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On the Application of TLS Techniques to AC Electrical Drives

This paper deals with the application of a new neuron, the TLS EXIN neuron, to AC induction motor drives. In particular, it addresses two important subjects of AC induction motor drives: the on-line estimation of the electrical parameters of the machine and the speed estimation in sensorless drives. On this basis, this work summarizes the parameter estimation and sensorless techniques already developed by the authors over these last few years, all based on the TLS EXIN. With regard to sensorless, two techniques are proposed: one based on the MRAS and the other based on the full-order Luenberger observer. The work show some of the most significant results obtained by the authors in these fields and stresses the important potentiality of this new neural technique in AC induction machine drives.

Keywords: Induction Motor drives, Parameter estimation, Sensorless Control, Total Least-Squares.

1. INTRODUCTION

Parameter identification and sensorless control in electrical drives with induction motors have been two very important issues dealt with in the literature. The on-line estimation of the electrical parameters of an induction motors [1][2] is recognized a key-element in many industrial applications of electrical drives with induction motors for its importance in the proper working of flux estimation in adjustable speed-drives. On the other hand in electrical drives with induction motors, which require both low and high performances, closed loop speed control is usually achieved by means of speed observers trying to avoid the employment of the speed sensors whose mounting arrangements on the shaft of the motor reduce its reliability and increase the overall cost of the drive, especially for low cost drives. For these reasons both parameter estimation [3]-[7] and sensorless control [8]-[18] techniques of induction motors are important subject of research since many years.

A great deal of methods have been developed to solve both problems, like the Extended Kalman Filter (EKF) or the Luenberger Observer (LO) or Model Adaptive Reference Systems (MRAS) or the Artificial Neural Networks (ANN) [1] or Least-Squares Methods. The suitable use of this last technique, sometimes in combination with the above first techniques has given rise to a research line carried out by the authors in the field of parameter estimation and sensorless control of induction motor drives. In particular, a novel neural technique called TLS EXIN neuron, has been theoretically developed [19][20] and applied experimentally to parameter estimation [21]-[26] and sensorless control [27]-[30].

With reference to the parameter estimation in the induction motor, the problem has been faced up to as a constrained minimisation of the residual error function of least-squares problems: actually classical least squares methods (Ordinary least Squares = OLS) have been shown not to be the best approach to this problem, because noise affects the measurements of stator voltages and currents; therefore orthogonal regression methods (Total Least Squares = TLS) have been employed. All the LS based parameter estimation methodologies have been applied numerically and experimentally to simply converter fed machines [24][25][26] and to field oriented control or direct torque control

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induction motor drives [21][22], for the on-line flux model adaptation. These methodologies have also been applied to retrieve, after a set of start-up tests, the variation law of the magnetic parameters of the machine versus the rotor magnetising current [23].

With reference to speed estimation in sensorless induction motor drives, the LS techniques have been combined with other well-known methodologies to create hybrid classic/neural speed observers. With this regard, firstly an MRAS speed observer has been devised, where the adaptive model is a ADALINE trained on-line by means of a classical OLS algorithm [27]. This observer has been then further improved [30], especially in its low and zero speed behaviour, by training on-line the adaptive neural model with a TLS-based law and by adopting a suitably devised adaptive integrator, which enables to cut-off definitely any DC bias present at the input of the integrator [31]. In the end, a new adaptive speed observer has been devised [29], based on the full-order Luenberger observer whose the adaptive speed estimation is based on a TLS algorithm. This speed observer has shown further better results both in its low and zero speed operation.

In the following a brief summary is given of the criteria adopted for the design and application of the TLS EXIN neuron to parameter estimation and sensorless control of induction motors. The most significant achieved results are presented in the last part.

2. THE LEAST-SQUARES TECHNIQUES

In general Least-Squares [32] solve a linear over-determined problem of the type $\mathbf{Ax} \approx \mathbf{b}$ in which $\mathbf{A} \in \Re^{m \times n}$ ($\Re$ is the set of real numbers), with m>n, is the data matrix, $\mathbf{b} \in \Re^{m}$ is the observation vector and $\mathbf{x} \in \Re^{n}$ is the vector of unknowns. In the following it is shown that both the parameter estimation problem, under certain simplifications, and the speed estimation problem, when applied to MRAS or adaptive full-order observers, can be formalised as a linear over-determined problem.

In the literature there generally exist three Least-Squares techniques: the Ordinary Least-Squares (OLS), the Total Least-Squares (TLS) and the Data Least-Squares (DLS) in accordance to where data errors are present.

In classical Ordinary Least-Squares (OLS) each element of the **A** matrix is assumed without any error: therefore all errors are confined to the observation vector **b**. However this assumption does not always correspond to the reality: modelling errors, measurement errors etc. can actually cause errors also in the **A** matrix. Thus in real world applications the employment of TLS would be very often better, because it takes into consideration also the errors in the data matrix. DLS, finally, deals with the case when all errors are confined in the data matrix.

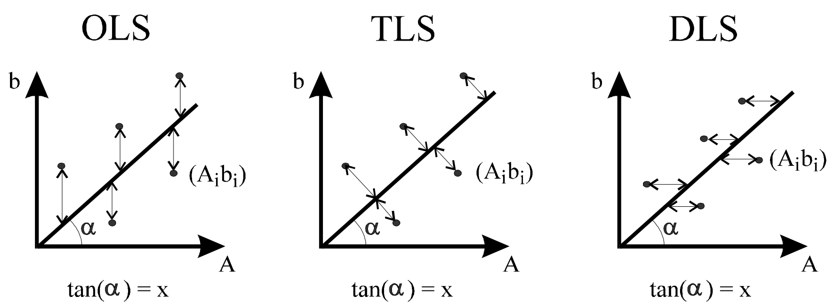

Fig. 1: Differences among LS techniques

In the mono-dimensional case (n=1) the resolution of the LS problem consists in determining the angular coefficient $\mathbf{x}$ of the straight line of equation $\mathbf{Ax} = \mathbf{b}$. The LS technique solves for this problem by computing the value of $\mathbf{x}$ which minimises the sum of squares of the distances among the elements $(\mathbf{A}_i, \ \mathbf{b}_i)$, with $i = 1, \cdots, m$, and the line itself. Fig. 1 shows the difference among the OLS, TLS and DLS. OLS minimises the sum of squares of the distances in the $\mathbf{b}$ direction (error only in the observation vector). TLS minimises the sum of squares in the direction orthogonal to the line (for this reason it is also called orthogonal regression), while DLS minimises the sum of squares in the $\mathbf{A}$ direction (errors only in the data matrix). In particular it must be expected that, in absence of noise, the results obtained with TLS are equal to those obtained with OLS; however in presence of increasing noise the performance of TLS proves to be generally better than that of OLS. TLS algorithm is therefore particularly suitable for estimation processes where data are affected by noise; this is certainly the case of the on-line estimation of induction motor parameters and sensorless control, where errors in the data matrix and the observation vector can easily occur.

3. THE TLS EXIN NEURON

Given the matrix equation $\mathbf{Ax} \approx \mathbf{b}$, it is well known that the TLS solution is obtained by minimising the following error function [19][20]:

$$\mathrm{E}_{TLS}(\mathbf{x}) = \frac{(\mathbf{Ax} - \mathbf{b})^T (\mathbf{Ax} - \mathbf{b})}{1 + \mathbf{x}^T \mathbf{x}} = \frac{\left\| [\mathbf{A}; \mathbf{b}] \left[\mathbf{x}^T; -1 \right]^T \right\|_2^2}{\left\| \left[\mathbf{x}^T; -1 \right]^T \right\|_2^2} \tag{1}$$

which is the Rayleigh Quotient of $[\mathbf{A}; \mathbf{b}]^T [\mathbf{A}; \mathbf{b}]$ constrained to the TLS hyperplane, defined by $\mathbf{x}_{n+1} = -1$. Hence, the TLS solution is parallel to the right singular vector ($\in \Re^{n+1}$) corresponding to the minimum singular value of $[\mathbf{A}; \mathbf{b}]$, that is its minor component (MC) vector. This TLS solution is called *generic*. The error (1) has $n+1$ critical points, i.e. one minimum (the generic TLS solution), one maximum and n-1 saddle points. If the MC vector is parallel to the TLS hyperplane, the TLS solution cannot be computed and the TLS problem is called *nongeneric*. This problem occurs whenever $\mathbf{A}$ is rank-deficient or when the set of equations is *highly conflicting*, as in the case of high modeling error. Although exact nongeneric TLS problems seldom occur, close-to-nongeneric TLS problems are not uncommon. In the latter case, the generic TLS solution *tends to infinity*. It has been proved in [20] that the nongeneric TLS solution is given by the saddle point of lowest error and in [32]-[34] that this solution can be achieved by adding a constraint to the TLS error minimisation (the solution is constrained to be orthogonal to the direction of the minimum), here defined as the *nongeneric constraint*. In the case of close-to-nongeneric TLS problems, the solution stands between this saddle and the minimum of the error function.

From (1) it holds:

$$\mathrm{E}_{TLS}(\mathrm{x}) = \sum_{i=1}^{m} \mathrm{E}^{(i)}(\mathrm{x}) \tag{2}$$

where:

$$\mathrm{E}^{(i)}(\mathbf{x}) = \frac{\left(\mathbf{a}_i^T \mathbf{x} - b_i\right)^2}{1 + \mathbf{x}^T \mathbf{x}} = \frac{\left(\sum_{j=1}^{n} a_{ij} x_j - b_i\right)^2}{1 + \mathbf{x}^T \mathbf{x}} = \frac{\delta^2}{1 + \mathbf{x}^T \mathbf{x}} \tag{3}$$

being i the index of the i-th row of $[\mathbf{A};\mathbf{b}]$. Hence, $\frac{dE^{(i)}}{d\mathbf{x}} = \frac{\delta \mathbf{a}_i}{1+\mathbf{x}^T\mathbf{x}} - \frac{\delta^2 \mathbf{x}}{\left(1+\mathbf{x}^T\mathbf{x}\right)^2}$ and the corresponding steepest descent discrete time formula is given by:

$$\mathbf{x}(t+1) = \mathbf{x}(t) - \alpha(t)\gamma(t)\mathbf{a}_i + \left[\alpha(t)\gamma^2(t)\right]\mathbf{x}(t) \tag{4}$$

where

$$\gamma(t) = \frac{\delta(t)}{1+\mathbf{x}^T(t)\mathbf{x}(t)} \tag{5}$$

This is the learning law of the TLS EXIN neuron [19][20] and $E^{(i)}$ is its error function. The TLS EXIN neuron is a linear unit with n inputs (vector $\mathbf{a}_i$), n weights (vector $\mathbf{x}$), one output (scalar $y_i = \mathbf{x}^T\mathbf{a}_i$) and one training error (scalar $\delta(t)$). In [19] it is proved that the Hessian matrix of the TLS error function is positive definite (which implies the nonsingularity) at the minimum of the error function. Thus it can be accelerated by the Newton and quasi-Newton (e.g. BFGS) techniques; however the algorithm requires a domain of convergence, i.e. it does not converge for every possible choice of the initial conditions. This domain has been analytically studied in [20] where it is proved the fundamental statement that the TLS origin always belongs to the TLS domain of convergence. In [20] it is also proved that the TLS EXIN neuron, for null initial conditions, unlike the direct methods which require a numerical rank estimation, yields the correct solution independently of the fact that the TLS problem is generic or not (in this case it automatically implements the nongeneric constraint) and is the only possible technique for solving the close-to-nongeneric TLS problems. As explained in [20] the TLS EXIN neuron is the best algorithm for solving the TLS problem in a recursive way. In [20] a complete theory about this neuron is given: the stability, the transient, the speed, the accuracy and its tracking capability in system identification are fully analyzed both analitically and experimentally. This justifies the adoption of this neuron for the on-line identification of an electrical machine.

4. TLS BASED IDENTIFICATION OF INDUCTION MACHINES

From the space-vector equations of the induction motor in the stator reference frame [1] the following matrix equation results:

$$\left(\frac{d\mathbf{i}_s}{dt}\;\; \mathbf{i}_s - j\omega_r \mathbf{i}_s - \frac{d\mathbf{u}_s}{dt} + j\omega_r \mathbf{u}_s - \mathbf{u}_s\right)\begin{pmatrix} K_1 \\ K_2 \\ K_{31} \\ K_4 \\ K_5 \end{pmatrix} = \left(-\frac{d^2\mathbf{i}_s}{dt^2} - j\omega_r \frac{d\mathbf{i}_s}{dt} - j\frac{d\omega_r}{dt}\beta\psi_r'\right) \tag{6}$$

where the following parameters, called K-parameters, are defined as in [25][26]:

$$K_1 = \frac{1}{\sigma T_s} + \frac{\beta_0}{\sigma}\ [\mathrm{s}^{-1}],\ K_2 = \frac{\beta_0}{\sigma T_s}\ [\mathrm{s}^{-2}],\ K_{31} = \frac{1}{\sigma T_s}\ [\mathrm{s}^{-1}]\ K_4 = \frac{1}{\sigma L_s}\ [\mathrm{H}^{-1}],\ K_5 = \frac{\beta_0}{\sigma L_s}\ [\mathrm{s}^{-1}\,\mathrm{H}^{-1}] \tag{7}$$

For the symbols see the list. Between these five K-parameters the following quadratic relationship exists:

$$K_2 K_4 = K_{31} K_5 \tag{8}$$

Under the assumption that:

$$d\omega_r / dt \approx 0 \tag{9}$$

i.e. considering the rotor at standstill, in slow transients or in sinusoidal steady-state, (6) can be split into the following scalar equations where the term containing ψ'_r disappears:

$$\begin{pmatrix} \dfrac{di_{sD}}{dt} & i_{sD} & \omega_r i_{sQ} & -\left(\dfrac{dv_{sD}}{dt}+\omega_r u_{sQ}\right) & -u_{sD} \\ \dfrac{di_{sQ}}{dt} & i_{sQ} & -\omega_r i_{sD} & -\left(\dfrac{dv_{sQ}}{dt}-\omega_r u_{sD}\right) & -u_{sQ} \end{pmatrix} \begin{pmatrix} K_1 \\ K_2 \\ K_{31} \\ K_4 \\ K_5 \end{pmatrix} = \begin{pmatrix} -\dfrac{d^2 i_{sD}}{dt^2} - \omega_r \dfrac{di_{sQ}}{dt} \\ -\dfrac{d^2 i_{sQ}}{dt^2} + \omega_r \dfrac{di_{sD}}{dt} \end{pmatrix} \tag{10}$$

This matrix equation (10) can be written in the above mentioned form:

$$\mathbf{Ax} \approx \mathbf{b} \tag{11}$$

The equation (11) can be solved for the K-parameters both in steady-state and transient in real-time by using any least-squares method. From the assumption (9) it results that in any case the LS solution is biased, because of neglecting the modelling error, i.e. the term containing ψ_r'.

From the K-parameters not all the five electrical parameters (R_s, R_r, L_s, L_r, L_m) can be retrieved, because no rotor measurements are available: in fact the K-parameters determine only four independent parameters in the following way:

$$T_r = \frac{K_4}{K_5},\ R_s = \frac{K_2}{K_5} = \frac{K_{31}}{K_4},\ L_s = \frac{K_1 - K_{31}}{K_5},\ \sigma = \frac{K_5}{K_4\left(K_1 - K_{31}\right)} \tag{12}$$

The identification problem with least-squares algorithms is usually solved for by means of an unconstrained minimisation of the 2-norm of the error with a simple gradient descent algorithm [3]. This approach fails in computing K_2 because the particular structure of matrix A implies a very low value of the 2nd column of the matrix $\mathbf{R} = \mathbf{A}^T\mathbf{A}$ and this means that this problem is ill-conditioned (K_2 problem): this results in a flat error surface along the K_2 direction [26]. Numerical scaling does not help in solving this problem. In [24] this problem was attacked by devising an estimation method which considers the constraint (8) indirectly and has good tracking capabilities: in particular in transient conditions all four electrical parameters can be retrieved, since the data matrix is full rank, while in sinusoidal steady-state only two K-parameters can be computed, since the data matrix has rank 2. Consequently only one electrical parameter can be obtained in sinusoidal steady-state, in particular the rotor time constant for vector-controlled induction motor drives and the stator resistance for direct-torque controlled induction motor drives. In these works a selection algorithm has been then developed for choosing the parameters to be estimated in all working conditions.

4.1 Results

As an example, the experimental results of a test is shown in the following. The motor has been supplied by giving to the voltage source inverter a reference sinusoidal voltage of 220 V and 50 Hz. The whole speed transient from zero speed to steady state speed has been exploited to estimate all four electrical parameters of the induction motor (rotor time constant, stator resistance, stator inductance, global leakage factor). Fig. 2 a shows the rotor speed and the i_{sD}, i_{sQ} stator current components during the start-up of the motor with no load obtained in the experimental test (see the appendix for some detail on the test setup). Fig. 2 b shows the true parameters of the machine (obtained with the classic no-load and locked rotor tests) and the waveforms of the estimated ones, computed respectively with a classic OLS and with the TLS EXIN, when a uniformly distributed noise between –0.05 and +0.05 p.u. of the rated voltage and current has been given to each acquired signal, so as to have noisy elements both in the data matrix and the observation vector. This has been done to emulate an electromagnetically polluted environment in which the data from sensors are corrupted by noise.

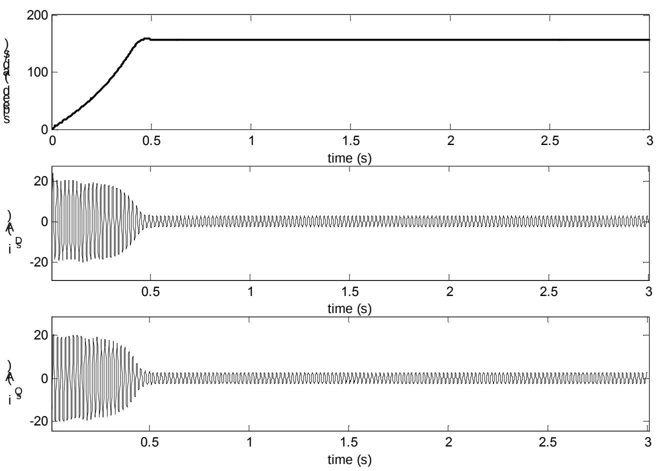

Fig. 2 a: Rotor speed and i_{sD}, i_{sQ} stator current components

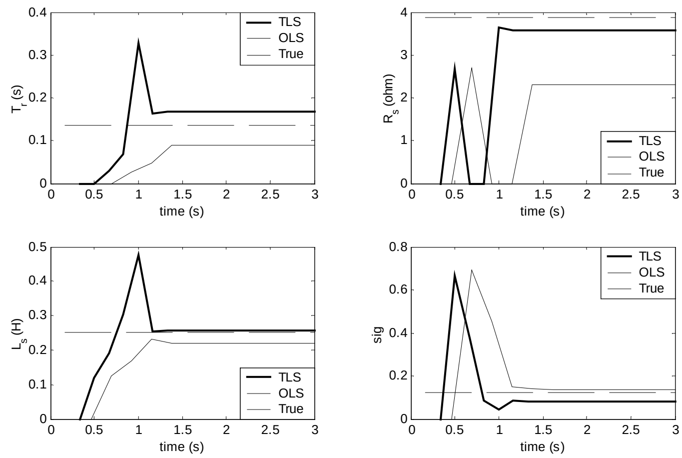

Fig. 2 b. Real and estimated electrical parameters of the motor with noise

5. TLS BASED SENSORLESS CONTROL

LS based techniques can be suitably employed to improve the performances of the existing speed observers. The most of speed observers in literature based on the approximation of sinusoidal windings employ a flux estimator, which can be a simple open-loop flux estimator [11] or even a closed-loop full-order [13][14] or reduced order [12] observer, and then an adaptive law is devised to compute on-line the value of the speed of the machine. This adaptation law is usually found on the basis either of the Popov hyperstability theorem [11][12] or the Lyapunov stability function [13], in order to guarantee the overall stability of the speed observer. A completely different approach has been followed by the authors, based on the idea that the induction machine equations can be rewritten in a matrix form of the type $\mathbf{Ax} \approx \mathbf{b}$, where the vector of unknown $\mathbf{x}$ is in this case the scalar variable "rotor speed". This matrix equation can be suitably solved on-line by means of any recursive LS technique and since, as it will be clearly shown in the following, the data matrix is supposed to be affected by errors due to incorrect modelling and noisy measurements, the TLS EXIN should be used to retrieve the rotor speed. In addition, since the behaviour of this neuron has been theoretically investigated [19][20], the stability of the speed observers is guaranteed and it has been analytically proved. This idea has given rise to the development of two speed observers which employ the TLS EXIN neuron, the first is an MRAS-based speed observer [30] and the second is a full order adaptive speed observer [29].

5.1 TLS MRAS Speed observer

In the proposed MRAS speed observer [30] the reference model is based on the stator equations of the induction motor [1][2], while the adaptive model is an Artificial Neural Network. In particular the reference model, because of the open-loop integration, employs an adaptive integrator [31] instead of low-pass filters to avoid the DC drift problem. The adaptive model is an ADALINE (Linear Neural Network) which reproduces the rotor equations of the induction motor (current model) [1][2]. The speed is then computed by employing the rotor flux linkage error between the voltage and the current models, as shown in Fig. 3. The ANN has 4 inputs and 2 outputs and is described by the following discrete equations :

$$\begin{cases} \hat{\psi}_{rd}(k) = w_1 \ \hat{\psi}_{rd}(k-1) - w_2 \ \hat{\psi}_{rq}(k-1) + w_3 \ i_{sD}(k-1) \\ \hat{\psi}_{rq}(k) = w_1 \ \hat{\psi}_{rq}(k-1) + w_2 \ \hat{\psi}_{rd}(k-1) + w_3 \ i_{sQ}(k-1) \end{cases} \tag{13}$$

where k is the current time sample, $\hat{\psi}_{rd}$ and $\hat{\psi}_{rq}$ are the direct and quadrature components of the rotor flux linkage in the stator reference frame and w_1, w_2, w_3 are the weights of the neural networks which, to satisfy the rotor equations of the induction motor, must be equal to: $w_1 = 1 - T/T_r$ $w_2 = T\omega_r$, $w_3 = TL_m/T_r$, where T is the sampling time of the control system.

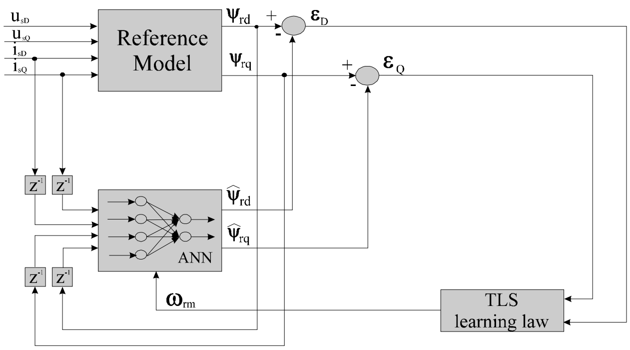

Fig. 3: Block diagram of the ANN MRAS observer

It should be remarked that the values of the rotor flux-linkage components at the input of the ANN are those coming from the reference model, and not from the adaptive one as in [16]. The neural network is not therefore used in the usual "simulation" mode, where its delayed output is used as its input, but in the "prediction" mode, where the delayed output of the voltage model is used as input to the neural network: this trick which enables a quicker and more stable convergence of the estimation algorithm. In the ANN the weights w_1 and w_3 are kept constant to their values computed off-line while only w_2 is adapted on-line by means of the TLS EXIN algorithm. Eq (13) can be written in the following matrix form, considering the fact that the ANN is used as a predictor and not as a simulator:

$$\begin{bmatrix} \psi_{rq}(k-1) \\ -\psi_{rd}(k-1) \end{bmatrix} w_2 = \begin{bmatrix} \hat{\psi}_{rd}(k)-w_1 & \psi_{rd}(k-1)-w_3 & i_{sD}(k-1) \\ \hat{\psi}_{rq}(k)-w_1 & \psi_{rq}(k-1)-w_3 & i_{sQ}(k-1) \end{bmatrix} \tag{14}$$

which is a classical matrix equation of the type **Ax≈b**. In this respect (14) shows that the matrix **A** is composed of the dq axis components of the rotor flux linkage which can be affected by errors and noise resulting from open-loop integration of the model reference or measurements and the same can be said for the observation vector **b** which is also composed of the dq axis components of the rotor flux linkage and the dq components of the stator current space vector: then this problem is a TLS one, rather than an ordinary LS problem, so any Least-Squares technique different from TLS would be inadequate.

5.2 TLS Full-order Speed Observer

The state equations in the stationary reference frame of the induction machine are given by**:**

$$\frac{d}{dt}\begin{bmatrix} \mathbf{i}_s \\ \psi'_r \end{bmatrix} = \begin{bmatrix} \mathbf{A}_{11} & \mathbf{A}_{12} \\ \mathbf{A}_{21} & \mathbf{A}_{22} \end{bmatrix} \begin{bmatrix} \mathbf{i}_s \\ \psi'_r \end{bmatrix} + \begin{bmatrix} \mathbf{B}_1 \\ 0 \end{bmatrix} \mathbf{u}_s = \mathbf{Ax} + \mathbf{Bu}_s \tag{15a}$$

$$\mathbf{i_s} = \mathbf{Cx} \tag{15b}$$

where:

$$\mathbf{A}_{11} = -\left\{R_s/(\sigma L_s) + (1-\sigma)/(\sigma T_r)\right\}\mathbf{I} = a_{11}\mathbf{I},$$

$$\mathbf{A}_{12} = L_m/(\sigma L_s L_r)\left\{(1/T_r)\mathbf{I} - \omega_r \mathbf{J}\right\} = a_{12}\left\{(1/T_r)\mathbf{I} - \omega_r \mathbf{J}\right\},$$

$$\mathbf{A}_{21} = \left\{L_m/T_r\right\}\mathbf{I} = a_{21}\mathbf{I}, \ \mathbf{A}_{22} = -(1/T_r)\mathbf{I} + \omega_r\mathbf{J} = a_{22}\left\{(1/T_r)\mathbf{I} - \omega_r\mathbf{J}\right\}$$

$$\mathbf{B}_1 = 1/(\sigma L_s)\mathbf{I} = b\mathbf{I} \tag{16a,b,c,d, e}$$

with:

$$\mathbf{i}_s = \begin{bmatrix} i_{sD} & i_{sQ} \end{bmatrix}^T, \quad \mathbf{u}_s = \begin{bmatrix} u_{sD} & u_{sQ} \end{bmatrix}^T, \quad \mathbf{\Psi}'_r = \begin{bmatrix} \psi_{rd} & \psi_{rq} \end{bmatrix}^T, \quad \mathbf{C}' = [\mathbf{0} \ \ \mathbf{I}], \quad \mathbf{C} = [\mathbf{I} \ \ \mathbf{0}], \quad \mathbf{I} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix},$$

$$\mathbf{J} = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$$

See the list of symbols in the appendix.

The full order Luenberger state observer estimating the stator current and the rotor flux is given as usual by [13]:

$$\frac{d\ \hat{\mathbf{x}}}{dt} = \hat{\mathbf{A}}\hat{\mathbf{x}} + \mathbf{Bu}_s + \mathbf{G}\left(\hat{\mathbf{i}}_s - \mathbf{i}_s\right) \tag{17}$$

where $\wedge$ means the estimated values and **G** is the observer gain matrix which is designed so that the above observer can be stable.

The Total Least-Squares (TLS) based speed observer derives from a modification of (15) with **G**=**0** in the sense that it exploits the two first scalar equations to estimate the rotor speed, as shown below in discrete form for digital implementation:

$$\begin{bmatrix} -a_{12}T_s\hat{\psi}_{rq}(k-1) \\ a_{12}T_s\hat{\psi}_{rd}(k-1) \end{bmatrix}\omega_r(k-1)=\begin{bmatrix} i_{sD}(k)-i_{sD}(k-1)-a_{11}T_s i_{sD}(k-1)-a_{12}p_r T_s\hat{\psi}_{rd}(k-1)-bT_s u_{sD}(k-1) \\ i_{sQ}(k)-i_{sQ}(k-1)-a_{11}T_s i_{sQ}(k-1)-a_{12}p_r T_s\hat{\psi}_{rq}(k-1)-bT_s u_{sQ}(k-1) \end{bmatrix} \tag{18}$$

where $p_r = 1/T_r$ T_s is the sampling time of the control algorithm and k is the current time sample. Even eq. (18) is a matrix equation of the type **Ax≈b**, and for the same reasons explained in §4.1 the most suitable technique to be used to compute on-line the rotor speed is the TLS. Also in this case, the TLS EXIN neuron has been adopted to solve the TLS problem on-line in a recursive form.

Fig. 4 shows the block diagram of the new adaptive TLS based speed observer. It should be remarked that the computation of the rotor speed by means of the TLS estimator is performed through the minimisation of the residual of the matrix equation (18).

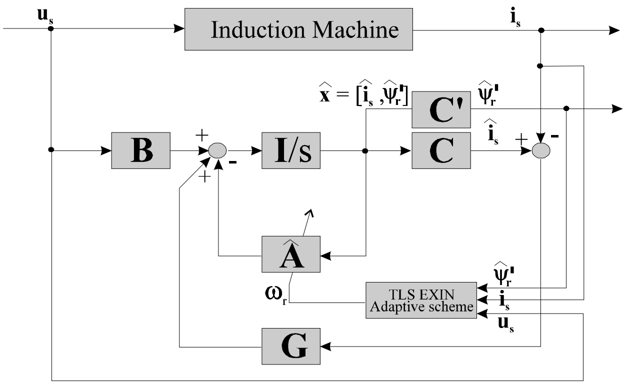

Fig. 4: Block diagram of the TLS based adaptive speed observer

5.3 Results

As an example, the experimental results of one test obtained with each sensorless scheme are shown in the following. It should be remarked that the two proposed sensorless schemes have been employed in a rotor-flux-oriented vector control scheme [30]. To highlight the performance of the proposed sensorless schemes, a speed reversal has been given the drive at very low speed with machine magnetized at rated flux (1 Wb in this case). In particular, speed reversals from -10 to 10 rad/s and from 1 to -1 rad/s have been commanded, respectively to the TLS MRAS observer and to the TLS adaptive observer. Fig.s 5 and 6 show the reference, the estimated and the measured speed under this test with both speed observers (the measured speed is employed only for assessing the observer since the observed speed is fed-back to the control system). It should be remarked that the TLS adaptive observer permits the speed reversal to be performed at a lower speed that that achievable with the TLS MRAS, as expected.

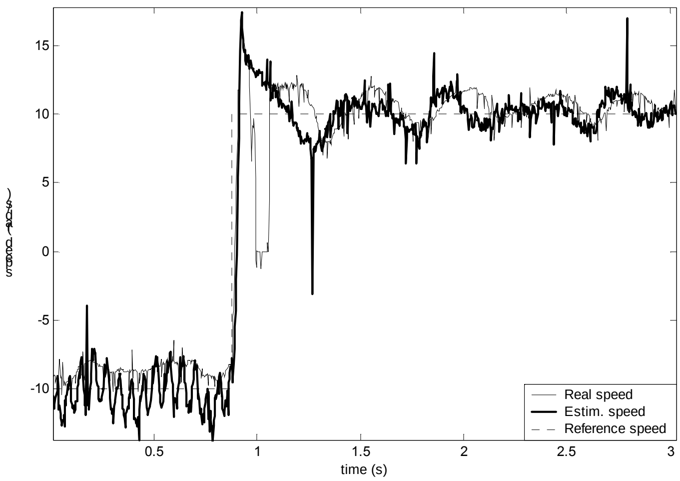

Fig.5: Reference, estimated and measured speed during a speed reversal from –10 rad/s to 10 rad/s at no-load with the TLS MRAS Observer

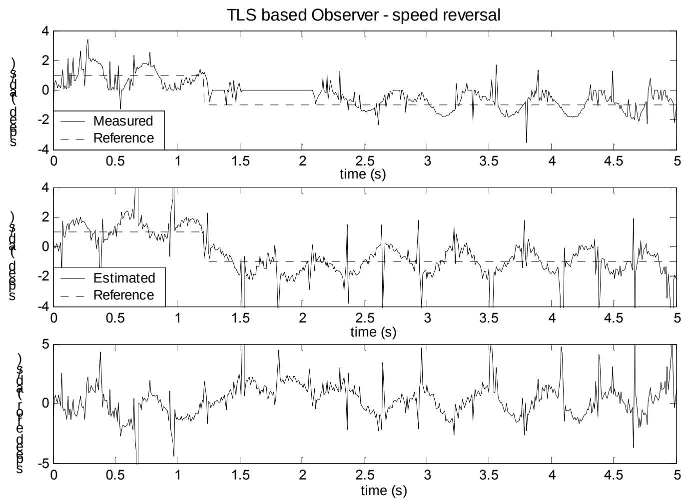

Fig. 6: Reference, estimated, measured speed and speed estimation error during a speed reversal from 1 rad/s to –1 rad/s with the TLS adaptive observer

6. CONCLUSION

This paper deals with the application of a new ANN technique, the so-called TLS EXIN neuron, to AC induction motor drives. In particular, it addresses two important subjects of AC induction motor drives: the on-line estimation of the electrical parameters of the machine, to be used for example for flux model adaptation in high-performance drives, and the speed estimation in sensorless drives. On this basis, this paper summarizes the results obtained in these two fields by the authors over the last few years and stresses the important potentiality of this new neural technique in AC drives. In detail, the employment of the TLS EXIN neuron permits the performance of classic techniques to be enhanced, both in parameter estimation and sensorless control, for the following reasons:

- Higher accuracy of the parameter estimation can be achieved, especially in presence of noisy data, which are typical of electromagnetically polluted environments;
- In sensorless drives lower working speeds can be achieved with high accuracy speed estimation, both at no-load and at load; correct zero speed operation at no-load and at medium-low loads can also be attained.

APPENDIX: TEST SETUP

The employed test set up consists of [26][30]:

- A three-phase induction motor or rated power 2.2 kW;
- A frequency converter which consists of a three-phase diode rectifier and a 7.5 kVA, three-phase VSI;
- A DC machine for loading the induction machine of rated power 1.5 kW;
- An electronic AC-DC converter (three-phase diode rectifier and a full-bridge DC-DC converter) for supplying the DC machine of rated power 4 kVA;
- A dSPACE card (DS1103) with a PowerPC 604e at 400 MHz and a floating-point DSP TMS320F240**.**

LIST OF SYMBOLS

$\mathbf{u}_s$= space vector of the stator voltages in the stator reference frame;

u_{sD}, u_{sQ} = direct and quadrature components of the stator voltages in the stator reference frame;

$\mathbf{i}_s$= space vector of the stator currents in the stator reference frame;

i_{sD}, i_{sQ} = direct and quadrature components of the stator currents in the stator reference frame;

$\boldsymbol{\psi}'_r$= space vector of the rotor flux-linkages in the stator reference frame;

ψ_{rd}, ψ_{rq} = direct and quadrature component of the rotor flux linkage in the stator reference frame;

L_s = stator inductance.

L_r = rotor inductance.

L_m = total static magnetising inductance;

R_s = resistance of a stator phase winding.

R_r = resistance of a rotor phase winding.

T_s = stator time constant;

T_r = rotor time constant;

$\beta_0 = R_r/L_r$=inverse of the rotor time constant T_r

$\beta = L_m / (\sigma L_s L_r)$

$\sigma = 1 - L_m^2 / (L_s L_r)$ =total leakage factor;

p = number of pole pairs;

ω_{mr} = angular rotor speed (in mechanical angles per second);

ω_r = angular rotor speed (in electrical angles per second);

T = sampling time of the control system.

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