Induction motor rotor time constant inverse estimation using neural network

N. Kabache B. Chetate

***Abstract*— This paper proposes a new estimator for induction motor rotor time constant inverse basing on a simple hidden layer neural network. An online algorithm is developed for the training of the suggested neural network estimator parameters. This algorithm use the model reference principle by comparing measured and estimated stator currents. So, beside the measured currants which present the reference model (ideal model), it suggested to reconstitute these currants via the motor model which present the actual model (real model). thereafter the errors between measured and estimated currants are exploited for the neural network parameters adaptation. The obtained results show that beside its simplicity, the proposed estimator provides satisfactory performances even at very low speeds.**

I. INTRODUCTION

The induction motor have many interesting features such as low cost and ruggedness which make it the basic supply of mechanical energy in industrial applications. However, its dynamic behavior is highly nonlinear and coupled with time varying parameters and no accessed rotor [1]. Therefore, any control scheme for this motor must deal with two important problems: the rotor flux estimation and the parameter identification. To be noted that all motor's parameters are time varying, in particular, the rotor time constant which is extremely affected by the heating effect [1]. In literature, several adaptive control methods were proposed for the induction motor with estimation of rotor flux and rotor time constant [2], [3], [4], [5], [6], [7], [8] but these approaches suffer from the same problems such as complexity, validity at low speeds and light loads.

To avoid some drawbacks of existing alternatives and improve the induction motor responses, a neural networks-based approach is suggested in this paper for the rotor time constant inverse estimation. Indeed, over the last years, new architectures have been proposed for the neural networks where with the use of some nonlinear adaptive theories [9], many powerful online learning algorithms were developed neural networks training [10], [12], [13], [14], [15], [16], [17]. Via such algorithms, the neural network has currently become one of the most powerful means for the identification and control of uncertain nonlinear systems.

The contribution of this paper is the use of this new neural network architecture to develop an estimator for rotor time constant inverse. Thereafter the estimated parameter is used with motor model to estimate rotor flux. For the training of the suggested neural network estimator we propose the use of a new error function based on stator currents dynamics. Indeed, stator currents are available for measurement and provide a good index to detect and observe the parameter variation in motor. Using the estimated rotor time constant, the stator currents are estimated through the motor model. Thereafter, the dynamics of errors between estimated and measured currents are developed while revealing a correspondence between these dynamics and neural network weights estimate errors. Based on this error dynamics, the adaptive law [9], [13], [16], [17] is exploited so as to generate the training algorithm for neural network weights. The proposed estimator is checked under all operating conditions and a satisfactory estimate for rotor time constant inverse, even at light load and very low speed are reached.

N. Kabache is with Department of electrical engineering, Doctor Yahia Fares University, Medea, Algeria.

B. Chetate is with Laboratory of research on industrial enterprises electrification, University of Boumerdes, Algeria

II. DEVELOPMENT OF THE PROPOSED NEURAL NETWORK ESTIMATOR FOR ROTOR RESISTANCE

As mentioned above, the establishment of the suggested estimator is based on stator currants dynamics, so to start and by using the induction motor model in the fixed frame [16], these lasts are given as follow:

$$\dot{I} = -\gamma I + \alpha\beta\Phi + \begin{bmatrix} 0 & \beta\omega_r \\ -\beta\omega_r & 0 \end{bmatrix} \Phi + \frac{1}{\delta} U_s \quad (1)$$

With, $I = \begin{bmatrix} I_a & I_b \end{bmatrix}^T$, $\Phi = \begin{bmatrix} \Phi_a & \Phi_b \end{bmatrix}^T$, $U_s = \begin{bmatrix} V_a & V_b \end{bmatrix}^T$, where: I_a, I_b are the stator currents, V_a, V_b are the stator voltages, Φ_a, Φ_b are the rotor flux components, ω_r is the rotor speed, R_s, L_s are stator resistance and inductance, R_r, L_r rotor resistance and inductance, M is the magnetizing inductance. And $\beta = \frac{M}{\delta L_r}$, $\gamma = \alpha\beta M + \frac{R_s}{\delta}$, $\delta = L_s(1 - \frac{M^2}{L_s L_r})$, $\alpha = \frac{R_r}{L_r}$

To establish the proposed estimator, supposing that for induction motor rotor time constant only its nominal value is known (the rated is that obtained off-line from some standard tests on induction motor) and our goal is to estimate its unknown variation. According to this supposition, the actual value rotor time constant inverse (α) and γ can be given as:

$$\begin{aligned} \alpha &= \alpha_n + \Delta_\alpha \\ \gamma &= \gamma_n + \beta M \Delta_\alpha + \tfrac{R_s}{\delta} \end{aligned} \quad (2)$$

With

- $\alpha_n = \frac{R_{rn}}{L_{rn}}$ is the rated value of rotor time constant inverse where R_{rn} and L_{rn} are the rated values of rotor resistance ind inductance;
- Δ_α: Is the unknown variation in rotor time constant inverse;

- $\gamma_n = \alpha_n \beta M + \frac{R_s}{\delta}$

By using a neural network estimator, the unknown Δ_α (the unknown variation in rotor time constant inverse) can estimated as follows:

$$\hat{\Delta}_\alpha = \hat{N}\sigma(\hat{N}_c X^T) \tag{3}$$

And thereafter (2) become:

$$\begin{array}{l} \hat{\alpha} = \alpha_n + \hat{\Delta}_\alpha \\ \hat{\gamma} = \gamma_n + \beta M \hat{\Delta}_\alpha + \frac{R_s}{\delta} \end{array} \tag{4}$$

With:

- $\hat{\alpha}_r$: The estimated value of λ_r;
- $\hat{\gamma}$: The estimated value of γ;
- $\hat{\Delta}_\alpha$: The estimated value of Δ_α;
- $\hat{N}(1 \times n_c)$: The matrix of estimate weights between hidden and output layers;
- $\hat{N}_c(n_c \times n_e)$: The matrix of estimate weights between input ant hidden layers;
- $X(1 \times n_e)$: The input vector;
- σ: Is a sigmoid function;
- n_e, n_c: The number of neurons in input and hidden layers.

As explained above, we will use the stator currants For the training of our neural network estimator (3). therefore it is suggested to exploit the estimated rotor time constant inverse for the estimation of the stator currents throw (1) and thereafter, the error between estimated and measured currents will be used for the adaptation of neural network parameters. Therefore, by introducing (4) in (1), the stator currents can be estimated as follow:

$$\dot{\hat{I}} = -\hat{\gamma}\hat{I} + \hat{\alpha}\beta\hat{\Phi} + \begin{bmatrix} 0 & \beta\omega_r \\ -\beta\omega_r & 0 \end{bmatrix} \hat{\Phi} + \frac{1}{\delta} U_s \tag{5}$$

With $\hat{I} = \begin{bmatrix} \hat{I}_a & \hat{I}_b \end{bmatrix}^T$, $\hat{\Phi} = \begin{bmatrix} \hat{\Phi}_a & \hat{\Phi}_b \end{bmatrix}^T$, where $\hat{I}_a$, $\hat{I}_b$, $\hat{\Phi}_a$ and $\hat{\Phi}_b$ are the estimate values of stator currents and rotor flux.

Supposing now that there exists a neural network with ideal parameters that it can provide the exact value of rotor time constant inverse variation Δ_α so that through (1) it will be possible to obtain the exact values of stator currents which are in our case the measured currents. under such situation, the ideal value of rotor time constant inverse variation can be given by the ideal neural network as follows:

$$\Delta_\alpha = N\sigma(N_c X^T) \tag{6}$$

Where N and N_c are the matrix of ideal weights for the ideal neural network .

Considering now the estimate errors for the stator currents as follow:

$$\tilde{I} = \begin{bmatrix} I_a - \hat{I}_a & I_b - \hat{I}_b \end{bmatrix}^T \tag{7}$$

Using (1) and (7), the stator currents estimate error dynamics can be expressed as:

$$\dot{\tilde{I}} = -\gamma_n \tilde{I} + B\tilde{\Delta}_\alpha + \zeta_1 \tag{8}$$

With $\tilde{\Delta}_\alpha = \Delta_\alpha - \hat{\Delta}_\alpha$, $\tilde{\Phi} = \begin{bmatrix} \Phi_a - \hat{\Phi}_a & \Phi_b - \hat{\Phi}_b \end{bmatrix}^T$ and

$$B = \begin{bmatrix} \beta\alpha_n\hat{\Phi}_a - \frac{M^2\alpha_n}{\delta L_r} I_a \\ \beta\alpha_n\hat{\Phi}_b - \frac{M^2\alpha_n}{\delta L_r} I_b \end{bmatrix} \tag{9}$$

$$\zeta_1 = \begin{bmatrix} \beta\alpha_n & n_p\beta\omega \\ -n_p\beta\omega & \beta\alpha_n \end{bmatrix} \tilde{\Phi} \tag{10}$$

The use of (3), (6) and with a Taylor expansion of $\sigma\left(N_c X^T\right)$ around $\left(\hat{N}_c X^T\right)$ (by neglecting high orders), the expression (8) becomes [13], [16], [17]:

$$\dot{\tilde{I}} = -\gamma_n \tilde{I} + B\left(\tilde{N}\left(\hat{\sigma} - \dot{\hat{\sigma}}\hat{N}_c X^T\right) + \hat{N}\dot{\hat{\sigma}}\tilde{N}_c X^T\right) + \zeta_2 \tag{11}$$

Where $\tilde{N} = N - \hat{N}$, $\tilde{N}_c = N_c - \hat{N}_c$, $\hat{\sigma} = \sigma\left(\hat{N}_c X^T\right)$ and $\zeta_2 = \zeta_1 + \psi\left(\tilde{N}, \tilde{N}_c\right)$ with ψ is a bounded error function correspond to the used Taylor expansion.

Basing on the stator currents estimate error dynamics (11), training algorithm for neural network weights can be given as [13], [16], [17]:

$$\begin{array}{l} \dot{\hat{N}} = B^T\left(\hat{\sigma} - \dot{\hat{\sigma}}\hat{N}_c X^T\right)\left[\tilde{I}\right]^T + \tau\left|\tilde{I}\right|\hat{N} \\ \dot{\hat{N}}_c = B^T\hat{N}\dot{\hat{\sigma}}X^T\left[\tilde{I}\right]^T + \tau_c\left|\tilde{I}\right|\hat{N}_c \end{array} \tag{12}$$

with τ_1, τ_2, τ_{c1}, and τ_{c2} are appropriate positive constants.

III. Simulation results

For testing the suggested neural estimator it has been used with the control scheme of [16]. The simulation study is carried for several operating conditions where different step and linear (ramp) variations were introduced on rotor time constant see (Fig. 1), for the motor parameters see [16].

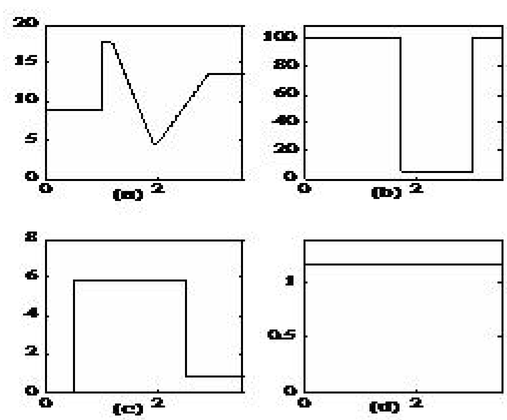

Fig. 1. reference values for (a) rotor time constant inverse (b) speed (c) torque (d) rotor flux

The estimated rotor time constant inverse values, given by the proposed neural network estimator, are illustrated on

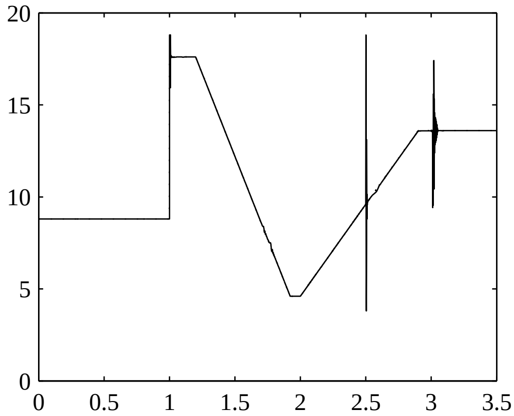

Fig. 2. Response of the proposed estimator for rotor time constant inverse variations

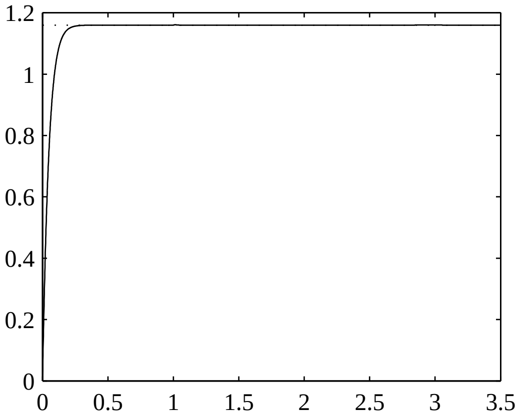

Fig. 5. Evolution of rotor flux amplitude with rotor time constant inverse estimation

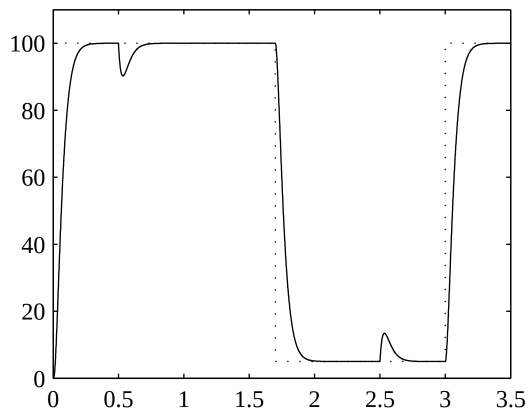

Fig. 3. Evolution of motor speed with rotor time constant inverse estimation

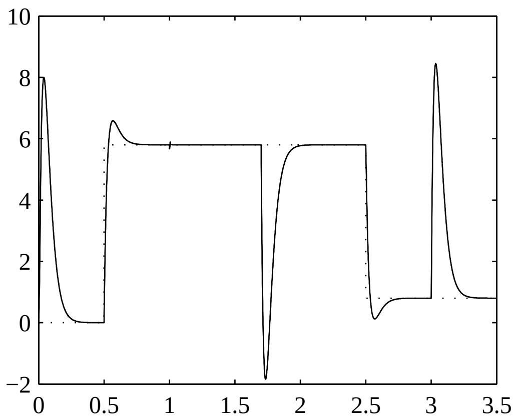

Fig. 4. Evolution of motor torque with rotor time constant inverse estimation

figure (2). It is obvious that without considering some small fluctuations, in transient regimes, the estimated rotor time constant inverse corresponds well to its ideal (true) values even for very low speeds and weak loads. This accuracy can be seen in motor responses where, the speed (Fig. 3), the torque (Fig. 4) and rotor flux (Fig. 5) are not affected even for a variation of 100% of rotor resistance.

IV. CONCLUSION

In this paper, a new neural network estimator is proposed for estimation of the induction motor rotor time constant inverse. The obtained results show clearly the capacity of the suggested estimator to give a satisfactory estimation for rotor time constant in all induction motor operating conditions even at very law speed and weak load. Besides, the proposed estimator is characterized by a simple architecture of only two neurons in hidden layer with simple adaptation training algorithm. It uses simply errors between estimated and measured stator currents for the neural network parameters adaptation. The obtained results permit also to extend the perspective of the proposed approach to estimate other important parameters such that the stator time constant, load torque and motor speed which allow establishing a control without speed sensor for the induction motor which is very indicated in recent applications.

REFERENCES

[1] Leonhard W. *Control of electrical drives.* Spring Verlag, New York, 1990.

[2] Marino R, Peresada S, Valigi P. Adaptive input-output linearizing control of induction motors. *IEEE Trans. Autom. Control* 1993; **38**:208–221.

[3] Marino R, Peresada S, Tomei P. Global adaptive output feedback control of induction motors with uncertain rotor resistance. *IEEE Trans. Autom. Control* 1999; **44**:967–983.

[4] Marino R, Tomei P, Verrelli C. Adaptive control for speed-sensorless induction motors with uncertain load torque and rotor resistance. *Int. J. Adapt. Control Signal Process* 2005; **19**:661–685.

[5] Akatsu K, Kawamura A. Online rotor resistance estimation using the transient state under the speed sensorless control of induction motor. *IEEE Trans. Power Electron* 2000; **15**:553–559.

[6] Wade S, Dunnigan M, Williams B. Online rotor resistance estimation using the transient state under the speed sensorless control of induction motor. *IEE Proc. Electron. Power Appl.* 1997; **144**:285–294.

[7] Kwan C, Lewis F, Yeung K. Adaptive control of induction motor without flux measurements. *Automatica* 1996; **32**:903–908.

[8] Verghese GC, Sanders SR. Observers for flux estimation in induction machines. *IEEE Trans. Ind. Electron.* 1998; **35**:85–94.

[9] Narendra K.S, Annaswamy A.M. A new adaptive law for robust adaptation without persistent excitation. *IEEE Trans. Autom. Control* 1987; **32**:134–145.

[10] Boskovic J, Narendra K. Comparison of linear, nonlinear and neural-network-based adaptive controllers for a class of fed-batch fermentation processes. *Automatica* 1995; **31**:817–840.

[11] Chen F, Liu C. Adaptively controlling nonlinear continuous-time systems using multi-layer neural networks. *IEEE Trans. Power Electron* 1994; **39**:1306–1310.

[12] Commuri S, Lewis F. CMAC neural networks for control of nonlinear dynamical systems: Structure and passivity. *Automatica* 1997; **33**:635–641. Yasildirek A, Lewis F (1995) Feedback linearization using neural networks. Automatica, 31: 1695-1664

[13] Yasildirek A, Lewis F. Feedback linearization using neural networks. *Automatica* 1995; **31**:1695–1664.

[14] Yu S.H, Annaswamy A.M. Stable neural controllers for nonlinear dynamic systems. *Automatica* 1998; **34**:641–650.

[15] Zhang T, Ge S.S, Hang C.C. Design and performance analysis of a direct adaptive controller for nonlinear systems. *Automatica* 1999; **35**:1809–1817.

[16] Chetate B, Kabache N, Ladygin A.N. Adaptive control in an asynchronous electric drive on the basis of an artificial neural network with calculation of the rotor flux. *Russian Electrical Engineering* 2007; **78**:315–321.

[17] Kabache N., Chetate B. Adaptive Nonlinear Control of Induction Motor Using Neural Networks *IEEE proc., Int. Conf. on Phys. and Control, St. Petersburg, Russia* 2003; **1**:259–264.