Stator Resistance Tuning Based on a Neural Network in an Indirect Rotor Field Oriented Control System of an Induction Motor

Dinko Vukadinovic, Mateo Basic, and Ljubomir Kulisic

Faculty of Electrical Engineering Mechanical Engineering and Naval Architecture,
R. Boskovica bb, 21000 Split, Croatia
dvukad@fesb.hr, mateo.basic@gmail.com, ljubomir.kulisic@fesb.hr

Abstract. This paper presents an ANN-based (artificial neural network-based) method of stator resistance tuning in an IRFO (indirect rotor field oriented) control system of an induction motor. This method is based on the conventional two-layer ANN in which the rotor time constant is not a constant parameter and is identified using a model reference adaptive system (MRAS) - based procedure. During the training, rotor speed estimation of the induction motor is enabled. The difference between the actual and the estimated rotor speed is used as a signal for manual stator resistance tuning. Computer simulations and experimental results show the effectiveness of the described approach in a low rotor speed region.

Keywords: induction motor, indirect field-oriented control, neural network, adaptive control.

1 Introduction

An induction motor is the most commonly used electric motor in modern electric drives (e. g. an indirect rotor field oriented (IRFO) control system). In addition, induction motor control systems are known to be extremely non-linear control systems because of induction motor parameter variability under different conditions. Heating of motor windings depends on stator and rotor currents leading to variability of stator and rotor resistances. The accuracy and control quality of the IRFO control system is greatly influenced by the value of rotor resistance R_r used for control. In the past, several methods have been developed for rotor resistance identification. A brief review of the methods for rotor resistance estimation is in [11] and includes the following classification:

1. Spectral analysis techniques ([1])
2. Observer-based techniques ([4, 12, 5])
3. Model reference adaptive system-based techniques ([8])
4. Other methods

The other methods are based on the neural networks or fuzzy logic schemes. In recent years, the use of artificial neural networks (ANNs) in ac drives has been proposed ([5], [2]). Supervised learning methods, where the neural network is trained to learn the input/output pattern presented to it, are typically used ([6]). Two-layer

I. Lovrek, R.J. Howlett, and L.C. Jain (Eds.): KES 2008, Part I, LNAI 5177, pp. 658–665, 2008.

neural networks, where the training step is not required, are, therefore, preferable ([9], [10]). That type of ANN is utilized in this paper.

This paper deals with the IRFO system including inverse rotor time constant identification and stator resistance adjustment. In this paper, the rotor flux space vector is estimated using four different types of induction motor models (so called voltage and current models), and each is described in the stationary reference frame (α,β) or in an synchronously rotating reference frame (d,q). First, the rotor flux magnitude is estimated in the stationary reference frame by the voltage model (reference model) and by the current model (adaptive model). The error signal of the rotor flux magnitude of the two estimators is applied to drive a PI mechanism which provides correction of the inverse rotor time constant. Compared with the method described in [8], the stator resistance is not a constant parameter, but is identified by the two-layer neural network as described hereafter. Second, the rotor flux space vector is estimated in the d,q reference frame by the voltage model (reference model) and by the two-layer ANN model (adaptive model). The errors between rotor flux components are applied to drive a PI estimator which provides rotor speed estimation. The weights dependent on the inverse rotor time constant are tuned based on the inverse rotor time constant identification as described above. The weights dependent on the rotor speed are tuned based upon estimated rotor speed. Any mismatch between actual and estimated rotor speed will result from inaccurate stator resistance. Stator resistance is manually adopted in order to achieve zero error between the actual and estimated rotor speed.

2 IRFO Control System

Fig. 1 shows the IRFO control system of induction motor including both inverse rotor time constant identification and stator resistance identification.

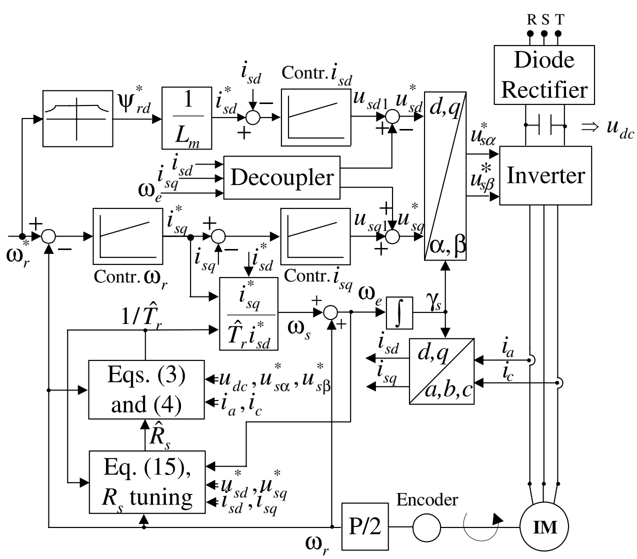

Fig. 1. ANN-based IRFO control system

An induction motor can be described by the following equations in a synchronously rotating (d,q) reference frame [7]:

$$0 = \frac{1}{T_r}\boldsymbol{\psi}_r - \frac{L_m}{T_r}\mathbf{i}_s + s\boldsymbol{\psi}_r + j(\omega_e - \omega_r)\boldsymbol{\psi}_r \tag{1}$$

$$\mathbf{u}_s = (R_s + (s + j\omega_e)\sigma L_s)\mathbf{i}_s + (s + j\omega_e)\frac{L_m}{L_r}\boldsymbol{\psi}_r \,. \tag{2}$$

where T_r is the rotor time constant, and s is the Laplace operator (=d/dt).

In equations (1) and (2) the space vectors are denoted in the bold face. Equation (1) is well known as the current model and (2) as the voltage model of the induction machine.

3 Identification of Inverse Rotor Time Constant

This paper utilizes the identification of inverse rotor time constant described in [8]. Equations (1) and (2) described in the α,β reference frame (ω_e=0) become

$$0 = \frac{1}{\hat{T}_r}\boldsymbol{\psi}_r - \frac{L_m}{\hat{T}_r}\mathbf{i}_s + s\boldsymbol{\psi}_r - j\omega_r\boldsymbol{\psi}_r \tag{3}$$

$$\mathbf{u}_s = (\hat{R}_s + s\sigma L_s)\mathbf{i}_s + s\frac{L_m}{L_r}\boldsymbol{\psi}_r \,. \tag{4}$$

A hat above a symbol in (3) and (4) denotes estimated parameters. Equation (3) (adaptive model) gives an estimation of the rotor flux space vector based upon easily measured stator currents and rotor speed. This estimation mainly depends on the accuracy of the inverse rotor time constant identification. Equation (4) is independent of the inverse rotor time constant and, accordingly, can be used as the reference model of the rotor flux space vector. An adaptive mechanism (PI) provides correction of the inverse rotor time constant (Fig. 2.).

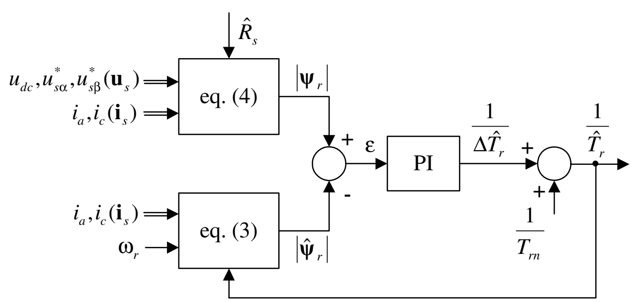

Fig. 2. Inverse rotor time constant identification

In our case, the inverse rotor time constant identification is valid beyond a rotor speed that is approximately 15 % of the rated speed.

4 Stator Resistance Tuning Based on ANN

The MRAS theory, as described in the section 1, has been utilized in order to estimate the rotor speed of induction motor. The rotor flux space vector is estimated in the d,q reference frame by the voltage model (reference model) and by the ANN-based model (adaptive model) of the induction motor. The difference between flux space vectors estimated using the two ways is then used in an adaptation mechanism that outputs the estimated value of the rotor speed and adjusts the adaptive model until good performances are obtained.

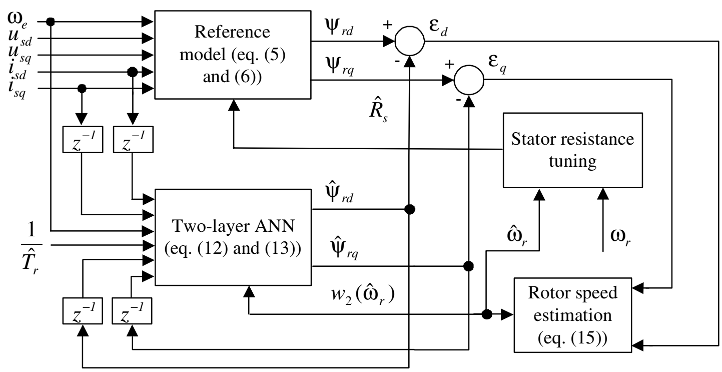

Fig. 3. Stator resistance tuning based on MRAS theory and ANN

The inputs to the reference model are the d- and q- axis stator voltages and currents of the induction motor and the angular stator frequency ω_e. The outputs of the reference model are the components of the rotor flux space vector in the d,q reference frame, which can be obtained from equation (2) as follows:

$$\frac{d\psi_{rd}}{dt} = \frac{L_r}{L_m}\left\{u_{sd} - \hat{R}_s i_{sd} - \sigma L_s \frac{di_{sd}}{dt} + \omega_e \sigma L_s i_{sq}\right\} + \omega_e \psi_{rq} \tag{5}$$

$$\frac{d\psi_{rq}}{dt} = \frac{L_r}{L_m}\left\{u_{sq} - \hat{R}_s i_{sq} - \sigma L_s \frac{di_{sq}}{dt} - \omega_e \sigma L_s i_{sd}\right\} - \omega_e \psi_{rd}\,. \tag{6}$$

These equations do not contain the rotor speed. However, equation (1) contains the rotor flux space vector and the rotor speed as well. This is the equation of the adaptive model. Rewriting (1) yields

$$\frac{d\hat{\psi}_{rd}}{dt} = \frac{1}{\hat{T}_r}\left(L_m i_{sd} - \hat{\psi}_{rd}\right) + \left(\omega_e - \omega_r\right)\hat{\psi}_{rq} \tag{7}$$

$$\frac{d\hat{\psi}_{rq}}{dt} = \frac{1}{\hat{T}_r}\left(L_m i_{sd} - \hat{\psi}_{rq}\right) - \left(\omega_e - \omega_r\right)\hat{\psi}_{rd}\,. \tag{8}$$

Equations (7) and (8) contain the rotor speed which, in general, is changing, and the intent is to estimate this speed by using an ANN. Consequently, equations (7) and (8) can be implemented by a two-layer ANN, which contains variable weights proportional to the rotor speed.

When there is no mismatch between the actual and estimated parameters of the induction motor, then the errors ε_d and ε_q (Fig. 3.) are zero in the steady state. In this case, the estimated rotor speed must be the same as the speed estimated by the ANN. The difference between the actual and the estimated rotor speed can be caused due to the following two reasons:

a) incorrect rotor resistance identification (incorrect inverse rotor time constant), and

b) incorrect stator resistance identification.

When the stator resistance is incorrectly identified, then the inverse rotor time constant is incorrectly identified as well. As a result, there is a mismatch between the actual rotor speed and the estimated rotor speed in the steady state. To obtain the weight adjustment in the ANN, the sampled data forms of equations (7) and (8) are derived. The actual rotor speed is now replaced by the estimated rotor speed. The rotor flux components can be described in the recursive form as follows:

$$\hat{\psi}_{rd}(k) = \hat{\psi}_{rd}(k-1)\left(1 - \frac{T}{\hat{T}_r}\right) + \left(\omega_e - \hat{\omega}_r\right)T\hat{\psi}_{rq}(k-1) + \frac{T}{\hat{T}_r}L_m i_{sd}(k-1) \tag{9}$$

$$\hat{\psi}_{rq}(k) = \hat{\psi}_{rq}(k-1)\left(1 - \frac{T}{\hat{T}_r}\right) - \left(\omega_e - \hat{\omega}_r\right)T\hat{\psi}_{rd}(k-1) + \frac{T}{\hat{T}_r}L_m i_{sq}(k-1), \tag{10}$$

where T is the sampling rate.

In equations (9) and (10) the following weights are introduced:

$$w_1 = 1 - \frac{T}{T_r},\, w_2 = -\left(\omega_e - \hat{\omega}_r\right)T,\, w_3 = \frac{T}{T_r}L_m\,. \tag{11}$$

It can be seen that w_2 is a variable weight and is proportional to the speed. From the viewpoint of the training procedure of the ANN, the weights w_1 and w_3 do not depend on the ANN training, than on the inverse rotor time constant procedure described in the section 3.

Equations (9) and (10) can be expressed in the following forms:

$$\hat{\psi}_{rd}(k) = w_1\hat{\psi}_{rd}(k-1) - w_2\hat{\psi}_{rq}(k-1) + w_3 i_{sd}(k-1) \tag{12}$$

$$\hat{\psi}_{rq}(k) = w_1\hat{\psi}_{rq}(k-1) + w_2\hat{\psi}_{rd}(k-1) + w_3 i_{sq}(k-1). \tag{13}$$

Equations (12) and (13) present the two-layer ANN. There are four input nodes and two output nodes. The weight adjustment can be obtained from ([13])

$$w_2(k) = w_2(k-1) + \eta\left\{-\left[\psi_{rd}(k) - \hat{\psi}_{rd}(k)\right]\hat{\psi}_{rq}(k-1) + \left[\psi_{rq}(k) - \hat{\psi}_{rq}(k)\right]\hat{\psi}_{rd}(k-1)\right\}. \tag{14}$$

The estimated rotor speed can be obtained as follows ([13]):

$$\hat{\omega}_r(k) = \omega_e(k) + \frac{w_2(k-1)}{T} + \frac{\eta}{T}\left\{-\left[\psi_{rd}(k) - \hat{\psi}_{rd}(k)\right]\hat{\psi}_{rq}(k-1) + \left[\psi_{rq}(k) - \hat{\psi}_{rq}(k)\right]\hat{\psi}_{rd}(k-1)\right\}, \quad (15)$$

where η is the so-called learning rate.

Equation (15) presents the simple algorithm of the rotor speed estimation by the ANN. In comparison with the similar ANN described in reference [13], there are the two differences: the inverse rotor time constant is not a constant parameter but is identified, and the rotor flux is estimated in the d,q frame.

5 Simulation and Experimental Results

A simulation program of the complete control system in MATLAB-Simulink environment has been developed. In order to compare the theory with a test case, a control algorithm was executed on the dSpace DS1104 board. Parameters of the induction motor are given in Appendix.

5.1 Simulation Results

Fig. 4 demonstrates the dynamic performance of the IRFO system with half of the rated load torque.

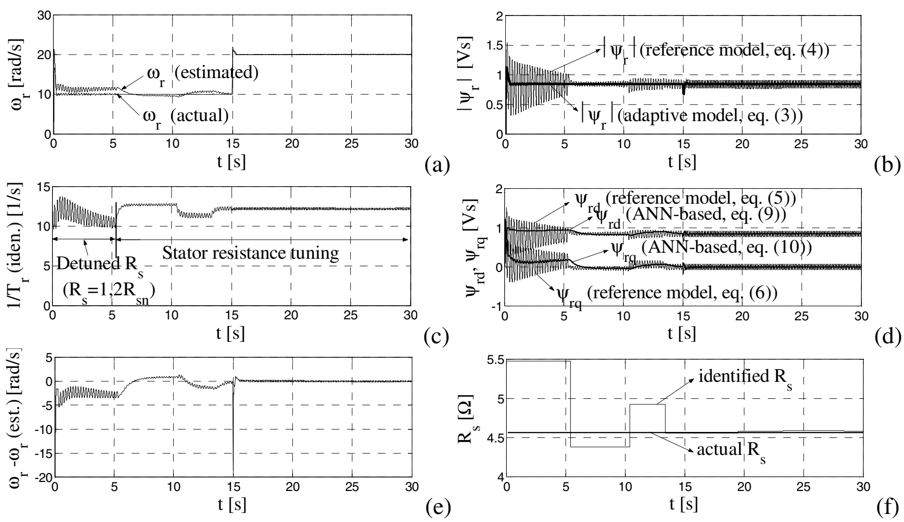

Fig. 4. Dynamic performance of the proposed control system (simulation)

The induction motor starts with the stator resistance initially overestimated by 20 % of the rated stator resistance. Stator resistance tuning starts at time 5.5 s, as shown in Fig. 4f. At time 15 s, the rotor speed reference value rapidly changes from 10 rad/s to 20 rad/s. The actual rotor speed and the estimated rotor speed are shown in Fig. 4a. As the identified rotor resistance reaches the actual resistance that the actual and estimated rotor speeds correspond closely. The estimated rotor flux magnitude is shown in Fig. 4b. As a consequence of this estimation procedure, the inverse rotor time constant identification is enabled (Fig. 4c). Fig. 4d shows the components of the rotor flux space vector in the d,q frame. The difference between the corresponding components enables rotor speed estimation as shown in Fig. 3. The sampling rate of 0.5 ms and the learning rate of 10^{-5} were chosen.

5.2 Experimental Results

Fig. 5 shows experimental results obtained at a rotor speed reference of 40 rad/s. At time t=1.2 s a step load of 5.5 Nm is applied. Fig. 5a shows the actual rotor speed. Fig. 5b shows the estimated rotor speed obtained by the ANN. The identified inverse rotor time constant is shown in Fig. 5c (it has an upper limit 15 s^{-1}).

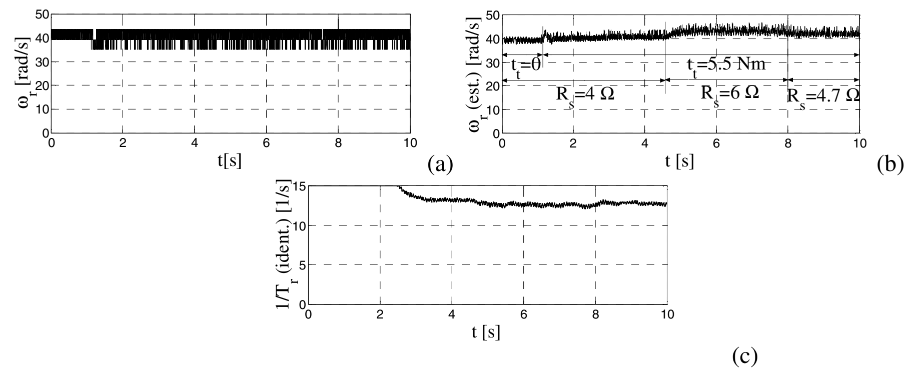

Fig. 5. Dynamic performance of the proposed control system (experiment)

By observing the performance shown in Fig. 5 the following could be concluded:

a) identification of the inverse rotor time constant does not work well at zero load torque,
b) when the identified stator resistance is higher than the actual resistance, then the estimated rotor speed is higher than actual speed, and vice versa.

6 Conclusion

A study of the IRFO control system of an induction motor including deviations in the stator resistance has been carried out. MRAS-based identification of the inverse rotor time constant has been included in the observed system. The identified inverse rotor time constant is an input parameter for a two-layer ANN. The ANN presents the adaptive model of the induction motor. Simultaneously, the components of the rotor flux space vector have been estimated by the reference model (voltage model) in the same reference frame. As a result of these simultaneous estimation procedures, the rotor speed estimation is enabled. The difference between the actual and estimated rotor speed converge to zero if the identified rotor resistance is near to the actual one. Therefore, the difference between the actual and estimated rotor speed has been utilized for manual stator resistance tuning. The overall control system exhibits excellent performances of operation over a low speed range (up to 15 % of the rated rotor speed). We expect to replace manual stator resistance tuning with an automated procedure.

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Appendix (Induction Motor Parameters)

P_n=1.5 kW, U_n=380 V, P=4, Y, I_n=3.81 A, n_n=1391 r/min, L_m=0.3269 H, L_{sl}=0.01823 H, L_{rl}=0.02185 H, $R_s = 4.5633\ \Omega$, $R_r = 3.866\ \Omega$, t_n=10.5 Nm, J=0.0071 kgm^2.