An Adaptive Flux Observer based Neuro-Fuzzy for Sensorless Speed Control of Induction Motor Drives

S. Chekroun, M. Zerikat, A. Mechernene and N. Benharir

Abstract-- **In this paper, we propose an adaptive neuro-fuzzy inference system for high performance induction motor drive. The simultaneous observation of rotor speed and stator resistance in induction drive is obtained through a neuro fuzzy observer trained with a backpropagation algorithm. The dynamic performance and robustness of the proposed neuro fuzzy adaptive observer are evaluated under a variety of operation conditions. The results demonstrate the effectiveness of the proposed structure.**

I. INTRODUCTION

THE sensorless control of induction motor drives based on the properties of the observability constitutes a vast subject, and the technology has further advanced in recent years. The control of the asynchronous machine is complex because the dynamics of the machine are non linear, multivariable, and highly coupled. Furthermore, there are various uncertainties and disturbances in the system. The induction motor is controlled through field orientation technique. The field oriented control method of sensorless vector control has been generally applied to drive the induction motor vector-controlled induction motor drives have been widely used in high-performance applications. Conventional vector control methods [1] require motor speed as a feedback signal. To obtain the speed information, transducers such as shaft-mounted tachogenerators, resolvers, or digital shaft position encoders are used, which degrade the system's reliability, especially in hostile environment. However, the speed accuracy is generally sensitive to model parameter mismatch if the machine is loaded, especially in the field-weakening region and in the low-speed range. The parameter contributing to this variation is [2]:

· Rotor resistance variation with temperature,
· Stator resistance variation with temperature,
· Stator inductance variation due to saturation of the stator teeth.

Conventional speed-sensorless flux estimators, such as the speed-adaptive full-order flux observer [3], are based on the standard dynamic motor model. Performance comparable to that of drives equipped with the speed sensor can be achieved in a wide speed and load range. However the application of the Fuzzy-neural observer have been successfully used for a few numbers of non linear and complex processes, ANFIS are robust and their performances are insensible to parameter variations contrary to conventional observer [4]. This work deals with sensorless control of induction motor drives and in particular with the stator resistance and rotor speed estimation by means of Adaptive flux observer and Adaptive Neuro-Fuzzy Inference System [5], based on the fundamental dynamic model of the induction machines. This paper is organized as follows: the adaptive flux observer is presented in Section 2. In section 3 the adaptive Neuro-Fuzzy Inference System which describes the structure of the proposed ANFIS observer with resistance parameters and rotor speed estimation. In section 4, the implementation of the studied observer proposed is associated to the direct-field-oriented control where stator resistance and rotor speed was replaced by those delivered by the estimated. Finally, in section 5, we give some comments and conclusions.

II. ADAPTIVE FLUX OBSERVER

A. Motor model

The state equations of an induction motor in the rotor-speed reference frame can be expressed as follows [6]:

$$\frac{dX}{dt} = AX + BU \tag{1}$$

$$Y_t = C.X_t \tag{2}$$

with:

$X = [i_{sd}\ i_{sq}\ \phi_{rd}\ \phi_{rq}]^T$, $Y = [i_{sd}\ i_{sq}]^T$, $U = [u_{sd}\ u_{sq}]^T$

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$

$$a_{11} = -\left(\frac{R_s}{(\sigma L_s)} + \frac{(1-\sigma)}{(\sigma T_r)}\right) I = a_{r11} I$$

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S. Chekroun is with the Department of Automatic, USTO, BP.1505,El Mnaouer, Oran, 31000, Algeria (corresponding author to provide phone; fax: +213 41 29 07 74; e-mail: schekroun@hotmail.fr).

M. Zerikat is with the Department of Electrical Engineering, ENSET, BP.1523 El Mnaouer, Oran, 31000, Algeria (e-mail: , mokhtar.zerikat@enset-oran.dz).

A. Mechernene is with the Department of Electrical Engineering, USTO, BP.1505,El Mnaouer, Oran, 31000, Algeria (e-mail: mechernene_aek@hotmail.com).

N. Benharir is with the Department of Electrical Engineering, ENSET, BP.1523 El Mnaouer, Oran, 31000, Algeria (e-mail: benharir@yahoo.fr).

$$a_{12} = \frac{L_m}{(\sigma L_s L_r)}.((1/T_r)I - \omega_r J) = a_{r12}I + a_{i12}J$$

$$a_{21} = \left(\frac{L_m}{T_r}\right)I + \omega_r J = a_{r12}I + a_{i22}J$$

$$a_{22} = \frac{-1}{T_r}I + \omega_r J = a_{r12}I + a_{i22}J$$

$$B = \frac{1}{\sigma L_s}I \; ; I = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \; ; J = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$$

Where

s, r	Stator and rotor subscripts
d, q	Direct and quadrate Park subscripts
v, i, ϕ	Voltage/ Current/ Flux variables
R_s, R_r	Stator, rotor resistances
L_s, L_r	Stator, rotor inductance
L_m	Mutual magnetizing inductances
σ	Total leakage factor $\sigma = 1 - (L_m / (L_s L_r))$
ω_s	Stator frequency
ω_r	Rotor angular speed
ω_m	Nominal frequency
Ω	Rotor speed
θ_s	Rotor flux position
J	Inertia
f	Friction coefficient
T_r	Rotor time constant
p	Number of pole pair
^	Superscript of estimated quantity

B. Adaptive speed, flux and resistance observers

Let's consider the speed like a constant and unknown parameter, it is about to determine a law of adaptation for estimating its value. The observer can be described by the following state equation:

$$\frac{d\hat{X}}{dt} = \hat{A}\hat{X} + BU + G\left(\hat{i}_s - i_s\right) \quad (3)$$

The matrix A is separated in two terms, one for the speed and the other for stator resistance, as follows:

$$\hat{A} = A(\hat{\omega}_r) + A(\hat{R}_s) \quad (4)$$

where

$$A(\hat{\omega}_r) = \begin{bmatrix} -a_1 L_m & 0 & a_1 & a_2\hat{\omega}_r \\ 0 & -a_1 L_m & -a_2\hat{\omega}_r & a_1 \\ a_3 & 0 & a_4 & -\hat{\omega}_r \\ 0 & a_3 & \hat{\omega}_r & a_4 \end{bmatrix} \quad (5)$$

$$A(\hat{R}s) = \begin{bmatrix} -a_5 R_s & 0 & 0 & 0 \\ 0 & -a_5 R_s & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad (6)$$

Where

$$a_1 = \frac{L_m}{\sigma L_s L_r T_r}; \quad a_2 = -\frac{L_m}{\sigma L_s L_r}; a_3 = \frac{L_m}{T_r}; a_4 = -\frac{1}{T_r};$$
$$a_5 = \frac{1}{\sigma L_s}$$

The matrix K represents the gain of the observation matrix; it governs the dynamics and the observer's robustness and is defined as follows [3]:

$$G = \begin{bmatrix} g_1 & g_2 & g_3 & g_4 \\ -g_2 & g_1 & -g_4 & g_3 \end{bmatrix} \quad (7)$$

$$g_1 = (k-1)(a_{r11} + a_{r22}) \quad (8)$$

$$g_2 = (k-1)a_{i22} \quad (9)$$

$$g_3 = (k^2-1)(ca_{r11} + a_{r22}) - c(k-1)(a_{r11} + a_{r22}) \quad (10)$$

$$g_4 = -c(k-1)a_{i22} \quad (11)$$

with $c = (\sigma L_s L_r)/L_m$

The coefficient *k* is chosen for impose an observer dynamic faster than the system. The difference between the observer and the model of the motor, represents the estimation error of stator current and rotor, it is given by:

$$\frac{d}{dt}e = (A + GC)e - \Delta A\hat{X} \quad (12)$$

With: $e = X - \hat{X}$

$\Delta A = \hat{A} - A$

$$= \begin{bmatrix} 0 & 0 & 0 & -a_3\Delta\omega_r \\ 0 & 0 & -a_3\Delta\omega_r & 0 \\ 0 & 0 & 0 & \Delta\omega_r \\ 0 & 0 & \Delta\omega_r & 0 \end{bmatrix} + \begin{bmatrix} -a_6\Delta R_s & 0 & 0 & 0 \\ 0 & -a_6\Delta R_s & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad (13)$$

The coefficient k is chosen for impose an observer dynamic faster than the system. If we choose an adequate candidate function, Lyapunov theory gives the adaptation law for the speed [10]:

$$\hat{\omega}_r = \left(K_{p\omega} + \frac{K_{i\omega}}{s} \right) \left(e_{is\alpha} \hat{\psi}_{r\beta} - e_{is\beta} \hat{\psi}_{r\alpha} \right) \tag{14}$$

where $e_{is\alpha} = i_{s\alpha} - \hat{i}_{s\alpha}$ $\quad e_{is\beta} = i_{s\beta} - \hat{i}_{s\beta}$

The stator resistance estimation is given by the second adaptation law defined by [11]:

$$\hat{R}_s = -\left(K_{pRs} + \frac{K_{iRs}}{s} \right) \left(e_{is\alpha} \hat{i}_{s\alpha} + e_{is\beta} \hat{i}_{s\beta} \right) \tag{15}$$

$K_{p\omega}$, $K_{i\omega}$ and K_{pRs} , K_{iRs} are positive constants.
The object of adaptive mechanisms is to minimize the following errors:

$$\begin{cases} \varepsilon_{\omega} = \left(e_{is\alpha} \hat{\psi}_{r\beta} - e_{is\beta} \hat{\psi}_{r\alpha} \right) \\ \varepsilon_{RS} = -\left(e_{is\alpha} \hat{i}_{s\alpha} + e_{is\beta} \hat{i}_{s\beta} \right) \end{cases} \tag{16}$$

The adaptive observer is stable, so the induction motor and its control system will be stable over a wide range.

III. Adaptive Neuro-Fuzzy Inference System

A. ANFIS Structure

The Adaptive Neuro-Fuzzy Inference System (ANFIS) has proven to be an excellent function approximation tool [7,12]. ANFIS implements a first order Takagi-Sugeno fuzzy system. As a simple example, a fuzzy inference system with two inputs x_1 and x_2 and one output y is assumed. The first order Sugeno fuzzy model, a typical rule set with two fuzzy If–Then rules can be expressed as:

IF x_1 *is* A_1 *AND* x_2 *is* B_1 *THEN* $y_1 = p_1 x_1 + q_1 x_2 + r_1$

IF x_1 *is* A_2 *AND* x_2 *is* B_2 *THEN* $y_2 = p_2 x_1 + q_2 x_2 + r_2$

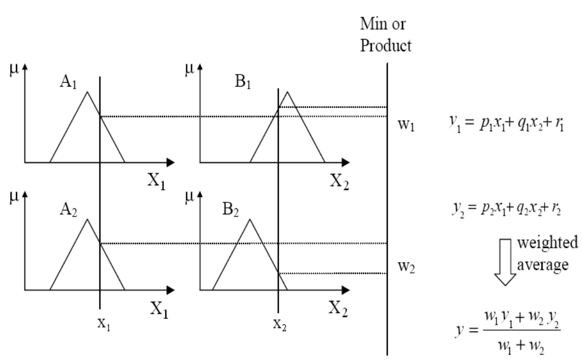


Fig. 1. Two-input first-order Sugeno fuzzy model with two rules

The resulting Sugeno fuzzy reasoning system is shown in Fig.1. Here, the output y is the weighted average of the individual rules outputs and is itself a crisp value.
In the control system of the induction motor, the x_1 *and* x_2 significance the stator currents and voltage measured respectably.

B. Adaptive speed, flux and resistances observer

The corresponding ANFIS architecture is shown in Fig.2. Nodes at the same layer have similar functions. The output of the i^th node in layer l is denoted as $O_{l,i}$. The information is propagated in five layers.

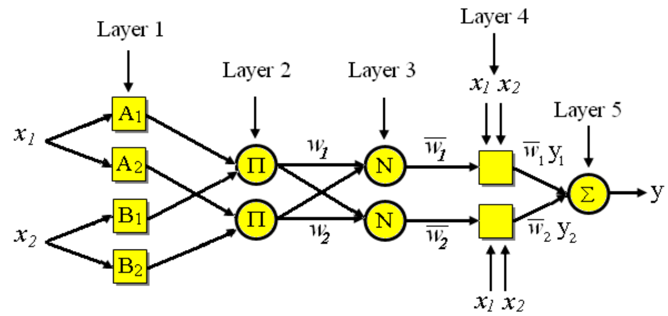


Fig. 2. Equivalent ANFIS architecture

Layer 1: Every node i in this layer is an adaptive node with node function:

$$O_{l,i} = \mu A_{i(x)} \quad For\ i = 1,2,\ or$$
$$O_{l,i} = \mu B_{i-2(y)} \quad For\ i = 3,4. \tag{17}$$

where x (or y) is the input to the i^th node and A_i (or B_{i-2}) is a linguistic label (such as "low" or "high") associated with this node. In words, $O_{l,i}$ is the membership grade of a fuzzy set A (= A_1, A_2, B_1, or B_2) and it specifies the degree to which the given input x (or y) satisfies the quantifier A.

Layer 2: This layer consists of the nodes labeled Π which multiply incoming signals and send the product out. For instance,

$$O_{2,I} = w_i = \mu A_{i(x)}\, \mu B_{i(y)} \quad i = 1,2 \tag{18}$$

Each node output represents the firing strength of a rule.

Layer 3: In this layer, the nodes labeled N calculate the ratio of the ith rule's firing strength to the sum of all rules' firing strengths.

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2} \quad i = 1,2 \tag{19}$$

The outputs of this layer are called normalized firing strengths.

Layer 4: This layer's nodes are adaptive with node functions

$$O_{4,i} = \overline{w_i} y_i = \overline{w_i} \left(p_i x_1 + q_i x_2 + r_i \right) \tag{20}$$

where w_i is the output of layer 3, and $\{p_i, q_i, r_i\}$ are the parameter set. Parameters of this layer are referred to as consequent parameters.

Layer 5: This layer's single fixed node labeled Σ computes the final output as the summation of all incoming signals.

$$O_{5,i} = y = \sum_{i=1} \overline{w_i} y_i = \frac{\sum_i w_i y_i}{\sum_i w_i} \tag{21}$$

Thus, an adaptive network which is functionally equivalent to a Sugeno first-order fuzzy inference system is created.

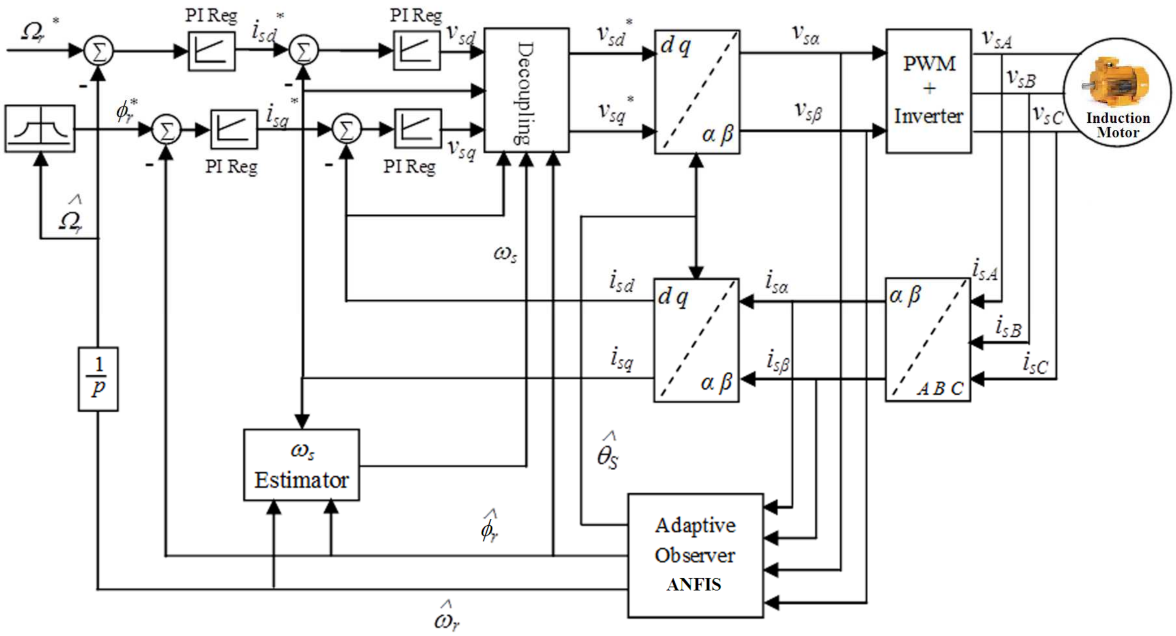


Fig.3. Sensorless Control induction motor equipped with ANFIS Observer.

C. ANFIS Speed Observer

In the neuro-fuzzy control system, which is based on the error back-propagation training algorithm is adopted to perform identification and control, applied to dynamic system[8,9,11]. The algorithm is based on the gradient descent search technique that minimizes a cost function of the mean square errors. The minimization process is done by adjusting the weighting vector of the neural network. Several training algorithms have been proposed to adjust the weight values in dynamic recurrent neural network. The cost function being minimized is the error between the network output and the desired output given by equation (22).

$$E = \frac{1}{2}\sum_j e_j^2(k) = \frac{1}{2}\sum_j [y_j^* - y_j(k)]^2 \qquad (22)$$

Where $y_i(k)$ is the output of neuron j and $y_j^*(k)$ is the desired pattern for that neuron. Let $\eta_{ji}(k)$ denote the learning rate parameter assigned to synaptic weight $w_{ji}(k)$ at iteration number k. Miniminzing equation (22) leads to a sequence of update of the weight vector. The weights of the interconnections between two adjacent layers can be update based on the following formula (McClelland et al., 1986).

$$w_{ji}(k+1) = w_{ji}(k) - \eta_{ji}(k+1)\frac{\partial E(k,w)}{\partial wji(k)} + \alpha \Delta w_{ji}(k) \qquad (23)$$

α is the momentum gain , is susceptible to local minima and needs additional computation for gradient evaluation and $\Delta w_{ji}(k)$ is weight change based on gradient of the cost function $E_{k,w}$ and k is the iteration number.

The fig.3 show the structure of sensorless control induction motor equipped with ANFIS observer. The dynamic model of speed induction motor drive can be controlled by classic numerical PI (Proportional an Integral) regulator is well suited to regulating the torque. The regulation of the stator currents in direct filed oriented control of induction motorcis assigned to two identical PI. Another PI controller regulates the rotor flux and minimizes the error between its reference value, obtained by field weakening block and its reference value delivred by the observer. In addition à decoupling block is introduced to separate the mutual action of the two orthogonal axes. The reference voltage impose the flux and electromagnetic torque, after reference change by an inverse transformation via the voltage inverter. Fig. 4 shows the adaptive Neuro-Fuzzy illustrate in Fig.3 [5.,11], it contains six inputs: $R_s(k-1)$, ϕ_r $u_{s\alpha}$, $u_{s\beta}$, $i_{s\alpha}$, $i_{s\beta}$ and two outputs R_s and ω_{rest}, based on the error back-propagation training algorithm is adopted to perform of observer, applied to sensorless induction motor drive.

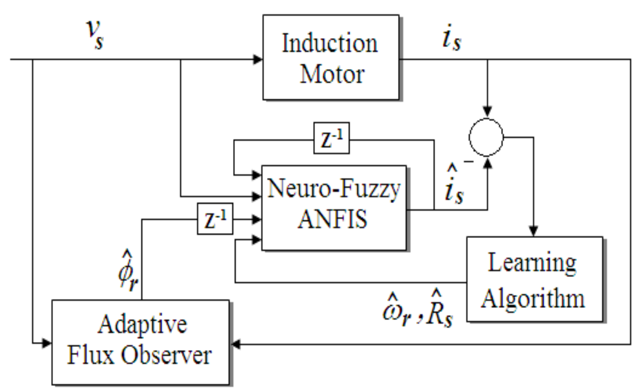
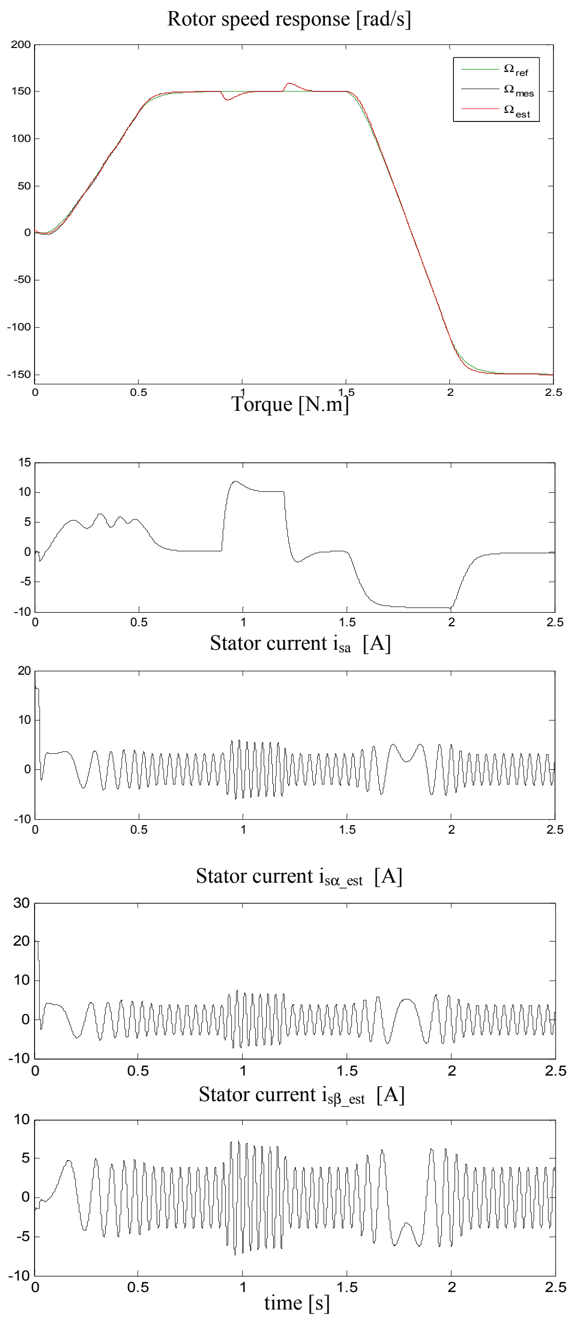


Fig.4 An adaptive Neuro-Fuzzy based Adaptive observer

IV. RESULTS AND DISCUSSION

The described observer structure show in fig.3 was implemented in the environment software Matlab/Simulink, and tested in various operating conditions. This software allows digital simulation of the systems using a same expression of the ordinary differential equations in the dynamic machine model as well as the controller. The numerical method for solving the equations is Runge-Kutta method. Fixed-step mode is chosen for the computational time interval, this will emulate the fixed sampling frequency of the real-time control. The sampling period is 1e-4 sec.



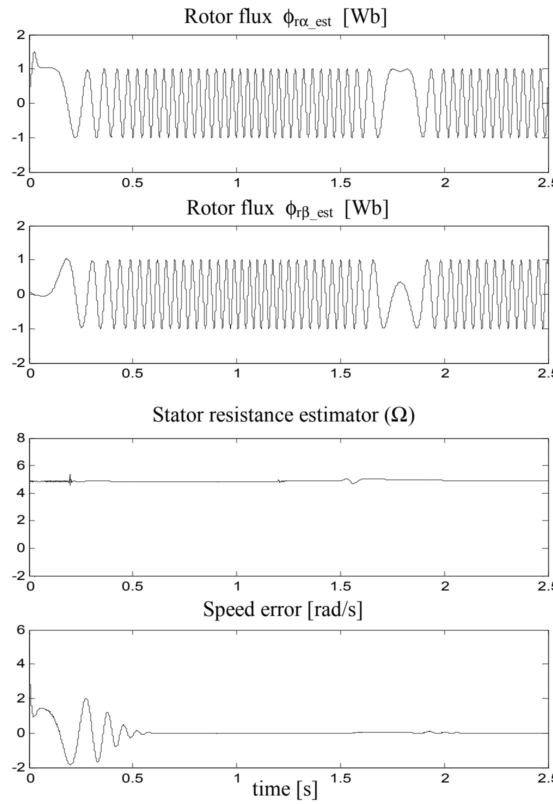


Fig.5. Performance of adaptive ANFIS observer with speed reverse, current, and load charge change.

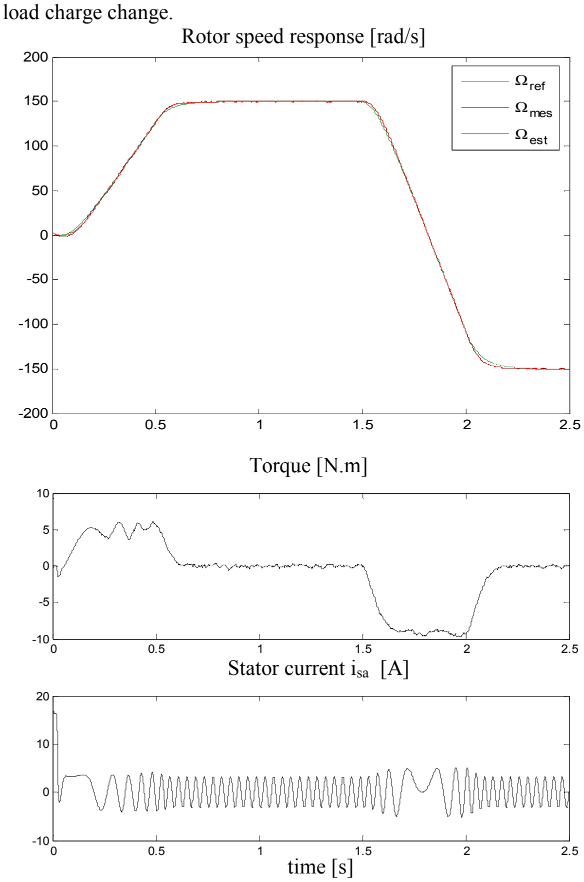


Fig.6. Performance during starting operation with load change.

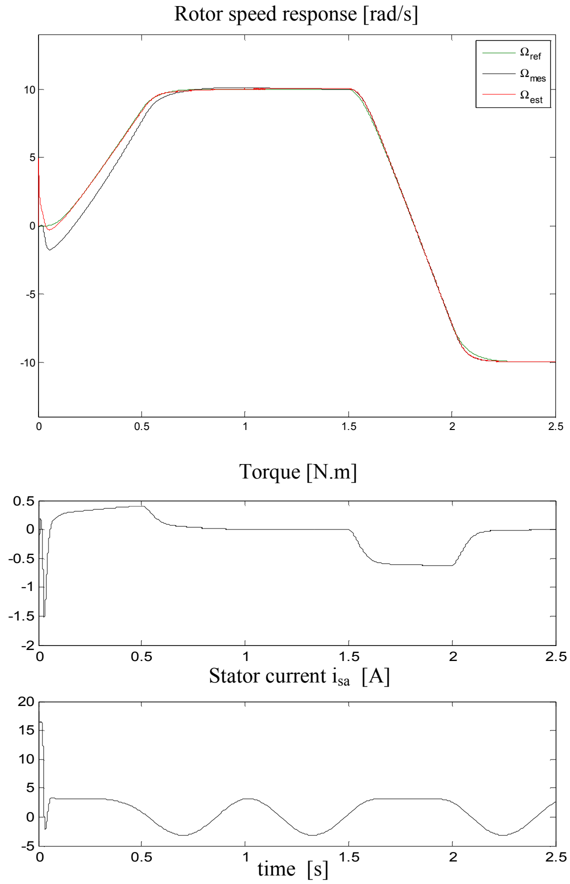


Fig.7. Performance at low speed region during speed reversal from 10 to -10 rad/s.

The parameters of the induction motor and gains of different controllers used are given in Appendix. Figure 5 shows the response of the proposed speed sensorless system based adaptive ANFIS observer with a speed reverse at t=2sec and under load change to the nominal motor parameters at t=0.8sec and t=1.5sec. Figure 6 illustrates the performances of the observer under conditions of load charge change between 10 Nm and -10 Nm. These observers have good accuracy in the estimation of speed and stator resistance. The speed and fluxes responses confirm a very low sensitiveness to disturbances, a good precision around zero speed, and the control system rejects the load disturbances. These results show clearly very satisfactory performance for the proposed sensorless controller in tracking and a remarkable pursuit between measured and estimed speed of the reference model speed. Figure 7 illustrate a response of sensorless drive system during starting operation with load 4 Nm, under conditions of low speed and with changes in load torque. The reference command imposes a speed step from 10 to -10 rad/s, the results obtained show excellent performance even at low speeds, with precise estimates motor speed.

V. Concluding Remarks

In this research, a robust controller using adaptive flux observer based neuro-fuzzy for sensorless speed control of induction motor drive the NN observer is presented. The synthesis procedure of the adaptive observer with rotor speed and stator resistance estimations is based on the hyper-stability theory. The speed and stator resistance estimations method was implemented in a speed-sensorless space vector control system based adaptive ANFIS observer. The Neuro-Fuzzy observer has a number of advantages over conventional adaptive observer. The validity and effectiveness of the proposed method are confirmed through simulation.

Appendix

Motor Parameters

1.5 kW, 3-phase, 220/380 V, 2.8/4.8 A, 50 Hz, 4 poles, 1420 tr/mn. R_s = 4.85Ω, R_r = 3.805Ω, L_s = 0.274 H, L_r=0.274H, L_m = 0.258 H, J = 0.031 kg.m^2, F = 0.00114 kg.m/s.

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