SYNCHRONOUS MOTOR VSS CONTROL USING NEURAL NETWORKS MODEL OF REDUCED ORDER.

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Abstract: A nonlinear complete order model of a synchronous motor is identified using a dynamic neural network. Based on this model a sliding mode controller is derived. This neural network identifier and the proposed control law allow to reject external load torque perturbations. Simulations illustrate the applicability of the proposed approach.

Keywords: Dynamic neural network, sliding mode controller, nonlinear.

1. INTRODUCTION

A fundamental problem in the design of feedback controllers is stabilizing and achieving a specified transient performance in presence of external disturbances and plant parameter variations. A relatively simple approach, especially for nonlinear plants, is based on the use of sliding mode control, see (Utkin, *et al*., 1992). This technique was successfully implemented to design a discontinuous control scheme for permanent magnet synchronous motors, see (Utkin, *et al*., 1999; Dodds *et al*., 1996).

In this paper, we investigate a robust control for the detailed (7th order) model of synchronous motors, with controlled excitation flux, taking in the account the dynamics of the damper windings. The considered model for synchronous motors is a high nonlinear multivariable system, with external disturbances. In this paper, it is assumed that all synchronous motor parameters can change in a wide range. Particularly the rotor resistance and the load torque can vary as continuous functions of the time. To determine the synchronous motor model, a neural networks identification is applied. Most of the application of neural networks to nonlinear identification and control is based on feedforward ones (Gupta and Rao, 1994), (Hunt, et al., 1995). Lately, the use of recurrent neural networks, which allows a more efficient modeling of dynamic systems, is increasing (Suykens, et al., 1996), (Poznyak, et al., 1999). A very efficient algorithm, for nonlinear identification, which ensures error exponential convergence, using dynamic neural networks is proposed in (Kosmatopoulos, et al., 1997).

In this paper, modifying existing identification schemes based on recurrent neural networks (Kosmatopoulos, et al., 1997), a neural network identifier of block controllable form for a synchronous motor is proposed. $\hat{\Psi}_{fd}, i_d$, have relative degree 1, so these variables are controlled first. This allow us to propose a 5th neural network order model. Based on this model a discontinuous control law, which combines block control (Loukianov, 1998) and VSC with sliding mode techniques (Utkin, 1992), is 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 synchronous motors.

2. SYNCHRONOUS MOTOR MODEL

The complete mathematical model of the synchronous machine consists of electrical and mechanical dynamics. The electrical dynamics, considering stator and rotor damper windings, with currents as the state variables, can be expressed in the rotor coordinate frame, the (d,q) coordinates, as follows (see (Krause, 1987))

$$L\frac{di}{dt} = Gi + V \tag{1}$$

where

$$L=\begin{bmatrix} L_d & 0 & L_{md} & L_{md} & 0 & 0\\ 0 & L_q & 0 & 0 & L_{mq} & L_{mq}\\ L_{md} & 0 & L_{fd} & L_{md} & 0 & 0\\ L_{md} & 0 & L_{md} & L_{kd} & 0 & 0\\ 0 & L_{mq} & 0 & 0 & L_{1q} & L_{mq}\\ 0 & L_{mq} & 0 & 0 & L_{mq} & L_{2q}\end{bmatrix},$$

$$G=\begin{bmatrix} -R_s & w_sL_q & 0 & 0 & w_sL_{mq} & w_sL_{mq}\\ -w_sL_d & -R_s & -w_sL_{md} & -w_sL_{md} & 0 & 0\\ 0 & 0 & -R_{fd} & 0 & 0 & 0\\ 0 & 0 & 0 & -R_{kd} & 0 & 0\\ 0 & 0 & 0 & 0 & -R_{1q} & 0\\ 0 & 0 & 0 & 0 & -R_{2q} & 0\end{bmatrix}$$

$i=\left(i_d,i_q,i_{fd},i_{kd},i_{1q},i_d\right)^T$,

$V=\left(V_d,V_q,V_{fd},0,0,0\right)^T$, i_d and i_q are the direct-axis and quadrature-axis stator currents; V_d, V_q and V_{fd} are the direct-axis and quadrature-axis stator voltages control input and the excitation voltage control input; i_{fd} is the field current; i_{kd}, i_{1q}, and i_{2q} are the direct-axis and quadrature-axis damper windings currents respectively; R_s and R_{fd} are the stator and field resistances; R_{kd}, R_{1q} and R_{2q} are the damper winding resistances; L_d and L_q are the direct-axis and quadrature-axis self-inductances; L_{fd} is the rotor self-inductance; L_{kd}, L_{1q} and L_{2q} are, respectively, the direct-axis and quadrature-axis damper windings self-inductances; L_{md} and L_{mq} are the direct –axis and quadrature-axis magnetizing inductances.

The complete mathematical description includes also the mechanical equation given by

$$J\frac{dw_s}{dt}=T_e-T_L \tag{2}$$

where w_s is the angular velocity. J is the moment of inertia; T_L is the load torque, and T_e is the electrical torque, which can be expressed in terms of the currents as follows:

$$T_e=\frac{3P}{4}\left[\left(L_d-L_q\right)i_di_q+L_{md}i_q\left(i_{fd}+i_{kd}\right)-L_{mq}i_d\left(i_{1q}+i_{2q}\right)\right] \tag{3}$$

It is better to formulate the electrical dynamics as function of the stator currents i_q and i_d, the field flux Ψ_{fd} and the rotor fluxes, Ψ_{kd}, Ψ_{1q} and Ψ_{2q}. This can be obtained using the following transformation between fluxes and currents

$$\Psi=L_0 i \tag{4}$$

where $\Psi=\left(\Psi_{fd},\Psi_{kd},\Psi_{1q},\Psi_{2q}\right)^T$ and

$$L_0=\begin{bmatrix} L_{md} & 0 & L_{fd} & L_{md} & 0 & 0\\ L_{md} & 0 & L_{md} & L_{kd} & 0 & 0\\ 0 & L_{mq} & 0 & 0 & L_{1q} & L_{mq}\\ 0 & L_{mq} & 0 & 0 & L_{mq} & L_{2q}\end{bmatrix}.$$

Here all state variables as well as the parameters for the model (1)-(4) are expressed in real unit. Combining equations (1)-(3) and using relationship (4), the complete model for the synchronous motor as form

$$\dot{\chi}=f(\chi,T_L)+Bu \tag{5}$$

where $x^T=\left(x_1^T,x_2^T\right)$ is the state vector with $x_1^T=\left(w_s,i_q,i_d,\Psi_{fd}\right)$ and $x_2^T=\left(\Psi_{kd},\Psi_{1q},\Psi_{2q}\right)$; $u^T=\left(V_q,V_d,V_{fd}\right)$ is the vector control input; $f^T=\left(f_1^T,f_2^T\right)$, and $B^T=\left(B_1^T,B_2^T\right)$ are given by $f_1=\left[f_{11}\quad f_{12}\quad f_{13}\quad f_{14}\right]^T$

$$f_1=\begin{bmatrix} a_{11}i_qi_d+a_{12}i_d\Psi_{1q}+a_{13}i_d\Psi_{2q}+a_{14}i_q\Psi_{fd}+a_{15}i_q\Psi_{kd}-a_LT_L\\ a_{21}w_si_d+a_{22}i_q+w_s\left(a_{23}\Psi_{fd}+a_{24}\Psi_{kd}\right)+a_{25}\Psi_{1q}+a_{26}\Psi_{2q}\\ a_{31}i_d+a_{32}w_si_q+a_{33}\Psi_{fd}+a_{34}\Psi_{kd}+w_s\left(a_{35}\Psi_{1q}+a_{36}\Psi_{2q}\right)\\ a_{43}i_d+a_{44}\Psi_{fd}+a_{45}\Psi_{kd}\end{bmatrix}$$

$$f_2=\begin{bmatrix} f_{25}\\ f_{26}\\ f_{27}\end{bmatrix}=\begin{bmatrix} a_{53}i_d+a_{54}\Psi_{fd}+a_{55}\Psi_{kd}\\ a_{62}i_q+a_{66}\Psi_{1q}+a_{67}\Psi_{2q}\\ a_{72}i_q+a_{76}\Psi_{1q}+a_{77}\Psi_{2q}\end{bmatrix},$$

$$B_1=\begin{bmatrix} 0 & 0 & 0\\ b_{21} & 0 & 0\\ 0 & b_{32} & b_{33}\\ 0 & 0 & b_{43}\end{bmatrix},\quad B_2=0.$$

where $a_{ij},\left(i=1,...,7;\ j=1,...,7\right)$ and a_L are constants, which depend on the synchronous motor parameters:

R_s, R_{fd}, R_{kd}, R_{1q}, R_{2q}, L_q, L_d, L_{md}, L_{mq}, L_{fd}, L_{kd}, L_{1q}, L_{2q}, poles number P and moment of inertia J. Assume that the load torque T_L changes at a very slow rate. Thus,

$$\dot{T}_L = 0 \tag{6}$$

Employing the rotor fluxes $(\Psi_{fd}, \Psi_{kd}, \Psi_{1q}, \Psi_{2q})$ and stator currents (i_q, i_d) as state variables in (5) instead of the rotor currents, enables to represent the rotor dynamics as a linear subsystem with constant parameters, given the possibility of design an observer for the estimation of the rotor fluxes.

3. OBSERVER DESIGN

Since the currents and velocity are the only measurable variables, rotor fluxes estimation is required for neural network identification. To obtain a flux estimation, only the rotor flux dynamics is used. Rotor flux can be estimated by means of the observer described by

$$\begin{aligned}
\dot{\hat{\Psi}}_{fd} &= a_{43} i_d + a_{44} \hat{\Psi}_{fd} + a_{45} \hat{\Psi}_{kd} + b_{43} V_{fd} \\
\dot{\hat{\Psi}}_{kd} &= a_{53} i_d + a_{54} \hat{\Psi}_{fd} + a_{55} \hat{\Psi}_{kd} \\
\dot{\hat{\Psi}}_{1q} &= a_{62} i_d + a_{66} \hat{\Psi}_{1q} + a_{67} \hat{\Psi}_{2q} \\
\dot{\hat{\Psi}}_{2q} &= a_{72} i_d + a_{76} \hat{\Psi}_{1q} + a_{77} \hat{\Psi}_{2q}
\end{aligned} \tag{7}$$

where $\hat{\Psi}_{fd}, \hat{\Psi}_{kd}, \hat{\Psi}_{1q}$ and $\hat{\Psi}_{2q}$ are the estimated rotor fluxes. The stability of observer (7) can be analyzed by examining the following estimation error system:

$$\dot{\varepsilon} = A_{\Psi} \varepsilon \tag{8}$$

where $\varepsilon = \Psi - \hat{\Psi}$, and $A_{\Psi} = \begin{bmatrix} a_{44} & a_{45} & 0 & 0 \\ a_{54} & a_{55} & 0 & 0 \\ 0 & 0 & a_{66} & a_{67} \\ 0 & 0 & a_{76} & a_{77} \end{bmatrix}$.

Because of the matrix A_{Ψ} (see section 5) is Hurwitz we have $\lim_{t \to \infty} \varepsilon(t) = 0$.

4. RECURRENT HIGH ORDER NEURAL NETWORK IDENTIFICATION

4.1 Recurrent Block Controllable Neural Network for synchronous motor.

In order to reduce the neural networks model it is necessary to design a control first for $\hat{\Psi}_{fd}$ and i_d.

Then the proposed model based on the mathematical model of the synchronous motor, is given by

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \\ \dot{x}_4 \\ \dot{x}_5 \end{bmatrix} = \begin{bmatrix} -a_1 x_1 + w_{11} S(x_1) + w_{12} S(x_2) + w_{13} S(x_3) + w_{14} x_2 + w_{15} x_3 x_2 \\ -a_2 x_2 + w_{21} S(x_1) + w_{22} S(x_2) + w_{23} S(x_3) + w_{24} S(x_4) + w_{25} S(x_5) \\ -a_3 x_3 + w_{31} S(x_1) + w_{32} S(x_3) \\ -a_4 x_4 + w_{41} S(x_2) + w_{42} S(x_4) + w_{43} S(x_5) \\ -a_5 x_5 + w_{51} S(x_2) + w_{52} S(x_4) + w_{53} S(x_5) \end{bmatrix} + \begin{bmatrix} 0 \\ w_{26} \\ 0 \\ 0 \\ 0 \end{bmatrix} \begin{bmatrix} V_q \end{bmatrix} \tag{9}$$

where $S(x) = \dfrac{1}{1 + \exp(-\beta x)} + \varepsilon$, β is a positive constant and ε is real number positive small, w_{14}, w_{15}, w_{26} which are fixed weights.

4.2. Updating weight law.

In order to identify the dynamics of synchronous motor, we can use either serial or parallel configuration:

PARALLEL: each state of RHONN is represented by

$$\dot{x}_i = -a_i x_i + \omega_i^T z_{Ii}(x, u) \tag{10}$$

SERIAL-PARALLEL: each state of RHONN is represented by

$$\dot{x}_i = -a_i x_i + \omega_i^T z_{Ii}(\chi, u) \tag{11}$$

Next, we use a lemma which demonstrates the identity of modified RHONN model and RHONN filter-regressor version utilized in order to develop the updating laws. This Lemma is taken from [Kosmatopoulus *et al.*, 1997]

Lemma 1. *The models (10), (11) can be expressed by*

$$\dot{\varsigma}_i = -a_i \varsigma_i + z_{Ii}(\xi, u) \tag{12}$$

$$x_i = \omega_i^T \varsigma_i + e^{-a_i t} x_i(0) - e^{-a_i t} \omega_i^T \varsigma_i(0) \tag{13}$$

where $\varsigma_i \in \Re^{Li}$, $x_i(0)$ is the RHONN's initial state and $\xi = x$ in (10) case and $\xi = X$ (11).

Using Lemma 1, the state x of the RHONN can be rewritten as

$$x_i = \omega_i^T \varsigma_i + \varepsilon \tag{14}$$

where ε is a term which vanishes in finite time and can be eliminated. It is worth to point out that

$$\begin{aligned} \varsigma_i &= \left[\varsigma_i^{'T} \ \varsigma_i^{''T}\right]^T \\ \dot{\varsigma}_i^{'} &= -a_i\varsigma_i^{'} + z_{Ii}^{'} \\ \dot{\varsigma}_i^{''} &= -a_i\varsigma_i^{''} + z_{Ii}^{''} \end{aligned} \tag{15}$$

From (11), (12), (13) and (14) it is possible to obtain the updating law algorithm. Defining the identification error as

$$e_i = x_i - \chi_i \tag{16}$$

using (13) and taking the derivative

$$\dot{e}_i = \dot{\omega}_i^T\varsigma_i + \omega_i^T\dot{\varsigma}_i - \dot{\chi}_i \tag{17}$$

Taking $\dot{\omega}_i$ as a control variable, we design the updating weight law of the form

$$\dot{\omega}_{ik} = \left(-\gamma e_i + \dot{\chi}_i - \omega_i^T\dot{\varsigma}_i\right)\frac{\eta_{ik}}{\varsigma_{ik}} \tag{18}$$

$$\dot{\omega}_{ij} = 0. \tag{19}$$

where $k \in \{1,...,L_i^{'}\}$, $j \in \{L_i^{'}+1,...,L_i\}$, (18) are fixed weights $\omega_i^{''T}$, (17) are weights that will be adjusted $\omega_i^{'T}$ and n_{ik} are constants such that

$$\sum_{k=1}^{L_i^{'}} n_{ik} = 1 \tag{20}$$

substituting (17) in (16) we obtain

$$\dot{e}_i = -\gamma e_i \tag{21}$$

The law (17) is not easy to implement due to the χ_i term. This can be solved if (17) is rewritten as

$$\begin{aligned} \omega_{ik} &= v_{ik} + \varphi_{ik} \\ \dot{v}_{ik} &= -\gamma\frac{e_i\eta_{ik}}{\varsigma_{ik}} \\ \varphi &= \frac{\chi_i n_{ik}}{\varsigma_{ik}} + \eta_{ik} \\ \dot{\eta}_{ik} &= -X_i\frac{d}{dt}\left(\frac{\eta_{ik}}{\varsigma_{ik}}\right) - \frac{\omega_i^T\dot{\varsigma}_i}{\varsigma_{ik}}. \end{aligned} \tag{22}$$

Then the error e_i converges exponentially to zero.

5. SYNCHRONOUS MOTOR CONTROL

The control goal is to make the speed w_s be equal to a reference signal w_{ref}. Hence the error can be defined as

$$e_w = w_s - w_{ref} \tag{23}$$

Having three control inputs V_q, V_d, and V_{fd}, we can select two additional outputs to be controlled: the flux in the winding excitation, $\hat{\Psi}_{fd}$, and the current i_d. Thus two additional errors are defined as

$$e_{fd} = \hat{\Psi}_{fd} - \Psi_{ref} \tag{24}$$

and

$$e_d = i_d - i_{ref} \tag{25}$$

where $\hat{\Psi}_{ref}$ and i_{ref} are reference constant signals for flux $\hat{\Psi}_{fd}$ and i_d, respectively.

Both auxiliary control outputs $\hat{\Psi}_{fd}$ and i_d have relative degree equal to 1, while the main control output w_s has relative degree 2. In order to simplify the neural network and the control design, first will be implemented the flux $\hat{\Psi}_{fd}$ controller, then the current i_d control loop and finally the speed w_s controller. Once $\hat{\Psi}_{fd}$ and i_d have reached their set points, the neural networks model can be reduced to 5th order, (9) see page 3, which is more simple than identifying the whole 7th order.

5.1. Flux $\hat{\Psi}_{fd}$ control loop.

Dynamics for e_{fd} is derived from (24) as

$$\dot{e}_{fd} = f_{14}(x) + b_{43}V_{fd} \tag{26}$$

Because of $\hat{\Psi}_{fd}$ has relative degree 1, a control strategy can be proposed as

$$V_{fd} = -U_{fd0}\,sign(e_{fd}) \tag{27}$$

The sliding mode existence condition for discontinuous control (32), gives (Utkin, 1992)

$$\dot{e}_{fd}e_{fd} = f_{14}(x)e_{fd} - b_{43}U_{fd0}\,sign(e_{fd})e_{fd} < 0\,.$$

Therefore, we assume that the following condition is satisfied:

$$U_{fd0} > \left|V_{fd}^{eq}(x)\right| \tag{28}$$

where $V_{fd}^{eq}(x)$ is the equivalent control which is calculated from $\dot{e}_{fd} = 0$ as

$$V_{fd}^{eq} = -b_{43}^{-1}f_{14}(x)\,. \tag{29}$$

By virtue of the condition (27) the values of e_{fd} and $\dot{e}_{fd}$ have opposite signs, therefore the error e_{fd} reaches zero after a finite time interval t_{s1}.

5.2. Current i_d control loop.

We choose i_{ref} equal to zero since with the absence of d-axis stator current there is no reluctance torque, and in this case only the q-axis reactance is involved in finding the terminal voltage, i.e. there is no direct magnetization or demagnetization of d-axis, only the field winding acts to produce flux in this direction.

Dynamics of e_d is governed by

$$\dot{e}_d = f_{13}(x) + b_{32}V_d + b_{33}V_{fd} . \quad (30)$$

The following control law is selected as:

$$V_d = -U_{d0}\, sign(e_d). \quad (31)$$

After $t > t_{s1}$, we have that

$$V_{fd} = V_{fd}^{eq}(x) = -b_{43}^{-1} f_4(x)$$

hence, the sliding mode stability condition for this case can be derived of the following form:

$$U_{d0} > \left| b_{32}^{-1}\left[f_{13}(x) + b_{33}b_{43}^{-1} f_{14}(x)\right]\right|$$

Under this condition the current i_d converges to zero in a finite time t_{s2}, $t_{s2} > t_{s1}$.

5.3. Speed w_s control loop.

We have already defined

$$z_1 = x_1 - w_{ref} \quad (32)$$

Taking the derivative of (31) we obtain

$$\dot{z}_1 = \hat{f}_1(x_1, x_2, x_3, \dot{w}_{ref}) + \hat{B}(x_3)x_2 \quad (33)$$

where

$$\hat{f}_1(x_1, x_2, x_3, \dot{w}_r) = -a_1 x_1 + w_{11}S(x_1) + w_{12}S(x_2) + w_{13}S(x_3) - \dot{w}_{ref}$$

$$\hat{B}_1(x_3) = w_{14} + w_{15}x_3 .$$

So x_2 can be selected as a quasi control

$$x_2 = x_2^c(x_1, x_2, x_3, w_{ref}, \dot{w}_{ref}) - \hat{B}_1^{-1}(x_3)(k_1 z_1 + z_2)$$

with $x_2^c(x_1, x_2, x_3, w_{ref}, \dot{w}_{ref}) = -\hat{B}_1^{-1}(x_3)\,\hat{f}_1(x_1, x_2, x_3, w_{ref}, \dot{w}_{ref})$

where $\hat{B}_1^{-1}(x_3) = \dfrac{1}{w_{14} + w_{15}x_3}$.

Thus (33) can be written as

$$\dot{z}_1 = -k_1 z_1 + z_2 \quad (34)$$

from (33) and (34), it follows

$$z_2 = \hat{f}_1(x_1, x_2, x_3, w_{ref}, \dot{w}_{ref}) + k_1 z_1 + \frac{1}{w_{14} + w_{15}x_3} x_2$$

deriving results in

$$\dot{z}_2 = \bar{f}_2(x_1, x_2, x_3, w_{ref}, \dot{w}_{ref}, \ddot{w}_{ref}) + \frac{w_{26}V_q}{w_{14} + w_{15}x_3}$$

where

$$\bar{f}_2(x_1, x_2, x_3, w_{ref}, \dot{w}_{ref}, \ddot{w}_{ref}) = \dot{\hat{f}}_1(x_1, x_2, x_3, \dot{w}_{ref}) + k_1\dot{z}_1 + \frac{1}{w_{14} + w_{15}x_3}(-a_2x_2 + w_{21}S(x_1) + \ldots + w_{25}S(x_5)).$$

The proposed control law

$$V_q = -U_{q0}\, sign(z_2)$$

under the following

$$\left|\bar{f}_2(x_1, x_2, x_3, w_{ref}, \dot{w}_{ref}, \ddot{w}_{ref})\right| < \frac{w_{26}V_q}{w_{14} + w_{15}x_3}$$

guarantees convergence of z_2 to zero in a finite time. The sliding mode equation $\dot{z}_1 = -k_1 z_1$ is stable, so $\lim_{t\to\infty} z_1(t) = 0$.

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 synchronous motor are: $R_s = 0.1\Omega$, $R_{fd} = 0.016\Omega$,

$R_{kd} = R_{1q} = R_{2q} = 0.1133\Omega$, $J = 0.2Kgm$, $L_d = 4.89mH$,

$L_q = 4.79mH$, $L_{fd} = 4.48mH$, $L_{kd} = 4.39mH$,

$L_{1q} = L_{2q} = 2.91mH$, $L_{mq} = 2mH$, $L_{md} = 4mH$

The neural network parameters are: $a_1 = a_2 = 50$ $a_3 = a_4 = a_5 = a_6 = a_7 = 50$, $\beta = 1e-5$, $E = 0.1$, $\gamma = 50$.

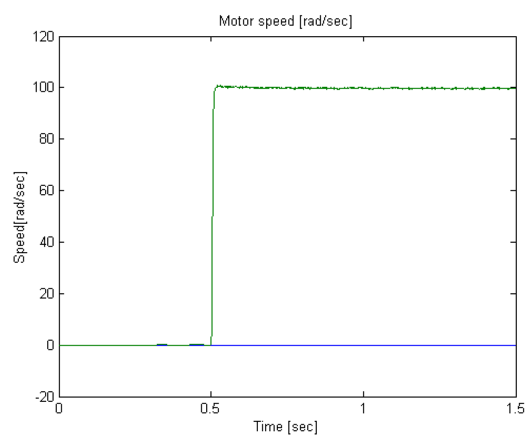

Fig. 1 Motor with 100 rad/sec reference speed and 40 N-m torque perturbation applied at 0.7s y 1.0s.

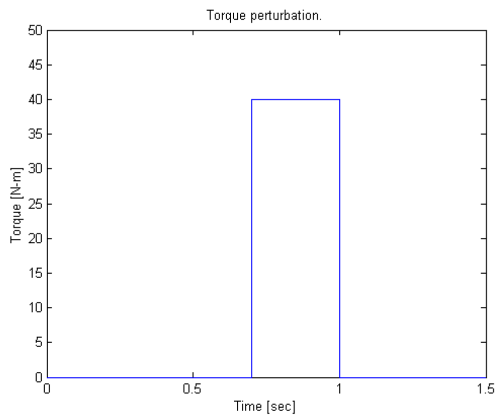

Fig. 2 Torque perturbation applied at 0.7s and 1.0s.

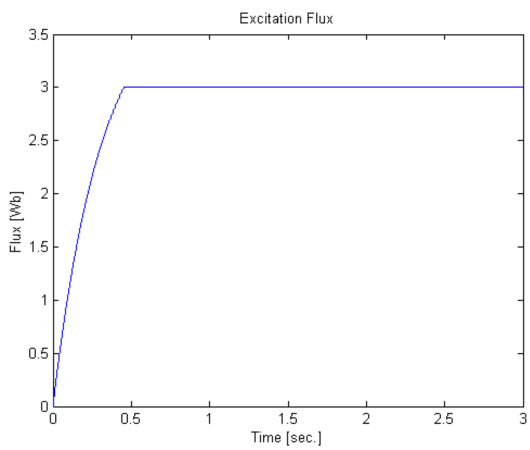

Fig. 3 Excitation Flux.

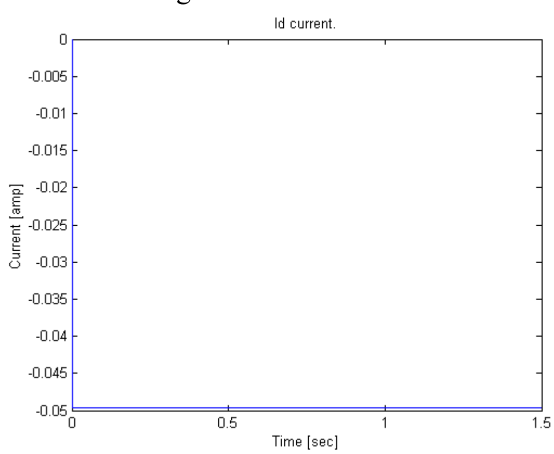

Fig. 4 Current Id.

Simulations show a good performance. The system is able to reject load torque disturbance. In this case, a step change of 40 N-m. applied at 0.7 and 1.0 seconds, Fig. 1 shows that this disturbance has no effect on the motor speed. The flux is controlled at a fixed reference of 3 Wb, it reaches the set point quickly and there is no overshoot.

5. CONCLUSIONS

The authors have presented a robust controller based on dynamic neural networks and Variable Structure Systems. The proposed RHONN model, used to identify a full order synchronous motor, has been tested as a good identifier and allows to use sliding mode control technique to force the close loop trajectory to converge and to stay in the sliding manifolds, which guarantees that the tracking error is zero.

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