4th WSEAS Int. Conf. on NON-LINEAR ANALYSIS, NON-LINEAR SYSTEMS and CHAOS, Sofia, Bulgaria, October 27-29, 2005 (pp94-102)

Sensorless Speed and Position Control of Induction Motor Servo Drives Using MLP Neural Network and Sliding Mode Controller

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Abstract- In this paper, the sensorless speed and position control of induction motor drive is studied. A Sliding Mode Controller (SMC) is designed and analyzed to achieve high-dynamic performance both in the speed and position command tracking and load regulation responses based on the closed-loop tracking transfer function. An artificial neural network (ANN) is adopted to estimate the motor speed and thus provide a sensorless speed estimator according to the required specifications for the IM servo drive system. The performance of the proposed controller for induction motor servo drive is investigated by some simulations including startup, step changes in reference speed, unknown load torque and parameters variations. In spite of the simple structure of the proposed speed and position controller, the obtained results show that this controller can provide a fast and accurate dynamic response in tracking and disturbance rejection characteristics under parameter variations. At the same time, a reduction of the computation time has been occurred as a result of the simple construction of the sliding mode controller. The proposed SMC can compensate the induction machine drive system at nominal values and is insignificantly affected by variations in the induction machine's parameters. The position response of the proposed SM position control scheme is influenced slightly by the load disturbance, whether the system parameters varied or not.

Key-Words- Induction Motor, Sensorless Speed Controller, MLP Neural Network, Sliding Mode Control

1 Introduction

Variable speed motor drives play an important role in modern industries because they are utilized extensively in factory automation to store energy or to meet stringent load requirements. The use of variable speed motor drives is ever increasing and will maintain its momentum for several decades to come. Among all different kinds of electric motor drives, the induction motor (IM) has become the subject of a large body of research in the field of electric motor drives. This is partly because the motor has an intrinsically simple and rugged structure and low manufacturing cost [1,2]. Moreover, induction motor drives have the wide speed range, high efficiencies, and robustness. This servo drive system is essential in many applications such as robotics, actuation, numerically controlled machinery and guided manipulation where precise control is required. All these merits make the motor a good candidate for the industrial applications. Induction machine servo drive system is considered high-performance when the rotor position, rotor speed and stator currents can be controlled to follow a reference for tracking at all times [3-6]. A track is a desired time history of the motor current, speed or position.

Sensorless vector control of induction motor drives is now receiving wide attention. The main reason is that the speed sensor spoils the ruggedness and simplicity of induction motor. In a hostile environment, speed sensors can not even be mounted. However, due to the high order and nonlinearity of the dynamics of an induction motor, estimation of the angle speed and rotor flux without the measurement of mechanical variables becomes a challenging problem [7,8,9]. The advantages of position and speed sensorless induction motor drives are reduced hardware complexity and lower cost, reduce size of drive machine, eliminate of sensor cable, better noise immunity, increasing reliability and less maintenance requirements. Various position and speed control algorithms for induction motor drives have been devised in the literature. Among them, PID controllers [11], optimal, nonlinear and robust control strategies [12], and fuzzy approaches are to be mentioned [13-15]. However, most of the above proposed methods have problem based on IM parameter changes due to saturation in iron and thermal changes of stator and rotor resistance. To overcome the drawbacks of the above controllers and to achieve high- dynamic performance, IM sensorless control system based on MLP Neural Network and Sliding Mode Control (SMC) theory is analyzed in this paper. This control system is based on the fact that rotor flux vector can be estimated in two ways: using voltage and current model. The minimization of the difference between value and angle of that two flux vectors is achieved by the SMC theory. A proposed on-line trained NN position controller is designed in addition to the sliding mode position controller to improve the dynamic performance of the IM drive system. The output of the NN position controller is added to the sliding mode speed controller output to compensate the error between the reference model and the IM drive system output under parameter variations and load disturbances. The dynamic performance of the IM drive system has been studied under load changes and parameter variations. The simulation results are given to demonstrate the effectiveness of the proposed controllers.

2. Mathematical Model of Induction motors

Many schemes based on simplified motor models have been devised to sense the speed of the induction motor from measured terminal quantities for control purposes. In order to obtain an accurate dynamic representation of the motor speed, it is necessary to base the calculation on the coupled circuit equations of the motor. Since the motor voltages and currents are measured in a stationary frame of reference, it is also convenient to express these equations in that stationary frame. From the stator voltage equations in the stationary frame it is obtained [16]:

$$\frac{d\lambda_{qr}}{dt} = \frac{L_r}{L_m}\left(V_{qs} - (R_s + \sigma L_s \frac{d}{dt})i_{ds}\right)$$
$$\frac{d\lambda_{dr}}{dt} = \frac{L_r}{L_m}\left(V_{ds} - (R_s + \sigma L_s \frac{d}{dt})i_{qs}\right) \qquad (1)$$

Where λ is the flux linkage; L is the inductance; V is the voltage; R is the resistance; i is the current, and $\sigma = 1 - \frac{L_m^2}{L_r L_s}$ is the motor leakage coefficient.

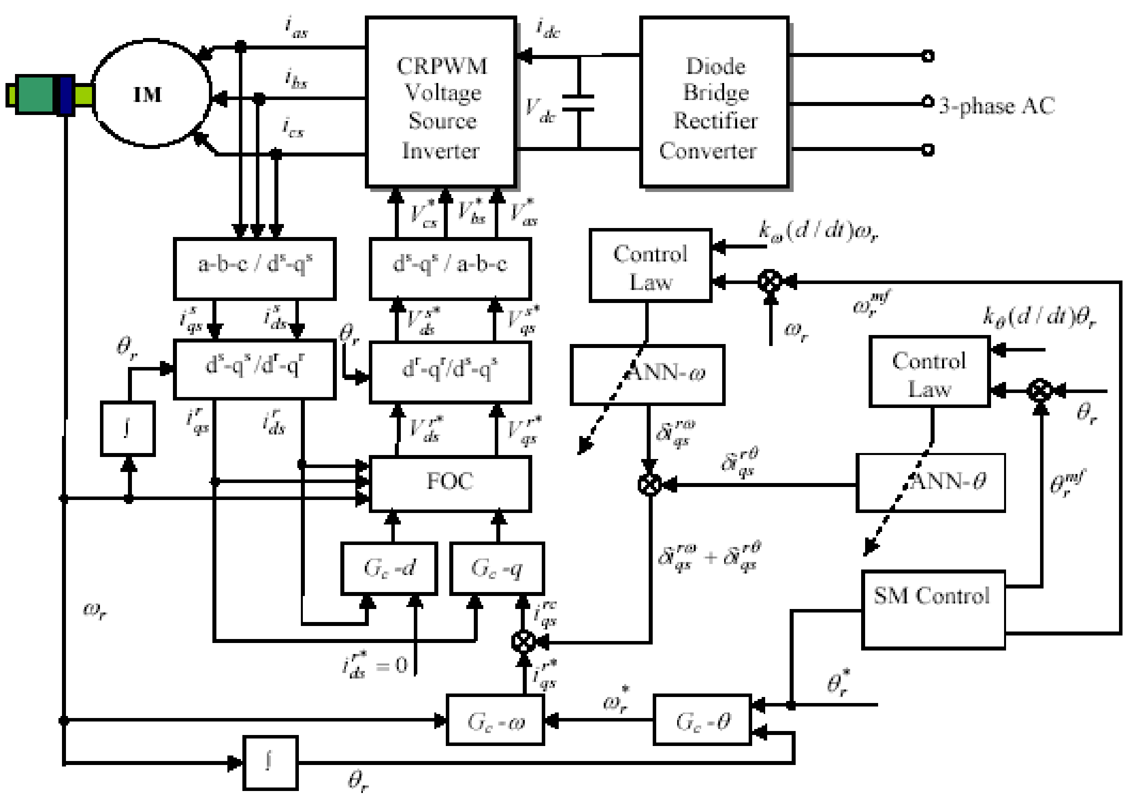

Fig. 1 The block schematic diagram of a vector controlled IM servo drive system

The subscripts r and s denotes the rotor and stator values respectively refereed to the stator, and the subscripts d and q denote the dq-axis components in the stationary reference frame. The rotor flux equations in the stationary frame are:

$$\begin{aligned} \frac{d\lambda_{dr}}{dt} &= \frac{L_m}{\tau_r} i_{ds} - \omega_r \lambda_{qr} - \frac{1}{\tau_r}\lambda_{dr} \\ \frac{d\lambda_{qr}}{dt} &= \frac{L_m}{\tau_r} i_{qs} + \omega_r \lambda_{dr} - \frac{1}{\tau_r}\lambda_{qr} \end{aligned} \tag{2}$$

Where ω_r is the rotor electrical speed and $\tau_r = \frac{L_r}{R_r}$ is the rotor time constant. The synchronous frequency in stationary frame is defined as follows:

$$\omega_e = \frac{\lambda_{dr}\frac{d\lambda_{qr}}{dt} - \lambda_{qr}\frac{d\lambda_{dr}}{dt}}{\lambda_{dr}^2 + \lambda_{qr}^2} \tag{3}$$

Substituting the equation (2) in the equation (3) it is obtained:

$$\omega_e = \omega_r - \frac{L_m}{\tau_r}\left(\frac{\lambda_{dr} i_{qs} - \lambda_{qr} i_{ds}}{\lambda_{dr}^2 + \lambda_{qr}^2}\right) \tag{4}$$

Then substituting the equations (3) in the equation (4), and finding ω_r we obtain:

$$\omega_r = \frac{1}{\lambda_{dr}^2 + \lambda_{qr}^2}\begin{bmatrix} \lambda_{dr}\frac{d\lambda_{qr}}{dt} - \lambda_{qr}\frac{d\lambda_{dr}}{dt} \\ -\frac{L_m}{\tau_r}\left(\lambda_{dr} i_{qs} - \lambda_{qr} i_{ds}\right) \end{bmatrix} \tag{5}$$

Therefore, given a complete knowledge of the motor parameters, the instantaneous speed ω_r can be calculated from the equation (5) where the stator currents and voltages are known along with the machine parameters, and the rotor flux linkages are obtained from equation (1).

3 Problem Formulations

The system configuration of the proposed speed and position control for an IM drive system is illustrated in Fig. 1. It basically consists of a current controller in d-q-axes and a neural-network system as speed estimator. A reference model is derived from the closed loop transfer function of the IM drive system. Although the desired tracking and regulation speed control can be obtained using the PI speed controller with the nominal IM parameters, the performance of the drive system still sensitive to parameter variations. To solve this problem, a hybrid speed controller combining the sliding mode speed controller and the neural-network controller is proposed.

4 Rotor speed estimation in vector control system – Neural Network

4.1. Artificial Neural Network

Artificial Neural Networks (ANN) represent a tool for solving of real problems, where conventional analytical methods do not suffice or where further simplification of the problem is not allowed. In systems that are conditioned with additional criteria of security and reliability of operation, they are used as an additional source of information for making final decisions. An ANN is composed of a large number of neurons that are mutually connected and process data in parallel, according to dynamic condition of the neural network and according to its inputs. Since ANNs are, through the process of learning, able to adapt to input information and pre-defined requirements, they are classified among adaptive systems. Two additional characteristics of ANNs, namely associativity and simplification, are connected with learning, too. An ANN is a robust system since it is possible to remove some neurons (process units) and the neural network will still operate properly, only the results will be slightly less accurate. The properties of robustness, learning, associativity and simplification contribute to an increased flexibility of ANNs [17].

In the field of power engineering the most widespread are open loop artificial neural networks with learning algorithms on the basis of error back-propagation. These neural networks are, after the learning process has been completed, able to give reasonable answers to the input data that have never been seen before; to approximate functions with a finite number of discontinuities; and to arrange input vectors in an order, defined by the user. This algorithm is based on minimizing the error of the neural network output compared to the required output. The required function is specified by the training set (a sequence of input / required network output pairs). The error of network E relative to the training set is defined as the sum of the partial errors of network E_k relative to the individual training patterns and depends on network configuration w, $E = \sum_{k=1}^{P} E_k$. The partial error of network E_k relative to the k-training pattern is proportional to the product of the squares of the deviations of the actual values of network yj outputs for the input of k-training pattern x_k from the corresponding required values of outputs for pattern dj,

$$E_k = \frac{1}{2}\sum_{j \in Y}\left(y_j - d_{kj}\right)^2 \tag{6}$$

where Y is the set of output neurons. The adaptation of weights (in time $t = 0$ the configuration weights $w^{(0)}$ are set randomly close to zero) takes place in discreet time steps corresponding to the training cycles. The new configuration in time $t > 0$ is calculated as follows

$$w_{ji}(k) = w_{ji}(k-1) - \alpha \frac{\partial E}{\partial w_{ji}} \tag{7}$$

Where $0 < \alpha < 1$ is the speed of learning. The speed of training is dependent on the set constant α If a low value is set, the network weights react very slowly. On the contrary, high values cause divergence -the algorithm fails. Therefore the parameter α is set experimentally. The basic problem in training a NN to recognize induction motor speed is that the functional relationship between the speed and stator parameters [18,19]. The proposed speed estimator based on above NN is described in the following subsection.

4.2. Rotor Speed Estimation based on NN

Figure 2 shows the Block diagram of speed estimation system using NN. As can be seen from this figure, Rotor flux and speed estimation in observer is based on well know (measured or calculated) stator voltage and current vectors (Eq. (1)-(5)).

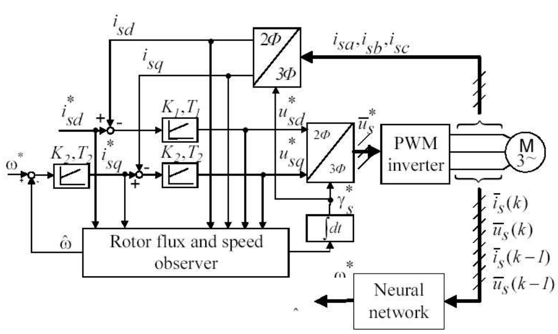

Figure 2. Sensorless vector control system

The researches were shown that saturation of mutual inductance L_m can strongly influence to the validity of rotor speed estimation. The observed IM has significant saturation effect in iron. Unsaturated value of mutual inductance L_m in analyzed observer (then mutual inductance L_m estimation error is about 200%, certainly taking into account saturation in iron) results with wrong rotor speed estimation, and system becomes unstable. Otherwise, if the estimation of mutual inductance is better, then the control system will be stable. It was shown that if estimation error of mutual inductance is less than 5 % then actual rotor speed ω and rotor speed estimated by observer $\hat{\omega}$ can satisfactory coincide. This fact can be assigned to mould of PI rotor speed controller that always minimizes difference between reference rotor speed and estimated rotor speed. If that relative estimation error of mutual inductance becomes higher then the control system becomes useless [20]. To reach a solution for estimation of the mutual inductance value *Lm* in control system is introduced an ANN. The ANN was trained with a goal to estimate rotor speed taking into account saturation effect in iron according to the reference. The method described in reference, is not possible directly implement, in this research stage, for on line work because it contains more logical *if-then* statements and branch statements. For IM rotor speed estimation in this paper is proposed four layer feedforward static ANN which structure is 8-9-1 (8 neurons in first hidden layer, 9 neurons in second hidden layer and one neuron in output layer). The activation function in hidden layers is tansigmoid function, and in output layer is a linear function. The selected ANN in this way was obtained by trial and error procedure. Topology of the proposed ANN is shown in Fig. 3.

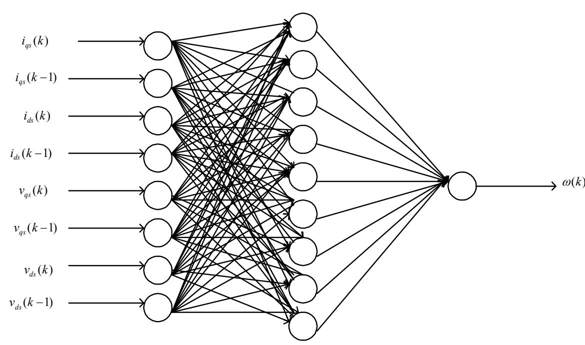

Figure 3. Topology of the 8-9-1 ANN for IM rotor speed estimation

Neural network works in any simulation step parallel with vector control system and ANN is independent about it. With assumption that the stator currents and voltages are known along with the machine parameters. Checking the validity of ANN rotor speed estimation is realized by comparison ANN estimated speed with actual rotor speed for four above-mentioned IM operating modes. Actual rotor speed and ANN estimated rotor speed for rotor speed reference value $\omega^* = 0.03$ [p.u.] is shown in Fig. 4. AS can be seen from this figure, the actual rotor speed is in agreement with ANN estimated rotor speed; during transient state (*t<0,5* [s]) difference is something higher than in steady state (*t>0,5* [s]). The mean value of estimated rotor speed in steady state is *0,0594* [p.u.], and this is a tolerance *1* % from actual rotor speed.

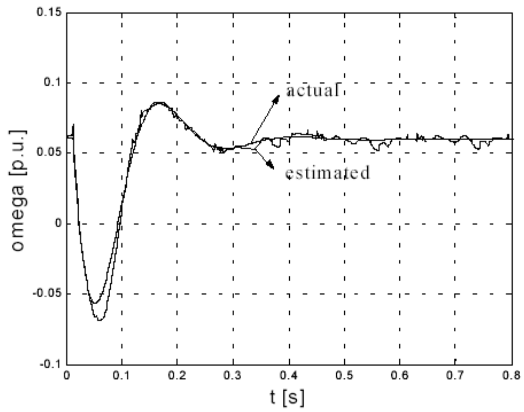

Figure 4. Actual rotor speed and ANN estimated rotor $\omega^* = 0.03$ [p.u.]

5. Sliding Mode Control

Nonlinear behaviours are very common in practice and usually are approximated by linearization around the operating point. This procedure may not be acceptable for complex and highly reliable systems. To overcome this difficultness various control strategy based on classical and intelligent methods have been investigated in literature. Two of the most common approaches are sliding mode control and adaptive control. Adaptive control approaches deal with parametric uncertainties by changing the control characteristics as data is gathered. However, these adaptations are typically made without memory of the events, which precipitated the changes. Sliding Mode Controller (SMC) is a particular type of variable structure control systems that is designed to drive and then constrain the system to lie within a neighborhood of the switching function. Then constrain the system to lie within a neighborhood of the switching function. There are two main advantages of this approach. Firstly, the dynamic behavior of the system may be tailored by the particular choice of switching functions [20]. Secondly, the closed-loop response becomes totally insensitive to a particular class of uncertainty and external disturbances. In addition, the ability to specify performance directly makes sliding mode control attractive from the design perspective [21,22,24].

Without lost of generality, consider the design of a sliding mode controller for the following second order system [23,25]:

$$\ddot{x} = f(x,\dot{x},t) + bu(t) \tag{8}$$

Here we assume $b > 0$. $u(t)$ is the input to the system. The following is a possible choice of the structure of a sliding mode controller [26]:

$$u = -k\,\mathrm{sgn}(s) + u_{eq} \tag{9}$$

where u_{eq} is called equivalent control which is used when the system state is in the sliding mode. k is a constant, representing the maximum controller output. s is called switching function because the control action switches its sign on the two sides of the switching surface $s = 0$. s is defined as :

$$s = \dot{e} + \lambda e \tag{10}$$

where $e = x - x_d$ and x_d is the desired state. λ is a constant. The definition of e here requires that k in (9) be positive. $\mathrm{sgn}(s)$ is a sign function, which is defined as:

$$\mathrm{sgn}(s) = \begin{cases} -1 & if \quad s < 0 \\ 1 & if \quad s > 0 \end{cases} \tag{11}$$

The control strategy adopted here will guarantee a system trajectory move toward and stay on the sliding surface $s = 0$ from any initial condition if the following condition meets:

$$s\dot{s} \leq -\eta|s| \tag{12}$$

where η is a positive constant that guarantees the system trajectories hit the sliding surface in finite time. Using a sign function often causes chattering in practice. One solution is to introduce a boundary layer around the switch surface:

$$u = -k sat(\frac{s}{\phi}) + u_{eq} \tag{13}$$

where constant factor ϕ defines the thickness of the boundary layer. $sat(\frac{s}{\phi})$ is a saturation function that is defined as [27]:

$$sat(\frac{s}{\phi}) = \begin{cases} \frac{s}{\phi} & if \quad \left|\frac{s}{\phi}\right| \leq 1 \\ \mathrm{sgn}(\frac{s}{\phi}) & if \quad \left|\frac{s}{\phi}\right| > 1 \end{cases} \tag{14}$$

This controller is actually a continuous approximation of the ideal relay control. The consequence of this control scheme is that invariance property of sliding mode control is lost. The system robustness is a function of the width of the boundary layer. A variation of the above controller structures is to use a hyperbolic tangent function instead of a saturation function [28]:

$$u = k \tanh\left(\frac{s}{\phi}\right) + u_{eq} \qquad (15)$$

It is proven that if k is large enough, the sliding model controllers of (9), (13) and (15) are guaranteed to be asymptotically stable.
For a 2-dimensional system, the controller structure and the corresponding control surface are illustrated in Fig 5.

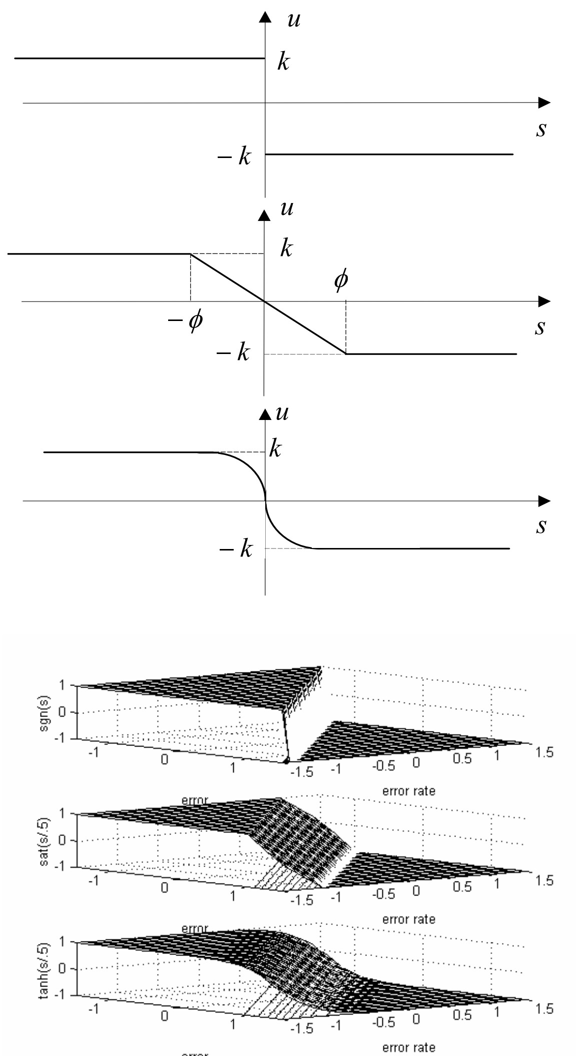

Fig 5. Various Sliding Mode Controllers and control surfaces.

6. Simulation Results of the Drive System

The simulation of the proposed control scheme for induction machine drive system has been carried out using MATLAB/SIMULINK package. The dynamic performance of the drive system for different operating conditions has been studied with the application of the sliding mode control to the d-q currents, speed and position loops and then compared with the conventional controllers. Taking into consideration the parameter variations of the induction machine, the drive system performance has been tested under load changes and set-point variations.

6.1 Dynamic Performance under Different Loads

The dynamic performance of the drive system under the disturbances of step change in reference position and step change in load is shown in Figure 6. This figure shows the position tracking, speed response, current response, and load regulation performance under nominal parameters. At t=1.5 sec, an external load of 10 N.m is applied to the drive system for both controllers. It is obvious that the proposed sliding mode controller provides a rapid and accurate response for the reference within 0.55 sec. Also, this controller quickly returns the position to the command position within 0.55 sec under full load with a maximum dip of 0.01 radian. Fig. 7 proves that IFOC is achieved during load changes ($\lambda_{dr} = \lambda_r$ and $\lambda_{qr} = 0$). Also, this figure illustrates that the proposed sliding mode control scheme provides robust performance than the other controllers. The dynamic performance introduced through Figure 7 reveals that the proposed sliding mode control scheme has an extremely quick position response and is influenced slightly by the load disturbance.

6.2 Influences of Parameter Variations

The position response and the load regulation performance of the proposed sliding mode controller are shown in Figures (8-9) respectively under parameter variation of the machine. It can be seen that from these figures that the drive system with sliding mode controller is insignificantly affected by variations in the induction machine parameters of the parameter variations.

6. Conclusion

In this paper, a sliding mode speed and position control system design for induction machine drive system was presented. Furthermore GRNN was designed to estimate velocity in the whole speed range to provide a sensorless speed estimator system. The sliding mode control constitutes a simple structure that is applied to the induction machine drive system. In spite of the simple structure of SMC, the obtained results show that that controller can provide a fast and accurate dynamic response in tracking and disturbance rejection characteristics under parameter variations. At the same time, a reduction of the computation time was occurred as a result of the simple construction of the SMC. The proposed SM controller can compensate the induction machine drive system at nominal values and is insignificantly affected by variations in the induction machine's parameters. The position response of this proposed SMC scheme was influenced slightly by the load disturbance, whether the system parameters varied or not.

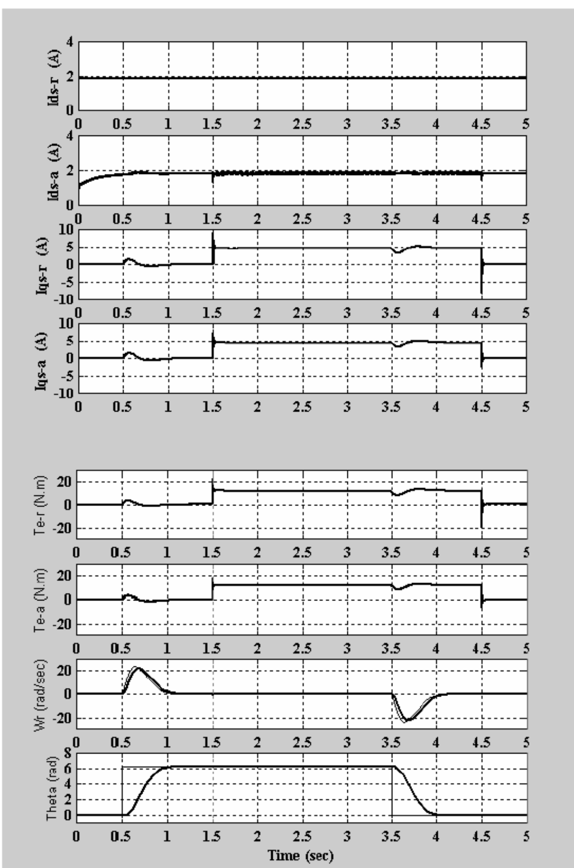

Fig. 6. Dynamic performance of the current, speed and position with the proposed sliding mode controller

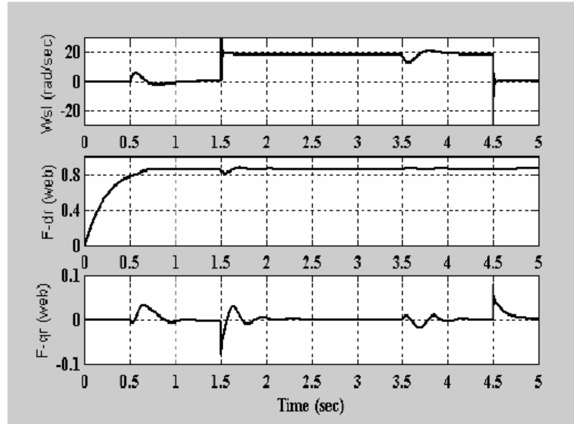

Fig. 7. Performance of the IM variables ω_{sl}, λ_{dr} and λ_{qr} with sliding mode controller

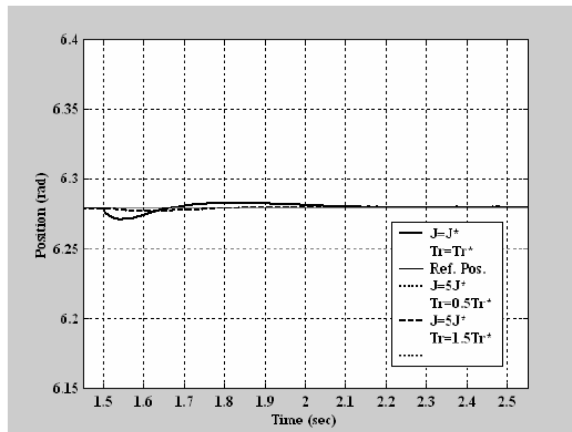

Fig. 8. Load regulation performance under parameter variations with the proposed sliding mode controller

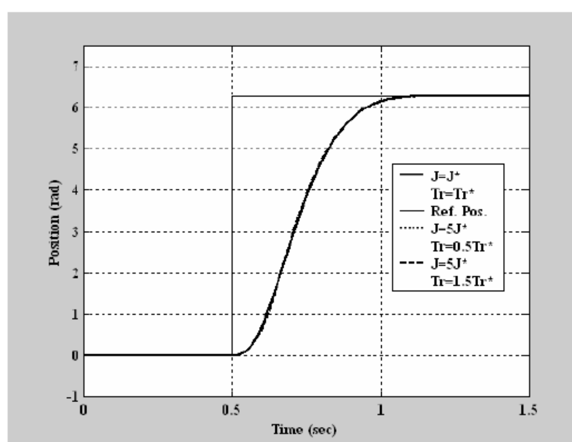

Fig. 9. Step response performance under parameter variations with the proposed sliding mode controller

Appendix

The induction motor considered in this paper has the following data and parameters:

3 phase, 380V, 15KW, 31A, 2 poles ,2895rpm

R_r =1.46Ω, R_s =0.603Ω, L_{lr} =4.72mH,

L_{ls} =4.72mH, L_m =330.2mH

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