DEVELOPMENT OF A SPEED SENSORLESS INDUCTION MOTOR DRIVES USING AN ADAPTIVE NEURO-FUZZY FLUX OBSERVER

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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 suggested approach is designed and simulated in the laboratory and its effectiveness in tracking application is verified. The results have shown excellent tracking performance of the proposed speed sensorless control system and have convincingly demonstrated the usefulness of the hybrid neuro-fuzzy flux observer in high performance drives with uncertainties.

Keywords: *Induction Motor, Sensorless Control, Adaptive flux observer, ANFIS, Estimation*

1. 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 ux 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 Neuro-Fuzzy 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.

2. Adaptive flux observer

2.1 Motor model

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

$$\frac{d\,X}{dt} = A\,X + B\,U \tag{1}$$

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

with:

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

$U = [u_{sd}\ u_{sq}]^T,\ A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$

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

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

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

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

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

2.2 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:

$$\frac{d\hat{X}}{dt} = \hat{A}\,\hat{X} + B U + G\left(\hat{i}_s - i_s\right) \tag{3}$$

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

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

where

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

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

Where

$a_1 = \dfrac{L_m}{\sigma L_s L_r T_r}\ ;\qquad a_2 = -\dfrac{L_m}{\sigma L_s L_r}\ ; a_3 = \dfrac{L_m}{T_r}\ ;$

$a_4 = -\dfrac{1}{T_r}\ ;\ a_5 = \dfrac{1}{\sigma L_s}$

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

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

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

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

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

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

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:

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

With:

$e = X - \hat{X}$

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

$$= \begin{bmatrix} 0 & 0 & 0 & -a_5\Delta\omega_r \\ 0 & 0 & -a_5\Delta\omega_r & 0 \\ 0 & 0 & 0 & \Delta\omega_r \\ 0 & 0 & \Delta\omega_r & 0 \end{bmatrix} + \begin{bmatrix} -a_6\Delta R_s & 0 & 0 & 0 \\ 0 & -a_6\Delta R_s & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} (13)$$

The Lyapunov theory gives the adaptation law for the speed [10]:

$$\overset{\wedge}{\omega}_r = \left(K_{p\omega} + \frac{K_{i\omega}}{s} \right) \cdot \left(e_{is\alpha} \overset{\wedge}{\phi}_{r\beta} - e_{is\beta} \overset{\wedge}{\phi}_{r\alpha} \right) \quad (14)$$

where

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

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

$$\hat{R}_s = -\left(K_{pR_s} + \frac{K_{iR_s}}{s} \right) \cdot \left(e_{is\alpha} \hat{i}_{s\alpha} + e_{is\beta} \hat{i}_{s\beta} \right) \quad (15)$$

$K_{p\omega}$, $K_{i\omega}$ and K_{pRs}, K_{iRs} are positive constants.

The object of adaptive mechanisms is to minimize the following errors:

$$\begin{cases} \varepsilon_\omega = \left(e_{is\alpha} \overset{\wedge}{\phi}_{r\beta} - e_{is\beta} \overset{\wedge}{\phi}_{r\alpha} \right) \\ \varepsilon_{R_s} = -\left(e_{is\alpha} \hat{i}_{s\alpha} - e_{is\beta} \hat{i}_{s\beta} \right) \end{cases} \quad (16)$$

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

3. Adaptive Neuro-Fuzzy Inference System Observer

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. 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 (17).

$$E = \frac{1}{2} \sum_j e_j^2(k) = \frac{1}{2} \sum_j [y_j^* - y_j(k)]^2 \quad (17)$$

Where $y_i(k)$ is the output of neuron j and $y_j^*(k)$ is the desired pattern for that neuron.
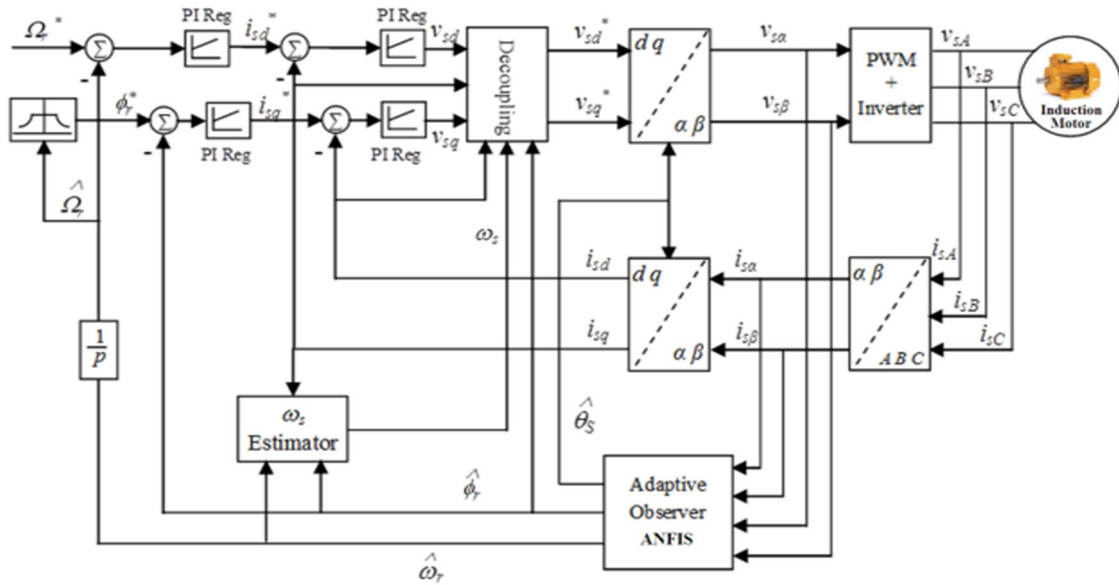

Fig. 1. Sensorless Control induction motor equipped with ANFIS Observer.

Let $\eta_{ji}(k)$ denote the learning rate parameter assigned to synaptic weight $w_{ji}(k)$ at iteration number k. Miniminzing equation (18) 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:

$$w_{ji}(k+1) = w_{ji}(k) - \eta_{ji}(k+1)\frac{\partial E(k,w)}{\partial w_{ji}(k)} + \alpha \Delta w_{ji}(k) \ (18)$$

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.
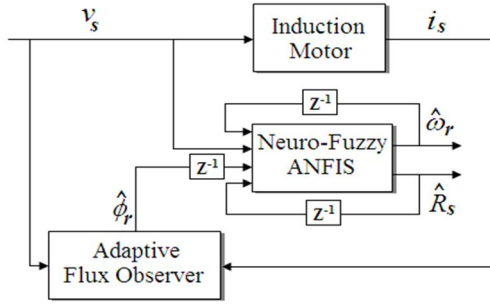

Fig. 2. An adaptive Neuro-Fuzzy based Adaptive observer

The fig.1 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. 2 shows the adaptive Neuro-Fuzzy illustrate in

Fig.1 [5]-[11], it contains seven inputs: $R_s(k-1)$, $\omega(k-1)$, 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 the observer, which is applied to sensorless induction motor drive.

4. 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. The parameters of the induction motor and gains of different controllers used are given in Appendix. Figure 3 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 4 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 5 illustrate a response of sensorless drive system during starting operation with load 10 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.
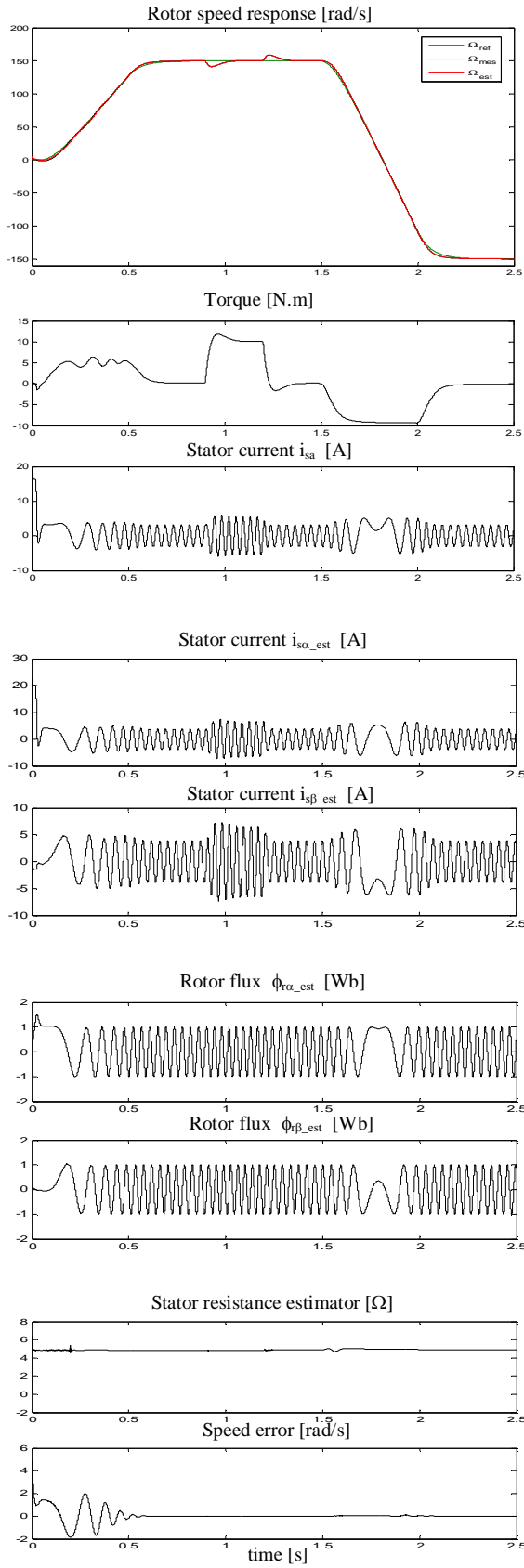
Fig.3. Performance of adaptive ANFIS observer with speed reverse, current, and load charge change.
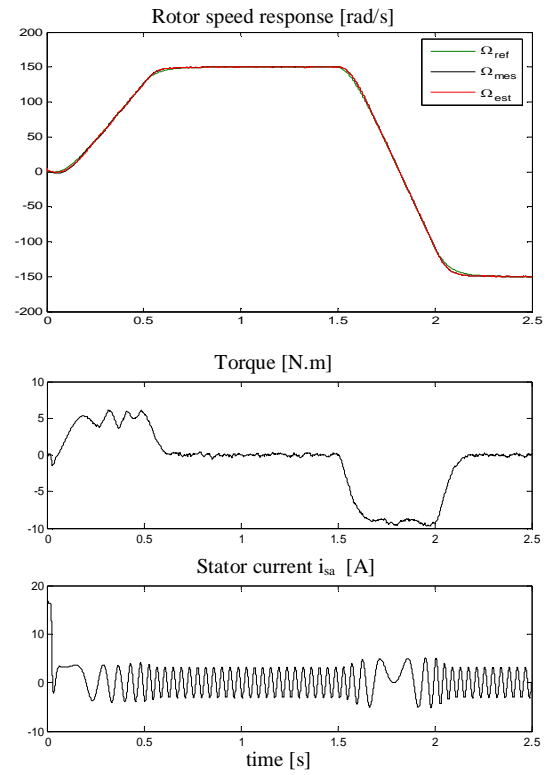

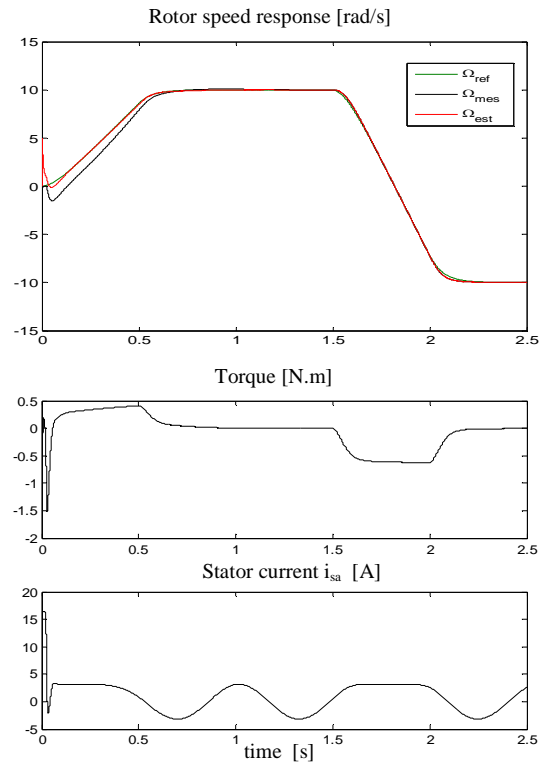Fig. 4. Performance during starting operation with load variation.

Fig. 5. Performance at low speed region during speed reversal from 10 to -10 rad/s.

5. Conclusion

In this research, a robust controller using adaptive flux observer based neuro-fuzzy for sensorless speed control of induction motor drive the ANFIS 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 effectiveness of the proposed sensorless schemes was confirmed by simulated results.

Appendix

TABLE 1. Induction Motor Parameters

Rated values	Power	1.5	kW
	Frequency	50	Hz
	Voltage Δ/Y	220/380	V
	Current Δ/Y	2.8/4.8	A
	Motor Speed	1420	Rpm
	Pole pair (p)	2	
Rated parameters	R_s	4.85	Ω
	R_r	3.805	Ω
	L_s	0.274	H
	L_r	0.274	H
	L_m	0.258	H
Constants	J	0.031	Kg.m^2
	f	0.00114	Kg.m/s

Nomenclature

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

References

[1] K. Kouzi, S. Nait-Said, E. Berthlot, *Fuzzy MRAS Estimator for Vector Control of an Induction Motor*, International Review of Electrical Engineering (IREE), *vol. 4 n.2*, April 2009, pp. 278 – 283.

[2] P.D. Marcetic, S.N. Slobodan, *Speed-Sensorless AC Drives With the Rotor Time Constant Parameter Update*, IEEE Transactions on Industrial Electronics, vol. 54, n.5, October 2007, pp. 2618-2625.

[3] H. Kubota, K. Matsuse, *Speed Sensorless Field-Oriented Control of Induction Motor with Rotor Resistance Adaptation*, IEEE Trans. Industry Applications, vol. 30, n. 5, Sept/Oct 1994, pp. 1219-1224.

[4] L. Rajaji, C. Kumar, M. Vasudevan, *Fuzzy and Anfis based Soft Starter Fed Induction Motor Drive for High Performance Applications*, ARPN Journal of Engineering and Applied Sciences, vol. 3, n. 4, August 2008, pp. 12-24.

[5] R.A. Gupta, R. Kumar, *An Adaptive Neuro-Fuzzy Based Speed Sensorless Induction Motor Drives*, Proceedings of the 2009 World Congress on Nature & Biologically Inspired Computing 2009 IEEE, pp. 397-402.

[6] M. Boussak, K. Jarray *A High-Performance Sensorless Indirect Stator Flux Orientation Control of Induction Motor Drive*, IEEE Transactions on Industrial Electronics, vol. 53, n 1, February 2006, pp 41-49.

[7] J-S.R. Jang, *ANFIS, Adaptive-Network-based Fuzzy Inference Systems*, IEEE Transactions on System, Man, and Cybernetics, vol. 23, n. 5, May 1993, pp. 665-685.

[8] M. Ben Ahmed, A. Abid, L. Sbita, *Neural Network Speed Sensorless Direct Vector Control of Induction Motor using Fuzzy Logic in Speed Control Loop*, International Review of Electrical Engineering (IREE), vol. 6 n.5, October 2011, pp. 2237 – 2246.

[9] M. Ghariani, M.R. Hachicha, I. Ben Salah and R. Neji, *Online Parameters Estimation Scheme Using Artificial Intelligence for Vector Controlled Speed Sensorless Induction Motor Drives*, Journal of Modelling and simulation of Systems, vol. 1, 2010, pp. 226-234.

[10] V. Vasic, S.N. Vukosavic, E. Levi, *A Stator Resistance Estimation Scheme for Sensorless Rotor Flux Oriented Induction Motor Drives*, IEEE Transactions on Energy Conversion, vol. 18, n 4, 2003, pp 476-483.

[11] D. Vukadinivic, M. Basic, L. Kulisic, *Stator Resistance Identification Based on Neural and Fuzzy Logic Principles in an Induction Motor Drive*, Journal of Neurocomputing, ELSEVIER, Vol. 73, 2010, pp. 602-612.

[12] O. Kisi, *Suspended sediment estimation using neuro-fuzzy and neural network approaches*, in Hydrological Sciences–Journal–des Sciences Hydrologiques, vol 50, n 4, August 2005, pp. 683-696.

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