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ON-LINE PARAMETER IDENTIFICATION USING ARTIFICIAL NEURAL NETWORKS FOR VECTOR CONTROLLED INDUCTION MOTOR DRIVE

B. Karanayil *, *M. F. Rahman* * *C. Grantham* * *and M.A. Rahman* **

* School of Electrical Engineering and Telecommunications
The University of New South Wales
Sydney, NSW 2052, AUSTRALIA
Email: f.rahman@unsw.edu.au

** Faculty of Engineering and Applied Science
Memorial University of Newfoundland
St. John's, Newfoundland
A1B 3X5, CANADA

ABSTRACT

This paper presents a new method of on-line estimation for the stator and rotor resistances of the induction motor in the indirect vector controlled drive, using artificial neural networks. The back propagation algorithm is used for training of the neural networks. The error between the desired state variable of an induction motor and the actual state variable of a neural model is back propagated to adjust the weights of the neural model, so that the actual state variable tracks the desired value. The performance of these resistance estimators and torque response of the drive, together with these estimators, are investigated with the help of simulations for variations in the stator and rotor resistance from their nominal values. Both these resistances are estimated experimentally, in a vector controlled induction motor drive and found to give accurate estimates.

1. INTRODUCTION

Indirect Field Oriented Vector Controlled Induction Motor Drives are widely used in high-performance drive systems, as induction motors are more reliable because of their construction and less expensive because of the materials used, than any other motors available in the market today. However, the performance of the vector controlled drive depends on the accuracy of the motor parameters, rotor resistance being the most critical, used in the controllers. Rotor resistance may vary up to 100% due to rotor heating and recovering this information with a thermal model or a temperature sensor is highly undesirable. In addition, rotor resistance can change significantly with rotor frequency due to skin / proximity effect in machines with double-cage and deep-bar rotors.

Several methods have been reported to minimize the consequences of parameter sensitivity in indirect vector controlled drives. The method discussed in [1] was based on model reference adaptation of fluxes. The second approach was to compensate for rotor resistance variation by adaptive feedback linearization control with unknown rotor resistance which was developed in [2]. The third identification method was to detect the output signal variation invoked by the artificial injection signal [3]. Also, an Extended Kalman filter was used for rotor resistance identification in [4]. These methods assumed that there is no change in the stator resistance during the rotor resistance estimation. To estimate stator resistance, online identification has been developed using model reference adaptation [5]. Combined stator and rotor resistance identification has been reported in [6]. However even in these cases, one parameter is assumed to be constant during the estimation of the other parameter.

This paper addresses the situation of having the similar disturbances in both stator and rotor resistances simultaneously. Section II describes an on-line estimation of rotor resistance, R_r using on-line training of Artificial Neural Networks. However the R_r estimation algorithm requires the knowledge of stator resistance (R_s) which may also vary up to 50% during motor operation. The error in the values of R_s , hence leads to errors in R_r estimation. The problem is overcome by adding another on-line estimation for R_s to the system, giving the indirect vector control system, total immunity to resistance variations.

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2. ROTOR RESISTANCE ESTIMATION USING ARTIFICIAL NEURAL NETWORKS

The rotor resistance of an induction motor can be estimated with the adaptation scheme using the neural network, as illustrated in Fig. 1. Two independent observers are used to estimate the rotor flux vectors of the induction motor. Equation (1) is referred as voltage model which is based on measured stator voltages and stator currents from the induction motor and “(2)” as current model, which uses the stator currents and rotor speed. T_r is the rotor time constant, and is the ratio L_r/R_r and σ is the leakage coefficient.

$$\begin{bmatrix} \frac{d\lambda_{dr}^{vm}}{dt} \\ \frac{d\lambda_{qr}^{vm}}{dt} \end{bmatrix} = \frac{L_r}{L_m}\left\{ \begin{bmatrix} v_{ds} \\ v_{qs} \end{bmatrix} - R_s \begin{bmatrix} i_{ds} \\ i_{qs} \end{bmatrix} - \sigma L_s \begin{bmatrix} \frac{di_{ds}}{dt} \\ \frac{di_{qs}}{dt} \end{bmatrix} \right\} \quad (1)$$

$$\begin{bmatrix} \frac{d\lambda_{dr}^{im}}{dt} \\ \frac{d\lambda_{qr}^{im}}{dt} \end{bmatrix} = \begin{bmatrix} -\frac{1}{T_r} & -\omega_r \\ \omega_r & -\frac{1}{T_r} \end{bmatrix} \begin{bmatrix} \lambda_{dr}^{im} \\ \lambda_{qr}^{im} \end{bmatrix} + \frac{L_m}{T_r} \begin{bmatrix} i_{ds} \\ i_{qs} \end{bmatrix} \quad (2)$$

The sample-data model of current model equation is shown in equation (3).

$$\overrightarrow{\lambda_r^{nm}}(k) = (W_1 I + W_2 J)\overrightarrow{\lambda_r^{nm}}(k-1) + W_3 \vec{i}_s(k-1) \quad (3)$$

where

$$W_1 = 1 - \frac{T_s}{T_r}\ ;\quad W_2 = \omega_r T_s\ ;\quad W_3 = \frac{L_m}{T_r} T_s;\ I = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix},\quad J = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$$

Note: T_s is the sampling period. Equation (3) can also be written as:

$$\overrightarrow{\lambda_r^{nm}}(k) = W_1 X_1 + W_2 X_2 + W_3 X_3 \quad (4)$$

where,

$$X_1 = \begin{bmatrix} \lambda_{dr}^{nm}(k-1) \\ \lambda_{qr}^{nm}(k-1) \end{bmatrix};\ X_2 = \begin{bmatrix} -\lambda_{qr}^{nm}(k-1) \\ \lambda_{dr}^{nm}(k-1) \end{bmatrix};\ X_3 = \begin{bmatrix} i_{ds}(k-1) \\ i_{qs}(k-1) \end{bmatrix}$$

The neural network model represented by (4) is shown in Fig. 2, where W_1, W_2, W_3 represent the weights of the networks and X_1, X_2, X_3 are the three inputs to the network. If the network shown in Fig. 3 is used to estimate T_r , W_2 is already known and W_1 and W_3 need to be updated.

The weights between neurons, W_1 and W_3 are trained, so as to minimize the energy function,

$$E_1 = \frac{1}{2}\vec{\varepsilon}_1^{\,2}(k) = \frac{1}{2}\left\{\overrightarrow{\lambda_r^{vm}}(k) - \overrightarrow{\lambda_r^{im}}(k)\right\}^2 \quad (5)$$

The new weight W_1 is calculated as:

$$W_1(k) = W_1(k-1) - \eta_1 \vec{\delta} X_2 + \alpha_1 \Delta W_1(k-1) \quad (6)$$

where, η_1 is the training coefficient, and α_1 is a user-selected positive momentum constant.

and $$\vec{\delta} = \frac{\partial E_1}{\partial \overrightarrow{\lambda_r^{nm}}(k)} = \left[\overrightarrow{\lambda_r^{vm}}(k) - \overrightarrow{\lambda_r^{nm}}(k)\right]^T$$

Similarly the new weight W_3 is calculated as:

$$W_3(k) = W_3(k-1) - \eta_1 \vec{\delta} X_3 + \alpha_1 \Delta W_3(k-1) \quad (7)$$

The rotor resistance R_r can be found from either W_3 from equations (8).

$$\hat{R}_r = \frac{L_r W_3}{L_m T_s} \quad (8)$$

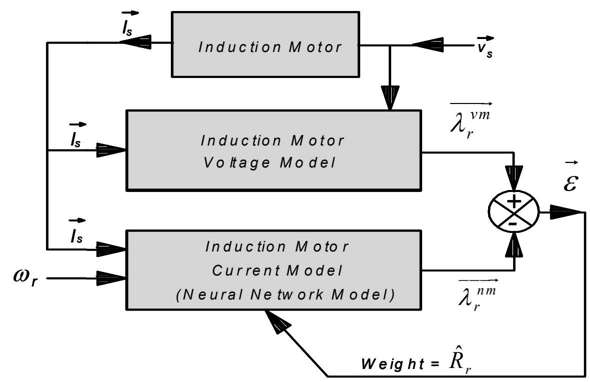

Fig. 1. Structure of the Neural Network System for R_r estimation.

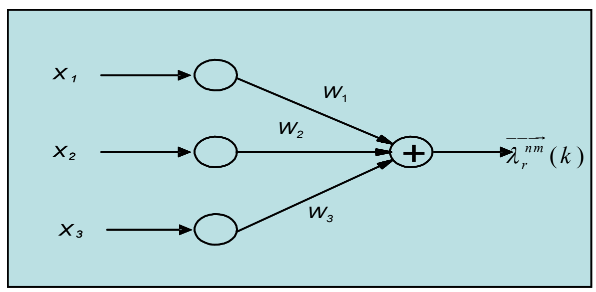

Fig. 2. Two layered neural network model.

3. STATOR RESISTANCE ESTIMATION USING ARTIFICIAL NEURAL NETWORKS

The stator resistance of an induction motor can be estimated with the adaptive estimator using neural networks as illustrated in Fig. 3.

Using the discrete form of equation (1), the new d – axis current estimate could be represented as:

$$i_{ds}^*(k) = W_4 i_{ds}^*(k-1) + W_5 \lambda_{dr}^{im}(k) + W_6 \omega_r \lambda_{qr}^{im}(k) + W_7 V_{ds}(k) \quad (9)$$

where, $$W_4 = 1 + \frac{T_s}{\sigma L_s}\frac{L_m^2}{L_r T_r} + \frac{T_s}{\sigma L_s} R_s\ ;\quad W_5 = \frac{T_s}{\sigma L_s}\frac{L_m}{L_r T_r}$$

$$W_6 = \frac{T_s}{\sigma L_s}\frac{L_m}{L_r}\omega_r\quad ;\quad W_7 = \frac{T_s}{\sigma L_s}$$

The weights W_5, W_6, and W_7 are calculated from the motor parameters, motor speed ω_r and the sampling interval T_s. The weight between the neurons, W_4 is trained so as to minimize the energy function E_2.

$$E_2 = \frac{1}{2}\vec{\varepsilon}_2^{\,2}(k) = \frac{1}{2}\left\{i_{ds}(k) - i_{ds}^*(k)\right\}^2 \qquad (10)$$

The weight variation for W_4 is given by:

$$\Delta W_4(k)\,\alpha\left[i_{ds}(k) - i_{ds}^*(k)\right] i_{ds}^*(k-1) \qquad (11)$$

Equation (9) can be represented by a recurrent neural network as shown in Fig. 4.

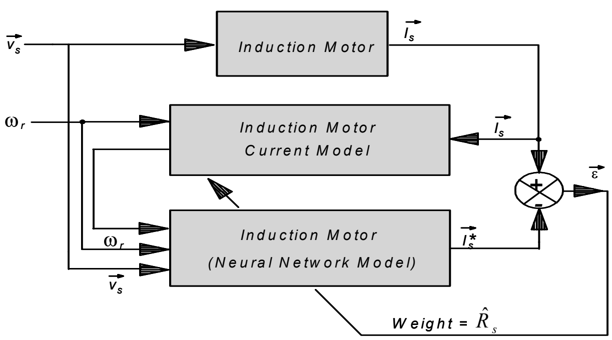

Fig. 3. R_s estimation using Artificial Neural Network.

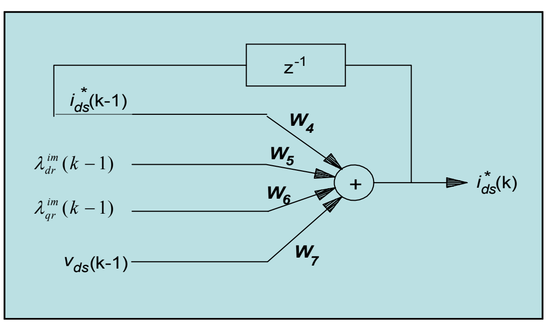

Fig. 4. *d*-axis stator current estimation using recurrent network based on (9).

To accelerate the convergence of the error back propagation learning algorithm, the current weight adjustment is supplemented with a fraction of the most recent weight adjustment, as in equation (12).

$$W_4(k) = W_4(k-1) + \eta_2 \Delta W_4(k) + \alpha_2\, \Delta W_4(k-1) \qquad (12)$$

where η_2 is the training coefficient, α_2 is a user-selected positive momentum constant.

The stator resistance can be calculated from (13).

$$\hat{R}_s = \left\{W_4 - 1 - \frac{T_s}{\sigma L_s}\frac{L_m^{\,2}}{L_r T_r}\right\}\frac{\sigma L_s}{T_s} \qquad (13)$$

4. MODELING RESULTS

The block diagram of a rotor flux oriented induction motor drive, together with both stator and rotor resistance identifications, is shown in Fig. 5.

In order to investigate the performance of the drive for parameter variations in rotor resistance R_r, a series of simulations were conducted by introducing error between the actual value R_r and the value used in the controller R_r'. Similarly, another series of simulations were conducted by introducing error between the actual stator resistance R_s and the one used in the controller R_s'. The parameters of the motor used for modeling studies are in Table I.

Initially a 40% error was introduced between R_r and R_r' and R_s and R_s' simultaneously at 1.5 second, after switching off both the Rotor Resistance Estimation (RRE) and Stator Resistance Estimation (SRE) blocks in Fig. 5. Later, simulations were repeated after switching on only the Rotor Resistance Estimation block with the SRE block switched off. The $\hat{R}_r$ estimated in this case is higher than the R_r by 1.7% as shown in Fig. 6(i). Finally, the simulations were carried out with both the RRE and SRE blocks switched on. The estimated rotor resistance has tracked the real rotor resistance of the motor very well, as the estimation error now drops to 0.3% as in Fig. 6 (i).

5. EXPERIMENTAL RESULTS

The experimental set-up for both rotor and stator resistance identification is implemented using a dSPACE DS1104 controller board. An IGBT inverter with a switching frequency of 5 kHz is used. Hand coded C programs with the Real-Time Reference library functions are used to develop the control programs. Both the stator and rotor resistances are estimated successfully in the experimental set-up. The results of R_r estimation is shown in Fig. 7, here the data is logged for 60 minutes. The coefficients used for training are, η = 0.005 and α =10.0e-6.

To test the stator resistance estimation, an additional 3.4 Ω is added in series with the induction motor stator, when the motor is running at 1000 rpm, and load torque of 7.4Nm. The estimated stator resistance together with the actual stator resistance is shown in Fig. 8. The estimated stator resistance converges to 9.4Ω within 450 millisecond. The coefficients used for training are, η=0.00216 and α = 10.0e-6.

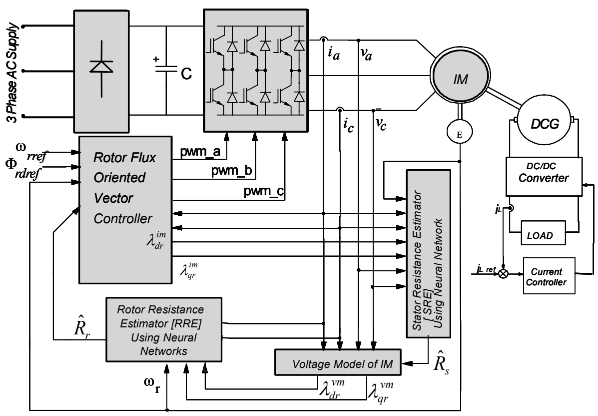

Fig. 5. Vector controlled induction motor drive with on-line stator and rotor resistance tracking

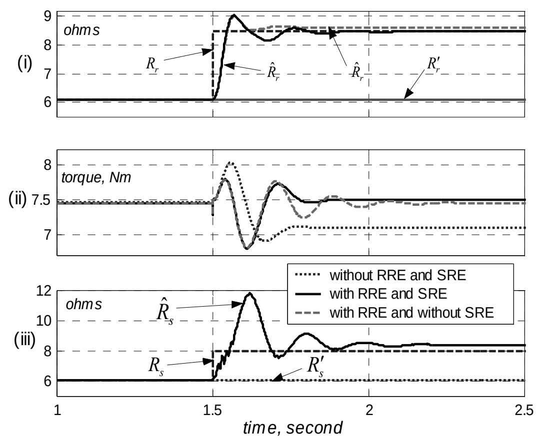

Fig. 6. Performance of the drive with and without rotor and stator resistance compensations.

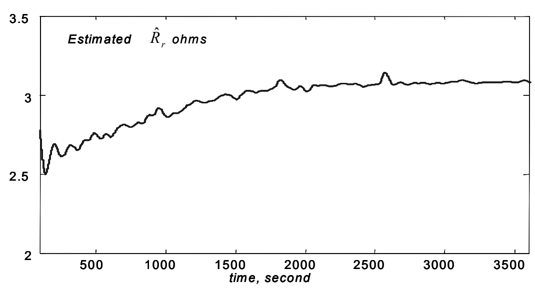

Fig. 7. Estimated $\hat{R}_r$ in experiment

6. CONCLUSION

The investigation carried out in this paper was aimed at identifying the parameters in a vector controlled induction motor drive using artificial neural networks.

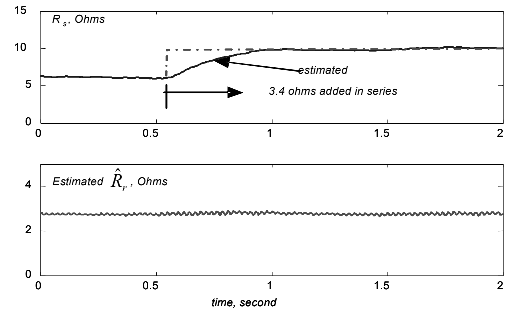

Fig. 8. Estimated $\hat{R}_s$ in experiment

TABLE I. INDUCTION MOTOR PARAMETERS

1.1kW, 1415 RPM, 415V, 2.77A, 3 phase , 4 pole, 50Hz.	
Stator Resistance R_s	6.03 Ω
Rotor Leakage Inductance L_{rs}	29.9mH
Stator Leakage Inductance L_{ls}	29.9 mH
Magnetizing Inductance L_m	489.3mH
Rotor Resistance R_r	6.085 Ω at 50Hz
Moment of Inertia J_T	0.011787 kgm2

Both the rotor resistance R_r and the stator resistance R_s variations were successfully estimated using the adaptation capabilities of neural networks. The feasibility and validity of the proposed identification has been verified by the experimental results.

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