A Sliding Mode Control Scheme for Induction Motors Using Neural Networks for Rotor Speed Estimation

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***Abstract*— This paper tackles the problem of the speed control of an induction motor in a very general sense. On the one hand, the power of feedforward artificial neural network to capture and emulate detailed nonlinear mappings is used to implement a rotor speed estimator, and on the other hand a robust control strategy based on the sliding-mode controller type is performed. The proposed control scheme also make use of the field oriented control theory to simplify the proposed control design. The stability analysis of the presented control scheme under parameter uncertainties and load disturbances is provided using the Lyapunov stability theory. Finally simulated results show that the presented controller with the proposed observer provides high-performance dynamic characteristics and that this scheme is robust with respect to plant parameter variations and external load disturbances.**

keywords: Neural Netwoks, Induction Motor Control, Robust Control, Modelling, Simulation.

I. Introduction

Traditionally, mathematical-model-based analysis techniques have always been used for the analysis of the induction motor drives. There are many techniques, but they mainly differ in their complexity and the many assumptions used. One of the most popular techniques is the field oriented control theory and it has been utilized extensively for the development of various high performance induction motor drive controls (Vas 1994, Leonhard 1996, Bose 2001).

In general, when space vector theory is used for the control of a variable speed drive system, the stator and rotor voltage space vector equations (in the appropriate reference frame) of the machine considered are solved together with the equation of motion and the equations governing the controller and converter. This results in a system of first-order non-linear differential equations, plus several algebraic equations. In this way, it is possible to compute or estimate various machine quantities, as for example, rotor speed, flux linkages, electromagnetic torque, etc. However, it should be noted that the accuracy of this computed or estimated machine quantities has a strong dependence with the precision of the mathematical model of the system employed. The modelling errors of the system mathematical model can have two fundamental sources. On the one hand these errors can be originated from the existence of some unmodelled dynamic of the system, which should be referred as modelling structural errors, and on the other hand these errors can be originated from the existence of the some errors in the parameters of the system model equations, which should be referred as modelling parametric errors.

To overcome the above errors it is possible to design the estimators of the machine quantities using Artificial Neural Networks, which do not require a mathematical model of the drive system and therefore the performance of this approach do not exhibit any dependence with the modelling errors. In ANN based estimators, if the ANN uses a supervised training technique, then the estimator is based on information available for the training and this information is obtained from system input and output measurements previously calculated for training purposes.

On the other hand, it has been proved that Artificial Neural Network can approximate a wide range of nonlinear functions to any desired degree of accuracy under certain conditions (Omidvar, 1997).

Due to the above mentioned characteristics, in the past few years, active research has been carried out in Artificial Neural Network applied to identification and control of complex dynamical systems (Narendra, 1990, Weersooriya 1991, Huang 1998, Pinto 2000, Wai 2002).

Although diverse neural architecture and learning algorithms can be used, we have chosen a particular one, the multilayer feedforward network and the so-called backpropagation with momentum algorithm which is a gradient descent algorithm of the performance function. Properly trained backpropagation networks tend to give reasonable answers when they are presented with inputs that they have never computed

(Haykin 1994).

On the other hand, as it has been pointed out by several authors (Slotine 1991, Barambones 2002), adaptive control techniques and robust control methods are two complementary approaches to dealing with model uncertainty.

In this context, the idea of combining neural and robust control methods as a way to improve the performance and robustness in presence of model imprecissions of control systems is developed in this paper combining neural network estimation scheme with sliding-mode robust controller, which are applied to the control of induction motor drive.

The field-oriented technique guarantees the decoupling of torque and flux control commands of the induction motor, so that the induction motor can be controlled linearly as a separated excited D.C. motor. However, the control performance of the resulting linear system is still influenced by uncertainties, which usually are composed of unpredictable parameter variations, external load disturbances, and unmodelled and nonlinear dynamics. Many studies have been made on the motor drives in order to preserve the performance under these parameter variations and external load disturbances, such as nonlinear control, optimal control, variable structure system control, adaptive control and neural control (Lin 1993, Ortega 1993, Marino 1998).

This paper presents a new sensorless vector control scheme consisting, on the one hand of an artificial neural network based speed estimation algorithm, and on the other hand, of a new variable structure control.

The rotor speed estimation scheme based on an artificial neural network utilizes stator voltage and current measured values to calculate the rotor speed.

The variable structure control presented here, unlike the traditional variable structure designs (Sabanovic 1981, Utkin 1993), has a integral sliding surface. The traditional sliding surfaces requires an acceleration signal, but it is well known that transforming the sensed or the estimated speed into an acceleration signal is very sensitive to noisy effects. In order to remove the drawbacks mentioned above it is proposed a new variable structure control with an integral sliding surface in order to regulate the induction motor speed.

Using this novel variable structure control in the induction motor drive, the controlled speed is insensitive to variations in the motor parameters and load disturbances, and besides the acceleration signal used in conventional variable structure speed control is not required. This new variable structure control provides a good transient response and exponential convergence of the speed trajectory tracking in spite of parameter uncertainties and load torque disturbances.

This report is organized as follows. The artificial neural network design for the rotor speed estimation is introduced in Section 2. Then, the proposed variable structure robust speed control is presented in Section 3. In the Section 4, artificial neural network computation is carried out. Then, some simulation results are presented in section 5. Finally, some concluding remarks are stated in Section 6.

II. Neural Network model for speed estimation

An artificial neural network will be designed to estimate the rotor speed. Various input variables to the neural network can be considered, among them: stator voltages and currents, stator and rotor fluxes, etc. One may attempt to use excessive number of inputs variables to achieve required performance and robustness against some motor parameters changes, but of course an excessive number of correlated variables is not useful at all. Next, we will determine an adequate input variable set to the neural network.

Since the motor voltages and currents are measured in a stationary frame of reference, it is also convenient to express the induction motor dynamical equations in this stationary reference frame.

The rotor voltage equations of a squirrel cage induction motor drive in the stationary frame may be written as (Bose 2001):

$$\begin{aligned} v_{dr} = \quad 0 = \quad & L_m \frac{d}{dt} i_{ds} + w_r L_m i_{qs} + R_r\, i_{dr} + L_r \frac{d}{dt} i_{dr} \\ & + w_r L_r i_{qr} \qquad (1) \\ v_{qr} = \quad 0 = \quad & -w_r L_m i_{ds} + L_m \frac{d}{dt} i_{qs} - w_r L_r i_{dr} + R_r\, i_{qr} \\ & + L_r \frac{d}{dt} i_{qr} \qquad (2) \end{aligned}$$

where v is the voltage; L is the inductance; R is the resistance, i is the current and w_r is the rotor electrical speed. The subscript r denotes the rotor values, the subscript s denotes the stator values and the subscripts d and q denote the dq-axis components in the stationary reference frame.

In the same way, the stator voltage equations in the stationary frame may be written as:

$$v_{ds} = R_s\, i_{ds} + L_s \frac{d}{dt} i_{ds} + L_m \frac{d}{dt} i_{dr} \qquad (3)$$

$$v_{qs} = R_s\, i_{qs} + L_s \frac{d}{dt} i_{qs} + L_m \frac{d}{dt} i_{qr} \qquad (4)$$

By an arrangement of equation 2, the rotor speed can be derived:

$$w_r = \frac{L_m \frac{d}{dt} i_{qs} + R_r\, i_{qr} + L_r \frac{d}{dt} i_{qr}}{L_m i_{ds} + L_r i_{dr}} \qquad (5)$$

Equation 5 reveals that the rotor speed can be found through calculations of stator and rotor currents. The stator currents are easy to measure, while the rotor currents are quite difficult, if not impossible, to measure.

From equations 3 and 4, the rotor derivative with respect to time can be found in terms of stator voltages and currents which are easy to measure:

$$\frac{d}{dt}\, i_{dr} = \frac{1}{L_m} v_{ds} - \frac{R_s}{L_m} i_{ds} - \frac{L_s}{L_m} \frac{d}{dt} i_{ds} \qquad (6)$$

$$\frac{d}{dt}\, i_{qr} = \frac{1}{L_m} v_{qs} - \frac{R_s}{L_m} i_{qs} - \frac{L_s}{L_m} \frac{d}{dt} i_{qs} \qquad (7)$$

Integrating the previous equations, it is obtained:

$$i_{dr} = \frac{1}{L_m}\int\left(v_{ds} - \frac{R_s}{L_m}i_{ds}\right)\mathrm{d}t - \frac{L_s}{L_m}i_{ds} \quad (8)$$

$$i_{qr} = \frac{1}{L_m}\int\left(v_{qs} - \frac{R_s}{L_m}i_{qs}\right)\mathrm{d}t - \frac{L_s}{L_m}i_{qs} \quad (9)$$

Substituting equations 6, 7, 8 and 9 in the equation 5, relationships between speed and stator variables are concluded as a function mapping:

$$w_r = f(v_{ds}, v_{qs}, i_{ds}, i_{qs}) \quad (10)$$

where $f()$ represents a nonlinear function.

Therefore, can we conclude that the rotor speed is a non-linear function of the stator voltages and currents, and then these variables will be an adequate input signals to estimate the rotor speed using an artificial neural network.

The artificial neural network is modelled as a massively parallel interconnected network of elementary processors or neurons. This highly connected array of elementary processors defines the system hardware. Various software algorithms are then crafted to synthesize a mapping between input and output variables by learning a set of interconnecting weights and neuron thresholds from training examples. From a computational point of view, neural networks come with the advantage of massive parallelism.

In the proposed design a multilayer feedforward artificial neural network (FANN) was adopted as the neural network paradigm. The neural network has four input signals, the stator voltages and currents: v_{ds}, v_{qs}, i_{ds} and i_{qs}, and one output, w_r, which is the estimated rotor speed.

The number of hidden layers and the number of nodes per layer are not definitive. There are no general guidelines for determining a priori which combinations of neurons and hidden layers will perform the best for a given problem. In this problem, the number of hidden layers and the number of neurons in each hidden layer were chosen heuristically on a trial and error basis. The FANN selected has three hidden layers. These hidden layers have a tansigmoid activation function, and the output layer has a linear activation function.

Then the output of the FANN will be,

$$y(k) = \Gamma_3(\,W_3\Gamma_2(\,W_2\Gamma_1(\,u(k) + b_1) + b_2) + b_3) \quad (11)$$

where W_1, W_2 and W_3 are the weight matrices, b_1, b_2 and b_3 are the bias vectors, $u = [i_{ds}, i_{qs}, v_{ds}, v_{qs}]$ are the input and $y = \hat{w}_r$ is the output of the neural network.

The training algorithm selected to train the neural network is the backpropagation with momentum. This algorithm is an extension of the conventional error backpropagation training algorithm (Narendra 1990). It is based on the minimization principle of a cost function of the error between the desired output and the actual output of a FANN. The minimization is achieved by varying the adjustable parameters of the FANN in the direction of the gradient descent of the cost function. Besides, the momentum term allows a network to respond not only to the local gradient, but also to recent trends in the error surface. Acting like a low-pass filter, momentum allows the network to ignore small features in the error surface. Without momentum the network may get stuck in a shallow local minimum, however with momentum the network can slide through such a minimum (Hagan 1996).

In the backpropagation algorithm it is useful to rearrange the elements of the weight matrices W_i and the bias vectors b_i into a vector θ which contains all the adjustable parameters of the network. Then, the cost function in the backpropagation algorithm is chosen to be:

$$J_k(\theta) = \frac{1}{T}\sum_{n=k}^{k+T-1}[y(n) - y_d(n)]^2 \quad (12)$$

where k denotes the time instant, the parameter T is referred to as the update window size and equals the number of time instants over which the gradient of the cost function J is computed, and y_d is the desired output of the neural network.

The backpropagation algorithm begins by initially assigning small randomly chosen values for the weights and biases, and then during the training process this values are iteratively adjusted to minimize the neural network cost function.

The adjustable parameter can be updated following a gradient descendent with momentum procedure,

$$\theta(k+T) = \theta(k) + \Delta\theta(k) \quad (13)$$

where the increment term of the adjustable parameters is

$$\Delta\theta(k) = -\alpha\frac{\partial J_k(\theta)}{\partial\theta} + \mu\Delta\theta(k-T) \quad (14)$$

where α is the learning rate and μ is the momentum constant.

and the partial derivatives of J with respect to an adjustable parameters θ is given by,

$$\frac{\partial J_k(\theta)}{\partial\theta} = \frac{2}{T}\sum_{n=k}^{k+T-1}[y(n) - y_d(n)]\frac{\partial y(n)}{\partial\theta} \quad (15)$$

The period of time comprising T time instants is called an epoch, so that each adjustable parameter is updated once every epoch. The update window size T, the learning rate α and the momentum constant μ, are three parameters that has an important role in the performance of the algorithm. If the learning rate is made too large, the algorithm becomes unstable, and if the learning rate is set too small, the algorithm takes a long time to converge. Usually, increasing the update window size T has the same effect as lowering the value of the learning rate α. On the other hand, the magnitude of the effect that the previous weight change is allowed to have is mediated by a momentum constant, μ, which can be any number between 0 and 1. When the momentum constant is set to 0, a weight change is based solely on the gradient.

The training is terminated when $\|y(k) - y_d(k)\|$ falls below a user specified tolerance. The most important and large step in the backpropagation algorithm is the computation of the partial derivatives of the output of the network with respect to each of its adjustable parameters. These partial derivatives are used in computing the gradient of J, every T instants. In this sense, the main inconvenient of the backpropagation algorithm is the computational expense it entails in the calculations of these partial derivatives.

III. Variable structure robust speed control

In general, the mechanical equation of an induction motor can be written as:

$$J\dot{w}_m + Bw_m + T_L = T_e \tag{16}$$

where J and B are the inertia constant and the viscous friction coefficient of the induction motor system respectively; T_L is the external load; w_m is the rotor mechanical speed in terms of angular frequency, which is related to the rotor electrical speed by $w_m = 2\,w_r/p$ where p is the pole numbers and T_e denotes the generated torque of an induction motor, defined as (Bose 2001):

$$T_e = \frac{3p}{4}\frac{L_m}{L_r}(\psi^e_{dr} i^e_{qs} - \psi^e_{qr} i^e_{ds}) \tag{17}$$

where ψ^e_{dr} and ψ^e_{qr} are the rotor-flux linkages, with the subscript 'e' denoting that the quantity is refereed to the synchronously rotating reference frame; i^e_{qs} and i^e_{ds} are the stator currents, and p is the pole numbers.

The relation between the synchronously rotating reference frame and the stationary reference frame is performed by the so-called reverse Park's transformation:

$$\begin{bmatrix} x_a \\ x_b \\ x_c \end{bmatrix} = \begin{bmatrix} \cos(\theta_e) & -\sin(\theta_e) \\ \cos(\theta_e - 2\pi/3) & -\sin(\theta_e - 2\pi/3) \\ \cos(\theta_e + 2\pi/3) & -\sin(\theta_e + 2\pi/3) \end{bmatrix} \begin{bmatrix} x_d \\ x_q \end{bmatrix} \tag{18}$$

where θ_e is the angle position between the d-axis of the synchronously rotating reference frame and the a-axis of the stationary reference frame, and it is assumed that the quantities are balanced.

Using the field-orientation control principle (Bose 2001), the current component i^e_{ds} is aligned in the direction of the rotor flux vector $\bar{\psi}_r$, and the current component i^e_{qs} is aligned in the direction perpendicular to it. With this condition, it is satisfied that:

$$\psi^e_{qr} = 0, \qquad \psi^e_{dr} = |\bar{\psi}_r| \tag{19}$$

With the above mentioned proper field orientation, the dynamics of the rotor flux is given by (Bose 2001):

$$\frac{d\psi^e_{dr}}{dt} + \frac{\psi^e_{dr}}{T_r} - \frac{L_m}{T_r}\, i^e_{ds} = 0 \tag{20}$$

$$-\frac{L_m}{T_r} i^e_{qs} + w_{sl}\psi^e_{dr} = 0 \tag{21}$$

where $T_r = \dfrac{L_r}{R_r}$ is the rotor time constant and the slip frecuency is $w_{sl} = w_e - w_r$, where w_e is the stator supply frequency and w_r is the rotor electrical speed.

The slip frequency can be calculated from the equation 21,

$$w_{sl} = \frac{L_m}{T_r}\frac{i^e_{qs}}{\psi^e_{dr}} \tag{22}$$

Hence, the angular position of the rotor flux θ_e can be calculated from,

$$\theta_e = \int w_e \,\mathrm{d}t = \int \hat{w}_r \,\mathrm{d}t + \int w_{sl} \,\mathrm{d}t \tag{23}$$

where $\hat{w}_r$ denotes the ANN stimated rotor speed.

Taking into account the results of field-orientation vector control presented in equation (19), the equation of induction motor torque (17) is simplified to:

$$T_e = \frac{3p}{4}\frac{L_m}{L_r}\psi^e_{dr} i^e_{qs} = K_T\, i^e_{qs} \tag{24}$$

where K_T is the torque constant, defined as follows:

$$K_T = \frac{3p}{4}\frac{L_m}{L_r}\psi^{e^*}_{dr} \tag{25}$$

where $\psi^{e^*}_{dr}$ denotes the command rotor flux.

Then, the mechanical equation (16) becomes:

$$\dot{w}_m + a\,w_m + f = b\,i^e_{qs} \tag{26}$$

where the parameters are defined as:

$$a = \frac{B}{J}, \quad b = \frac{K_T}{J}, \quad f = \frac{T_L}{J}; \tag{27}$$

Now, we are going to consider the previous mechanical equation (26) with uncertainties as follows:

$$\dot{w}_m = -(a + \triangle a)w_m - (f + \triangle f) + (b + \triangle b)i^e_{qs} \tag{28}$$

where the terms $\triangle a$, $\triangle b$ and $\triangle f$ represents the uncertainties of the terms a, b and f respectively.

Let us define the tracking speed error as follows:

$$e(t) = w_m(t) - w^*_m(t) \tag{29}$$

where w^*_m is the rotor speed command.

Taking the derivative of the previous equation with respect to time yields:

$$\dot{e}(t) = \dot{w}_m - \dot{w}^*_m = -a\,e(t) + u(t) + d(t) \tag{30}$$

where the following terms have been collected in the signal $u(t)$,

$$u(t) = b\,i^e_{qs}(t) - a\,w^*_m(t) - f(t) - \dot{w}^*_m(t) \tag{31}$$

and the uncertainty terms have been collected in the signal $d(t)$,

$$d(t) = -\triangle a\,w_m(t) - \triangle f(t) + \triangle b\; i^e_{qs}(t) \tag{32}$$

Now, we are going to define the sliding variable $S(t)$ with an integral component as:

$$S(t) = e(t) - \int_0^t (k - a)e(\tau)\,d\tau \tag{33}$$

where k is a constant gain.

In order to obtain the speed trajectory tracking, the following assumption should be formulated:

$(\mathcal{A}\,1)$ The gain k must be chosen so that the term $(k-a)$ is strictly negative, and therefore $k<0$.

Then, the sliding surface is defined as:

$$S(t)=e(t)-\int_0^t (k-a)e(\tau)\,d\tau=0 \tag{34}$$

The variable structure speed controller is designed as:

$$u(t)=k\,e(t)-\beta\,\mathrm{sgn}(S) \tag{35}$$

where the k is the previously defined gain, β is the switching gain, S is the sliding variable defined in eqn. (33) and $\mathrm{sgn}(\cdot)$ is the sign function.

In order to obtain the speed trajectory tracking, the following assumption should be formulated:

$(\mathcal{A}\,2)$ The gain β must be chosen so that $\beta \geq |d(t)|$ for all time.

Theorem 1: Consider the induction motor given by equation (28). Then, if assumptions $(\mathcal{A}\,1)$ and $(\mathcal{A}\,2)$ are verified, the control law (35) leads the rotor mechanical speed $w_m(t)$ so that the speed tracking error $e(t)=w_m(t)-w_m^*(t)$ tends to zero as the time tends to infinity.

The proof of this theorem will be carried out using the Lyapunov stability theory.

Proof : Define the Lyapunov function candidate:

$$V(t)=\frac{1}{2}S(t)S(t) \tag{36}$$

Its time derivative is calculated as:

$$\begin{aligned}\dot{V}(t) =\;& S(t)\dot{S}(t)\\ &= S\cdot[\dot{e}-(k-a)e]\\ &= S\cdot[(-a\,e+u+d)-(k\,e-a\,e)]\\ &= S\cdot[u+d-k\,e]\\ &= S\cdot[k\,e-\beta\,\mathrm{sgn}(S)+d-k\,e]\\ &= S\cdot[d-\beta\,\mathrm{sgn}(S)]\\ &\leq -(\beta-|d|)|S|\\ &\leq 0\end{aligned} \tag{37}$$

It should be noted that the eqns. (33),(30) and (35), and the assumption $(\mathcal{A}\,2)$ have been used in the proof.

Using the Lyapunov's direct method, since $V(t)$ is clearly positive-definite, $\dot{V}(t)$ is negative definite and $V(t)$ tends to infinity as $S(t)$ tends to infinity, then the equilibrium at the origin $S(t)=0$ is globally asymptotically stable. Therefore $S(t)$ tends to zero as the time t tends to infinity. Moreover, all trajectories starting off the sliding surface $S=0$ must reach it in finite time and then they will remain on this surface. This system's behavior, once on the sliding surface is usually called *sliding mode* (Utkin 1993).

When the sliding mode occurs on the sliding surface (34), then $S(t)=\dot{S}(t)=0$, and therefore the dynamic behavior of the tracking problem (30) is equivalently governed by the following equation:

$$\dot{S}(t)=0 \quad\Rightarrow\quad \dot{e}(t)=(k-a)e(t) \tag{38}$$

Then, under assumption $(\mathcal{A}\,1)$, the tracking error $e(t)$ converges to zero exponentially.

It should be noted that, a typical motion under sliding mode control consists of a *reaching phase* during which trajectories starting off the sliding surface $S=0$ move toward it and reach it in finite time, followed by *sliding phase* during which the motion will be confined to this surface and the system tracking error will be represented by the reduced-order model (38), where the tracking error tends to zero.

Finally, the torque current command, $i_{qs}^*(t)$, can be obtained directly substituting eqn. (35) in eqn. (31):

$$i_{qs}^*(t)=\frac{1}{b}\left[k\,e-\beta\,\mathrm{sgn}(S)+a\,w_m^*+\dot{w}_m^*+f\right] \tag{39}$$

Therefore, the proposed variable structure speed control resolves the speed tracking problem for the induction motor with some uncertainties in mechanical parameters and load torque.

IV. Artificial Neural Network computation

A multi-layer feedforward artificial neural network is proposed to approximate the rotor speed. This neural network has three hidden layers, the first hidden layer has 7 neurons, the second has 9 neurons and the third hidden layer has 15 neurons. The activation functions used in the three hidden layers are tansigmoid functions. The output layer has one neuron and the activation function is a purelin function. The inputs to the neural network are the stator voltages and currents and the output is the estimated rotor speed. The network weights are adjusted such that the network output error is minimized. The technique used to train the network is the backpropagation with momentum algorithm (Hagan 1996).

Figures 1, 2, 3, 4, 5 show the waveform of Artificial Neural Network training data. This training data are obtained by means of forcing the induction motor to follow a ramdomly generated step reference speed, while ramdomly load changes are simultaneosly applied to the drive.

The signals of figures 2, 3, 4, 5 are the d and q components of the stator currents and voltages that are applied to the AC induction motor. This signals are filtered firstly, in order to eliminate the high frequency components, and then are utilized as the network input data to train the neural network. The signal shown in figure 1 is the speed response of the motor drive in the presence of the previous stator voltages and currents input signals, and this signal serves as the network target to train the neural network.

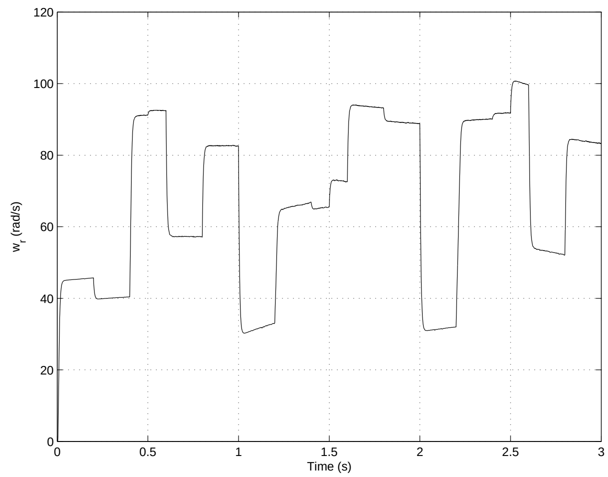

Fig. 1. Rotor speed signal (rad/s)

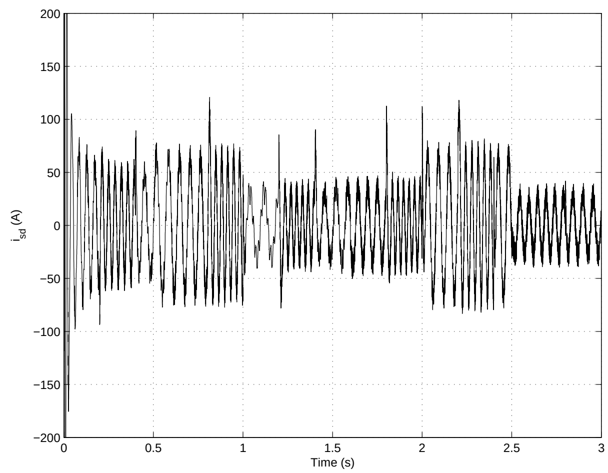

Fig. 2. Stator Current i_{sd} (A)

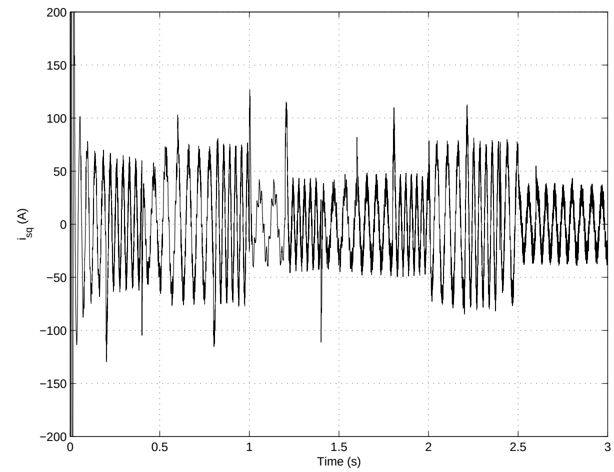

Fig. 3. Stator Current i_{sq} (A)

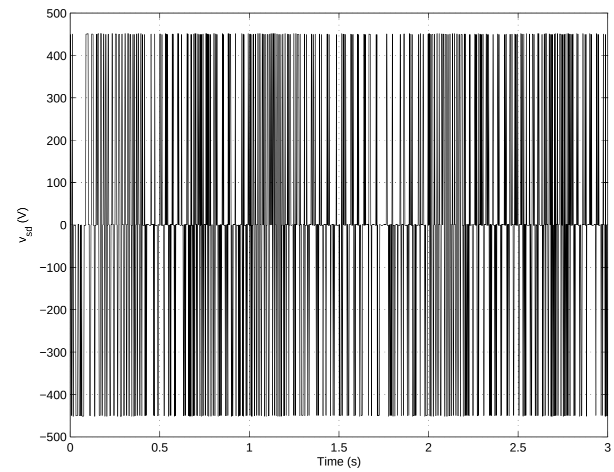

Fig. 4. Stator Current v_{sd} (V)

The parameters of the neural network training algorithm was selected as follows: a learning rate of $\alpha = 0.25$, a momentum gain of $\mu = 0.35$ and an epoch of $T = 5$ time instants.

Figure 6 shows the learning curve of the artificial neural network. In this figure it is represented the average squared error versus number of training epochs, which represent a set of training patterns.

Once the neural network was well trained, the rotor speed can be obtained from the network output.

V. SIMULATION RESULTS

In this section we will study the speed regulation performance of the proposed neural network based speed estimator and the designed sliding-mode field oriented control, versus reference and load torque variations by means of simulation examples.

The block diagram of the proposed robust control scheme is presented in Figure 7. The function of the blocks that appear in this figure are:

The block 'VSC Controller' represent the proposed sliding-mode controller, and it is implemented by equations (33), (39). The block 'limiter' limits the current applied to the motor windings so that it remains within the limit value, being implemented by a saturation function. The block '$dq^e \rightarrow abc$' makes the conversion between the synchronously rotating and stationary reference frames, and it is implemented by equation (18). The block 'Current Controller' consists of a three hysteresis-band current PWM control, which is basically an instantaneous feedback current control method of PWM where the actual current (i_{abc}) continuously tracks the command current (i^*_{abc}) within a hysteresis band. The block 'PWM Inverter' is a six IGBT-diode bridge inverter with 780 V DC voltage source. The block 'Field Weakening' gives the flux command based on rotor speed, so that the PWM controller does not saturate. The block 'i^{e*}_{ds} Calculation' provides the current reference i^{e*}_{ds} from the rotor flux reference through the equation (20).

The block 'ANN' is the Artificial Neural Network designed in section II to estimate the rotor speed. The block 'θ_e

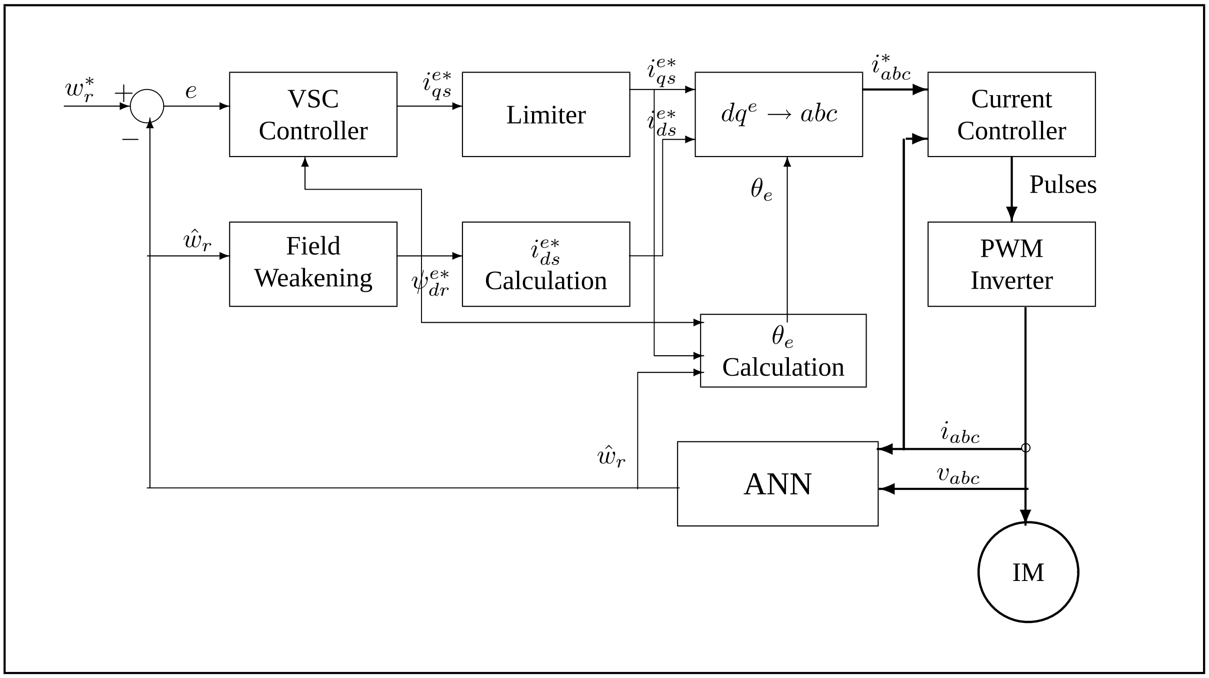

Fig. 7. Block diagram of the proposed sliding-mode field oriented control

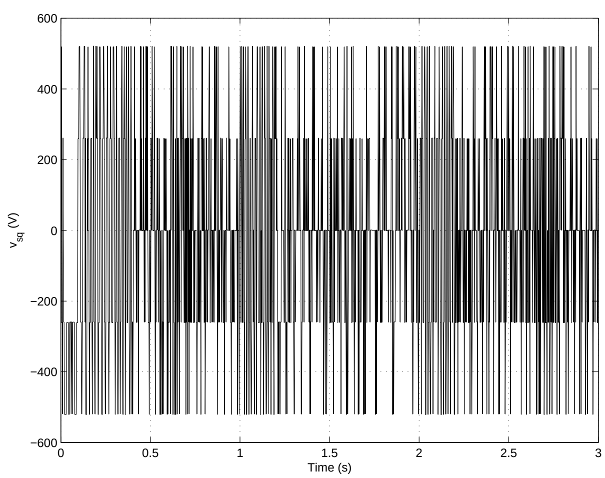

Fig. 5. Stator Current v_{sq} (V)

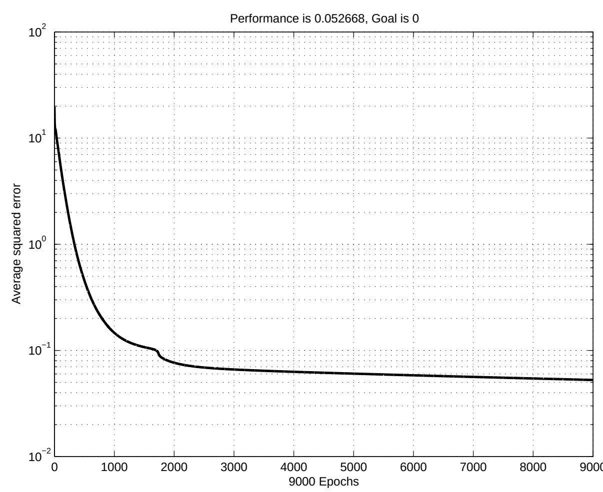

Fig. 6. Learning curve

Calculation' provides the angular position of the rotor flux vector, and it is implemented by the equation (23). Finally, the block 'IM' represents the induction motor.

The induction motor used in this case study is a 50 HP, 460 V, four pole, 60 Hz motor having the following parameters: $R_s = 0.08\,\Omega$, $R_r = 0.20\,\Omega$, $L_s = 30\,mH$, $L_r = 30\,mH$, and $L_m = 29\,mH$.

The system has the following mechanical parameters: $J = 0.05\,kg.m^2$ and $B = 0.15\,N.m.s$. It is assumed that there is an uncertainty of around 20 % in the system parameters, that will be overcome by the proposed sliding control.

The following values have been chosen for the state observer and the rotor speed adaptation algorithm:

$$G = \begin{bmatrix} 75 & 0 \\ 0 & 75 \\ 0 & -1 \\ 1 & 0 \end{bmatrix}, \quad \lambda = 9$$

Finally, the following values have been chosen for the controller parameters, $k = -90$, $\beta = 25$.

In this example the motor starts from a standstill state and we want that the rotor speed follows a speed command of $w_r = 50\,rad/s$ when the drive is bearing a load torque of $T_L = 20\,Nm$. Then, at time $t = 0.3\,s$, the load torque steps from $T_L = 20\,Nm$ to $T_L = 200\,Nm$. Later, at time $t = 0.6\,s$ the reference speed steps from $w_r = 50\,rad/s$ to $w_r = 200\,rad/s$. Therefore, In this example it is presented changes both in the reference speed and in the load torque.

Figure 8 shows the desired rotor speed (dashed line) and the real rotor speed (solid line). As it may be observed, the rotor speed tracks the desired speed in spite of system uncertainties. Moreover, the speed tracking, practically, is not affected by the load torque change at time $t = 0.3\,s$, because when the sliding surface is reached (sliding mode) the system becomes insensitive to the boundary external disturbances. Nevertheless, both at the starting of the simulation and at time $t = 0.6\,s$, that is, when the reference speed steps to a new value, the motor can not follow this reference change instantaneously due to the physical limitations of the system. However, after a transitory time in which the motor accelerates until the final speed the trajectory tracking is obtained.

Figures 9 and 10, show the d and q components of the stator current. It may be observed that in the initial state, the current signal presents a high value because it is necessary a high torque to increment the rotor speed. Then, in the constant speed region, the motor torque only has to compensate the friction and the load torque and so, the current is lower. At time $t = 0.3\,s$ the current increases because the load torque has been increased. Finally, at time $t = 0.6\,s$ there is an increment in the frequency of the current signal because the rotor reference speed has been increased.

Figures 11 and 12, show the d and q components of the stator voltage.

Figure 13 shows the motor torque. As in the case of the stator current (fig. 9 and 10), the motor torque has a high initial value in the speed acceleration zone. Then the value decreases in a constant region and next, at time $t = 0.3\,s$, the motor torque increases due to the load torque increment. Finally at time $t = 0.6\,s$ the torque also increases due to the step increment in the rotor reference speed which implies an acceleration zone.

In this figure it may be seen that in the motor torque appears the so-called chattering phenomenon, which usually appear in the sliding mode controller type. However this high frequency changes in the torque do not represent a problem for this system because they will be filtered by the mechanical system inertia.

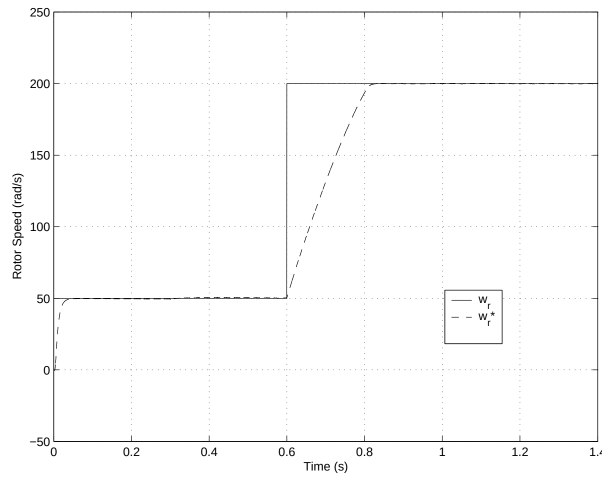

Fig. 8. Reference and real rotor speed signals (rad/s)

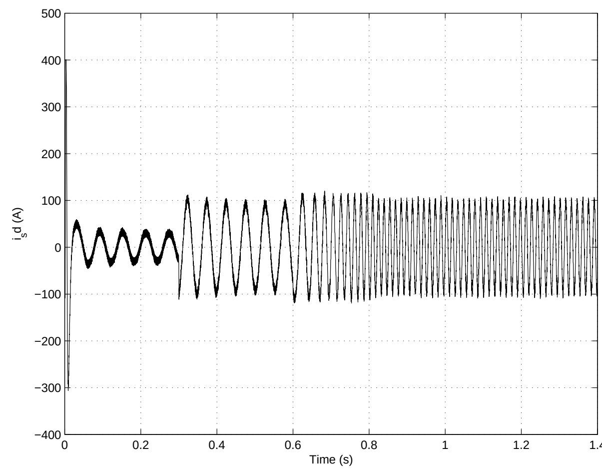

Fig. 9. Stator Current i_{sd} (A)

VI. Conclusion

In this paper a new sliding mode vector control with artificial neural network rotor speed estimation has been presented. The artificial neural network employed is a feedforward multilayer neural network and its weights and biases are updated using a backpropagation with momentun training algorithm. The output of the neural network is the estimated rotor speed and the inputs to the neural network are the measured stator voltages and currents, for which it has been proven that they are an appropriate input variable set to the neural network.

In addition, it is proposed a new variable structure control which has an integral sliding surface to relax the requirement of the acceleration signal, that is usual in conventional sliding mode speed control techniques. Due to the nature of the sliding control this control scheme is robust under uncertainties caused by parameter error or by changes in the load torque. The closed loop stability of the presented design has been proved through Lyapunov stability theory.

Finally, by means of simulation examples, it has been shown that the proposed control scheme performs reasonably well in practice, and that the speed tracking objective is achieved under uncertainties in the parameters and load torque. Also it is observed a robust speed estimation performance even at step load changes or under variable speed reference operation.

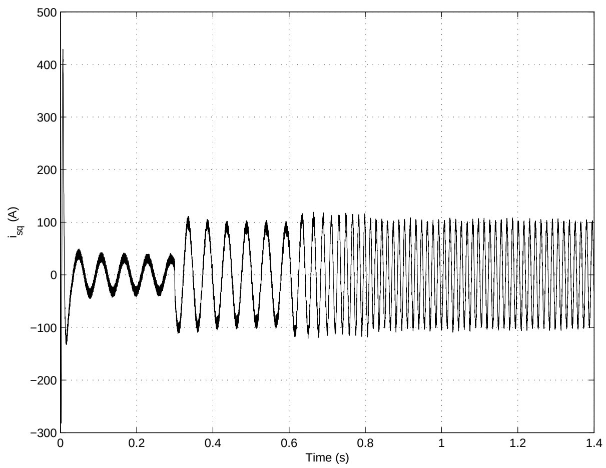

Fig. 10. Stator Current i_{sq} (A)

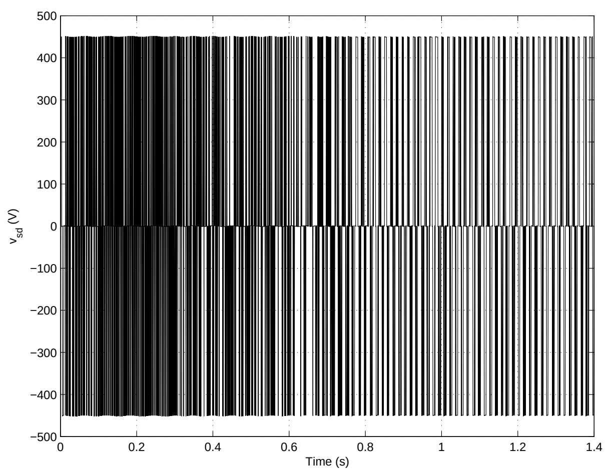

Fig. 11. Stator Voltage v_{sd} (V)

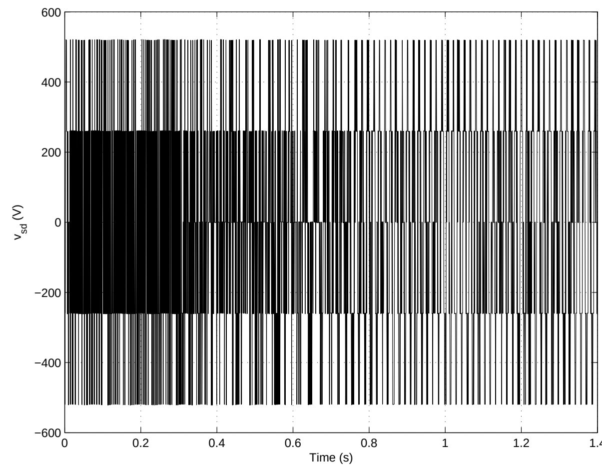

Fig. 12. Stator Voltage v_{sq} (V)

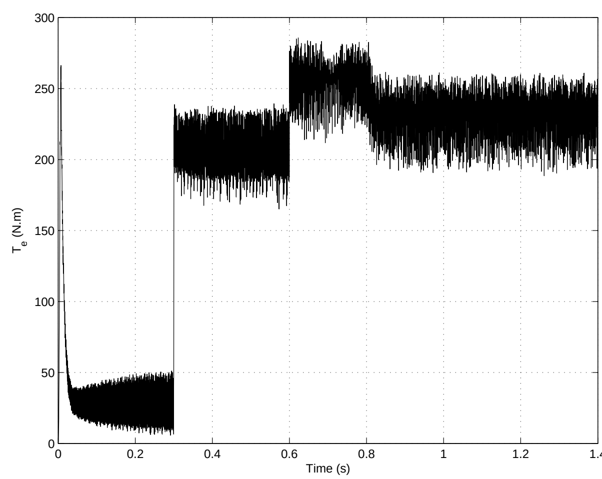

Fig. 13. Motor torque (N.m)

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