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INDUCTION MOTOR VSS CONTROL USING NEURAL NETWORKS

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Abstract: The authors present a novel approach to control this kind of motor. Modifying published results for nonlinear identification using dynamic neural networks, they propose a new neural network identifier of triangular form. Based on this model a new control law, which combines sliding mode and block control is derived. This new neural identifier and the proposed control law allow trajectory tracking for induction motors. Applicability of the approach is tested via simulations.

Keywords: Dynamic Neural Networks, Variable Stucture Systems, Nonlinear systems, Identification, Lyapunov methodology.

1. INTRODUCTION

Adaptive control of induction motors is one of most interesting application control problem. This problem has been extensively studied during the last decade, and considering that the rotor resistance and the load torque are unknown but *constant,* several adaptive controllers have been proposed, see for instance (Krstic, *et al.,* 1995; Kwan,*et al.,* 1996; Marino, *et al.*, 1996; Ortega, and Espinoza-Pérez, 1993).

In this paper it is assumed that all of the induction motor parameters can change in a wide range. Particularly the rotor resistance and the load torque can vary both as continuous and discontinuous functions of the time. To derive the induction motor model, a neural networks approach combining with the rotor flux sliding mode observer, is applied, and a novel approach is presented. Modifying existing identification schemes based on dynamic neural networks (Kosmatopoulos, et al., 1997), a neural network identifier of block controllable form is proposed. Based on this model, two versions of discontinuous control law, which combines block control (Loukianov, 1998) and VSS with sliding mode techniques (Utkin, 1992), are derived. The block control approach is used to design a nonlinear sliding surface such that the resulting sliding mode dynamics is described by a desired linear system. The proposed neural identifier and control strategy allow trajectory tracking for induction motors.

2. MOTOR MODEL

The starting point is the following set of induction motor equations presented in the stator-fixed $\alpha-\ \beta$ coordinate system, see for instance (Bose, 1986):

$$
\begin{aligned}
\frac{d\omega}{dt} &= c_1(\psi_\alpha i_\beta - \psi_\beta i_\alpha) - c_0 T_L \\
\frac{d\psi_\alpha}{dt} &= -c_2\psi_\alpha - n_p\omega\psi_\beta + c_3 i_\alpha \\
\frac{d\psi_\beta}{dt} &= -c_2\psi_\beta + n_p\omega\psi_\alpha + c_3 i_\beta \\
\frac{di_\alpha}{dt} &= c_4\psi_\alpha + c_5 n_p\omega\psi_\beta - c_6 i_\alpha + c_7 u_\alpha \\
\frac{di_\beta}{dt} &= c_4\psi_\beta - c_5 n_p\omega\psi_\alpha - c_6 i_\beta + c_7 u_\alpha
\end{aligned}
\qquad (1)
$$

where ω represents the angular velocity of the motor shaft, ψ_a and ψ_β are, respectively, the rotor magnetic flux leakage components, i_α and i_β are, respectively, the stator current components, u_α and u_β stand, respectively, for the voltage applied on the stator windings, and T_L represents the load torque perturbation. The constants c_i, $i = 0, ..., 7$ are calculated as follows

$c_0 = \frac{1}{J}$, $c_1 = \frac{3}{2}\frac{Mn_p}{JL_r}$, $c_2 = \frac{R_r}{L_r}$, $c_3 = \frac{R_r M}{L_r}$, $c_4 = \frac{R_r}{L_r}\frac{M}{L_s L_r - M^2}$, $c_5 = \frac{M}{L_s L_r - M^2}$, $c_6 = \frac{R_s L_r^2 + R_r M^2}{L_s(L_s L_r - M^2)}$, $c_7 = \frac{L_r}{L_s L_r - M^2}$ with L_s, L_r and M, respectively, the stator and rotor inductances and mutual inductance between the rotor and the stator, R_s and R_r, the stator and rotor resistances, J the rotor moment of inertia, and n_p the number of stator winding pole pairs. The magnitude of the control should be bounded

$$|u_\alpha| \leq u_0 \quad \text{and} \quad |u_\beta| \leq u_0, \quad u_0 > 0. \quad (2)$$

It is more suitable for neural network identification to present the induction motor model (1) in new variables defined as $\chi_1 = \omega$, $\chi_2 = \psi_\alpha$, $\chi_3 = \psi_\beta$, $\chi_4 = i_\alpha$, $\chi_5 = i_\beta$. Henceforth, the model (1) can be rewritten as

$$\begin{aligned}
\dot{\chi}_1 &= c_1(\chi_2\chi_5 - \chi_3\chi_4) - c_0 T_L \\
\dot{\chi}_2 &= -c_2\chi_2 - n_p\chi_1\chi_3 + c_3\chi_4 \\
\dot{\chi}_3 &= -c_2\chi_3 + n_p\chi_1\chi_2 + c_3\chi_5 \\
\dot{\chi}_5 &= c_4\chi_2 + c_5 n_p\chi_1\chi_3 - c_6\chi_4 + c_7 u_\alpha \\
\dot{\chi}_6 &= c_4\chi_3 - c_5 n_p\chi_1\chi_2 - c_6\chi_5 + c_7 u_\beta.
\end{aligned} \quad (3)$$

This system is a quasi Nonlinear Block Controllable Form (or NBC-form), (Loukianov, 1998). Based on this fact, the so-called dynamic block controllable neural network is proposed below.

3. NONLINEAR OBSERVER

Since only the rotor speed and the stator currents are measured, rotor fluxes estimation is required for neural networks identification. In order to get the flux estimation, the only the stator currents dynamics, which does not depend on the external perturbation, is used. The proposed observer has the following form:

$$\begin{aligned}
\dot{\tilde{\chi}}_4 &= -c_5\chi_4 + c_6 u_1 + v_\alpha \\
\dot{\tilde{\chi}}_5 &= -c_5\chi_5 + c_6 u_2 + v_\beta
\end{aligned}$$

where $\tilde{\chi}_4$ and $\tilde{\chi}_5$ are the estimations of the currents χ_4 and χ_5. Observer inputs v_α and v_β are chosen as

$$v_\alpha = l_1 \frac{\varepsilon_\alpha}{|\varepsilon_\alpha| + \delta} \text{ and } v_\beta = l_2 \frac{\varepsilon_\beta}{|\varepsilon_\beta| + \delta}$$

where l_1, l_2 and δ are positive observer parameters. Then, the error dynamics have the following form:

$$\begin{aligned}
\dot{\varepsilon}_\alpha &= c_4\chi_2 + c_5 n_p\chi_1\chi_3 - l_1 \frac{\varepsilon_\alpha}{|\varepsilon_\alpha| + \delta} \\
\dot{\varepsilon}_\alpha &= c_4\chi_3 - c_5 n_p\chi_1\chi_2 - l_2 \frac{\varepsilon_\beta}{|\varepsilon_\beta| + \delta}
\end{aligned}$$

where $\varepsilon_\alpha = \chi_4 - \tilde{\chi}_4$ and $\varepsilon_\beta = \chi_5 - \tilde{\chi}_5$. For sufficiently large values of l_1 and l_2, and small value of δ, the sliding surfaces $\varepsilon_\alpha = 0$ and $\varepsilon_\beta = 0$ are attractive, and ones the trajectory reaches these surfaces, its remain on these surfaces (Utkin, 1991). It means that $\dot{\varepsilon}_\alpha = 0$ and $\dot{\varepsilon}_\alpha = 0$, or

$$\begin{aligned}
0 &= c_4\chi_2 + c_5 n_p\chi_1\chi_3 - v_{\alpha eq} \\
0 &= c_4\chi_3 - c_5 n_p\chi_1\chi_2 - v_{\alpha eq}
\end{aligned} \quad (4)$$

where $v_{\alpha eq}$ and $v_{\beta eq}$ are the equivalent values of v_α and v_β respectively. Measuring these values, it is possible to obtain from (4) estimations $\hat{\chi}_2$ and $\hat{\chi}_3$ of χ_2 and χ_3, as

$$\begin{bmatrix} \hat{\chi}_2 \\ \hat{\chi}_3 \end{bmatrix} = \frac{1}{c_4^2 + (c_5 n_p \chi_1)^2} \begin{bmatrix} c_4 & -c_5 n_p \chi_1 \\ c_5 n_p \chi_1 & c_4 \end{bmatrix} \begin{bmatrix} v_{\alpha eq} \\ v_{\beta eq} \end{bmatrix}$$

The obtained estimated fluxes $\hat{\chi}_2$ and $\hat{\chi}_3$ will be used for the neural network identification.

4. RECURRENT HIGH ORDER NEURAL NETWORK IDENTIFICATION

In this section, the problem of the identifying of nonlinear model (3), is considered.

4.1 *Dynamic Block Controllable Neural Network for Induction Motors*

Based on the mathematical model for induction motors (3), the following Recurrent Neural Network High Order (RHONN), is proposed:

$$\begin{aligned}
\dot{x}_1 &= -a_1 x_1 + w_{11} S(x_1) + w_{12} S(x_3) x_4 \\
&\quad + w_{13} S(x_2) x_5 \qquad (5) \\
\dot{x}_2 &= -a_2 x_2 + w_{21} S(x_2) + w_{22} S(x_1) S(x_3) \\
&\quad + w_{23} x_4 \\
\dot{x}_3 &= -a_3 x_3 + w_{31} S(x_3) + w_{32} S(x_1) S(x_2) \quad (6) \\
&\quad + w_{33} x_5 \\
\dot{x}_4 &= -a_4 x_4 + w_{41} S(x_1) + w_{42} S(x_2) \\
&\quad + w_{43} S(x_3) + w_{44} S(x_4) + w_{45} u_1 \\
\dot{x}_5 &= -a_5 x_5 + w_{51} S(x_1) + w_{52} S(x_2) \\
&\quad + w_{53} S(x_3) + w_{54} S(x_5) + w_{55} u_2
\end{aligned}$$

where x_i, $i = 1, ..., 5$ is the i-th component of the RHONN; $a_i > 0$, $i = 1, ..., 5$; $w_{i,j}$ are time-varying weights, and $S(\cdot)$ a smooth sigmoid function formulated by:

$$S(x) = \frac{2}{1 + \exp(-\beta x)} - 1$$

for the sigmoid $S(x) \in [-1, 1]$. This new structure is more flexible than the classical neural networks (Kosmatopoulos, et al., 1997), and allows to incorporate to the identification model a priori information about the plant structure. It is worth noting that this structure, with conditions defined below for the case of induction motors, guarantees controllability. On the basis of this model, in the following subsection an algorithm for on-line identification of the motor, is considered.

4.2 *On-line Identification*

In order to identify the induction motor model (3), it is assumed, that this system is approximated by the following system:

$$\dot{\chi}_i = -a_i\chi_i + w_i^{*\top}\rho_i(\chi,u) + v_i(\chi,u) \qquad (7)$$

and, instead of RHONN (6) it is used the following so-called series-parallel model:

$$\dot{x}_i = -a_i x_i + w_i^T\rho_i(\chi,u), \qquad i = 1,...,5 \qquad (8)$$

where the optimal unknown parameters vector w_i^* is defined as

$$w_i^* = \arg\min_{w_i}\left\{\begin{array}{c}\sup_{\chi,u}|f_i(\chi)+g_i(\chi)u\\ +a_i\chi_i - w_i^T\rho_i(\chi,u)|\end{array}\right\}$$

with $\rho_1 = [S(\chi_1), S(\chi_2), S(\chi_3)x_4, S(\chi_2)\chi_5]^\top$,
$\rho_2 = [S(\chi_2), S(\chi_1)S(\chi_3), \chi_4]^\top$,
$\rho_3 = [S(\chi_3), S(\chi_1)S(\chi_2), \chi_5]^\top$,
$\rho_4 = [S(\chi_1), S(\chi_2), S(\chi_3), S(\chi_4), u_1]^\top$, and
$\rho_5 = [S(\chi_1), S(\chi_2), S(\chi_3), S(\chi_5), u_2]^\top$.

Hence, the modelling error term $v_i(\chi,u)$ in (7) can be defined as

$$v_i(\chi,u) = f_i(\chi) + g_i(\chi)u + a_i\chi_i - w_i^{*T}\rho_i(\chi,u)$$

4.3 *On-Line Weight Update Law*

Let define the $i-$th identification error

$$e_i = x_i - \chi_i$$

and the $i-$th parameter error

$$\tilde{w}_i = w_i - w_i^*.$$

Then the error equation can be derived from (8) and (7) as

$$\dot{e}_i = -a_i e_i + \tilde{w}_i^\top\rho_i + v_i(\chi,u), \quad i = 1,...,5. \quad (9)$$

In order to guarantee the boundness of the identification error and weights, the following adaptive law adaptive law is applied:

$$\dot{w}_i = -\Gamma_i^{-1}(e_i\rho_i - \sigma_i w_i), \quad i = 1...,5 \qquad (10)$$

with the σ-modification

$$\sigma_i = \begin{cases} 0, & \text{if } ||w_i|| \le M_i \\ \left(\dfrac{||w_i||}{M_i}\right)^q\sigma_{i0}, & \text{if } M_i < ||w_i|| \le 2M_i \\ \sigma_{i0}, & \text{if } ||w_i|| > 2M_i \end{cases}$$

where Γ_i is a symmetric positive definite matrix; integer $q \ge 1$, and σ_{i_0} and M_i are positive constants.

Lemma 1. Consider the system (7) and the RHONN (6) whose parameters are adapted using the law (10), and suppose that

$$\|v_i(\chi,u)\| \le d_0 \qquad (11)$$

Then e_i and w_i are bounded.

Proof. The derivative of the Lyapunov function candidate

$$V_i = \frac{1}{2}(e_i^2 + \tilde{w}_i^\top\Gamma_i\tilde{w}_i) \qquad (12)$$

along the trajectories of (9) and (10) is given by

$$\dot{V}_i = -a_i e_i^2 - \sigma_i\tilde{w}_i^\top w_i - e_i v_i(\chi,u).$$

Using (11) and applying the triangular inequality, gives

$$\dot{V}_i \le -a_i e_i^2 - \sigma_i\tilde{w}_i^\top w_i + \frac{e_i^2}{2} + \frac{{d_0}^2}{2}.$$

Since $\tilde{w}_i = w_i - w_i^*$, then

$$-\tilde{w}_i^\top w_i \le -(\tilde{w}_i^\top\tilde{w}_i + \tilde{w}_i^\top w_i^*) \le -\frac{1}{2}||\tilde{w}_i||^2 + \frac{1}{2}||w_i^*||^2.$$

Therefore

$$\dot{V}_i \le -\alpha e_i^2 - \frac{1}{2}\sigma_i||\tilde{w}_i||^2 + \frac{1}{2}\sigma_i||w_i^*||^2 + \frac{d_0^2}{2}$$

where $\alpha = a_i - \frac{1}{2}$. Substituting e_i from (12) in the above inequality, gives

$$\dot{V}_i \le -\alpha V_i + \alpha\tilde{w}_i^\top\Gamma_i\tilde{w}_i - \frac{1}{2}\sigma_i||\tilde{w}_i||^2 + \frac{1}{2}\sigma_i||w_i^*||^2 + \frac{d_0^2}{2}.$$

Considering the worst case, when $||w_i|| > 2M_i$, the parameter σ_{io} is selected as

$$\sigma_{io} > 2\alpha||\Gamma_i||$$

then

$$\dot{V}_i \le -\alpha V_i + \frac{1}{2}\sigma_{io}||w_i^*||^2 + \frac{d_0^2}{2}.$$

Therefore e_i and w_i converge exponentially to the residual set

$$\mathcal{D} = \left\{ e_i, w_i \,\middle|\, V_i \le \frac{1}{2\alpha}\sigma_{io}||w_i^*||^2 + \frac{d_0^2}{2\alpha} \right\}$$

and the proof is complete.

4.4 *Identifier Initialization*

Before to apply the control law, the system was excited in order to get a good estimation of the optimal parameters. These values will be used as initial values for the identifier parameters when we apply the control law.

The inputs to excite the plant are

$$u_\alpha = 200\cos(800(\cos(0.1t)^2)t)$$
$$u_\beta = 200\sin(800(\cos(0.1t)^2)t)]$$

Figure 1 shows the behavior of the parameters. The obtained values guarantee that the identifier is block controllable initially, and these values do not vary much, hence controllability is not lost.

5. INDUCTION MOTOR CONTROL

In this section, the control law for the induction motor is developed, on the basis of the neural identifier, and using the block control and VSS techniques. Assuming that $x_i = \chi_i$, $i = 1, ..., 5$, two control strategies will be considered:

Type I: Control of the speed and the rotor flux, and

Type II: Control of the speed only.

5.1 *Control Law I*

The neural model (6) has the quasi NBC-form consisting of two blocks:

$$\begin{aligned}\dot{\mathbf{x}}_1 &= \mathbf{f}_1(\mathbf{x}_1) + \mathbf{B}_1(\mathbf{x}_1)\mathbf{x}_2 \\ \dot{\mathbf{x}}_2 &= \mathbf{f}_2(\mathbf{x}_1, \mathbf{x}_2) + \mathbf{B}_2\mathbf{u}\end{aligned} \tag{13}$$

with $\mathbf{x} = [\mathbf{x}_1, \mathbf{x}_2]^T$, $\mathbf{x}_1 = [x_1, x_2, x_3]^T$, $\mathbf{x}_2 = [x_4, x_5]^T$, $\mathbf{u} = [u_\alpha, u_\beta]^T$,

$$\mathbf{f}_1 = \begin{bmatrix} -a_1x_1 + w_{11}S(x_1) \\ -a_2x_2 + w_{21}S(x_2) + w_{22}S(x_1)S(x_3) \\ -a_3x_3 + w_{31}S(x_3) + w_{32}S(x_1)S(x_2) \end{bmatrix}$$

$$\mathbf{f}_2 = \begin{bmatrix} -a_4x_4 + -a_4x_4 + \sum_{i=1}^{4} w_{4,i}S(x_i) \\ -a_5x_5 + \sum_{i=1}^{5} w_{5,i}S(x_i), \quad i \neq 4 \end{bmatrix}$$

$$\mathbf{B}_1 = \begin{bmatrix} -w_{12}S(x_3) & w_{13}S(x_2) \\ w_{23} & 0 \\ 0 & w_{33} \end{bmatrix} \text{ and}$$

$$\mathbf{B}_2 = \begin{bmatrix} w_{45} & 0 \\ 0 & w_{55} \end{bmatrix}.$$

For the speed, x_1 and flux amplitude φ, $\varphi = |\Psi|^2 = x_2^2 + x_3^2$, tracking objectives, define the tracking errors as

$$\begin{aligned} z_1 &= x_1 - \omega_{ref} \\ z_2 &= \varphi - \varphi_{ref} \end{aligned} \tag{14}$$

where ω_{ref} and φ_{ref} are the smooth bounded reference signals for the speed and flux magnitude consequently. Then, the first block of the NBC-form can be expressed as

$$\begin{bmatrix} \dot{z}_1 \\ \dot{z}_2 \end{bmatrix} = \bar{\mathbf{f}}_1(\mathbf{x}_1) + \bar{\mathbf{B}}_1(\mathbf{x}_1)\mathbf{x}_2 \tag{15}$$

where

$$\bar{\mathbf{f}}_1 = \begin{bmatrix} \bar{f}_1 \\ \bar{f}_2 \end{bmatrix}, \ \bar{\mathbf{B}}_1 = \begin{bmatrix} w_{12}S(x_3) & w_{13}S(x_2) \\ 2w_{23}x_2 & 2w_{33}x_3 \end{bmatrix}$$

$$\bar{f}_1 = -a_1x_1 + w_{11}S(x_2) - \dot{\omega}_{ref}$$

$$\begin{aligned}\bar{f}_2 = & 2x_2(-a_2x_2 + w_{21}S(x_2) + w_{22}S(x_1)S(x_3) + \\ & 2x_3(-a_3x_3 + w_{31}S(x_3) + w_{32}S(x_1)S(x_2) - \dot{\varphi}_{ref}\end{aligned}$$

Following the block control strategy, the quasi control vector $\mathbf{x}_2$ in (15) can be formulated as

$$\mathbf{x}_2 = \begin{bmatrix} x_4 \\ x_5 \end{bmatrix} = \mathbf{x}_2^c - \bar{\mathbf{B}}_1^{-1} \begin{bmatrix} k_1z_1 \\ k_2z_2 \end{bmatrix} + \begin{bmatrix} z_4 \\ z_5 \end{bmatrix} \tag{16}$$

with

$$\mathbf{x}_2^c = -\bar{\mathbf{B}}_1^{-1}\bar{\mathbf{f}}_1 \tag{17}$$

where z_4 and z_5 are new variables, k_1 and k_2 are scalar positive parameters, and

$$\bar{\mathbf{B}}_1^{-1} = \frac{1}{\delta}\begin{bmatrix} 2w_{33}x_3 & -2w_{23}x_2 \\ -w_{13}S(x_2) & w_{12}S(x_3) \end{bmatrix}$$

with $\delta = 2w_{12}w_{33}x_3S(x_3) - 2w_{13}w_{23}x_2S(x_2)$. The equations (16) and (17) give the following transformation:

$$\begin{aligned}\begin{bmatrix} z_4 \\ z_5 \end{bmatrix} &= \bar{\mathbf{B}}_1^{-1}\begin{bmatrix} k_1(x_1 - \omega_{ref}) + \bar{f}_1 \\ k_2(\varphi - \varphi_{ref}) + \bar{f}_2 \end{bmatrix} + \begin{bmatrix} x_4 \\ x_5 \end{bmatrix} \\ &:= \boldsymbol{\alpha}(\mathbf{x}_1, \mathbf{x}_2, \gamma), \quad \gamma = (\omega_{ref}, \varphi_{ref})^T. \end{aligned} \tag{18}$$

On the second step, taking the derivative of (18) along the trajectories of (13), the second block of the NBC-form in the new variables z_4 and z_5 can be presented of the form

$$\begin{bmatrix} \dot{z}_4 \\ \dot{z}_5 \end{bmatrix} = \bar{\mathbf{f}}_2 + \mathbf{B}_2\begin{bmatrix} u_\alpha \\ u_\beta \end{bmatrix}$$

where $\bar{\mathbf{f}}_2 = \frac{\partial\alpha}{\partial\mathbf{x}_1}\mathbf{f}_1 + \frac{\partial\alpha}{\partial\mathbf{x}_2}\mathbf{f}_2 + \frac{\partial\alpha}{\partial\gamma}\dot{\gamma}$.

Now, taking in the account the bound (2), the VSS control strategy, formulated as

$$\begin{aligned} u_\alpha &= -u_0 sign(w_{45}) sign(z_4) \\ u_\beta &= -u_0 sign(w_{55}) sign(z_5) \end{aligned}$$

under condition

$$|w_{45}|\, u_0 \ \geq \left|\bar{f}_4(x^1, x^2, \gamma)\right| \leq, \quad |w_{55}|\, u_0 \geq \left|\bar{f}_5(x^1, x^2, \gamma)\right|$$

guarantees a sliding mode on the surfaces

$$z_4 = 0 \quad \text{and} \quad z_5 = 0$$

in finite time. The sliding dynamics, in the tracking errors variables z_1 and z_2 (14), is governed by the second order linear system

$$\begin{aligned} \dot{z}_1 &= -k_1z_1 \\ \dot{z}_2 &= -k_2z_2 \end{aligned}$$

with desired eigenvalues $-k_1$ and $-k_2$.

5.2 *Control Law 2*

Given a reference ω_{ref}, the following tracking error, is defined:

$$z_1 = x_1 - \omega_{ref}. \tag{19}$$

Differentiating (19) along the trajectories of (13), gives

$$\dot{z}_1 = \hat{f}_1 + \hat{\mathbf{B}}_1\mathbf{x}_2 \tag{20}$$

where $\hat{f}_1 = -a_1x_1 + w_{11}S(x_1) - \dot{\omega}_{ref}$, $\hat{\mathbf{B}}_1 = \begin{bmatrix} w_{12}S(x_3) & w_{13}S(x_2) \end{bmatrix}$.

On the next step, following the block control technique, the quasi control $\mathbf{x}_2$ in (20) is chosen of the form

$$\mathbf{x}_2 = \mathbf{x}_2^c - \hat{\mathbf{B}}_1^+(c_1 z_1), \ \mathbf{x}_2^c = -\hat{\mathbf{B}}_1^+ \hat{f}_1, \ c_1 > 0 \quad (21)$$

that gives the following transformation:

$$z_2 = c_1(x_1 - \omega_{ref}) + \hat{f}_1 + \hat{\mathbf{B}}_1 \mathbf{x}_2 \qquad (22)$$

and (20) with (21) becomes

$$\dot{z}_1 = -k_1 z_1 + z_2$$

Differentiating (22) along the trajectories of (13) gives

$$\dot{z}_2 = \hat{f}_2 + \hat{\mathbf{B}}_2 \mathbf{u} \qquad (23)$$

where $\hat{f}_2$ is a bounded function of the variables and parameters of (13), and

$$\hat{\mathbf{B}}_2 = \hat{\mathbf{B}}_1 \mathbf{B}_2 = \left[\, w_{12}w_{45}S(x_3) \ \ w_{13}w_{55}S(x_2) \,\right]$$

Now the discontinuous control law is proposed as

$$\mathbf{u} = \begin{bmatrix} u_\alpha \\ u_\beta \end{bmatrix} = \begin{bmatrix} -u_0 sign(w_{12}w_{45}S(x_3)) sign(z_2) \\ -u_0 sign(w_{12}w_{45}S(x_3)) sign(z_2) \end{bmatrix} \qquad (24)$$

Then (23) with (24) can be rewritten of the form

$$\dot{z}_2 = \hat{f}_2 - u_0(|w_{12}w_{45}S(x_3)| + |w_{13}w_{55}S(x_2)|) sign(z_2)$$

Under the following condition:

$$(|w_{14}w_{55}S(x_2)| + |w_{14}w_{45}S(x_3)|)u_0 > |\hat{f}_2|$$

a singular sliding mode motion (two components of the vector control have the same switching function, z_2) arises on the surface $z_2 = 0$, and this motion is described by the reduced first order system

$$\dot{z}_1 = -c_1 z_1$$

with eigenvalue $-c_1$. Therefore, the tracking error z_1 converges asymptotically to zero.

6. SIMULATIONS

In this section, the authors present results obtained using the identification scheme and the control law proposed above. The nominal values of the induction motor parameters are given in the next table

Parameter	Value	Description
R_s	14Ω	Stator Resistance
L_s	$400mH$	Stator self Inductance
M	$377mH$	Mutual Inductance
R_r	10.1Ω	Rotor Resistance
L_r	$412.8mH$	Rotor self Inductance
n_p	2	Number of pairs of poles
J	$0.01Kgm$	Inertia Momentum

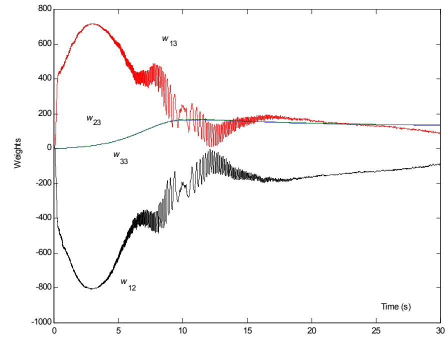

Fig. 1. Weights w_{12}, w_{13}, w_{23} and w_{33}

The design parameters for the fluxes observer are $l_1 = l_2 = 3500$. The neural network parameters are selected as $a_1 = 100$, $a_2 = a_3 = a_4 = a_5 = 500$, $\beta = 0.1$, $\Gamma_1^{-1} = diag\{500, 500, 500\}$, $\Gamma_2^{-1} = \Gamma_3^{-1} = diag\{500, 500, 50\}$, $\Gamma_4^{-1} = \Gamma_5^{-1} = diag\{500, 500, 500, 500, 500\}$, and the controller gains for control law 1 are $k_1 = 600$ and $k_2 = 140$, and for the control law 2 $c_1 = 600$. In order to test the proposed scheme performance, a variation of 2 Ohm per second is added to the stator resistance. In addition, a square load torque perturbation with an amplitude of 2 Nm and a period of 0.3 seconds is performed.

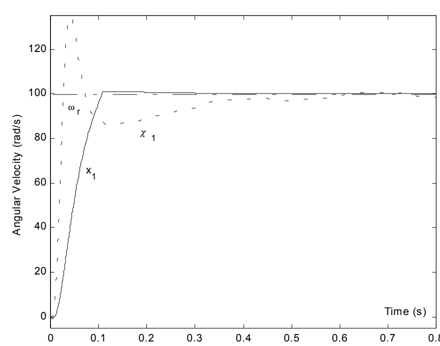

Fig. 2. Real speed χ_1, reference speed ω_r and speed estimation x_1.

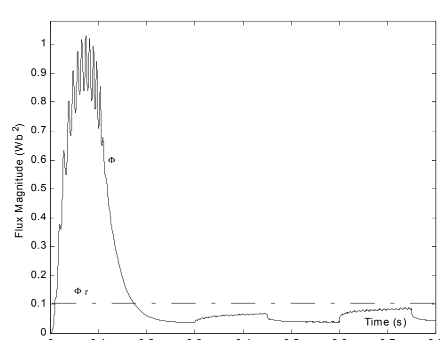

Fig. 3. Flux magnitude φ and flux reference φ.

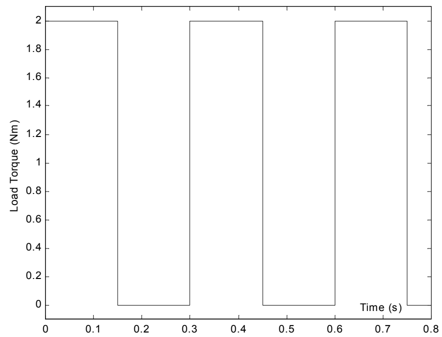

Fig. 4. Load torque T_L

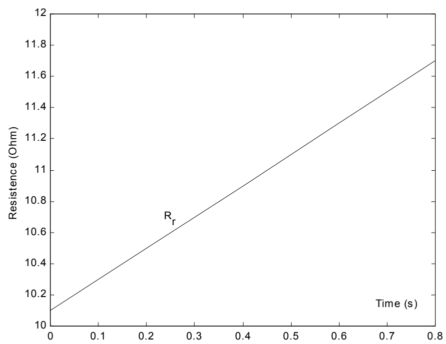

Fig. 5. Rotor Resistence R_r

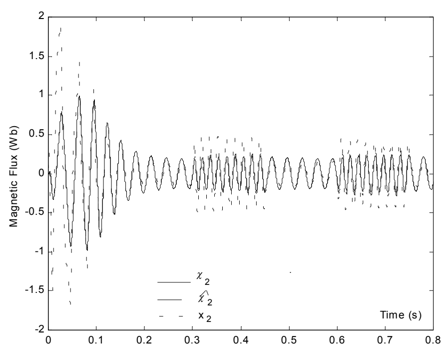

Fig. 6. Flux χ_2, flux observer estimation $\hat{\chi}_2$ and flux identifier estimation x_2.

The results for velocity and flux are presented in Fig. 2 and Fig. 3, respectively. As can be seen, the performance of the proposed scheme is very satisfactory. Even is the flux desired value is not obtained, it is important to remind that the main objective control is to track the reference signal for velocity, which is indeed attained.

7. CONCLUSIONS

In this paper, the authors have presented a new identification and tracking control, based on dynamic neural networks and VSS methodology, for induction motors. The stability, for both the identifier and the controller, is analyzed, and it is proved that the proposed control laws force the closed loop trajectory to converge and stay in sliding manifolds, which guarantees that the tracking error is zero. Work is progress to test the robustness of this control scheme in presence of different kind of disturbances such as load torque variations and change on the induction motor parameters.

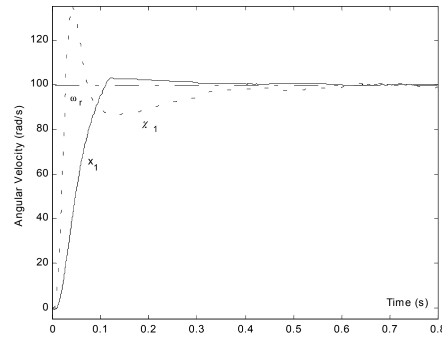

Fig. 7. Control 2. Real speed χ_1, speed reference ω_r, speed identifier estimation x_1.

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