Intelligent Rotor Time Constant Identification Approach in Indirect Field Oriented Induction Motor Drive

Moulay Rachid Douiri and Mohamed Cherkaoui

Mohammadia Engineering School, Department of Electrical Engineering,
Ibn Sina Avenue, 765, Agdal-Rabat, Morocco
douirirachid@hotmail.com

Abstract. This paper proposes a novel control scheme for rotor time constant identification using artificial neural networks. This approach, based on estimation of the rotor time constant from motor terminal variables (stator voltage, stator current and rotor speed), can be applied to indirect field oriented control and used to tune the actual rotor time constant of the induction motor to its set value programmed in the decoupling controller. The neural estimators use the back-propagation learning process to update their weights. The performance of the proposed scheme is carried out by extensive simulations confirming the feasibility of the proposed control strategy.

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

Nomenclature

ANNs	Artificial Neural Networks
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	motor pole number
σ	leakage coefficient

F. Castro, A. Gelbukh, and M. González (Eds.): MICAI 2013, Part II, LNAI 8266, pp. 162–171, 2013.

1 Introduction

Development of vector control techniques applied to induction motors, power converters and digital controllers has initiated the decline of the supremacy of DC machines in high performance adjustable speed drives. The vector control can be realized in a direct or indirect fashion [1]. The latter arouses more interest since it does not imply any modification to the structure of the machine. The method of indirect orientation of the rotor flux is widely used due to its simplicity and because it lends itself well to a generalized implementation for general-purpose induction motors. The principal drawback of the indirect method is its sensitivity to parameters variation [2]. The differences between the parameter programmed in the regulators and the real parameters of the machine deteriorate the performances of the drive not only in transients, but also in steady state [3]. The estimation of the rotor time constant is thus necessary for the implementation of high performance vector control schemes based on indirect method of rotor flux orientation. Various techniques are explored nowadays by research team's al1 around the world. All have the aim of obtaining correct values of the motor parameters, required in the implementation of indirect vector controls insensitive to parameters variation [4]-[5]-[6]-[7]-[8]-[9]-[10]-[11].

The contribution of this paper lies in the use of artificial neural networks (ANNs) for the implementation of vector controlled induction motor. The advantages of ANNs have been highlighted in several fields of application and they arouse, currently, much interest in the fields of power electronics and electrical machines control [12]. The main objective of this research is to estimate the rotor time constant of an induction motor drive, in order to realize an indirect field oriented control insensitive to the variation of this parameter. The originality of this work lies in the approaches used. Indeed, three new estimation strategies have been developed. These techniques use either ANNs or the motor model equations under dynamic conditions in the stationary reference frame. To achieve this goal, several sub-objectives are to consider in particular, the development of a simulation library of induction motor, the development of learning methods ANNs, and finding appropriate architectures.

2 Indirect Field Orientated Control

The indirect field orientation uses the slip relation to estimate the flux position to the rotor. There are no sensing devices placed inside the motor, meaning there is no direct measurement of the magnetic field. Instead, the rotor speed (i.e. rotor frequency) is measured and slip frequency is calculated. Addition of these frequencies yields an optimal stator frequency for motor control. A sensor on the motor shaft measures the rotor angle θ_r (or measures the rotor speed ω_r, followed by an integrator for calculation of the angle). The input signals for current control are used for calculation of the desired slip frequency, ω_{sl}, which is integrated, giving a slip angle, θ_{sl}, which is added to the rotor angle. (The slip angle is required to adjust the inclination of the d-axis so that the magnetization of the motor is along this axis). The sum of the two angles gives the instantaneous rotor flux position angle.

The decoupling conditions may be written:

$$\lambda_r = \lambda_{dr} + j\lambda_{qr} = \lambda_{dr}, \quad \lambda_{qr} = 0, \text{ and } \quad i_{qs} = \left(-\frac{L_r}{L_m}\right) i_{qr} \tag{1}$$

Then, the torque equation becomes:

$$T_{em} = \frac{3n_p L_m}{2L_r} \lambda_r i_{qs} \tag{2}$$

And the rotor flux equation becomes:

$$\lambda_r = \left(\frac{L_m}{1 + s\tau_r}\right) i_{ds} \tag{3}$$

The slip equations for an induction motor in an arbitrary synchronously rotating reference frame are given by:

$$\omega_e - \omega_r = \omega_{sl} = -\frac{R_r i_{qr}}{\lambda_{dr}} = \frac{R_r L_m}{\lambda_{dr} L_r} i_{qs} = \left[\left(1 + s\frac{L_r}{R_r}\right)\frac{1}{i_{ds}}\right]\frac{R_r}{L_r} i_{qs} \tag{4}$$

when i_{ds} and i_{qs} are decided by ω_{sl}, rotor flux position θ_e is given by:

$$\theta_e = \int_0^t \omega_e dt = \int_0^t \left(\omega_r + \omega_{sl}\right) dt \tag{5}$$

Indirect field orientation does not have inherent low speed problems (unlike direct field oriented control), and is thus preferred in most systems that must operate near zero speed. As well, flux can be obtained even down to zero frequency, making it suitable for position control. A major drawback, however, is that calculation of the rotor flux depends on the rotor the constant τ_r, where $\tau_r = L_r/R_r$. This time constant is dependent on rotor resistance, which is a function of rotor temperature and therefore tends to vary significantly due to temperature variations and the skin effect. This affects the accuracy of the flux magnitude and angle estimation, leading to degradation in system performance and quality of control.

3 Mathematical Development of Rotor Time Constant Estimator and Rotor Flux

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

$$v_{ds} i_{qs} - v_{qs} i_{ds} = \frac{d\lambda_{ds}}{dt} i_{qs} - \frac{d\lambda_{qs}}{dt} i_{ds} \tag{6}$$

Let us know that:

$$\lambda_{ds} = \frac{L_m}{L_r} \lambda_{dr} + \sigma L_s i_{ds} \tag{7}$$

$$\lambda_{qs} = \frac{L_m}{L_r} \lambda_{qr} + \sigma L_s i_{qs} \tag{8}$$

$$\frac{d\lambda_{dr}}{dt} = \frac{R_r}{L_r} \left(L_m i_{ds} - \lambda_{dr} \right) - \omega_r \lambda_{qr} \tag{9}$$

$$\frac{d\lambda_{qr}}{dt} = \frac{R_r}{L_r} \left(L_m i_{qs} - \lambda_{qr} \right) - \omega_r \lambda_{dr} \tag{10}$$

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

$$v_{ds} i_{qs} - v_{qs} i_{ds} = \left(\frac{L_m}{L_r} \frac{d\lambda_{dr}}{dt} + \sigma L_s \frac{di_{ds}}{dt} \right) i_{qs} - \left(\frac{L_m}{L_r} \frac{d\lambda_{qr}}{dt} + \sigma L_s \frac{di_{qs}}{dt} \right) i_{ds} \tag{11}$$

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

$$\begin{aligned} v_{ds} i_{qs} - v_{qs} i_{ds} &= \frac{L_m}{L_r} \left(-\frac{R_r}{L_r} \left(\lambda_{dr} i_{qs} - \lambda_{qr} i_{ds} \right) - \omega_r \left(\lambda_{qr} i_{qs} - \lambda_{dr} i_{ds} \right) \right) \\ &+ \sigma L_s \left(\frac{di_{ds}}{dt} i_{qs} - \frac{di_{qs}}{dt} i_{ds} \right) \end{aligned} \tag{12}$$

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

$$\tau_r = \frac{\left(\lambda_{qr} i_{ds} - \lambda_{dr} i_{qs} \right)}{\frac{L_r}{L_m} \left(\left(\lambda_{ds} i_{qs} - \lambda_{qr} i_{ds} \right) - \sigma L_s \left(\frac{di_{ds}}{dt} i_{qs} - \frac{di_{qs}}{dt} i_{ds} \right) \right) + \omega_r \left(\lambda_{qr} i_{qs} + \lambda_{dr} i_{ds} \right)} \tag{13}$$

Due to the mathematical complexity and quantity calculations of rotor time constant estimators, an implantation using ANNs 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. This type of network has excellent characteristics in the estimation and signal processing. In our application, we developed three ANNs that can be used in achieving a high performance control of induction motors controlled by indirect method of rotor flux orientation. ANNs we used are 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, a hidden layer and an output layer. We also tried two hidden layers networks, but the results and the learning curve is very comparable, for the same number of neurons, to those obtained from a hidden layer. Neurons used in ANNs developed are continuous neurons (sigmoid 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 ANNs capable of well generalize, the structure of ANNs has been developed following the cross-validation procedure proposed by [13]. Once the databank learning and the structure of ANNs 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 ANNs begins to learn by heart the training data (memorization).

As the goal is to develop ANNs that generalize, 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 ANNs.

$$I_s^2 = i_{ds}^2 + i_{qs}^2 \tag{14}$$

$$i_{qs} = \sqrt{I_s^2 - \left(\frac{\lambda_r}{L_m}\right)} \tag{15}$$

$$\lambda_r = \frac{L_m I_s}{\left(1 + s\tau_r^*\right)\sqrt{\left(\frac{1}{1+s\tau_r^*}\right)^2 + \tau_r^2\left(\frac{L_m i_{qs}^*}{\tau_r^* \lambda_r^*}\right)^2}} \tag{16}$$

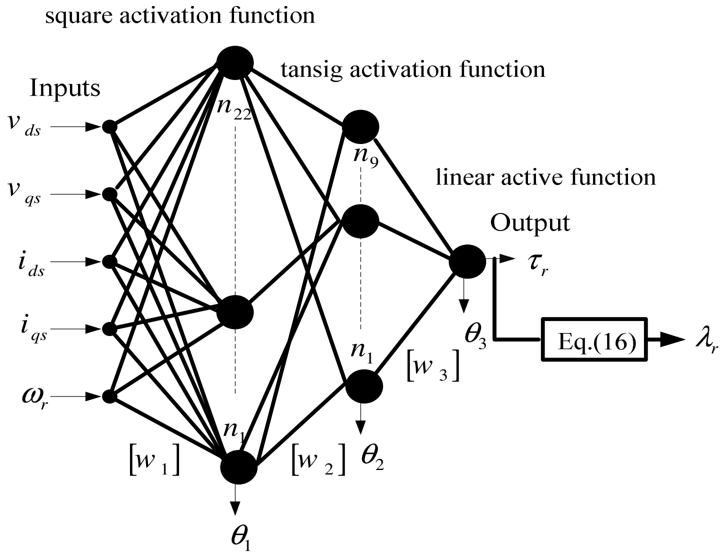

Fig. 1. Neural network for rotor time constant calculation

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 435 training epochs, the sum squared error arrives at zero.

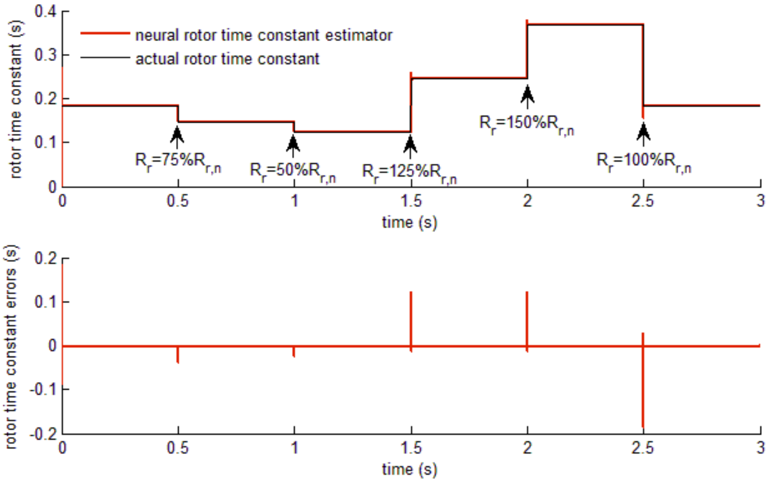

Fig. 2. Estimation results of the neural rotor time constant and estimation errors

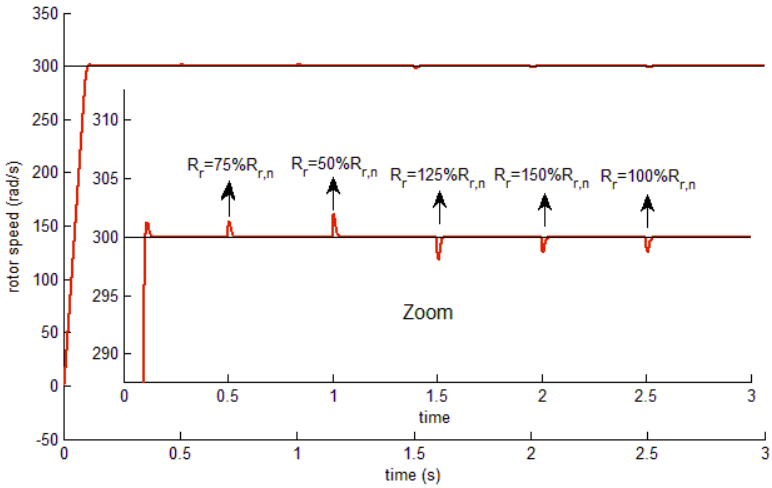

Fig. 3. Rotor speed

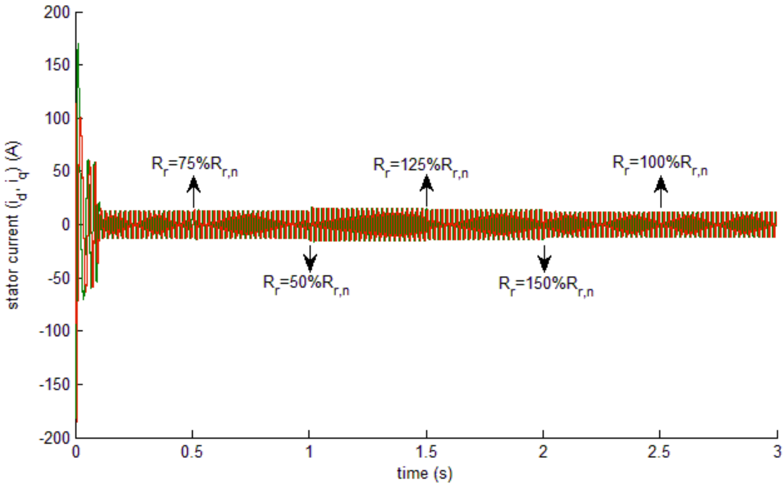

Fig. 4. Stator current (i_d, i_q)

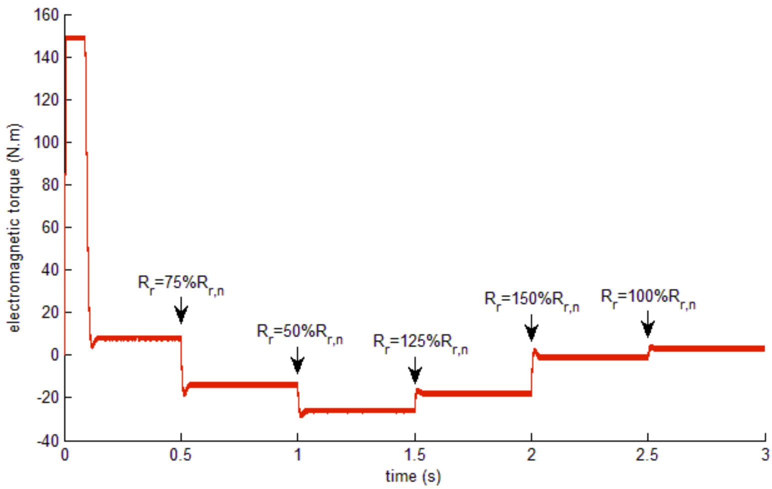

Fig. 5. Electromagnetic torque

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 $t = 0.5s$, $t = 1s$, $t = 1.5s$, $t = 2s$ and $t = 2.5s$ 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 ANNs is used to correct the set-point slip at vector controller level.

You can see in this figure the transient behavior of rotor time constant estimator based ANNs. 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 proposed a novel method for the adaptation of this quantity based on artificial 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. This approach should be useful in various applications where rotor time constant changes can seriously deteriorate the performance of the drive.

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