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Speed Estimation of Induction Motor Drive by Second-Order Sliding Mode MRAS with Adaptive Neural Network Controller

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Abstract

Variable speed Induction motor drives require wide speed variation and quick response, notwithstanding any disturbances and uncertainties (like load variation, parameters variation and un-modeled dynamics). The advancements done recently in field oriented control have reduced the price of power electronics devices and microprocessors which have created variable speed induction motor drives a cost-effective for several industrial applications. For rotor speed estimation, the MRAS based methods are used here, which has the advantages of simplicity, better performance and ease in implementation as in comparison with other speed estimation techniques. The MRAS based on flux is stable and provides good performance. One specific approach to robust-control management style is the second order sliding mode control methodology. In this paper, a SMO based MRAS with Artificial Neural Network controller (Function Fitting Neural Network with Levenberg-Marquardt training algorithm) is designed for an induction motor drive. ANN based methods overcome instability and parameter dependency problems as shown in this paper, and when trained properly, are capable of providing stable operation at all speeds. The comparison in the performances of Induction Motor drive by SMO based MRAS with and without ANN controller is shown in this paper and is simulated in the MATLAB/Simulink software.

Keywords: Induction motor (IM), Speed estimation, Sensorless control, Sliding mode observers, Model Reference Adaptive System (MRAS), Artificial Neural Network (ANN).

INTRODUCTION

Variable Speed Drives (VSDs) applications are immensely employed in the trade to regulate a large variation of speed and torque for machines, manufacturing method, pumps etc. Speed information can be obtained by using the machine model and its terminal quantities like voltage and current. These include different methods such as the use of simple open loop speed calculators, MRAS, EKF, Adaptive Flux Observer, Artificial Intelligence Techniques and Sliding Mode Observer (SMO). MRAS based methods for rotor speed estimation has simplicity, better performance and ease in implementation. The MRAS method can be used based on of three types, which include flux based, back-emf based and reactive power based. The advantages of Reactive power based model reference adaptive system is that reactive power based controllers perform well at low speeds and are inherently independent of stator resistance. Its disadvantages are such configuration fails to provide stability in the regenerative mode and it uses PI controller for the speed adaptation, but PI based adaption does not work so well in practice because they have high starting overshoot, insensitivity to controller gains and sluggish response to sudden disturbances. The advantage of back–emf based MRAS is it overcomes the problem of pure integrator and the performance is better at low speeds [1-3]. The disadvantage is its practical implementation requires different operation which can amplify noise in the system. The advantage of flux–based MRAS is stable in all the quadrants of operation and provides good performance. Its disadvantage is this estimator is dependent on all the machine parameters [4]. Sliding mode methods have the advantage of finite convergence unlike exponential convergence of observer based methods. They can also reject matched disturbances but have serious problem of chattering. The problem of chattering can be eliminated by using higher order sliding modes, but the cost of increased complexity in the system demanding a powerful controller. Artificial Neural Network (ANN) when trained properly is capable of providing stable operation at all the speeds, but they require training for the adjustments of weights of the neural network.

DESIGN OF A SLIDING MODE CONTROLLER

Sliding Mode Observer for Fluxes and Speed

The rotor equations are used in designing the adjustable model, this observer estimates both the fluxes and the speed. The speed is a discontinuous (sliding mode) term which is designed as a first order SM term. The equations of the observer are:

$$\frac{d\hat{\lambda}_\alpha}{dt} = -\eta\hat{\lambda}_\alpha - n_p\widehat{\omega}_r\hat{\lambda}_\beta + \eta L_m i_\alpha \quad (2.1$$

$$\frac{d\hat{\lambda}_\beta}{dt} = n_p\widehat{\omega}_r\hat{\lambda}_\alpha - \eta\hat{\lambda}_\beta + \eta L_m i_\beta \quad (2.2)$$

$$\widehat{\omega}_r = \mathrm{M} \cdot \mathrm{sign}\ (\mathrm{s}) \quad (2.3)$$

$$\mathrm{s} = \hat{\lambda}_\alpha\ \lambda_\beta - \hat{\lambda}_\beta\ \lambda_\alpha \quad (2.4)$$

The speed estimate $\widehat{\omega}_r$ is discontinuous and is represented by s. To show that the sliding mode has occurred, the (manifold) s is differentiated and is given by:

$$\dot{s} = n_p\omega_r\ (\hat{\lambda}_\alpha\ \lambda_\alpha + \hat{\lambda}_\beta\ \lambda_\beta) + 2\ \eta\ (\hat{\lambda}_\beta\ \lambda_\alpha - \hat{\lambda}_\alpha\ \lambda_\beta) + \eta\ L_m\ [(\hat{\lambda}_\alpha - \lambda_\alpha)\ i_\beta - (\hat{\lambda}_\beta - \lambda_\beta)\ i_\alpha] - n_p\ (\hat{\lambda}_\alpha\lambda_\alpha + \hat{\lambda}_\beta\lambda_\beta)\ \widehat{\omega}_r \quad (2.5)$$

As the adjustable model converges and $\hat{\lambda}_\alpha \to \lambda_\alpha$, $\hat{\lambda}_\beta \to \lambda_\beta$, the coefficient of $\hat{\omega}_r$ is a non- zero and is positive. Thus the last term of the above equation is written as

$$\dot{s} = f - n_p\, \lambda^2 \mathrm{M}\cdot \mathrm{sign}\ (s) \qquad (2.6)$$

The design gain M is chosen as a high value, the manifold s and its derivative $\dot{s}$ will have different signs. The manifold tends to zero and sliding mode occurs. s=0, $\dot{s}$=0 can also be assumed.

$$\omega_{r,eq} = \omega_r + \frac{\eta\, L_m\, [(\hat{\lambda}_\alpha - \lambda_\alpha) i_\beta - (\hat{\lambda}_\beta - \lambda_\beta) i_\alpha] + 2\,\eta\,(\hat{\lambda}_\beta\, \lambda_\alpha - \hat{\lambda}_\alpha\, \lambda_\beta)}{\hat{\lambda}_\alpha\, \lambda_\alpha + \hat{\lambda}_\beta\, \lambda_\beta} \qquad (2.7)$$

If the adjustable model converges, the numerator of the second term in the above equation is equal to zero, then $\omega_{r,eq} \to \omega_r$. Practically, $\omega_{r,eq}$ is obtained by low pass filtering the switching term M · sign(s) and represents the speed estimate of the method. With the first order SM, the speed estimate is obtained with significant ripples, which can be reduced by using heavy filtering but this deteriorates the transient of the speed estimate. So, second order SM is taken into consideration and the switching term is redesigned as:

$$\hat{\omega}_r = \alpha \sqrt{|s|}\ \mathrm{sign}\ (s) + \beta \int (\mathrm{sign}\ (s)) \qquad (2.8)$$

where α and β are constant design parameters and both are positive. The speed estimate obtained is smooth, it has small ripple and is close to the real speed [5-6].

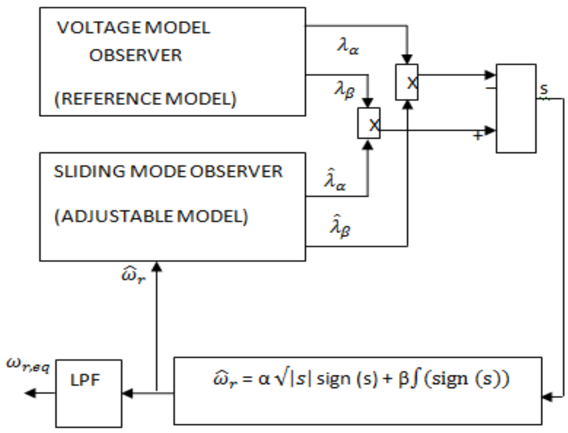

Figure 1. Block diagram of second order SM MRAS speed estimator

METHODOLOGY OF PROPOSED SYSTEM

Artificial Neural network

Levenberg-Marquardt Training Algorithm:

It is a network training function, which according to Levenberg-Marquardt optimization, updates bias and weight values. The advantage of this algorithm is that it is often the fastest back propagation algorithm for training a moderate-sized feedforward neural network available in the Matlab and is highly recommended as a first-choice supervised algorithm, although it does require more memory than other algorithms.

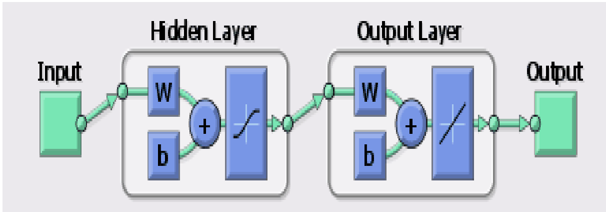

Fig.2: A two-layer feed-forward network with sigmoid hidden neurons and linear output neurons

Levenberg-Marquardt algorithm is designed here to approach second–order training speed. When performance function is in the form of sum of squares, then the Hessian matrix is approximated as

$$\mathrm{H} = \mathrm{J}^{\mathrm{T}}\mathrm{J} \qquad (3.1)$$

the gradient is computed as

$$\mathrm{g} = \mathrm{J}^{\mathrm{T}}\mathrm{e} \qquad (3.2)$$

where, **J**: the Jacobian matrix and contains the first derivatives of the network errors with respect to biases and weights, and **e**: a network errors vector. The Hessain matrix is very complex and thus the Jacobian matrix can be computed by using back propagation technique [7-10]. The Levenberg-Marquardt algorithm makes use of the approximation to the Hessian matrix in the following Newton like update:

(Gauss Newton method:

$$\mathrm{w}_{k+1} = \mathrm{w}_k - [J_k^T \mathrm{J}]^{-1} \mathrm{J}_k^{\mathrm{T}}\mathrm{e}) \qquad (3.3)$$

$$\mathrm{w}_{k+1} = \mathrm{w}_k - [J_k^T \mathrm{J}_k + \mu \mathrm{I}]^{-1} J_k^T \mathrm{e} \qquad (3.4)$$

where, **μ** is scalar and **I** is an Identity matrix .

SIMULATION DIAGRAMS AND RESULTS

Simulation diagram:

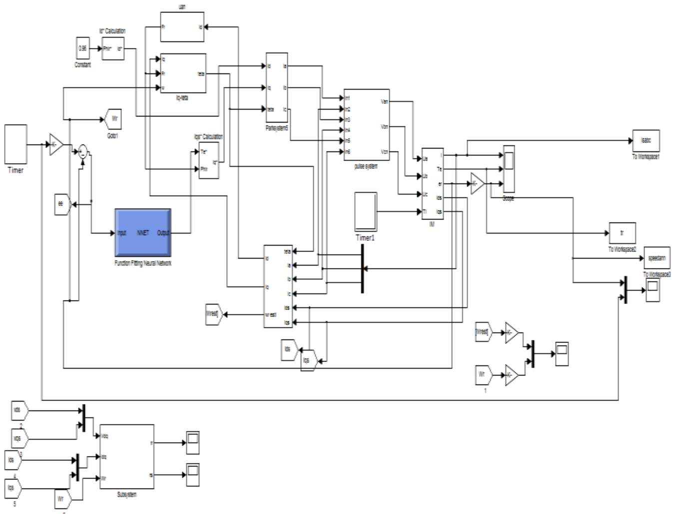

Figure 3. SMO based MRAS with ANN controller based Induction motor drive

SIMULATION RESULTS

i) Speed, Current and Torque waveforms of SMO based MRAS method

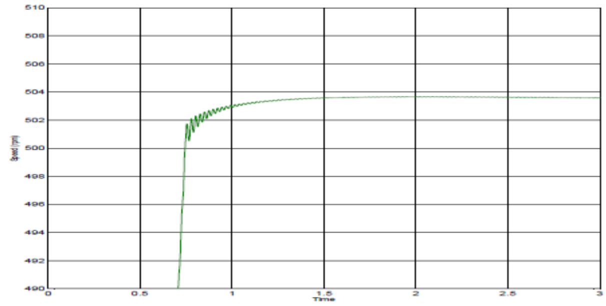

Figure 4. Speed obtained by SMO based MRAS method

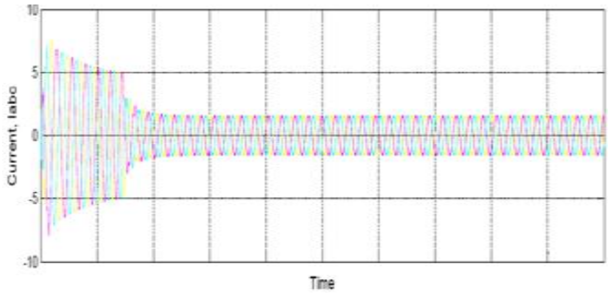

Figure 5: Current waveform obtained by SMO based MRAS method

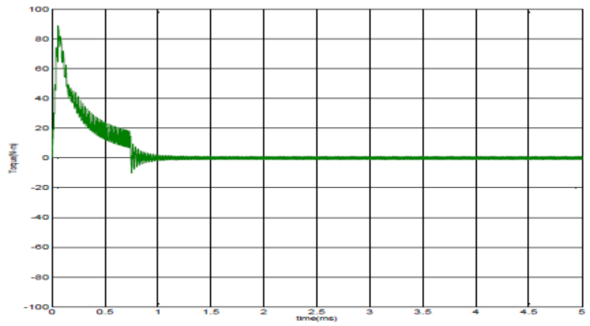

Figure 6. Torque due to SMO based MRAS method

ii) Speed, Current and Torque waveforms of SMO based MRAS with ANN controller

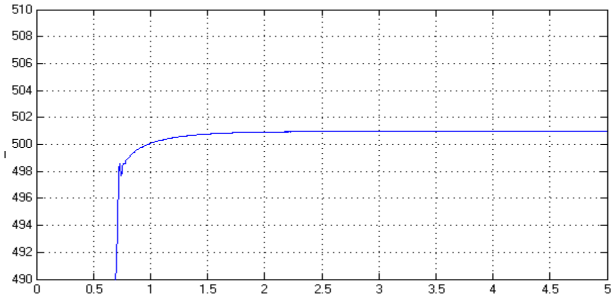

Figure 7. Speed estimation obtained from SMO based MRAS with ANN controller

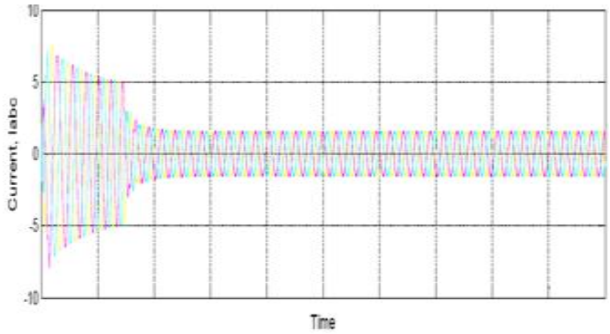

Figure 8. Current waveform obtained by SMO based MRAS with ANN controller

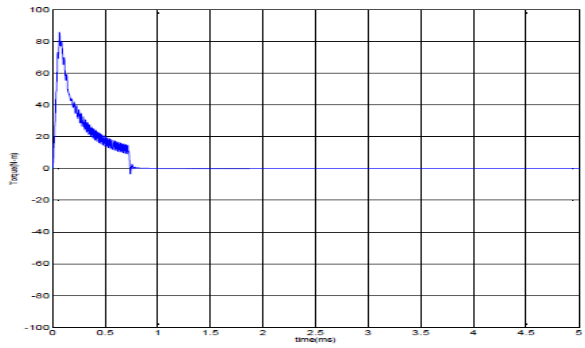

Figure 9. Torque waveform due to SMO based MRAS with ANN controller

Comparison of speed estimate obtained from SMO based MRAS with and without ANN controller:

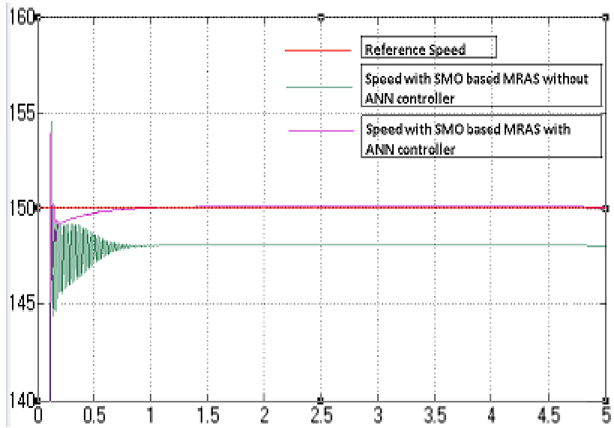

Figure10. Speed estimation obtained from SMO based MRAS with and without ANN controller

V. BEHAVIOR UNDER PARAMETER VARIATIONS:

This section describes the behavior of the second order SMO based MRAS speed estimator, rotor flux and resistance under variation of the parameter like stator resistance of the induction motor. SMO method is prone to disturbances in few parameters due to the variation in other parameters. From the following waveforms, it can be noticed that as the stator resistance is varied by a unit step at t=3s, some uncertain disturbance occurs in speed, stator current and derivative of rotor flux. Also it is found that the change in speed takes place when there is a variation in rotor resistance.

These parametric variations do not occur in the SMO based ANN controller as it has the ability to overcome the problems due to parameter dependency.

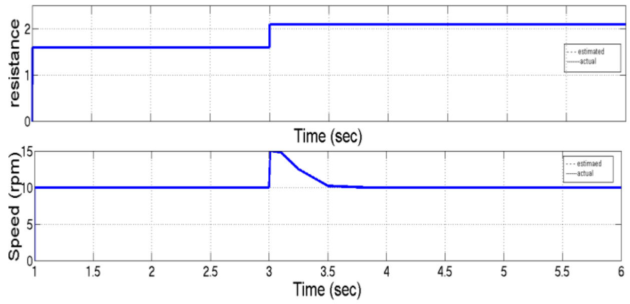

Figure 11. Speed Estimation and Stator Resistance Identification at Speed Command of 10 rpm and Sharp Variation of Stator Resistance.

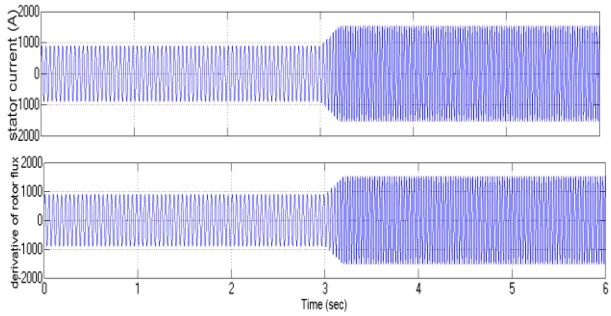

Figure 12. Stator current and rotor flux waveforms

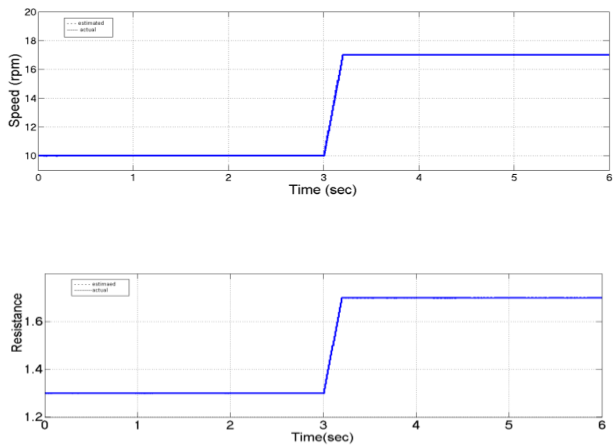

Figure 13. (a) Speed Estimation and (b) Rotor resistance

Performance of SMO based MRAS with ANN controller under low and high speeds:

As the speed and torque obtained in SMO with ANN controller are better than that in SMO based MRAS without ANN controller, the behavior of current, torque and speed waveforms are observed by ANN method at low speed and at high speed are as shown:

i) At low speed (150 rpm)

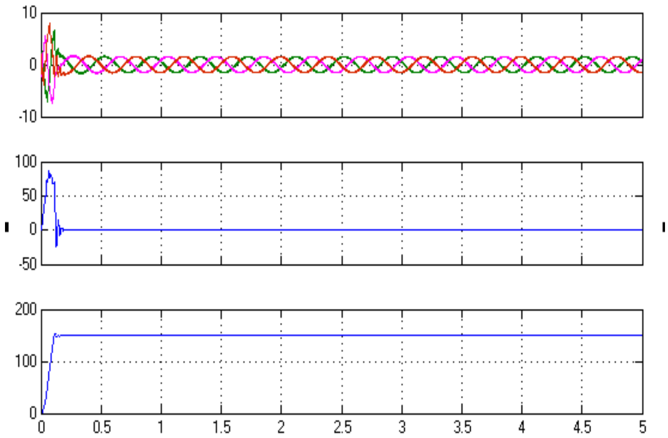

Figure 14. (a) Current, (b) Torque and (c) Speed waveforms

ii) At high speed (800 rpm)

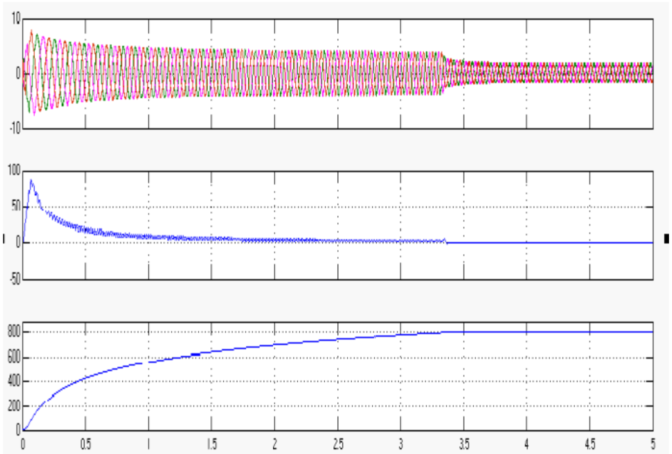

Figure 15. (a) Current, (b) Torque and (c) Speed waveforms

CONCLUSION

This paper presents a second-order sliding mode MRAS with ANN controller based speed estimator for the induction motor drives. In second-order sliding mode MRAS, the fluxes of the voltage model observer are used as references. The MRAS principle is used to adapt the speed in the current model. With the second-order approach, the switching behavior occurs only during transients - this yields a smoother speed estimate that has fewer ripples and requires less filtering. The simulation waveforms show that the speed estimate matches the real speed closely. The method can be used in a sensorless direct field oriented IM drive where the fluxes and speed are needed for control implementation. In SMO with ANN controller, a two layer neural network is considered with the function fitting neural network. The Levenberg-Marquardt training algorithm is used to train the network by adjusting the weight and bias of the hidden and output layers. The speed estimate obtained due to second-order sliding mode MRAS, is 148 rpm whereas due to SMO with ANN controller, it is 150 rpm which is much closer to the reference speed 150rpm and thus, is found to be better. Also, the transient speed response and the torque are found to be improved in SMO with ANN controller and it settles quite quickly as compared to sliding mode MRAS method. The behavior of speed under the parameter variations is significant in SMO method and it is overcome by using SMO with ANN controller as it resists any kind of changes due to parameter dependency.

The response of the speed, current and torque in SMO with ANN controller at low and high speeds are shown. It is found to have less delay time and hence settles faster to the reference speed with almost no error. Thus, the dynamic performance of SMO with ANN controller is obtained to be better than that of sliding mode MRAS method.

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