

Adaptive Speed Observer using Artificial Neural Network for Sensorless Vector Control of Induction Motor Drive

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This paper presents an adaptive speed observer for an induction motor using an artificial neural network with a direct field-oriented control drive. The speed and rotor flux are estimated with the only assumption that from stator voltages and currents are measurable. The estimation algorithm uses a state observer combined with an intelligent adaptive mechanism based on a recurrent neural network (RNN) to estimate rotor speed. The stator and rotor resistances are estimated by a simple Proportional-Integrator (PI) controller, which reduces sensitivity to variations, due essentially to the influence of temperature. The proposed sensorless control scheme is tested for various operating conditions of the induction motor drive. Experimental results demonstrate a good robustness against load torque disturbances, the estimated fluxes and rotor speed converge to their true values, which guarantees that a precise trajectory tracking with the prescribed dynamics.

Key words: Field oriented control, Induction motor drive, Recurrent neural network, Sensorless drive

Adaptivni estimator brzine za bessenzorsko vektorsko upravljanje asinkronim motorom zasnovan na umjetnoj neuronskoj mreži. Ovaj članak opisuje adaptivni estimator brzine temeljen na umjetnoj neuronskoj mreži, koji se primjenjuje na asinkroni motor pogonjen izravnim vektorskim upravljanjem. Brzina i magnetski tok rotora estimiraju se uz pretpostavku dostupnosti mjerenja napona i struja statora. Algoritam koristi estimator stanja u kombinaciji s inteligentnim adaptivnim mehanizmom temeljenim na povratnoj neuronskoj mreži (RNN) kako bi se estimirala brzina rotora. Otpori statora i rotora estimiraju se jednostavnim Proporcionalno-Integralnim (PI) regulatorom, čime se smanjuje osjetljivost na varijacije uzrokovane utjecajem temperature. Predložena bessenzorska upravljačka shema testirana je za različite radne uvjete asinkronog motora. Eksperimentalni rezultati pokazuju visoki stupanj robusnosti s obzirom na poremećaj momenta tereta, a estimirani tokovi i brzina rotora konvergiraju prema stvarnim vrijednostima što garantira precizno praćenje trajektorija uz zahtijevanu dinamiku.

Ključne riječi: vektorsko upravljanje, asinkroni motor, povratna neuronska mreža, bessenzorsko upravljanje

1 INTRODUCTION

The sensorless control techniques have contributed extensively to the acquisition of high performances for the induction motor drives. A mechanical speed sensor presents many disadvantages such as the increased cost and size of the mechanical coupling, the fragility and a complex association with motor shaft [1]. In recent years, several sensorless control schemes have been proposed and are currently used in various fields of electric drive. They usually consist in an adaptive system with a model of reference (MRAS) [2-3] or in Kalman filter [4-5]. Other works use a state observer with an adaptation loop [6]. These strategies require a perfect knowledge of the mathematical model of the motor. The performances are satisfactory for high and medium speeds, but they will degrade at very low speeds or at zero speed, that correspond to a critical zone due to the loss of observability. The speed estimation is affected

by the parameter variations especially the stator resistance due mainly to the increase in temperature and particularly at low speeds [7-8]. So an on-line adaptation algorithm of the resistive parameters is necessary.

This paper presents a sensorless vector control scheme of induction motor to estimate the rotor flux components, the rotor speed and the windings resistances. The proposed technique is based on the approach developed by H. Kubota and al [6] which uses an adaptive observer to estimate the motor speed. The contribution of this work is founded on the replacement of the adaptive mechanism, initially performed with a conventional PI controller, by a neural network. The aim is to increase the precision of the estimated speed in a wide speed range and reduce the effect of the parameter uncertainties.

This paper is organized as follows: the mathematical model of induction motor in (d - q) reference frame and the

principle of direct field oriented control are presented in Section 2. In Section 3, the conventional adaptive speed observer is presented with the estimation of stator and rotor resistances. Section 4 describes the design of the artificial neural network used as adaptive mechanism to estimate rotor speed. In Section 5, the experimental setup is briefly described and some experimental results showing the performance of the proposed observer are presented and discussed. Finally, Section 6 provides some comments and a conclusion.

2 MATHEMATICAL MODEL OF INDUCTION MOTOR AND VECTOR CONTROL

2.1 Model of IM in (d - q) Reference Frame

The mathematical model of three-phase induction motor can be expressed in the (d - q) synchronously rotating frame by the following nonlinear equations [7-8]:

$$\begin{cases} \dot{i}_{sd} = a_1 \cdot i_{sd} + \omega_s \cdot i_{sq} + a_2 \cdot \psi_{rd} \\ \quad - a_3 \cdot \omega_r \cdot \psi_{rq} + a_6 \cdot v_{sd} \\ \dot{i}_{sq} = -\omega_s \cdot i_{sd} + a_1 \cdot i_{sq} + a_3 \cdot \omega_r \cdot \psi_{rd} \\ \quad + a_2 \cdot \psi_{rq} + a_6 \cdot v_{sq} \\ \dot{\psi}_{rd} = a_4 \cdot i_{sd} + a_5 \cdot \psi_{rd} + (\omega_s - \omega_r) \cdot \psi_{rq} \\ \dot{\psi}_{rq} = a_4 \cdot i_{sq} - (\omega_s - \omega_r) \cdot \psi_{rd} + a_5 \cdot \psi_{rq}, \end{cases} \quad (1)$$

with

$$a_1 = -\left(\frac{1}{\sigma \cdot T_s} + \frac{(1-\sigma)}{\sigma \cdot T_r}\right), \quad a_2 = \frac{L_m}{\sigma \cdot L_s \cdot L_r} \cdot \frac{1}{T_r},$$

$$a_3 = -\frac{L_m}{\sigma \cdot L_s \cdot L_r}, \quad a_4 = \frac{L_m}{T_r}, \quad a_5 = -\frac{1}{T_r},$$

$$a_6 = \frac{1}{\sigma \cdot L_s}, \quad \sigma = 1 - \frac{L_m^2}{L_s \cdot L_r},$$

where i_{sd} , i_{sq} , ψ_{rd} and ψ_{rq} are respectively the stator currents and the rotor flux expressed by their (d - q) orthogonal components; ω_s and ω_r are the electrical angular frequencies of the stator and rotor; σ is the total leakage factor; R_s and R_r are the stator and rotor resistances; L_s and L_r are the stator and rotor inductances; L_m is the mutual inductance; T_s and T_r are the stator and rotor time constants.

The electromagnetic torque and the electrical rotor speed are given by:

$$T_e = \frac{3}{2} \cdot \frac{n_p \cdot L_m}{L_r} \cdot (\psi_{rd} \cdot i_{sq} - \psi_{rq} \cdot i_{sd}), \quad (2)$$

$$\frac{d\omega_r}{dt} = \frac{n_p}{J} \cdot (T_e - T_l) - \frac{B}{J} \cdot \omega_r. \quad (3)$$

n_p is the number of poles pair; J is the total mechanical moment inertia constant, B is the total friction coefficient; T_e is the electromagnetic torque and T_l is the torque of external load disturbance.

2.2 Direct Field-Oriented Control for Induction Motor

The field oriented control technique is very effective to obtain high-performances for induction motor drive in terms of the torque and speed. The principle of this strategy is to independently control the torque and the magnetic flux, as in DC motor for which exist a natural decoupling between these two quantities [8]. This is done by using a (d - q) rotating reference frame synchronously with the rotor flux space vector. In ideally field-oriented control, the rotor flux vector axis must be aligned on the direct d -axis, while the quadrature rotor flux component is forced to zero. For the induction motor, the decoupling is achieved by imposing the following condition [9]:

$$\psi_r = \psi_{rd} = L_m \cdot i_{sd} \quad \text{and} \quad \psi_{rq} = 0. \quad (4)$$

Hence, the rotor flux can be controlled directly from the direct stator current component i_{sd} , while the torque can be linearly controlled from the quadrature stator current component i_{sq} . Applying the flux orientation conditions (4), the torque equation becomes analogous to the DC machine and can be described as follows:

$$T_e = \frac{3}{2} \cdot \frac{n_p \cdot L_m}{L_r} \cdot (\psi_{rd} \cdot i_{sq}). \quad (5)$$

A perfect knowledge of the amplitude and the rotor flux position is required. In direct field oriented-control, the rotor flux amplitude is estimated and controlled in closed loop. The position is then usually obtained by integrating the stator angular frequency:

$$\theta_s = \int \omega_s \cdot dt \quad \text{with} \quad \omega_s = n_p \cdot \Omega_r + \frac{1}{T_r} \cdot \frac{i_{sq}^*}{i_{sd}^*}. \quad (6)$$

For the sensorless vector control proposed, this function is assigned to the flux deterministic full order observer. The rotor flux $\hat{\psi}_r$ and its position $\hat{\theta}_s$ are given by the following relations:

$$\hat{\psi}_r = \sqrt{\hat{\psi}_{r\alpha}^2 + \hat{\psi}_{r\beta}^2}, \quad (7)$$

$$\hat{\theta}_s = \tan^{-1} \left(\frac{\hat{\psi}_{r\beta}}{\hat{\psi}_{r\alpha}} \right). \quad (8)$$

The structure of direct field oriented control for IM motor with the proposed observer can be presented by the block diagram shown in Fig. 1.

The measured voltages and currents are filtered by low pass filters (LPF) and digitized by the analog-digital converters (ADC). The transformation blocks are used to convert these measured quantities in the references (α - β) and

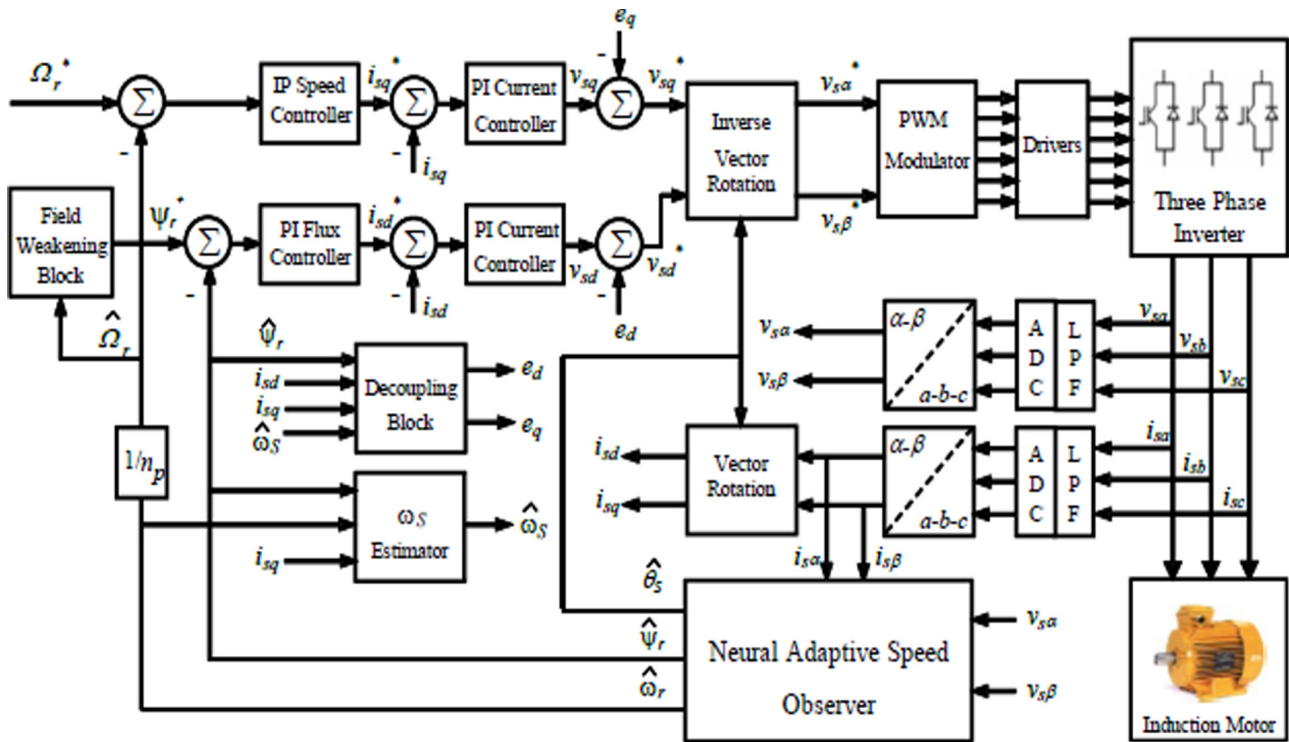


Fig. 1. Block diagram of direct field oriented control scheme based induction motor drive

(*d-q*). The control of direct and quadrature currents is obtained by two PI regulators. This method also provides the regulation of the rotor flux achieved by another PI controller.

The IP controller was preferred to the conventional PI regulator to stabilize the speed loop and improve the dynamic of the system during the transient state. This controller has several advantages, such as zero error in steady state and the absence of overshoot obtained by a judicious tuning of its parameters [10].

A field weakening block delivers the flux reference value of rotor ψ_r^* . Below the rated speed Ω_n , the motor operates at constant flux ψ_{rn} , while above ψ_r^* is weakened to become inversely proportional to the rotating speed Ω_n so that the motor is protected against over-voltages. The field weakening function is defined by the nonlinear following expression:

$$\psi_r^* = \begin{cases} \psi_{rn} & \text{if } |\Omega_r| \leq \Omega_n \\ \psi_{rn} \cdot \frac{\Omega_n}{|\Omega_r|} & \text{if } |\Omega_r| > \Omega_n. \end{cases} \quad (9)$$

A decoupling method with compensation is introduced to separate the mutual actions between the *d* and *q* axis. So two new variables are defined and their expressions are

given by the following equations:

$$\begin{aligned} e_d &= \omega_s \cdot \sigma \cdot L_s \cdot i_{sq} \\ e_q &= -\omega_s \cdot \sigma \cdot L_s \cdot i_{sd} - \frac{L_m}{L_r} \cdot \omega_s \cdot \psi_r. \end{aligned} \quad (10)$$

Finally, the voltages v_{sd}^* and v_{sq}^* are the reference inputs of the PWM control to drive the three phases voltage inverter through the drivers.

3 CONVENTIONAL ADAPTIVE OBSERVER

In this section, the conventional adaptive observer is presented. Its objective is the reconstruction of the rotor flux and speed without mechanical sensor. A simultaneous identification of stator and rotor resistances is also envisaged to improve the robustness and the stability of the variable speed drive. Firstly, a full order observer is built from the rotor flux model considering as inputs the stator current and voltage measurements. After that, an adaptive mechanism uses the error between estimated and measured stator currents to generate two adaptation laws, supplying respectively the estimated values of the rotor speed and the windings resistances.

3.1 Model of IM in (α - β) Reference Frame

The mathematical model of induction motor, expressed in (α - β) stationary reference frame, can be described by

the following state equation [7]:

$$\begin{cases} \dot{X} = A \cdot X + B \cdot U \\ Y = C \cdot X, \end{cases} \quad (11)$$

where

$$X = [i_{s\alpha} \quad i_{s\beta} \quad \psi_{r\alpha} \quad \psi_{r\beta}]^T,$$

$$Y = i_s = [i_{s\alpha} \quad i_{s\beta}]^T, \quad U = v_s = [v_{s\alpha} \quad v_{s\beta}]^T.$$

The state equations can be rewritten as:

$$\begin{cases} \dot{i}_{s\alpha} = a_1 \cdot i_{s\alpha} + a_2 \cdot \psi_{r\alpha} - a_3 \cdot \omega_r \cdot \psi_{r\beta} \\ \quad + a_6 \cdot v_{s\alpha} \\ \dot{i}_{s\beta} = a_1 \cdot i_{s\beta} + a_3 \cdot \omega_r \cdot \psi_{r\alpha} + a_2 \cdot \psi_{r\beta} \\ \quad + a_6 \cdot v_{s\beta} \\ \dot{\psi}_{r\alpha} = a_4 \cdot i_{s\alpha} + a_5 \cdot \psi_{r\alpha} - \omega_r \cdot \psi_{r\beta} \\ \dot{\psi}_{r\beta} = a_4 \cdot i_{s\beta} + \omega_r \cdot \psi_{r\alpha} + a_5 \cdot \psi_{r\beta}. \end{cases} \quad (12)$$

The coefficients a_1, a_2, a_3, a_4, a_5 and a_6 have the same expressions as those definite in equation (1).

3.2 Adaptive Speed, Flux and Resistances Observer

Consider the speed and stator resistance as constant parameters and unknown. The state equation of this observer is expressed by separating the state matrix in two, one for the speed and the other for the stator resistance [8]:

$$\dot{\hat{X}} = \left\{ A_\omega(\hat{\omega}_r) + A_{Rs}(\hat{R}_s) \right\} \cdot \hat{X} + B \cdot U + G \cdot (i_s - \hat{i}_s), \quad (13)$$

with

$$A_\omega(\hat{\omega}_r) = \begin{bmatrix} -a_2 \cdot L_m & 0 & a_2 & -a_3 \cdot \hat{\omega}_r \\ 0 & -a_2 \cdot L_m & -a_3 \cdot \hat{\omega}_r & a_2 \\ a_4 & 0 & a_5 & -\hat{\omega}_r \\ 0 & a_4 & \hat{\omega}_r & a_5 \end{bmatrix}$$

and

$$A_{Rs}(\hat{R}_s) = \begin{bmatrix} -a_6 \cdot R_s & 0 & 0 & 0 \\ 0 & -a_6 \cdot R_s & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}.$$

Where $\hat{\omega}_r$ and \hat{R}_s are the estimated values of the rotor speed and stator resistance; $i_s = [i_{s\alpha} \quad i_{s\beta}]^T$ and $\hat{i}_s = [\hat{i}_{s\alpha} \quad \hat{i}_{s\beta}]^T$ are respectively the vectors of the measured and the estimated stator currents. G is the observer gain matrix which governs its dynamics, it is calculated as follows:

$$G = \begin{bmatrix} g_1 & g_2 & g_3 & g_4 \\ -g_2 & g_1 & -g_4 & g_3 \end{bmatrix}^T. \quad (14)$$

The factors g_1, g_2, g_3 and g_4 are defined as:

$$g_1 = (\lambda - 1) \cdot (a_1 - a_5), \quad g_2 = (\lambda - 1) \cdot \hat{\omega}_r,$$

$$g_3 = a_3^{-1} \cdot [(1 - \lambda^2) \cdot (a_1 - a_3 \cdot a_5) + (\lambda - 1) \cdot (a_1 - a_5)],$$

$$g_4 = a_3^{-1} \cdot (\lambda - 1) \cdot \hat{\omega}_r, \quad \lambda > 1.$$

The coefficient λ is chosen so that the dynamic of the observer is faster than the system.

The adaptive mechanism can be deduced by the Lyapunov theory. By choosing an adequate candidate function, the following adaptation laws are obtained for the estimation of speed and stator resistance [5]:

$$\dot{\hat{\omega}}_r = \left(K_{p\omega} + \frac{K_{i\omega}}{s} \right) \cdot (e_{is\alpha} \cdot \hat{\psi}_{r\beta} - e_{is\beta} \cdot \hat{\psi}_{r\alpha}), \quad (15)$$

$$\dot{\hat{R}}_s = - \left(K_{pRs} + \frac{K_{iRs}}{s} \right) \cdot (e_{is\alpha} \cdot \hat{i}_{s\alpha} + e_{is\beta} \cdot \hat{i}_{s\beta}), \quad (16)$$

with

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

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

The role of the adaptive mechanism is to minimize the following errors $\varepsilon_\omega, \varepsilon_{Rs}$:

$$\begin{cases} \varepsilon_\omega = (e_{is\alpha} \cdot \hat{\psi}_{r\beta} - e_{is\beta} \cdot \hat{\psi}_{r\alpha}) \\ \varepsilon_{Rs} = - (e_{is\alpha} \cdot \hat{i}_{s\alpha} + e_{is\beta} \cdot \hat{i}_{s\beta}). \end{cases} \quad (17)$$

The matrix G is dependent on the resistances values of the motor, which weakening the robustness of the observer, so their estimation is necessary. The motor windings are practically at the same temperature, so their resistances vary proportionally [6-10]. For this reason the value of the rotor resistance can be determined by:

$$R_r = \frac{R_{rn}}{R_{sn}} \cdot R_s, \quad (18)$$

where R_{sn}, R_{rn} are the rated stator and rotor resistances. Finally, the values of speed and the windings resistance can be determined by simple PI controllers.

4 NEURAL ADAPTIVE SPEED OBSERVER

The improvement provided by this work consists of the replacement in the adaptive mechanism, the conventional PI controller by an artificial neural network. The artificial neural networks are excellent candidates to solve problems

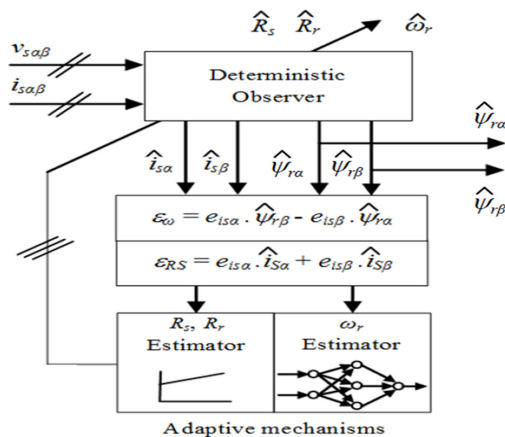


Fig. 2. Structure of the adaptive neural observer proposed

of modeling, identification and non-linear complex process control [11-12]. Therefore, the choice of a neural network is justified by non-linearities of the observer and by the capacity of this approach to compensate the uncertainties of the mathematical model [12]. The structure of the neural adaptive observer proposed is represented in Fig. 2.

The speed estimation by a recurrent neural network must increase the electrical drive system robustness against the noises, drifts or parametric variations of motor [13].

4.1 Structure of the Neural Adaptive Mechanism

The new mechanism is constituted by a neural adaptive network which includes a hidden layer with four neurons and an output layer with one neuron. The looped topology gives it a dynamic behavior.

The activation functions are sigmoid shapes for the hidden layer and linear for the neuron of the output layer [11-12]. Figure 3 illustrates the chosen neural network structure.

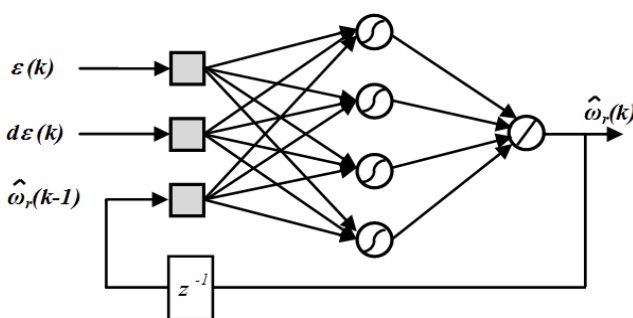


Fig. 3. Block diagram of recurrent neural network used to estimate rotor speed

The input vector of the proposed recurrent neural network (RNN) used to generate the value of the speed is constituted by the following variables:

- the error ϵ_{ω} , defined by equation (17) at time k
- the derivative of this error $d\epsilon_{\omega}$ at time k
- the electrical speed ω_r estimated at time $k - 1$.

Its output delivers the adaptive law for the deterministic observer and represents the estimated speed value.

4.2 Training Procedure

The present section describes the design procedure for the artificial neural network. The training operation has been achieved after identification of conventional adaptive mechanism. The objective is to create a learning pattern for the adaptive neural mechanism that will be integrated in the final structure. The back-propagation algorithm is the method most used in practice for neural network training. This algorithm is based on the gradient descent search technique that minimizes a cost function of the mean square error between desired and computed outputs [14-15]. The minimization process is achieved by adjusting the weights and while realizing their updating based on the learning error. The neural adaptive mechanism designed was trained with the supervised manner, using the Levenberg-Marquardt algorithm [11-15]. To collect a database for training the network, rich and representative, a speed profile has been imposed in the four quadrants, with the superposition of a white noise to take account of disturbances. The database consists of two groups uniformly divided, each with 5000 input/output data, one for learning network and one for evaluation. As soon as the network converges and generalizes correctly, it shall be inserted in the structure of the observer.

5 RESULTS AND DISCUSSION

5.1 Experimental Setup

The block diagram of the experimental setup is shown in Fig. 4. The drive system developed includes an induction motor coupled to a DC machine simulating the mechanical load. The test bench is also equipped with an inverter MOSFET with a switching frequency of 10 kHz and fed by the DC voltage issued to a bridge rectifier output connected to the three-phase AC supply 400/230V-50 Hz. The control system uses a controller board dSPACE DS1104 dSP plugged into a personal computer host. The experimentation has been achieved with the Matlab-Simulink-DSPACE system based on DSP TMS320F240 and using mainly S-function blocks written with the C language.

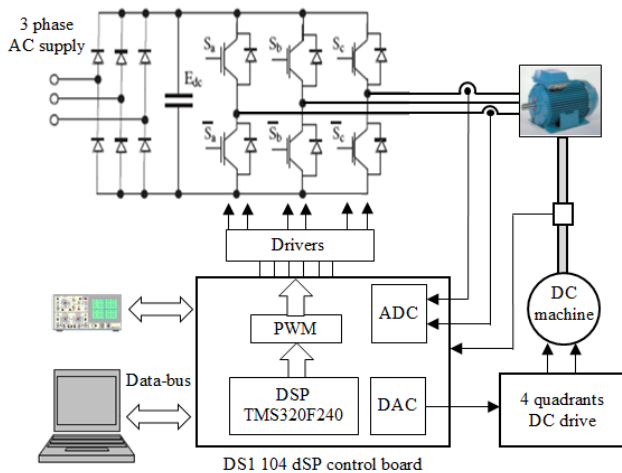


Fig. 4. Experimental setup

5.2 Experimental Results

To test the effectiveness of the control strategy and the proposed observer, the experimental tests are performed for the induction motor whose parameters are given in Appendix A. The performance of the proposed strategy is evaluated under various conditions, such as operating conditions with high and low speed. For each test the speed reference is filtered to protect the system during the states transient and for impose a pursuit model. The transfer function was chosen at first order with a time constant of $(1/16)$ s.

Figure 5 shows the step response of the sensorless system during starting operation at speed reference of 100 rad/s; this test is performed to the rated parameters of the motor. A disturbance is introduced by applying a load torque 10 Nm at 0.8 s. These results show very satisfactory performances in tracking, with a reaction time very low in transient state. The speed estimation is accurate and insensitive to load variations; the determination of the value of the stator resistance is also just and converges quickly.

Figure 6 shows the 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 0 to 20 rad/s, followed by a speed reversal between +20 and -5 rad/s. Finally the reference is reduced to the zero speed. The results obtained show excellent performance even at low speeds, with precise estimates motor speed and stator resistance. However, small oscillations are observed during start-up.

The case of no-load operation at low speeds with square reference change is studied. The actual speed and the stator current are given in Fig. 7. Again, a good tracking of

the reference trajectory and an excellent command of the current are observed.

Figure 8 presents the performance for the proposed sensorless drive system during a long speed reversal from -120 rad/s to 120 rad/s. The actual and estimated speeds are shown with two load changes from 0 to -10 Nm and from 0 to 10 Nm applied at 3 s and 10 s. It is seen that the observer converges correctly to the exact values; but the estimated speed shows a small deviation between the actual and estimated values around the zero speed region.

A comparison between the proposed neural speed observer and the conventional adaptive observer with a PI adaptive mechanism is suggested. Figure 9 shows the variations of the actual and estimated speeds for both observers. The tests were performed for the changes of the speed reference corresponding to a speed reversal between 15 to -5 rad/s via the zero speed region. This test is aimed not only at the performance verification of robustness against changes of stator and rotor resistances, but also for show the influence of external load disturbances. It is realized with the application of a load torque of 10 Nm in time $t = 3$ s and the variations of R_s and R_r up 30% and 60 % of its nominal values. Figure 9 show that the two observers have very similar behaviors. However the proposed adaptive neural observer has better performances. Indeed its speed converges slightly faster than the conventional observer, the disturbances rejection is better and the sensitivity to changes in resistances is very much low.

Finally, we can say that the proposed approach provides a sensorless drive system for high performance. In the light of these results, the neural speed observer has satisfactory performance in terms of convergence, robustness against variations of resistance and has a low influence during the load disturbances. However, his behavior at low speed is only slightly better than that of the conventional observer with a PI controller. The suggested technique is suitable for real time implementation due to its simplicity, but also mainly for its different way of designing the adaptive mechanism and its ease of tuning.

6 CONCLUDING REMARK

In this paper, a speed estimation technique of an induction motor associated with a direct field oriented control is presented. The proposed strategy consists in a speed observer with an adaptive mechanism based on an artificial neural network to estimate on line the motor speed and the windings resistance. The speed and rotor flux are estimated only with the stator voltage and current measurements. The neural mechanism evaluates the speed, while resistance values are determined by a simple PI controller.

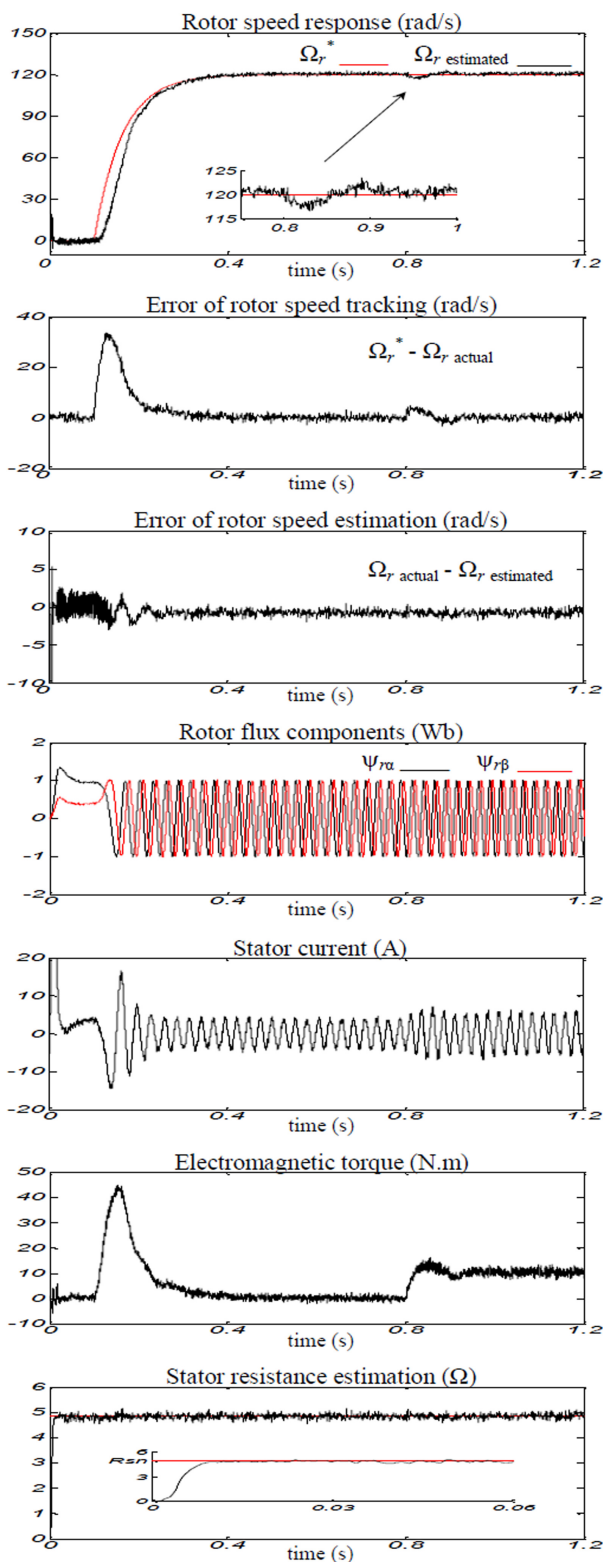


Fig. 5. Performance during starting operation with load change

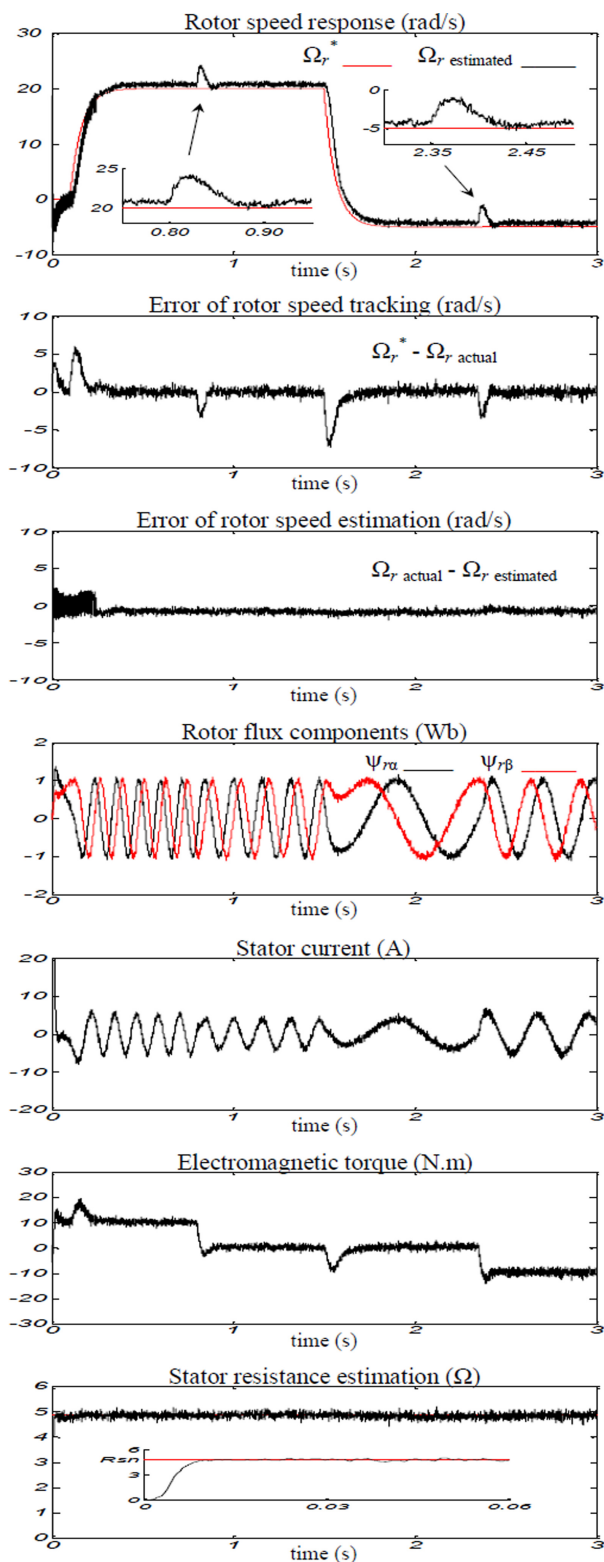


Fig. 6. Performance at low speed region during speed reversal from 20 to -5 rad/s and load change

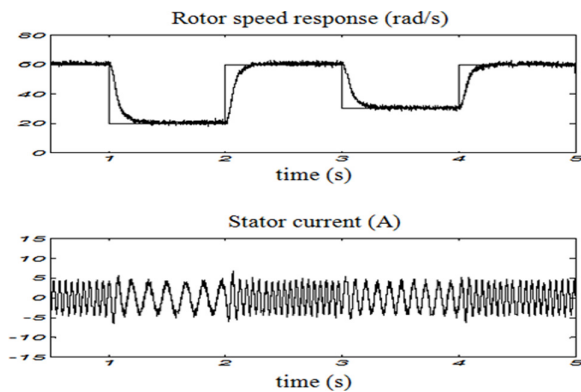


Fig. 7. Performance to low speed with a square reference

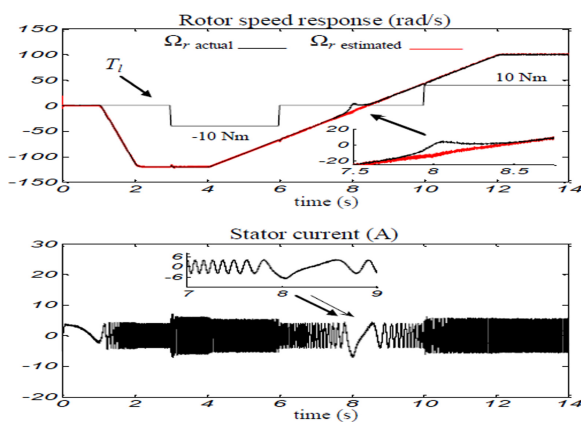


Fig. 8. Performance during a long speed reversal with two load variations

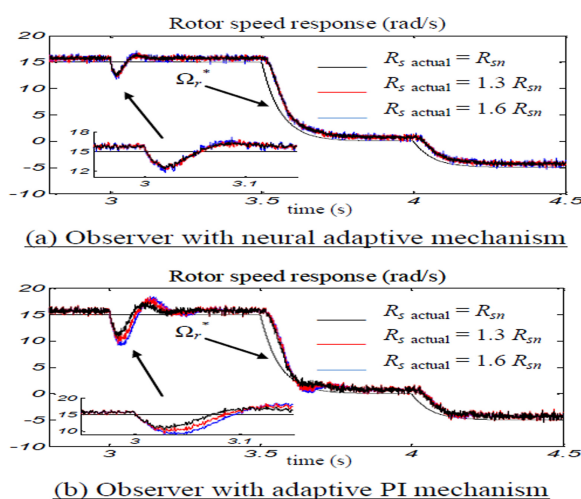


Fig. 9. Performance of the proposed observer (a) and the conventional adaptive observer (b) at low speed region during speed reversal and load change

The synthesis of the observer has been analyzed; the design of neural mechanism and its learning method are presented. Experimental results are exposed and discussed to confirm the validity and the feasibility of the proposed algorithm. The tracking properties and the robustness have been evaluated under a variety of operating conditions of the induction motor. The results demonstrate the effectiveness of this sensorless speed control and show an excellent quality of the estimate, a fast convergence and accurate for the algorithm developed, even at low speed and in zero speed region with a low sensitivity to external disturbances and to the variations of motor resistances.

This study proves that it is possible to achieve a robust adaptive speed observer with a high level of performance dedicated to the sensorless control for induction motor based on approaches of the artificial intelligence, and specially, the artificial neural networks.

APPENDIX A MOTOR PARAMETERS

1.5 kW, 3 phases, 220/380 V, 6.5/3.75 A, 50 Hz,

4 poles, 1420 rpm.

$R_s = 4.85 \Omega$, $R_r = 3.805 \Omega$,

$L_s = 0.274 \text{ H}$, $L_r = 0.274 \text{ H}$, $L_m = 0.258 \text{ H}$,

$J = 0.031 \text{ kg} \cdot \text{m}^2$, $B = 0.00334 \text{ kg} \cdot \text{m/s}$.

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Abdelkader Mechernene was born in Manosque (France) in 1961. He received the BS and the MS degrees in electrical engineering from the High School of Technical Education (ENSET) of Oran- Algeria, in 1983 and 2008 respectively. Since 1983, he teaches in the field of electrical engineering in several technical schools. Currently, he is working as an assistant-teacher in Department GEE, Faculty of Technology of Tlemcen-University Abou-Bekr Belkaid and simultaneously he is pursuing

Ph.D at the University of Sciences and Technology of Oran-Algeria (USTO). His research interests include power electronics, electric motor drive systems, estimation and observation techniques, application of artificial-intelligence (fuzzy logic and neural networks) with particular interest for sensorless-control algorithms to electrical drive systems.



Mokhtar Zerikat received the B.S degree in electrical engineering and the M.S. and Ph.D degrees in electronics from the University of Sciences and Technology of Oran, Algeria, in 1982, 1992, and 2002, respectively. Following graduation, he joined the university as a lecturer. He is currently a professor in the Department of Electrotechnics Engineering. Actually he is associate Professor at Electrical Engineering Institute (ENSET) of Oran- Algeria. His current research includes electrical machines, high-performance

motor drives, modeling and adaptive control systems and development intelligent applications. He is actively involved in many projects with industry while engaged in teaching, research and consulting in the area of artificial intelligence. Dr. Zerikat is a chairman of the institute of electrical and electronic engineers in the Algeria state. He is regularly reviews papers for several journals in his area. He is an active member of the industrial COST Education Committee.



Soufyane Chekroun was born in Tlemcen-Algeria in 1983. He received his B.S from University of Sciences and Technology of Oran-Algeria in 2006 and M.S degrees from ENSET of Oran in 2009. Following graduation, he joined the department of Electrical Engineering of ENSET-Oran as a research associate. His research interests include electrical machines and development of intelligent applications (fuzzy logic and neural networks) and the practical developments of high performance electrical motor

drives and their related knowledge control schemes.

AUTHORS' ADDRESSES

Abdelkader Mechernene, M.S.

**Department of Electrical Engineering,
University of Sciences and Technology USTO-Oran,
BP.1505, El Mnaouer,
Oran, 31000, Algeria.
email: mechernene_aek@hotmail.com**

Mokhtar Zerikat, Ph.D.

**Department of Electrical and Control Engineering,
High School of Electrical Engineering ENSET-Oran,
BP.1523, El Mnaouer,
Oran, 31000, Algeria.
email: mokhtar.zerikat@enset-oran.dz**

Soufyane Chekroun, M.S.

**Department of Automatic,
University of Sciences and Technology USTO-Oran,
BP.1505, El Mnaouer,
Oran, 31000, Algeria.
email: schekroun@hotmail.fr**

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