Rotor Time Constant Identification Approaches Based on Back-Propagation Neural Network for Indirect Vector Controlled Induction Machine

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Abstract. Nowadays, indirect field oriented control (IFOC) is a promising induction machine control method which leads to excellent motor dynamic performances. It is well known that in this IFOC scheme, the induction machine parameters change widely during the operation of the drive especially the value of rotor time constant which varies with rotor temperature and flux level of the machine. Therefore, the quality of the drive system decreases if no means for compensation or identification is applied. This paper deals with rotor time constant identification for vector controlled induction motor based on measurement of the stator voltages, currents and speed by applying the back-propagation neural networks approach in order to implement a robust control law for industrial application. A convenient formulation is in order to compute physical parameters of the machine. The back-propagation learning process algorithm is briefly presented and tested with different configuration of motor induction. Verification of the validity and feasibility of the technique is obtained from simulation results.

Keywords: artificial neural network, indirect field oriented control, induction motor drives, rotor time constant.

1 Introduction

In the field oriented control scheme, the stator current of an induction motor current is decoupled into torque and flux producing components, respectively, hence allowing independent control of torque and flux, like in a separately excited dc motor. This allows the drive system to produce the desired output torque and speed with much faster and more stable responses, compared with the conventional constant volt per hertz control scheme. The Indirect Field Oriented Control (IFOC) drive uses rotor speed information and the motor electrical parameters to compute the rotor flux position, and is therefore more easily adaptable on existing drives [1],[2]. The major problem associated with IFOC drives using rotor flux orientation, is the time variation of the rotor time constant, leading to an incorrectly calculated slip frequency command. Consequently, the required decoupling between torque and flux is lost, and the dynamic response of the drive is significantly degraded [3],[4],[5]. To maintain

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robustness of the drive, on-line identification of the rotor time constant or compensation for the parameter variations is required.

Many techniques has been reported [6],[7],[8] to solve the problem of motor parameter identification while the drive is in indirect field oriented control operation. Intelligent techniques have also been applied to achieve this goal [9],[10],[11].

Ba-Razzouk, A., et all. [12] proposed a rotor time constant estimation method using the back-propagation neural network, formed by log-sigmoidal neurons, and comprises 5 inputs, 6 neurons on the first hidden layer, 6 neurons on the second and one output neuron. It converges to a sum squared error of $9.26.10^{-4}$ after 14500 iterations (with randomly initialized weights and biases in the beginning of the training).

The main objective of this research is to estimate the rotor time constant of an induction motor drive that provides more precise results than obtained by Ba-Razzouk [12], in order to realize an indirect field oriented control insensitive to the variation of this parameter. To achieve this goal, several sub-objectives are to consider in particular, the development of a simulation library of induction motor, the development of artificial neural network (ANN) learning techniques, and finding appropriate architectures.

This paper is organized as follows: in section 2, describes principles of indirect vector control. In section 3, we present the mathematics equations of rotor time constant. In section 3, we develop the steps for training an ANN to rotor time constant. Section 4 presents the simulation results obtained for this approach. Paper ends with a brief conclusion in Section 5.

Nomenclature

d,q	Direct and quadrature components
R_s , R_r	Stator and rotor resistance [Ω]
i_{ds} , i_{qs}	Stator current dq –axis [A]
i_{dr} , i_{qr}	Rotor current dq –axis [A]
v_{ds} , v_{qs}	Stator voltage dq-axis [V]
v_{dr} , v_{qr}	Rotor voltage dq-axis [V]
L_s , L_r, L_m	Stator, rotor and mutual inductance [H]
λ_{ds}, λ_{qs}	dq stator fluxes [Wb]
λ_{dr}, λ_{qr}	dq rotor fluxes [Wb]
T_{em}	Electromagnetic torque [N.m]
ω_r, ω_e, ω_{sl}	Rotor, synchronous and slip frequency [rad/s]
τ_r	Rotor time constant
J	Inertia moment [Kg.m^2]
n_p	Number of poles
$\sigma = 1 - \frac{L_m^2}{L_s L_r}$	Leakage coefficient
s	Differential operator (d/dt)

2 Mathematic Model of IFOC Drive

The dynamic model of a three-phase squirrel cage Y-connected induction motor can be described in a fixed stator d-q reference frame [13],[14] as:

$$\begin{bmatrix} \dot{i}_{qs} \\ \dot{i}_{ds} \\ \dot{\lambda}_{qr} \\ \dot{\lambda}_{dr} \end{bmatrix} = \begin{bmatrix} -\left(\frac{R_s}{\sigma L_s}+\frac{1-\sigma}{\sigma\tau_r}\right) & -\omega_e & \frac{L_m}{\sigma L_s L_r \tau_r} & -\frac{L_m}{\sigma L_s L_r} n_p \omega_r \\ -\omega_e & -\left(\frac{R_s}{\sigma L_s}+\frac{1-\sigma}{\sigma\tau_r}\right) & \frac{L_m}{\sigma L_s L_r} n_p \omega_r & \frac{L_m}{\sigma L_s L_r \tau_r} \\ \frac{L_m}{L_r} & 0 & -\frac{1}{\tau_r} & -\left(\omega_e - n_p\omega_r\right) \\ 0 & \frac{L_m}{L_r} & \left(\omega_e - n_p\omega_r\right) & -\frac{1}{\tau_r} \end{bmatrix} \times \begin{bmatrix} i_{qs} \\ i_{ds} \\ \lambda_{qr} \\ \lambda_{dr} \end{bmatrix} + \begin{bmatrix} \frac{v_{qs}}{\sigma L_s} \\ \frac{v_{qs}}{\sigma L_s} \\ 0 \\ 0 \end{bmatrix} \tag{1}$$

Moreover, the electromagnetic torque equation can be expressed in terms of the stator current and rotor flux linkage as:

$$T_{em} = \frac{3}{2} n_p \frac{L_m}{L_r}\left(\lambda_{dr} i_{qs} - \lambda_{qr} i_{ds}\right) \tag{2}$$

In an ideally decoupled IM, the rotor flux linkage axis is forced to align with the d-axis. It follows that:

$$\lambda_{qr} = 0,\ \dot{\lambda}_{qr} = 0 \tag{3}$$

Using (3), the desired rotor flux linkage in terms of i_{ds} can be found from the last row of (1) as:

$$\lambda_{dr} = \frac{L_m / \tau_r}{s + \left(1/\tau_r\right)} i_{ds} \tag{4}$$

According to the third row of (1), the slip angular velocity ($\omega_{sl} = \omega_e = n_p\omega_r$) can be estimated using λ_{dr} in (4) and i_{qs} as follows:

$$\omega_{sl} = \frac{L_m}{\tau_r \lambda_{dr}} i_{qs} \tag{5}$$

In the steady state, the desired rotor flux linkage shown in (4) can be represented as $\lambda_{dr} = L_m i^*_{ds}$ in which i^*_{ds} is the flux current command. Moreover, the synchronous angular velocity (we) in the indirect field-oriented mechanism is generated by using the measured rotor angular velocity (ω_e) and the following estimated slip angular velocity:

$$\omega^*_{sl} = \frac{i^*_{qs}}{\tau_r i^*_{ds}} \tag{6}$$

where i^*_{qs} is the torque current command. Consequently, the electromagnetic torque can be simplified as:

$$T_{em} = K_t i^*_{qs} \tag{7}$$

with the torque constant K_t defined as:

$$K_t = \left(\frac{3n_p}{2}\right)\left(\frac{L_m^2}{L_r}\right) i^*_{ds} \tag{8}$$

According to the conventional Indirect Field Oriented Control (IFOC) technique the reference slip pulsation ω^*_{sl} is computed by mean of (6). It is clear that variations of τ_r with temperature or saturation cause an misalignment of the stator current vector with respect to the rotor flux vector resulting in incorrect amplitude and phase of the rotor flux vector as well as an incorrect torque.

The influence of the slip frequency on the rotor flux and torque in an IFOC drive has been used to develop a tuning procedure by exploiting the different time constants of torque and flux. This method is in principle simple and effective, unfortunately as in normal operations the system runs under the control of a closed loop speed regulator, the use of the above mentioned method require some operations on the system. Moreover this procedure is strictly dependent on the sensibility of the system operator.

3 Mathematical Determination of the Rotor Time Constant

Consider the stator voltages equations and calculate the term: ($v_{ds}i_{qs}$-$v_{qs}i_{ds}$),

$$v_{ds} i_{qs} - v_{qs} i_{ds} = \frac{d\lambda_{ds}}{dt} i_{qs} - \frac{d\lambda_{qs}}{dt} i_{ds} \tag{9}$$

Let us know that:

$$\lambda_{ds} = \frac{L_m}{L_r}\lambda_{dr} + \sigma L_s i_{ds} \tag{10}$$

$$\lambda_{qs} = \frac{L_m}{L_r}\lambda_{qr} + \sigma L_s i_{qs} \tag{11}$$

$$\frac{d\lambda_{dr}}{dt} = \frac{R_r}{L_r}\left(L_m i_{ds} - \lambda_{dr}\right) - \omega_r \lambda_{qr} \tag{12}$$

$$\frac{d\lambda_{qr}}{dt} = \frac{R_r}{L_r}\left(L_m i_{qs} - \lambda_{qr}\right) - \omega_r \lambda_{dr} \tag{13}$$

We replace (λ_{ds} and λ_{qs}) by their values given by (7) and (8), we find:

$$v_{ds} i_{qs} - v_{qs} i_{ds} = \left(\frac{L_m}{L_r}\frac{d\lambda_{dr}}{dt} + \sigma L_s \frac{di_{ds}}{dt}\right) i_{qs} - \left(\frac{L_m}{L_r}\frac{d\lambda_{qr}}{dt} + \sigma L_s \frac{di_{qs}}{dt}\right) i_{ds} \tag{14}$$

We replace ($d\lambda_{ds}/dt$ and $d\lambda_{qs}/dt$) by their values given by (9) and (10), we find:

$$\begin{aligned} v_{ds} i_{qs} - v_{qs} i_{ds} &= \frac{L_m}{L_r}\left(-\frac{R_r}{L_r}\left(\lambda_{dr} i_{qs} - \lambda_{qr} i_{ds}\right) - \omega_r \left(\lambda_{qr} i_{qs} - \lambda_{dr} i_{ds}\right)\right) \\ &+ \sigma L_s \left(\frac{di_{ds}}{dt} i_{qs} - \frac{di_{qs}}{dt} i_{ds}\right) \end{aligned} \tag{15}$$

Hence, we can derive the expression of the rotor time-constant ($\tau_r = L_r/R_r$):

$$\tau_r = \frac{\left(\lambda_{qr} i_{ds} - \lambda_{dr} i_{qs}\right)}{\frac{L_r}{L_m}\left(\left(\lambda_{ds} i_{qs} - \lambda_{qr} i_{ds}\right) - \sigma L_s \left(\frac{di_{ds}}{dt} i_{qs} - \frac{di_{qs}}{dt} i_{ds}\right)\right) + \omega_r \left(\lambda_{qr} i_{qs} + \lambda_{dr} i_{ds}\right)} \tag{16}$$

Due to the mathematical complexity and quantity calculations of rotor time constant estimators, an implantation using ANN seems interesting.

4 Neural Rotor Time Constant Estimator

Among the various neural networks and their associated algorithms, our choice fell on the study of continuous multilayer neural networks [15]. This type of network has excellent characteristics in the estimation and signal processing. In our application, we developed an ANN that can be used in achieving a high performance control of induction motors controlled by indirect method of rotor flux orientation. ANN we used is multi-layer networks, simple (the neurons of a layer are connected only to neurons of the next layer) and each neuron is connected to all neurons of the next layer. The network consists of an input layer, three hidden layer and an output layer. Neurons used in ANN developed are continuous neurons (square, tansig and linear). The methodology used consisted in preparing a databank fairly representative. This bank should take into account the maximum information on the different modes of training, enrolling in range where it is required to operate. Once this databank prepared and normalized, a part representing 20% is chosen to test the network generalization for data never learned. The remaining 80% is used as databank learning will be used to adapt the weights and biases of the ANN. As we mentioned goal is to realize ANN capable of well generalize, the structure of ANN has been developed following the cross-validation procedure proposed by [16]. Once the databank learning and the structure of ANN determined, the learning phase is started using the toolbox neural network MATLAB. During this learning phase, we proceed regularly to verify the network generalization. At the beginning of this phase, the training error and those generalization decrease progressively as the number of iterations increases. However, from a number of iterations, the generalization error starts to grow while the learning continues to decline. This is due to the fact that ANN begins to learn by heart the training data (memorization).

As the goal is to develop ANN that generalizes, it is necessary that the learning phase to be stopped as soon as the generalization error starts to grow. If both errors are far from the desired error, we add some neurons and restart the learning phase until obtaining a good compromise between the desired errors, learning and generalization.

Once the ANN has converged to an acceptable error, the optimal weights and biases are saved.

Development of the Neural Network

A neural network has been trained for estimating the rotor time constant variation in line using speed measurements, voltage and stator current (v_{ds}, v_{qs}, i_{ds}, i_{qs}, ω_r).

Signals networks learning were prepared from the machine phase model in which we programmed the rotor resistance variations. In addition, survey data from the machine experimental magnetization characteristic were used to develop a model that takes into account the saturation. For each rotor resistance variation, the rotor time constant is calculated and stored. A databank has been constructed from the input signals (v_{ds}, v_{qs}, i_{ds}, i_{qs}, ω_r), and network output τ_r. In preparing this databank, different operating conditions (torque and flux variables) were simulated. For the couple, the operations in the two rotation directions and even stoppage were simulated. It should be noted that learning could also be done with real signals captured in the laboratory, if we can by one means or another to vary the rotor time constant value. This is simpler in the case of a wound rotor machine, which can easily apply variations in rotor resistance. Each time constant value corresponds to a very precise combination of input signals. The artificial neural network role is therefore able to detect in the modifications imposed on the input signals, due to the rotor resistance variation, the time constant value at machine level. Once this databank prepared, it was subdivided at random into two subsets, one for training whose size represents 80% of this databank and another representing approximately 20% was reserved for testing the network generalization for data never learned. The databank contains prepared 5000 combinations of input signals - rotor time-constant, which represents a reasonable size for bank learning ANN.

$$I_s^2 = i_{ds}^2 + i_{qs}^2 \tag{17}$$

$$i_{qs} = \sqrt{I_s^2 - \left(\frac{\lambda_r}{L_m}\right)} \tag{18}$$

$$\lambda_r = \frac{L_m I_s}{\left(1 + s\tau_r^*\right)\sqrt{\left(\frac{1}{1 + s\tau_r^*}\right)^2 + \tau_r^2\left(\frac{L_m i_{qs}^*}{\tau_r^* \lambda_r^*}\right)^2}} \tag{19}$$

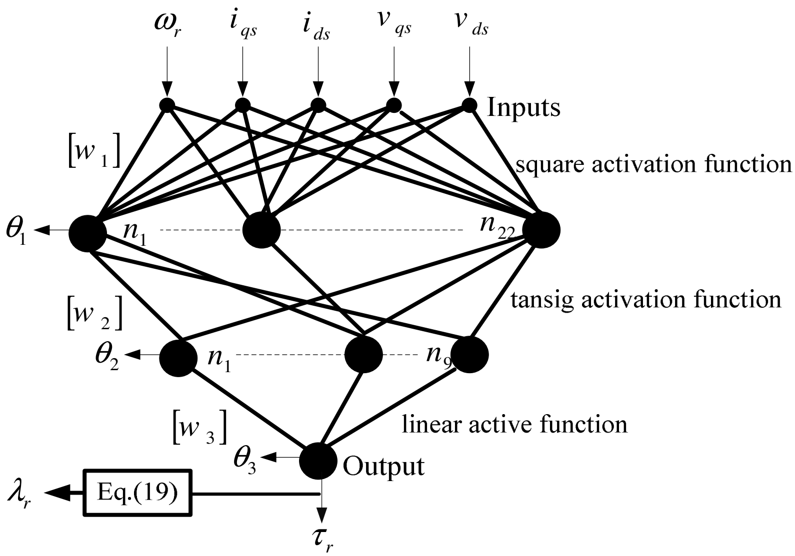

Fig. 1. Rotor time constant based on neural networks

A three-layer network with a total of 37 hard limit neurons is employed to implement the rotor time constant estimator as shown in Fig.1. The first hidden layer has 22 neurons (square activation function neuron with the w_1 and bias θ_1), 8 neurons in the second hidden layer (tansig activation function neuron with the weight w_2 and bias θ_2), and the output layer has one neuron (linear active function neuron with the weight w_3 and bias θ_3). The network is trained by a supervised method. After 63920 training epochs, the sum squared error arrives at $7.44.10^{-6}$.

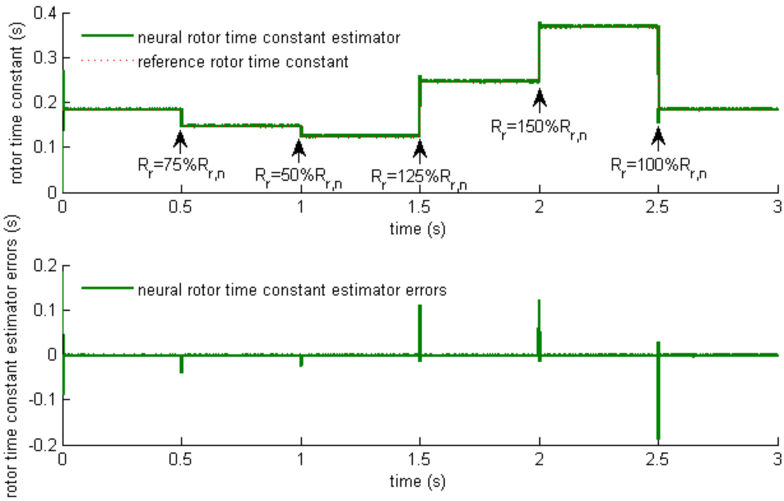

Fig. 2. Estimation results of the neural rotor time constant and estimation errors

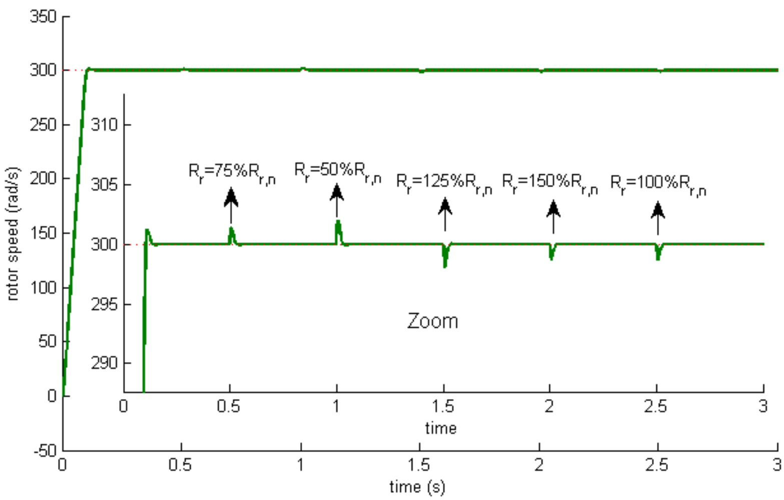

Fig. 3. Rotor speed

Fig.2 shows the results of neural rotor time constant estimating. This result is presented for rotor flux oriented drive operating at nominal set-points flux and torque, in which we have programmed a rotor resistance which varies between 100%, 75%, 50%, 125%, 150% and 100% at $t = 0.5$s, $t = 1$s, $t = 1.5$s, $t = 2$s and $t = 2.5$s respectively. The neural network was also used to adjust a rotor flux oriented drive with respect to the rotor resistance variation. The rotor time constant estimated by this ANN is used to correct the set-point slip at vector controller level.

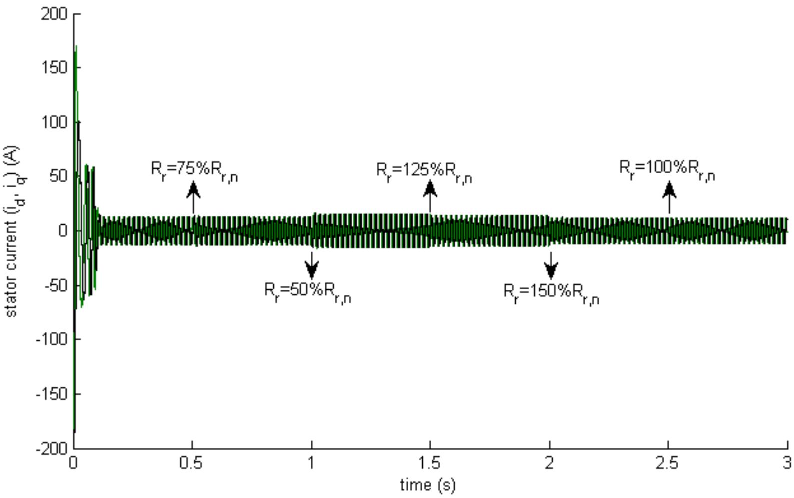

Fig. 4. Stator current (i_d, i_q)

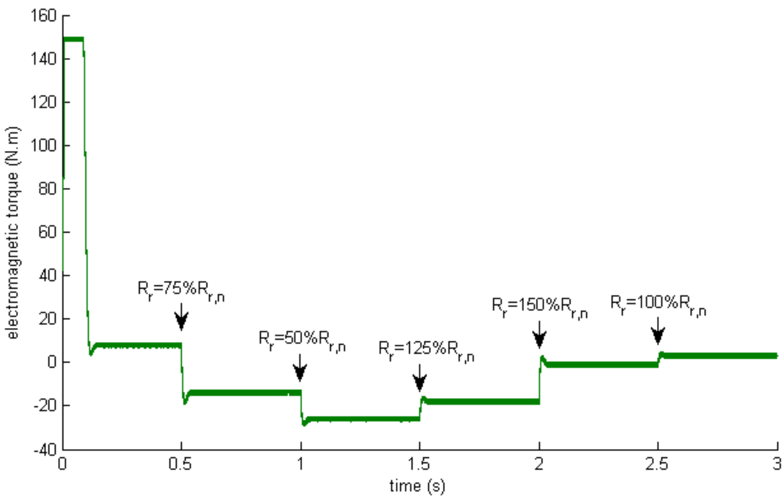

Fig. 5. Electromagnetic torque

You can see in this figure the transient behavior of rotor time constant estimator based ANN. We can also see that it responds precisely and variation index instantly applied to the rotor time constant. Indexical variations were used here in order to verify the dynamic performance estimation scheme. However, in practice the rotor time constant varies exponentially with the heating of the machine.

The rotor speed response shows that the drive can follow the low command speed very quickly and rapid rejection of disturbances, with a low dropout speed (Fig. 3).

The current responses are sinusoidal and balanced, and its distortion is small (Fig. 4).

The current and electromagnetic torque (Figs. 4 and 5) curves remain at their respective set-points despite the variation applied to the rotor resistance. This proves that the adaptation process of this parameter is actually performed and that decoupling is maintained, seen that electromagnetic torque and current in the machine remain at their respective set-points.

Induction motor parameters:

P_n = 2.2kW, V_n = 220/380V, f = 60Hz, R_s = 0.84Ω, R_r = 0.3858Ω, L_s = 0.0706H, L_r = 0.0706H, L_m = 0.0672H, J = 0.008kg·m^2, n_p = 2.

5 Conclusions

In this paper we presented the analysis and the discussion of the effect of the rotor time constant variations on the dynamic performance of rotor flux indirect field orientation drives. We have proposed a new method for rotor time constant estimation based on back-propagation neural networks. The computer simulations have shown the validity and the feasibility of the proposed method that possesses the advantages of neural network implementation: the high speed of processing. In addition this method is more adapted for practical implementation because it uses only stator terminal quantities (voltage, current and frequency) in the estimation of the rotor time constant.

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