-phase and b-phase.

6. Conclusions

Simulation results obtained show that stator flux estimation using a small neural network structure is effective and gives satisfactory results in a closed loop DTC scheme. A method to improve the performance of the DTC IM drive is presented. The MRAS-based scheme is simpler and it does not require additional transducers. With this method, the stator resistance is estimated using only the stator current and voltages, without interrupting the controller or motor operation.

The ANN algorithm is applied by minimizing the time loss between the computer simulation and physical motor drive using very fast DSP. Thus, any possible problem can be discovered early by the DSP, enabling the system to take measurements for checking itself automatically. The suggested methods are tested experimentally using the TMS320C6711 DSP, the IGBT voltage source inverter, and a three phase IM. Simulation and experimental results both demonstrate the improved performance of our proposed algorithm.

Compensating for the effects of voltage drop across the stator resistance is an important problem for the DTC, especially at low speeds, and is related to the variation of the coil resistance. Thus, these changes are estimated using an ANN based MRAS estimator over a short time and with a minimum error. These real values are substituted into the dynamic equations of the motor. With the functions now having better parameter estimates, we improved performance through the control process.

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