

ROTOR RESISTANCE IDENTIFICATION USING NEURAL NETWORKS FOR INDUCTION MOTOR DRIVES IN THE CASE OF INSENSITIVITY TO LOAD VARIATIONS*

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Abstract– For induction motor drives controlled by the indirect rotor flux oriented control (IRFOC), the rotor resistance variation results in an undesirable coupling between the flux and the torque of the machine, and loss of dynamic performance. This paper presents a scheme for the estimation of rotor resistance using a neural networks (NN) block. In this system the flux and torque have been estimated by using stator voltages and currents. A back-propagation NN receives the flux and torque errors and a supposed rotor resistance at the input and estimates the actual rotor resistance at the output, which is used in the control of an indirect vector-controlled drive system. The neural network has been trained off line with the mathematical model of the control scheme in detuning operations. IRFOC control, used with the NN estimator, has been studied in the detuning condition. The performance of the controller is good, even when the rotor time constant is increased from nominal rate to twice the nominal value, as well as torque variations. In this method, estimation is done quickly and accurately, and its design is simple. Simulation results for a 3-hp induction motor driven by a current-regulated pulse width modulation CRPWM inverter with an indirect vector controller are presented to validate the effectiveness of the proposed technique for the purpose of improving the performance and robustness of the drive.

Keywords– Neural network, vector control, induction motor, rotor resistance, field oriented control, flux estimation, torque estimation

1. INTRODUCTION

Vector control is becoming a standard tool for industrial motor drives. Two different approaches are possible in the area of vector control: the direct vector control in which the rotor flux position and amplitude are estimated, and the indirect vector control in which only the rotor flux position is used [1, 2].

The indirect rotor flux oriented control method (IRFOC) offers the most interesting characteristics and is thus widely used in high performance drives [3]. The main features of the IRFOC are the simplicity of its implementation and the linearity of its steady state torque–slip characteristics. So, it constitutes a judicious and attractive choice for a generalized implementation of high performance adjustable speed ac drives using induction motors.

The IRFOC is a feed-forward control method and is very sensitive to the variation of motor parameters [4, 5]. This is due to the fact that all indirect methods of field orientation are based on the inverse model of the machine [3] with constant parameters.

Indirect vector control of an induction motor presents good tracking for flux and immediate tracking for torque. With regard to the fact that a successful implementation of the field-oriented control requires

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an accurate calculation of the slip frequency, a mathematical model of the machine is used. The errors in the model parameters can cause incomplete decoupling between flux and torque; the result is a mismatch between the torque command and the motor torque in the steady state mode on the one hand, and an oscillatory response of the transient torque on the other [4].

Detuning of rotor time constant is the most effective in unsuccessful implementation of an IRFOC scheme [5], and unfortunately it may vary widely with the operational parameters of the motor such as temperature, frequency and the saturation level of the machine. High performance control requires an accurate estimate of the machine parameters in all operating points; it should be done continuously on-line to obtain a reliable estimate of machine variables.

Various schemes have been proposed for rotor time constant adaptation such as the model reference adaptive control (MRAC) technique [6, 7]. This adaptation is slow and load sensitive. Some of these techniques inject different test signals [8]. An extended kalman filter has also been employed [9]. Some other methods like recursive least squares methods have been proposed in [10, 11].

Artificial neural network (ANN) methods for the estimation of rotor time constant and induction motor parameters were also investigated [12-16]. However, most of the techniques require extensive on-line mathematical calculation, which will certainly increase the hardware complexities and cost. Also some of them are unrobust in load torque variation cause, making them unsuitable for practical applications. Hence a simple universally acceptable method is yet to be discovered [17, 18].

The proposed estimation block in this paper consists of two parts. At first, flux and torque are estimated by using the measured voltage and current. Then, a neural network estimator, which is fed by flux and torque errors and a supposed rotor resistance, estimates the actual rotor resistance. This method has shown some advantages such as stability, reliability, rapid convergence and robustness over load torque variations.

In section 2, the rotor time constant estimation schemes proposed in the literature have been reviewed. Section 3 describes the dynamic modeling of indirect vector control of an induction motor. The principles of artificial neural networks are presented in section 4. The principles of the proposed rotor resistance estimator, including rotor flux and torque estimation, neural network estimator and its training procedure are presented in section 5. System simulation studies are included in section 6. Concluding remarks are finally provided in section 7.

2. REVIEW OF ROTOR TIME CONSTANT ESTIMATION TECHNIQUES

The estimation of the rotor time constant constitutes a subject of interest for several research teams, and several solutions have been proposed in the literature [6-18]. Most of these methods require intensive calculations to converge and are time consuming [8, 9]. Furthermore, they either require accurate knowledge of stator resistance [8, 14] or are adapted only for specific operating conditions and are sensitive to load changing [6].

The model reference adaptive control (MRAC) has been used in references [6, 7]. This method requires calculation of two functions, F^* and F , using control variables that ensure the condition of flux orientation and machine variables, respectively. The difference between functions F^* and F constitutes a condition of de-tuning and must be canceled. In this method, precise estimation of stator resistance R_s is mandatory.

Reference [9] proposes using Extended Kalman Filter (EKF) to estimate rotor resistance. It has modeled the rotor resistance as an additional state variable of the machine, and the harmonic content generated by the PWM inverter is modeled as white Gaussian noise. This method requires intensive calculations and manipulation of large matrices and vectors. Moreover, before implementation, an off-line

calculation is necessary, using input variables corresponding to a certain operating point (linearization). This method presents the risk of nonconvergence, especially if the operating conditions are different from those used for off-line calculations.

The concept of a deviation angle of the flux vector along d-axis has been presented in reference [10]. Calculation of this angle requires knowledge of stator voltage and current, and depends on the stator resistance R_s , mutual inductance M and rotor inductance L_r . Since stator resistance is used, this estimation scheme cannot be reliably used in a low speed region; hence, an alternative precise identification process must be available.

The recursive least squares (RLS) [11] method is shown to provide a poor estimate of the rotor resistance, with errors of 20-30% in the estimated value compared with the possible thermal variations in rotor resistance of up to 50%.

Artificial neural network (ANN) methods for the estimation of the rotor time constant of the induction motor were also investigated. In [12], an adaptation scheme based on the steady state equations of a current-fed induction motor is proposed. Its principal limitations are related to: the dynamic time response, which is slower than the proposed estimator; the selection criteria of the training data sets that must precisely represent the operating conditions of the motor; and the training time of the ANN, which can be excessive. The result of [13, 14] shows that these systems converge within 75 ms and 2 s. However, these methods present the risk of slow convergence. The result of [15] is for one amount of torque reference, so it will be sensitive to load variation.

3. DYNAMIC MODELING OF INDIRECT ROTOR FLUX ORIENTED CONTROL OF AN INDUCTION MOTOR

In an IRFOC, the synthesis of the unit vector is independent of the machine terminal conditions. Fig. 1 explains the principles [3]. At any instant, the q^e electrical axis is at angular position θ_e with respect to the q^s axis. The angle θ_e is given by the sum of rotor angular position θ_r and slip angular position θ_{sl} . The rotor flux ψ_r is aligned with the d^e axis.

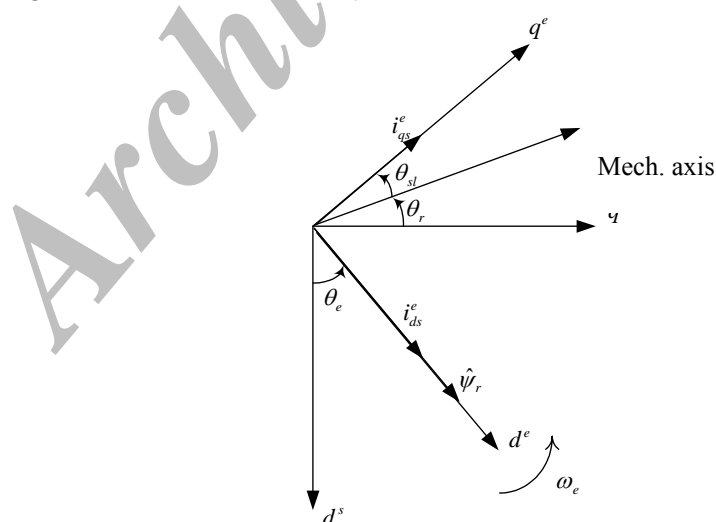


Fig. 1. Phasor diagram for indirect vector control

The following equations are valid for rotating frame d^e - q^e equivalent circuits

$$\frac{d\psi_{qr}^e}{dt} + \frac{R_r}{L_r}\psi_{qr}^e - \frac{L_m}{L_r}R_r i_{qs}^e + \omega_{sl}\psi_{dr}^e = 0 \tag{1}$$

$$\frac{d\psi_{dr}^e}{dt} + \frac{R_r}{L_r} \psi_{dr}^e - \frac{L_m}{L_r} R_r i_{ds}^e - \omega_{sl} \psi_{qr}^e = 0 \quad (2)$$

$$T_e = \frac{3}{2} \left(\frac{P}{2} \right) \frac{L_m}{L_r} (i_{qs}^e \psi_{dr}^e - i_{ds}^e \psi_{qr}^e) \quad (3)$$

For decoupling control it is desirable that

$$\psi_{qr}^e = \frac{d\psi_{qr}^e}{dt} = 0 \quad (4)$$

$$\psi_{dr}^e = \hat{\psi}_r = \text{constant} \quad (5)$$

$$\frac{d\psi_{dr}^e}{dt} = 0 \quad (6)$$

Substituting the first two conditions, Eqs. (1) and (2) can be simplified as:

$$\omega_{sl} = \frac{L_m}{\hat{\psi}_r} \left(\frac{R_r}{L_r} \right) i_{qs}^e \quad (7)$$

$$\frac{L_r}{R_r} \frac{d\hat{\psi}_r}{dt} + \hat{\psi}_r = L_m i_{ds}^e \quad (8)$$

Substituting $\psi_{qr}^e = 0$ and $\psi_{dr}^e = \hat{\psi}_r$ in the torque expression yields

$$T_e = \frac{3}{2} \left(\frac{P}{2} \right) \frac{L_m}{L_r} i_{qs}^e \hat{\psi}_r \quad (9)$$

The equations above, together with mechanical equation

$$\left(\frac{2}{p} \right) J \frac{d\omega_r}{dt} = T_e - T_l \quad (10)$$

describe the machine model in decoupling control.

Figure 2 shows a system using the indirect method of vector control. i_{ds}^* for the desired ψ_r^* is determined from Eq. (8), and i_{qs}^* for the desired T_e^* is determined from Eq. (9). The set value of slip ω_{sl}^* is related to current i_{qs}^* by Eq. (7). The slip frequency ω_{sl} is added to rotor speed ω_r to obtain ω_e and θ_e . In continuation, the computation for the coordinate changer and two-phase to three-phase transformer will be carried out. The three phase current command is produced by a CRPWM and fed to an induction motor. A successful implementation of the indirect field-oriented control requires an accurate calculation of the slip frequency (see Eq. (7)). The accuracy of this slip frequency calculation depends largely on the accuracy of the motor parameters, especially on the rotor time constant [4]. Hence, an on-line adaptation/estimation of the rotor time constant is necessary for a correct field-oriented operation.

4. PRINCIPLES OF ARTIFICIAL NEURAL NETWORKS

Artificial neural networks use a dense interconnection of computing nodes to approximate nonlinear function [19-21]. As shown in Fig. 2, each node constitutes a neuron and performs the multiplication of its input signals by constant weights, sums up the results and maps the sum to a nonlinear activation function ϕ ; the results are then transferred to its output. A feed-forward ANN is organized in layers: an input layer, one or more hidden layers, and an output layer. The mathematical model of a neuron is given by

$$y = \varphi \left(\sum_{i=1}^N w_i \cdot x_i - b \right) \tag{11}$$

where: (x_1, x_2, \dots, x_N) are inputs from the previous layer neurons, (w_1, w_2, \dots, w_N) are the corresponding weights and b is the bias of the neuron. φ is generally the logarithmic or tangent sigmoidal activation function.

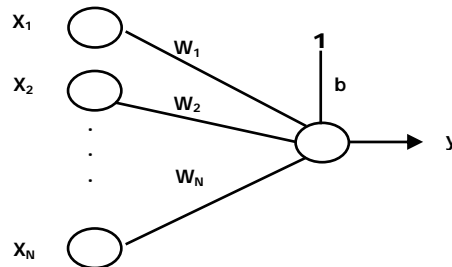


Fig. 2. Structure of neural network elements

The ANN is trained by a learning algorithm that performs the adaptation of weights of the network iteratively until the error between target vectors and the output of the ANN is less than an error goal. The most popular learning algorithm for multilayer networks is the back-propagation algorithm and its variants.

5. PRINCIPLES OF THE PROPOSED ROTOR RESISTANCE ESTIMATOR

Our goal is to develop a technique for estimating the rotor resistance using only stator voltages and currents. It consists of two parts; the first is a flux and torque estimation block whose inputs are voltage and current. It does not depend on rotor resistance. In continuation, the estimated flux and torque are compared with their commands and the errors are computed. If the rotor resistance in an indirect vector controller equals to actual rotor resistance of an induction motor, these errors will be equal to zero. Otherwise, if the rotor resistance has any change, these errors will appear; meanwhile, the magnitude of errors of flux and torque depend on load torque variations. Because the whole system is nonlinear and complex, it is not possible to estimate the rotor resistance simply by using these variables; so, in the second part a neural network (NN) has been used as a rotor resistance estimator. The whole system is shown in Fig. 3.

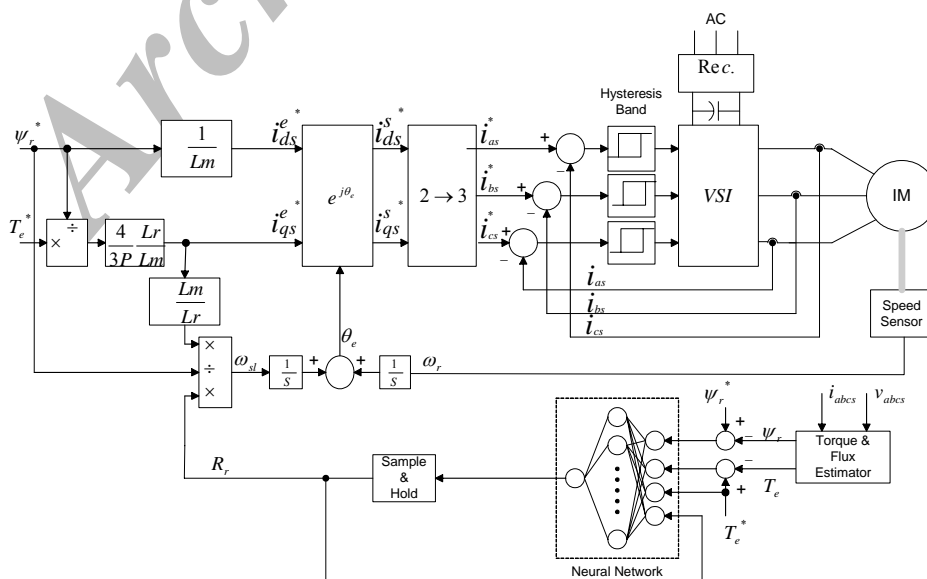


Fig. 3. Block diagram of indirect vector control of an induction motor drive and neural network rotor resistance estimator

a) Rotor flux and torque estimation model

In the proposed system, the inputs of NN block are flux and torque error. So these variables must be estimated. It is possible to establish a flux and torque model which does not use the monitored speed, but uses only the monitored values of stator voltages and currents. This model does not depend on rotor resistance; so, the estimated flux and torque are accurate and correct, even if the rotor resistance has some variation due to temperature variation and skin effect. For this purpose, terminal phase voltages and currents are sensed, and then they are transformed from a three-phase system to the stationary d^s-q^s reference frame.

The following equations of stator voltages and fluxes can be written from stationary frame equivalent circuits [22].

$$v_{qs}^s = R_s i_{qs}^s + \frac{d}{dt} \psi_{qs}^s \tag{12}$$

$$v_{ds}^s = R_s i_{ds}^s + \frac{d}{dt} \psi_{ds}^s \tag{13}$$

$$\psi_{qs}^s = L_s i_{qs}^s + L_m i_{qr}^s \tag{14}$$

$$\psi_{ds}^s = L_s i_{ds}^s + L_m i_{dr}^s \tag{15}$$

The rotor currents can be derived from stator voltages and currents as:

$$i_{qr}^s = \frac{1}{L_m} \int (v_{qs}^s - R_s i_{qs}^s) dt - \frac{L_s}{L_m} i_{qs}^s \tag{16}$$

$$i_{dr}^s = \frac{1}{L_m} \int (v_{ds}^s - R_s i_{ds}^s) dt - \frac{L_s}{L_m} i_{ds}^s \tag{17}$$

The rotor fluxes can be written as:

$$\psi_{qr}^s = L_r i_{qr}^s + L_m i_{qs}^s \tag{18}$$

$$\psi_{dr}^s = L_r i_{dr}^s + L_m i_{ds}^s \tag{19}$$

The rotor flux and torque equations are

$$|\psi_r| = \sqrt{\psi_{dr}^s{}^2 + \psi_{qr}^s{}^2} \tag{20}$$

$$T_e = \frac{3}{2} \times \frac{P}{2} \frac{L_m}{L_r} (i_{qs}^s \psi_{dr}^s - i_{ds}^s \psi_{qr}^s) \tag{21}$$

A computation flow diagram for estimating flux and torque is shown in Fig. 4.

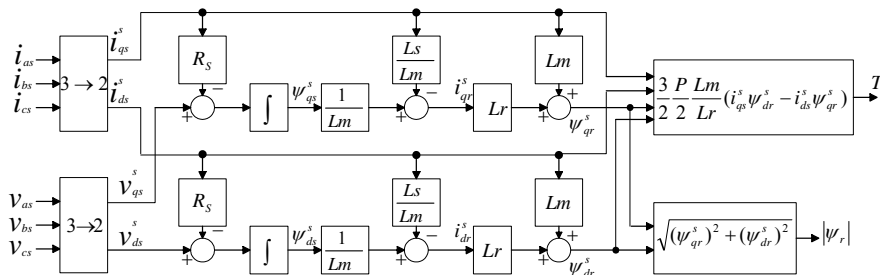


Fig. 4. Estimation of torque and rotor flux from stator currents and voltages

b) Neural network estimator structure

The structure of the proposed feed-forward neural network used for estimation is indicated in Fig. 5. The network is a MLP type neural network with four layers, i.e., input layer, two hidden layers, and the output layer. The circles in the network represent the neurons. The input and output layers have neurons equal to the respective number of signals, whereas each of the hidden layers in the present design has 10 neurons. The topology is defined as 4-10-10-1 network. The network is fully connected, i.e., the output of each neuron is connected to all the neurons in the forward layer through a weight. Besides, a bias signal is coupled to all the neurons of the hidden and output layers through a weight [23]. The hidden layer and output layer neurons have a sigmoid type nonlinear transfer function given as:

$$f(x) = \frac{1}{1 + e^{-(x+\theta)}} \quad (22)$$

where θ is the bias.

The nonlinear transfer function associated with neurons gives nonlinear mapping property of the network [19].

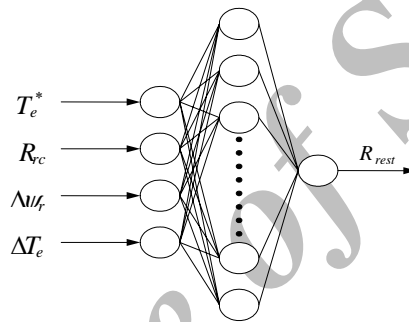


Fig. 5. Topology of the neural network for rotor resistance estimation

The input variable signals are converted to per-unit form through the normalizer gains, and then after computation, the output is brought back to actual values through denormalizer gains, as indicated. The training and the operating procedures are explained in the following sections.

c) Training procedure

The training procedure used in the present project can be summarized as follows:

- Simulate the induction motor drive system as shown in Fig. 3 by MATLAB/SIMULINK
- Generate the input/output data table for different operating conditions as shown in Fig. 6-a. The input data correspond to the estimated flux and torque errors, torque command and the amount of rotor resistance in controller R_{rc} . The output data correspond to the desired estimated rotor resistance R_{ra} .
- Convert the data table to per-unit form and feed to the neural network simulator program located in PC.
- Assign random weights initially to the network by the simulator.
- Select an input/output data pair from the table. For the given input data pattern calculate the network output and compare with the desired data output to derive the error pattern.
- As shown in Fig. 6-b from the error pattern, compute and adjust the network weights by a back-propagation algorithm (gradient descent with adaptive learning rate) so that the new error is small.
- Repeat the above steps with each set of input/output data patterns until the rms error for the entire training set converges below the desired threshold value.
- After completion of the training, test the network performance with arbitrary input pattern to ensure successful training.

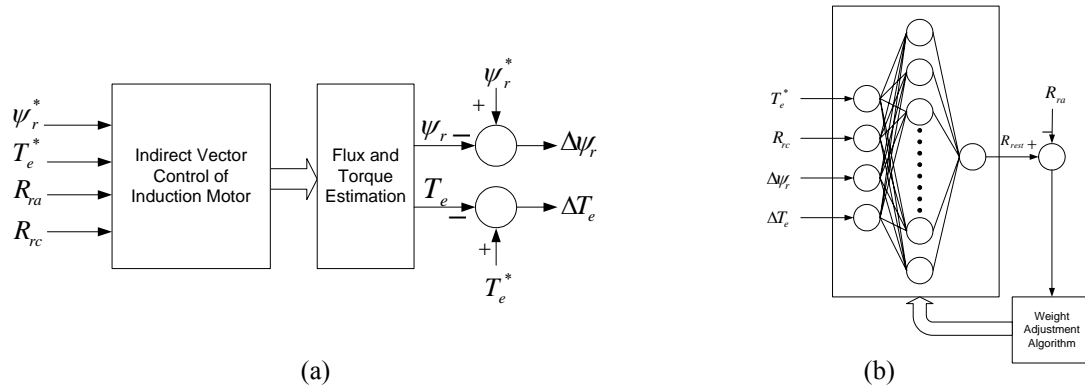


Fig. 6. (a) Generation of input/output data table (b) Procedure of training neural network

6. SYSTEM SIMULATION STUDIES

A 3-hp induction motor was used to simulate the indirect vector control of Fig. 3. Rating and parameters of the machine are given in the appendix. In this system the actual flux and torque are estimated by using stator voltage and current, and the rotor resistance is estimated by a neural network, this estimated value of the rotor resistance is used by IRFOC controller instead of a constant value.

a) Generate matrices of data and training NN

A matrix of input and output data in different operating conditions must be generated to use for training the NN. The input data matrix (23) corresponds to the error of flux $\Delta\psi_r$, error of torque ΔT_e , torque command T_e^* and the rotor resistance that is used in the controller R_{rc} .

$$[input\ data] = [\Delta\psi_r \quad \Delta T_e \quad T_e^* \quad R_{rc}] \tag{23}$$

The output data matrix (24) corresponds to the desired estimated rotor resistance R_{ra} .

$$[output\ data] = [R_{ra}] \tag{24}$$

To generate these data matrices, the above simulated system was tested for different values of R_{rc} , R_{ra} and T_e^* .

To achieve this purpose, the torque command T_e^* was varied from 0.2 pu to 1 pu in 5 steps, each of which it was increased 0.2 pu. The actual rotor resistance R_{ra} was varied from 1 pu to 2 pu in 9 steps, each of which it was increased 0.125 pu. The rotor resistance in the controller was varied from 1 pu to 2 pu in 9 steps, in each of which it was increased 0.125 pu. As a result of these changes of parameters, there will be 405 cases. The IRFOC of an induction motor with a flux and torque estimation block was simulated for all of these cases. In each case, the error of flux $\Delta\psi_r$ and that of torque ΔT_e were derived and saved, and also T_e^* , R_{rc} and R_{ra} were saved. As a result, the matrices of input and output data with 405 rows were produced.

By using these matrices of input and output data a 4-10-10-1 NN has been trained by back-propagation algorithm, as was explained in section 6-2. The initial learning rate η_1, η_2 and the momentum gain α were set to 0.35, 0.4 and 0.7, respectively. The convergence threshold error level was set to 0.001. After 500000 iterations the error level obtained threshold error.

b) Simulation results

After satisfactory training with the help of the simulator program, the weights are downloaded to the prototype network and attempts are made to operate the drive system of Fig. 2 with an NN as an estimator.

The system has been studied in three cases:

Case a: The nominal rotor resistance of 0.4Ω was taken for the controller even though the actual rotor resistance was 0.8Ω due to increasing the temperature. At 2 Sec. the NN estimator is activated, and the

rotor resistance is estimated immediately. Fig. 7a shows the actual and estimated rotor resistance, while Fig. 7b shows the percentage of error before and after using NN estimator. This error is less than % 0.01 after using the NN. Fig. 7c shows the command torque and electromagnetic torque before and after using NN estimator. The command torque is 5 Nm, the actual torque is 3 Nm before using NN estimator and 5 Nm after using it. Fig. 7d shows the command and actual flux before and after using NN. The command flux is 0.45 Wb and the actual flux is 0.5 Wb before using NN.

The results show that before using NN as an estimator the flux and torque have oscillation and some steady state errors.

At 4 Sec. the command torque decreases to 2 Nm and the vector control is done successfully, thus the actual torque and flux follow their commands accurately.

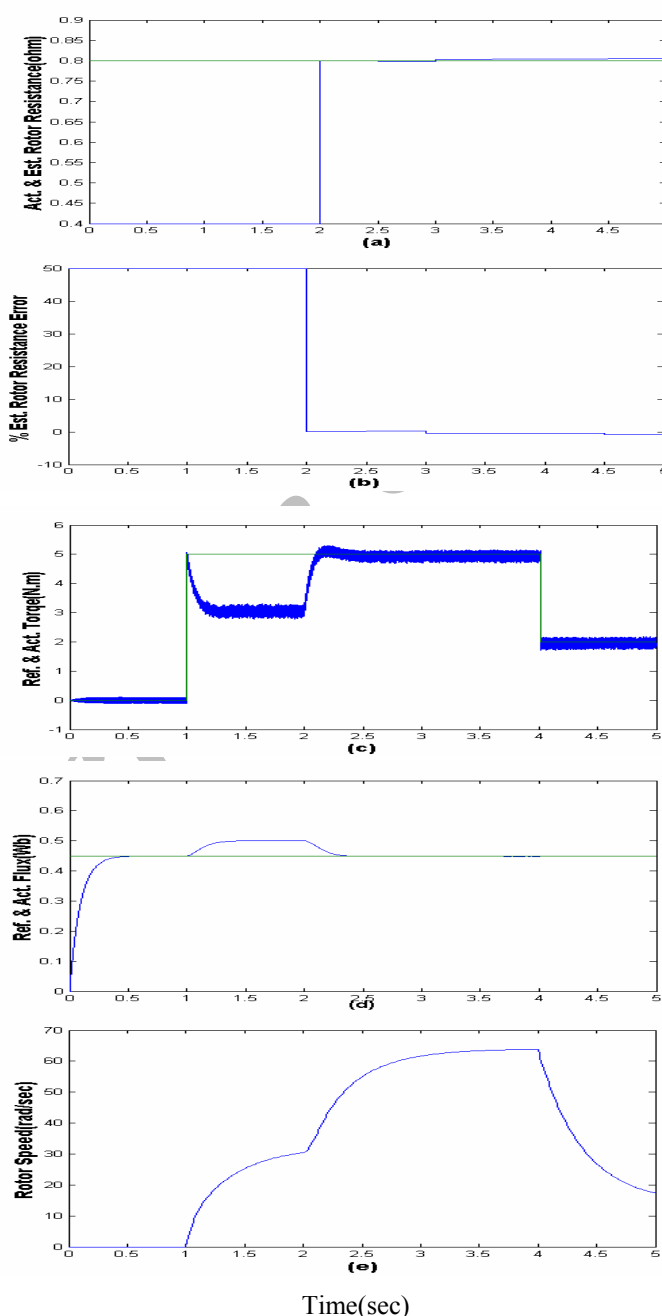


Fig. 7. The performance of the drive before and after using NN estimator, (a) actual and estimated rotor resistance, (b) percentage of estimated rotor resistance error, (c) command and actual torque, (d) command and actual flux, (e) rotor speed

Case b: The performance of the drive without a rotor resistance estimator has been studied. The rotor resistance gradually changes due to temperature changes caused by torque current changing. In Fig. 8a and 8c the variations of rotor resistance and command torque are shown. At first, it is assumed that the command torque is equal to zero, and the rotor resistance is equal to $0.4\ \Omega$. At 2 Sec. the command torque is increased to 2 Nm, and the rotor resistance begins to increase exponentially, reaching to $0.463\ \Omega$. At 7 Sec. the torque is increased to 5 Nm, and the resistance is increased to $0.8\ \Omega$. Then, the torque is decreased to 3 Nm at 15 Sec. and the resistance is exponentially decreased to $0.547\ \Omega$.

In this case, there is no estimator, so the actual rotor resistance has some variations, however the amount of rotor resistance in the controller block has been fixed to $0.4\ \Omega$. The percentage of error between them is shown in Fig. 8b. In Fig. 8c and 8d the command and actual torque and flux are shown. The results show that the performance of vector controller without the estimator will be distracted, so the flux and torque have some oscillations when the command torque is changed and there is some steady state error in them.

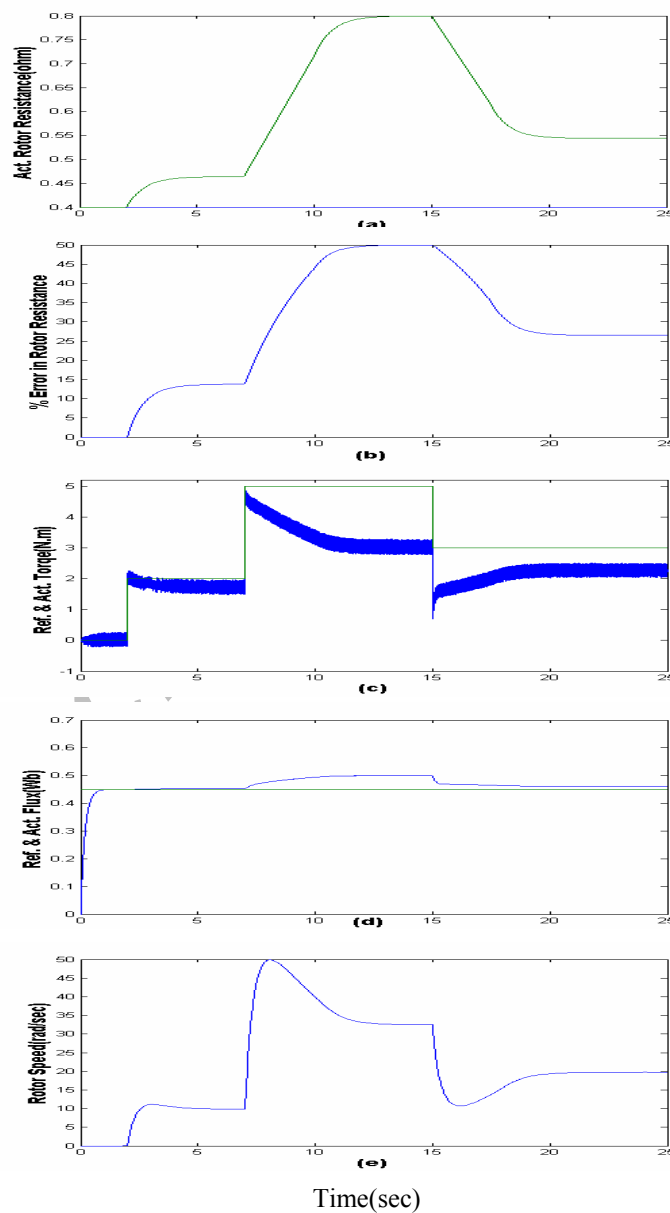


Fig. 8. The performance of the drive without any estimator, the rotor resistance has a gradual change, (a) actual rotor resistance, (b) percentage of estimated rotor resistance error, (c) command and actual torque, (d) command and actual flux, (e) rotor speed

Case c: The rotor resistance has a gradual change like case b, but it is assumed that the neural network estimator has been activated since the beginning of the process. The switching frequency of the network was 5 Hz, hence the neural network frequency was chosen to give the plant enough time to stabilize its output.

The actual rotor resistance and estimated resistance are shown in Fig. 9a. The estimated rotor resistance closely follows the actual rotor resistance. The magnitude of this estimation error is shown in Fig. 9b, the maximum error is less than $\pm 3\%$.

In Figs. 9c and 9d, the command and actual torque and flux are shown. The results show that the vector control is valid when the rotor resistance has some changing, and NN estimator is activated. The actual flux is fixed to its command value, and the actual torque is tracking its command value, without any oscillation or steady state errors.

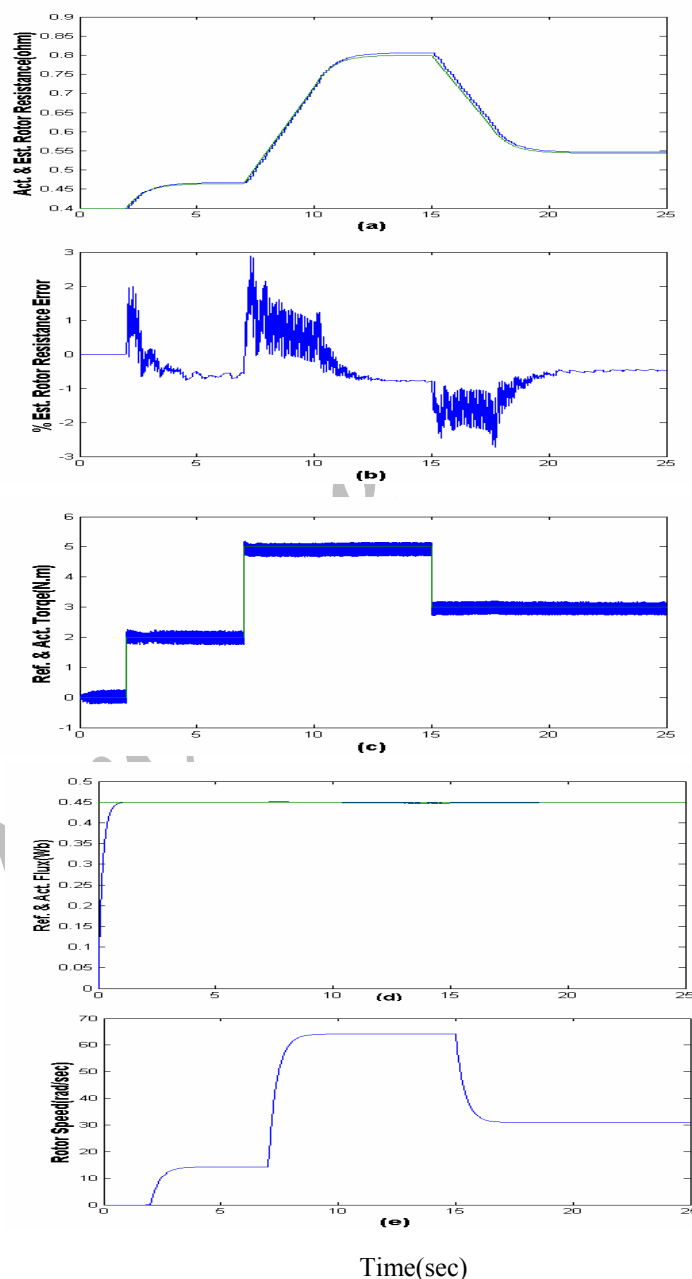


Fig. 9. The performance of the drive with NN estimator, the rotor resistance has a gradual change, (a) actual and estimated rotor resistance, (b) percentage of estimated rotor resistance error, (c) command and actual torque, (d) command and actual flux, (e) rotor speed

7. CONCLUSIONS

In this paper, a simple algorithm has been developed for the estimation of rotor resistance used in indirect rotor flux oriented control of induction motor drives. This estimator is based on neural networks principles and requires only a measurement of accessible variables (voltages and currents). By using these variables, the flux and the torque are estimated. In the next stage, a four-layer neural network with 4-10-10-1 structure is fed by the error of torque, error of flux, command torque, and the amount of rotor resistance in controllers to estimate the actual value of rotor resistance. The NN learning process has been performed off-line based on the mathematical model of the IRFOC system.

The computer simulation results have shown the validity and the feasibility of the proposed method. The switching frequency of the neural network was 5 Hz and the performance of the estimator was found to be excellent in a wide range of rotor resistance variations from $0.4\ \Omega$ to $0.8\ \Omega$. The system can adjust instantaneously and compensate the variation of rotor resistance caused by heating or eddy currents. The maximum estimation error is less than $\pm 3\%$.

Accurate, fast estimation, simplicity of design and insensitivity to load variations are the advantages of this method. The proposed method could be simply adapted to use in the other schemes of flux orientation; namely, stator and air gap flux orientation.

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NOMENCLATURE

i_{ds}, i_{qs}	stator current in d- and q-axis
L_m, L_r	rotor and magnetizing inductances
L_s	stator inductance
P	number of poles
R_r	rotor resistance
R_{ra}	estimated rotor resistance
R_{rc}	rotor resistance that is used in the controller
R_s	stator resistance
T_e^*	command torque
T_e, T_l	developed and load torque
v_{ds}, v_{qs}	stator voltage in d-and q-axis
ψ_{dr}, ψ_{qr}	rotor flux in d-and q-axis
ψ_r	rotor flux
ψ_{ds}, ψ_{qs}	stator flux in d-and q-axis

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APPENDIX

Induction motor data

Rated power	3 hp
Number of poles, p	4
Rated stator voltage	220 V
Rotor resistance, R_r	0.816 Ω

Stator resistance, R_s	0.435 Ω
Magnetizing resistance, X_m	26.13 Ω
Rotor leakage reactance, X_{lr}	0.754 Ω
Stator leakage reactance, X_{ls}	0.754 Ω
Mechanical inertia constant, J	0.089 kg.m ²

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