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On the state and parameter simultaneous estimation problem in induction motors

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Abstract: In the context of parameter estimation through state observers, we revisit the transformation of the induction motor model into a state-affine structure with respect to the unknown variables, then we compare in simulation the performances obtained through available adaptive and exponential forgetting factor observer designs.

1. INTRODUCTION

Referring to our previous work (Ţiclea and Besançon, 2006a,b), we reconsider in this note the problem of state and parameter simultaneous estimation in induction motors. This problem can be very challenging, especially when the mechanical speed is not measured, which motivated a lot of work in the electrical engineering community to the extent that there is a vast literature available on the subject.

Here we continue to resort to the solution proposed in (Ţiclea and Besançon, 2006a,b), because unlike other solutions in the literature it can handle some worst-case scenarios in which the mechanical speed is not measured and the electrical parameters (may be all) have to be estimated. This solution consists in using a state observer designed for some extended representation of the model obtained through immersion of the original one.

The first objective of the present paper concerns the construction of the immersion, for which we try to present some theoretical foundation and a somewhat systematic approach to its construction, as opposed to our previous work, where the construction was performed with an entirely heuristic approach. The second objective concerns the employed observer. In our previous work a Kalman-like observer was employed, which estimated the state variables and the parameters at the same speed. Here, we want to find out to which extent an adaptive observer can be used and with what performance.

The paper is organized as follows. In section 2 the considered problem is precisely stated. Section 3 discusses the immersion of nonlinear systems into state affine structures by resorting to output injection and proposes a solution to this problem, which is then applied to the induction motor model. In section 4 it is shown that the transformation of the induction motor model permits not only the use of a Kalman-like observer, but also the use of an adaptive one. Results of the comparison of the two observer through simulation tests are presented in section 5 and some conclusions are drawn in section 6.

2. INDUCTION MOTOR ESTIMATION PROBLEM

We consider an induction motor model expressed in the (α, β) reference frame (Leonhard, 1990; Vas, 1998) with state variables

$i_{s\alpha}, i_{s\beta}$ – the components of the stator current phasor
$\phi_{s\alpha}, \phi_{s\beta}$ – the components of the stator flux phasor
ω_r – the mechanical speed

and inputs the components of the stator voltage phasor $u_{s\alpha}, u_{s\beta}$, resulting into the following representation:

$$\begin{aligned}\frac{\mathrm{d}}{\mathrm{d}t}i_s =& [-(\tfrac{R_r}{\sigma L_r} + \tfrac{R_s}{\sigma L_s})I + p\omega_r J]i_s + \\ &+ (\tfrac{R_r}{\sigma L_s L_r} I - p\tfrac{1}{\sigma L_s}\omega_r J)\phi_s + \tfrac{1}{\sigma L_s}u_s \qquad (1a)\\ \frac{\mathrm{d}}{\mathrm{d}t}\phi_s =& -R_s i_s + u_s \qquad (1b)\\ \frac{\mathrm{d}}{\mathrm{d}t}\omega_r =& -\tfrac{f_v}{J_m}\omega_r + p\tfrac{1}{J_m}(i_{s\beta}\phi_{s\alpha} - i_{s\alpha}\phi_{s\beta}) - \tfrac{1}{J_m}\tau_l \qquad (1c)\\ y =& i_s. \qquad (1d)\end{aligned}$$

In the electrical part, L stands for inductance, R stands for resistance, $\sigma = 1 - \frac{M^2}{L_s L_r}$ with M the maximum mutual inductance between one stator and one rotor winding, the indexes s and r refer respectively to the stator and the rotor, and

$$I = \begin{bmatrix}1 & 0\\ 0 & 1\end{bmatrix}, \qquad J = \begin{bmatrix}0 & -1\\ 1 & 0\end{bmatrix}.$$

As far as the mechanical part is concerned, τ_l denotes the load torque, J_m the total inertia momentum (rotor plus load) and f_v the viscous friction coefficient. Finally, in both electrical and mechanical parts, p represents the number of pairs of poles.

For this system, uncertainties in the electrical parameters (for instance, resistances may vary with the temperature) as well as the absence of flux, torque and sometimes speed transducers lead to the problem of estimating the flux ϕ_s, mechanical speed ω_r, load torque τ_l and electrical parameters $\frac{R_r}{\sigma L_r}$, $\frac{R_s}{\sigma L_s}$, $\frac{R_r}{\sigma L_s L_r}$, $\frac{1}{\sigma L_s}$, R_s from available measurements of u_s and i_s when considering that the parameters in the mechanical equation f_v and J_m are perfectly known.

A possible approach to this problem is to turn the unknown parameters and load torque into state variables and then design a state observer for the extended system. Such a solution was presented in (Ţiclea and Besançon, 2006a,b), where the extended system was immersed into a state affine structure with output injection and a Kalman-like observer was used to perform the estimation. The presented construction of the immersion was entirely heuristic, but it appears that in case of the induction motors that type of approach can yield results for any choice of variables that need to be estimated from the set above, regardless the mechanical speed is measured or not.

In the following section we present another way to perform the same type of immersion, which is somewhat more systematic in nature. Although this approach may not be better than the pure heuristic approach in terms of results, it appears to work very well in the case of the induction motor.

3. IMMERSION TRANSFORMATION FOR OBSERVER DESIGN

3.1 Immersion into state-affine structures

The immersion of a general C^∞ system

$$\begin{aligned} \dot{x} &= f(x,u) = f_u(x) \\ y &= h(x) \end{aligned} \tag{2}$$

into a state affine structure

$$\begin{aligned} \dot{z} &= A(u)z + \varphi(u) \\ y &= Cz \end{aligned} \tag{3}$$

was studied by Fliess and Kupka (1983), who gave necessary and sufficient conditions for such a transformation. The interest towards the state-affine structure (3) is obvious: if the input u is fixed (as a function of time), the system becomes a linear time variant system and then a Kalman (Kalman and Bucy, 1961) or a Kalman-like observer such as the exponential forgetting factor observer (Hammouri and de Leon Morales, 1990) can be used to perform the estimation.

The result of (Fliess and Kupka, 1983) relies exclusively on the notion of observation space, which is reminded here for convenience.

Definition 1. (Observation space). For a general system (2), the *observation space* is the smallest $\mathbb{R}$-vector space that contains the components of the output map h and is invariant under the action of the vector fields of the family f_u.

We then have the following result:

Theorem 2. (cf. Fliess and Kupka (1983)).

(i) If the observation space of a system (2) has finite dimension, then the system can be immersed into a state-affine system.
(ii) If in addition the system is originally control-affine, then the immersion leads to a bilinear system.
(iii) If the class of admissible inputs contains the piecewise-constant inputs, then the immersion condition is also necessary.

Remark 3. If the immersion condition holds, the immersion map is constructed by taking any basis of the observation space.

The immersion condition of this theorem is, however, very strong, to the extent that there are many examples—quite simple ones—when it fails. A solution to weaken the immersion condition is to resort to output injection, which would give a state-affine structure

$$\begin{aligned} \dot{z} &= A(u,y) + \varphi(u,y) \\ y &= Cz. \end{aligned} \tag{4}$$

Note that in this case one can still use a Kalman-like observer for estimation, by simply considering the extended input $v = \left[\begin{smallmatrix} u \\ y \end{smallmatrix}\right]$ (Hammouri and Celle, 1991).

Unfortunately, the transformation conditions of a system (2) into a general state-affine structure (4) are very difficult to characterize in the sense that there are no transformation conditions of practical usefulness, and this is true for both diffeomorphism and immersion transformations. Conditions for transformation into particular forms of the structure (4) do indeed exist, for both diffeomorphism (Besançon and Bornard, 1997) and immersion (Hammouri and Celle, 1991) transformations, but as far as the immersion is concerned, they do not cover very much of the systems that can be immersed into a state affine structure.

We present here an idea from (Ţiclea and Besançon, 2007) for the immersion of a nonlinear system (2) into a state affine structure with output injection (4) that need not possess a particular form. This idea comes from the one that considers the extended output $v = \left[\begin{smallmatrix} u \\ y \end{smallmatrix}\right]$ for observer design. More precisely, we parametrize the family of vector fields f_u by the output y, consider v as input and use Theorem 2 for immersion. We then have the following sufficient condition for immersion:

Proposition 4. Given a system (2), if the family of vector fields $f(x,u)$ can be parameterized by the output y such that the observation space is finite dimensional when considering the extended input $\left[\begin{smallmatrix} u \\ y \end{smallmatrix}\right]$, then the system can be immersed into a state-affine structure (4).

Remark 5. The observation space in the above proposition is obviously not the real observation space of the system, but the result was formulated in this way in order to emphasize the connection with the result of Theorem 2. In a less ambiguous formulation, the immersion condition would have been "there exists a parametrization $f(x,u,y)$ of $f(x,u)$ such that the smallest $\mathbb{R}$-vector space which contains the components of h and is invariant under the vector fields of the family $f_{u,y}$ is finite-dimensional".

3.2 Immersion of the induction motor extended model

The idea in the preceding subsection was already applied to the induction motor state and parameter estimation problem of Section 2 in the case when the mechanical speed is also measured (Ţiclea and Besançon, 2007). Here, the objective is to show that the same idea can still be applied with success even when the speed is not available through measurement.

Just like in (Ţiclea and Besançon, 2007), we first perform a preliminary dynamical extension of the system, by building the state vector

$$x = \begin{bmatrix} i_s^T & \phi_s^T & \omega_r & \tau_l & \frac{R_r}{\sigma L_r} & \frac{R_r}{\sigma L_s L_r} & \frac{1}{\sigma L_s} & R_s \end{bmatrix}^T.$$

As far as the dynamics of the new variables are concerned, we know that the resistances are susceptible to vary with the temperature, but the precise dynamic is in general unknown and this is true for the load torque as well. For this reason, we assume that these dynamics will be slow compared with the dynamics of the employed observer and assimilate all new state variables with constants.

Under this assumption we define the following vector fields:

$$f_0 = \begin{bmatrix} \frac{R_r}{\sigma L_s L_r}\phi_{s\alpha} + \frac{p}{\sigma L_s}\omega_r\phi_{s\beta} \\ \frac{R_r}{\sigma L_s L_r}\phi_{s\beta} - \frac{p}{\sigma L_s}\omega_r\phi_{s\alpha} \\ 0 \\ 0 \\ -(\frac{f_v}{J_m}\omega_r + \frac{1}{J_m}\tau_l) \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \quad f_1 = \begin{bmatrix} -(\frac{R_r}{\sigma L_r} + \frac{R_s}{\sigma L_s}) \\ p\omega_r \\ -R_s \\ 0 \\ -p\frac{1}{J_m}\phi_{s\beta} \\ 0 \\ \vdots \\ 0 \end{bmatrix},$$

$$f_2 = \begin{bmatrix} -p\omega_r \\ -(\frac{R_r}{\sigma L_r} + \frac{R_s}{\sigma L_s}) \\ 0 \\ -R_s \\ p\frac{1}{J_m}\phi_{s\alpha} \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \quad f_3 = \begin{bmatrix} \frac{1}{\sigma L_s} \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \quad f_4 = \begin{bmatrix} 0 \\ \frac{1}{\sigma L_s} \\ 0 \\ 1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

and output map

$$h = \begin{bmatrix} i_{s\alpha} \\ i_{s\beta} \end{bmatrix}.$$

Then the original system (1) can be represented as

$$\dot{x} = f_0 + y(1)f_1 + y(2)f_2 + u(1)f_3 + u(2)f_4$$
$$y = h.$$

where $y(i)$ and $u(i)$ stand for component i of y and u respectively. It can be easily shown by computing iterated Lie derivatives of h along $f_0, \ldots, f_4$ that the space described in Remark 5 has finite dimension and a basis of this space can be chosen as: i_s, ϕ_s, $\frac{R_s}{\sigma L_s}\phi_s$, $\frac{1}{\sigma L_s}\phi_s$, $\frac{R_r}{\sigma L_s L_r}\phi_s$, $\frac{1}{\sigma L_s}{\phi_{s\alpha}}^2$, $\frac{1}{\sigma L_s}{\phi_{s\beta}}^2$, $\frac{1}{\sigma L_s}\phi_{s\alpha}\phi_{s\beta}$, $\tau_l\frac{1}{\sigma L_s}\phi_s$, ω_r, $\omega_r\frac{1}{\sigma L_s}\phi_s$, $\frac{R_s}{\sigma L_s}\omega_r$, $\frac{1}{\sigma L_s}\omega_r$, τ_l, $\frac{R_s}{\sigma L_s}\tau_l$, $\frac{1}{\sigma L_s}\tau_l$, $\frac{R_r}{\sigma L_r}$, $\frac{R_s}{\sigma L_s}$, $\frac{R_s R_r}{\sigma L_s L_r}$, $\frac{1}{\sigma L_s}$, $\frac{R_r}{\sigma L_s L_r}$, R_s, $\frac{R_s^2}{\sigma L_s}$ and 1, which is exactly the immersion obtained in (Ţiclea and Besançon, 2006a) up to a constant state with known value which can be obviously eliminated from the model.

4. EXPONENTIAL FORGETTING FACTOR VS. ADAPTIVE OBSERVER

The transformation in the preceding section puts the induction motor model into a form (4) with $\varphi(u, y) = \varphi(u)$, for which one can design a Kalman-like observer, namely the exponential forgetting factor observer

$$\dot{\hat{z}} = A(u, y)\hat{z} + \varphi(u) - S^{-1}C^T(C\hat{z} - y)$$
$$\dot{S} = -\lambda S - A(u, y)^T S - SA(u, y) + C^T C,$$

which can ensure arbitrarily fast exponential convergence through the tuning parameter $\lambda > 0$ for any $\hat{z}(0)$ and any $S(0) = S(0)^T$, provided the input is regularly persistent (Hammouri and de Leon Morales, 1990).

It is worth noticing at this point that in the case of the induction motor model transformation, the preliminary extension was of the type

$$\tilde{x} = \begin{bmatrix} x \\ \theta \end{bmatrix}$$

where x is the vector of the variables that need to be estimated fast (and this includes the load torque), while θ is a vector containing exclusively combinations of electrical parameters, which are supposed constant or very slow varying ($\dot{\theta} \approx 0$). This also induces a partition of the vector z into two subvectors $z = \left[\begin{smallmatrix} z_x \\ z_\theta \end{smallmatrix}\right]$ such that z_θ only depends on elements in θ, while z_x depends on all $\tilde{x}$, i.e.

$$z_x = \Big[i_s \;\; \phi_s \;\; \tfrac{R_s}{\sigma L_s}\phi_s \;\; \tfrac{1}{\sigma L_s}\phi_s \;\; \tfrac{R_r}{\sigma L_s L_r}\phi_s \;\; \tfrac{1}{\sigma L_s}{\phi_{s\alpha}}^2 \;\; \tfrac{1}{\sigma L_s}{\phi_{s\beta}}^2 \;\; \tfrac{1}{\sigma L_s}\phi_{s\alpha}\phi_{s\beta} \;\; \tau_l\tfrac{1}{\sigma L_s}\phi_s \;\; \omega_r \;\; \omega_r\tfrac{1}{\sigma L_s}\phi_s \;\; \tfrac{R_s}{\sigma L_s}\omega_r \;\; \tfrac{1}{\sigma L_s}\omega_r \;\; \tau_l \;\; \tfrac{R_s}{\sigma L_s}\tau_l \;\; \tfrac{1}{\sigma L_s}\tau_l \Big]$$

$$z_\theta = \Big[\tfrac{R_r}{\sigma L_r} \;\; \tfrac{R_s}{\sigma L_s} \;\; \tfrac{R_s R_r}{\sigma L_s L_r} \;\; \tfrac{1}{\sigma L_s} \;\; \tfrac{R_r}{\sigma L_s L_r} \;\; R_s \;\; \tfrac{R_s^2}{\sigma L_s} \Big].$$

It is not needed to estimate z_θ at the same speed as z_x, and clearly not desirable when the influence of the measurement noise is an issue. To address this problem, we note that the matrices $A(u, y)$, $\varphi(u, y)$ and C obtained after immersion admit partitions

$$A(u, y) = \begin{bmatrix} A_1(u, y) & A_2(u, y) \\ 0 & 0 \end{bmatrix} \qquad \varphi(u) = \begin{bmatrix} \varphi_1(u) \\ 0 \end{bmatrix}$$
$$C = [C_1 \;\; 0]$$

(here 0 stands for null matrices of appropriate dimensions) such that the system can be represented as

$$\dot{z}_x = A_1(u, y)z_x + A_2(u, y)z_\theta + \varphi_1(u)$$
$$y = C_1 z_x.$$

with $\dot{z}_\theta = 0$.

When the input u is fixed, this system can be assimilated with a linear time-varying system for which we can build, under specific hypothesis as to the persistence of the input, an adaptive observer (towards the parameters z_θ) with exponential convergence (Zhang, 2002). We present here a particular formulation of this observer, due to Besançon et al. (2006), which can be used to establish the tight link between this observer and the exponential forgetting factor observer above:

$$\begin{aligned} \dot{\hat{z}}_x =& A_1(u, y)\hat{z}_x + \varphi_1(u) + A_2(u, y)\hat{z}_\theta + \\ &+ \left[\Lambda S_\theta^{-1}\Lambda^T C_1^T + S_x^{-1}C_1^T\right]Q(y - C_1\hat{z}_x) \\ \dot{\hat{z}}_\theta =& S_\theta^{-1}\Lambda^T C_1^T Q(y - C_1\hat{z}_x) \\ \dot{\Lambda} =& \left[A_1(u, y) - S_x^{-1}C_1^T Q C_1\right]\Lambda + A_2(u, y) \\ \dot{S}_x =& -\lambda_x S_x - A_1(u, y)^T S_x - S_x A_1(u, y) + C_1^T Q C_1 \\ \dot{S}_\theta =& -\lambda_\theta S_\theta + \Lambda^T C_1^T Q C_1 \Lambda \end{aligned}$$

where $S_x(0)$, $S_\theta(0)$ and Q are positive definite matrices and λ_x and λ_θ are sufficiently high positive constants. The two tuning parameters allow us to obtain different convergence speeds for the estimation of z_x and z_θ. When $\lambda_x = \lambda_\theta$, it is shown in (Besançon et al., 2006) that this observer coincides with the exponential forgetting factor observer above, whose objective is the estimation of $z = \left[\begin{smallmatrix} z_x \\ z_\theta \end{smallmatrix}\right]$.

5. SIMULATION RESULTS

The performances of the exponential forgetting factor observer and adaptive observer were compared through simulation tests performed upon a speed control loop. The parameters of the induction motor model (1) were taken from a 7.5 kW motor with two pairs of poles, 1450 rpm rated speed and 16 A rated current, available at the control systems department of GIPSA-lab:

$$L_s = 0,097 \text{ H} \qquad L_r = 0,091 \text{ H} \qquad M = 0,091 \text{ H}$$
$$R_s = 0,63 \ \Omega \qquad R_r = 0,4 \ \Omega$$

for of the electrical parameters and

$$J_m = 0,22 \text{ kg} \cdot \text{m}^2 \qquad f_v = 0,001 \text{ N} \cdot \text{s/rad}$$

for the mechanical ones. In addition, changes of the resistances due to increases in the temperature were simulated through ramp evolutions of 10 % per minute in the case of R_s and 15 % per minute in the case of R_r.

The induction motor model was driven by a PWM voltage waveform generated by an ideal switches model of a voltage source inverter with 1 kHz sampled vector control. At its turn, the inverter model received the reference vector from a torque and flux controller obtained through available feedback linearization techniques (Isidori, 1995) applied to motors (e.g. as in (von Raumer et al., 1994)). Finally, speed regulation was performed through a PI controller.

The variables involved in the control laws were replaced by estimates provided by the observer whenever possible. Noise with enough bandwidth so to be assimilated with white noise was added to the measured signals, with peak values of about 10 mV in the case of the stator voltages and about 40 mA in the case of the stator currents.

The simulated scenario was as follows. Starting with the motor at rest and no load applied, the speed set point is set to 50 rad/s. At $t = 6$ s a load of 10 Nm (about 20% of the rated torque of the motor) is smoothly applied in steady-state conditions. At $t = 9$ s, after the stabilization of the observer and controller, the speed set point is set to 100 rad/s, followed at $t = 12$ s by another smooth change of 10 Nm in the load. At $t = 16$ s the speed set point is set to 0 rad/s and finally, at $t = 23$ s to 20 rad/s where it is kept until the end of the simulation, which occurs at $t = 30$ s.

We shall first present the results obtained with the exponential forgetting factor observer. Here, the value of the tuning parameter λ has to be such that a compromise be achieved between the speed of the observer and the influence of the measurement noise on the estimates. By setting $\lambda = 15$, we obtain the results presented in Figs. 1–4.

Overall, we observe very good speed tracking even at low speeds and acceptable regulation thanks to good response from the observer to disturbances. This comes however at the expense of fairly high influence of the measurement noise on the estimates, which, except for the stator resistance, is more important at low speeds. For instance, at zero mechanical speed we can read variations up to 10% in the estimation errors of L_s, $\frac{L_r}{R_r}$ and σ.

These results suggest that the observer should be faster for better rejection of perturbations in the estimates, hence for better speed regulation, but also that it should be slower as far as the parameters are concerned, for lower measurement noise influence. We try to achieve such an effect with the adaptive observer, by setting $\lambda_x = 25$ and $\lambda_\theta = 3$. The obtained results are presented in Figs. 5–8.

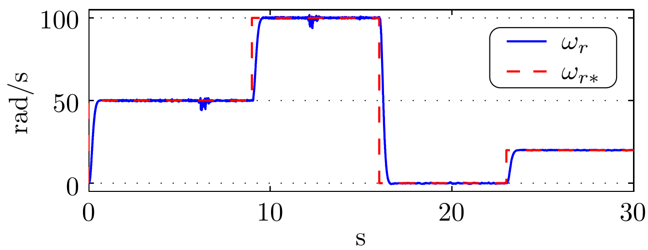

Fig. 1. Speed tracking with the exponential forgetting factor observer.

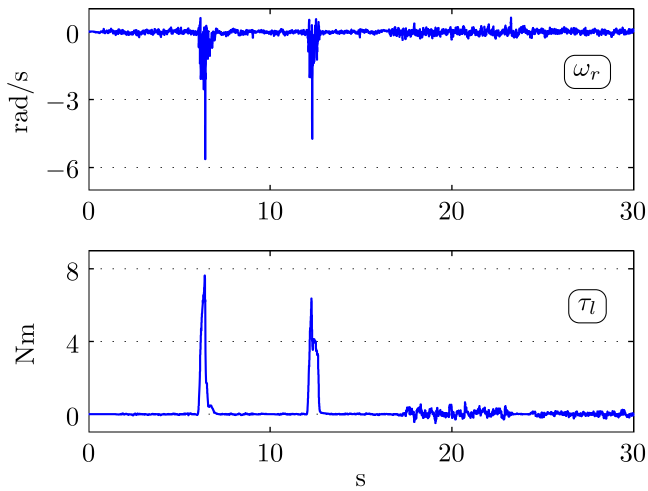

Fig. 2. Estimation errors in the mechanical equation with the exponential forgetting factor observer.

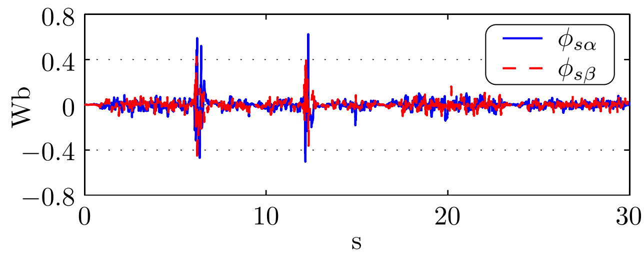

Fig. 3. Flux estimation errors with the exponential forgetting factor observer.

We obtain better speed regulation than in the preceding case, thanks to better rejection by the observer of the disturbances induced by the changes in the load torque. The influence of the measurement noise is much lower as far as the parameters are concerned while the observer is still able to cope with ramp evolutions of the resistances that simulate changes due to temperature increase.

6. CONCLUSIONS

A comparison in simulation between the exponential forgetting factor and adaptive observers has shown that as far as the state and parameters simultaneous estimation

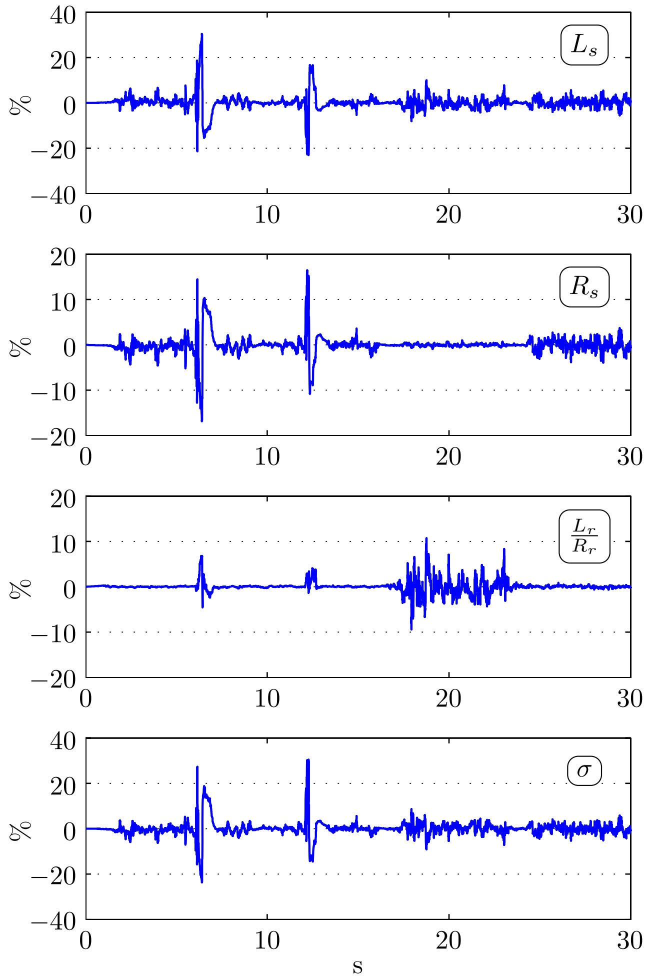

Fig. 4. Parameter estimation errors with the exponential forgetting factor observer.

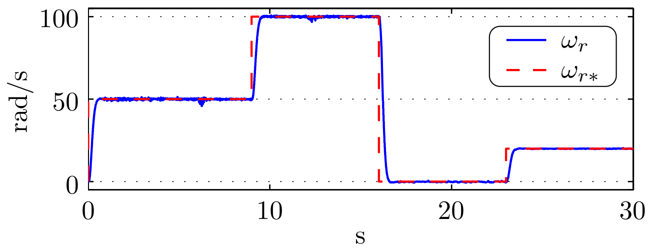

Fig. 5. Speed tracking with the adaptive observer.

in induction motors is concerned, the adaptive observer is more adequate for control purposes as it can combine fast state estimation with satisfactory parameter adaptation, which provides more robustness towards the measurement noise.

It would be interesting to confront these results with experimental ones, which requires a discrete-time approach of the problem. An available discrete-time formulation of the exponential forgetting factor observer (Besançon, 1996) has already been used for the estimation of the induction motor, with both simulated and real data (Ţiclea and Besançon, 2006b). The adaptive observer also possesses a discrete-time counterpart (Guyader and Zhang, 2003). However, it is not yet clear whether there exists

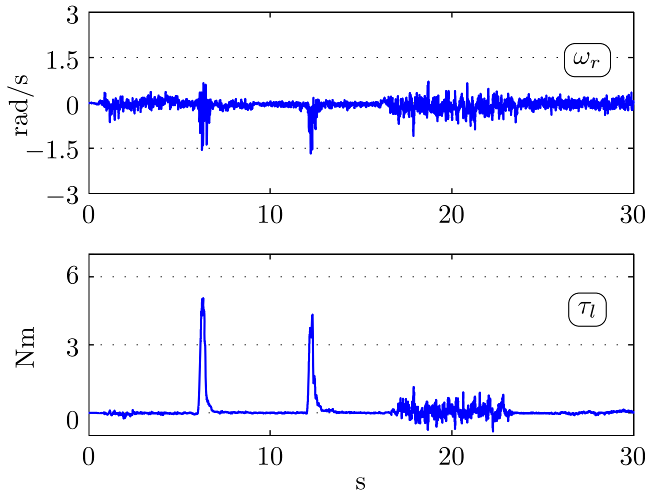

Fig. 6. Estimation errors in the mechanical equation with the adaptive observer.

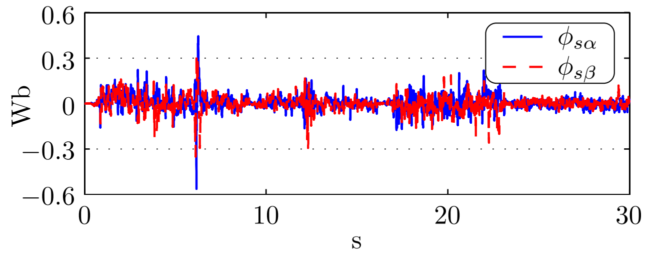

Fig. 7. Flux estimation errors with the adaptive observer.

an equivalence relation between the exponential forgetting factor observer and the adaptive observer in discrete-time as well, this aspect being currently under study.

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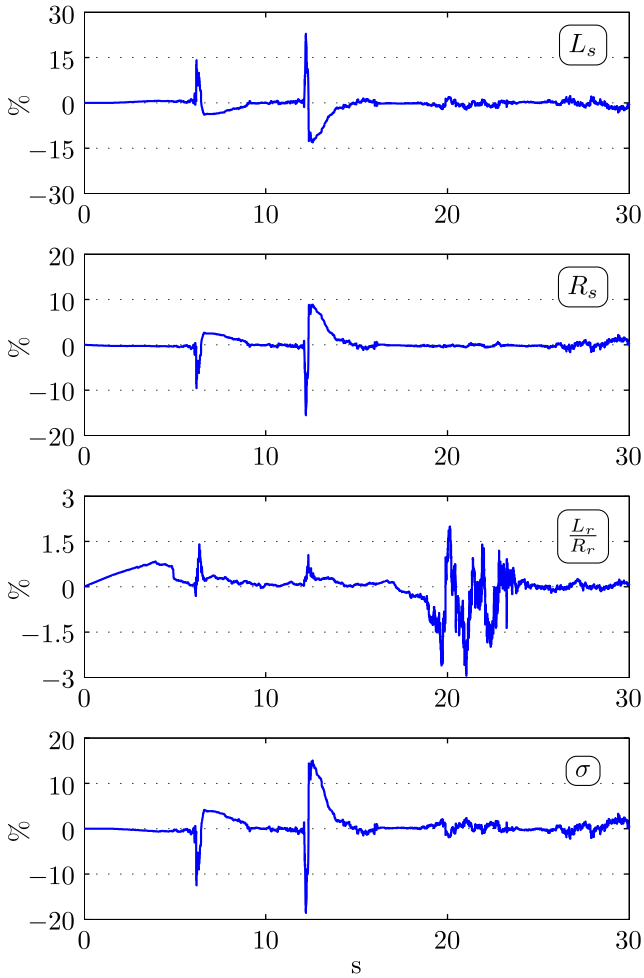

Fig. 8. Parameter estimation errors with the adaptive observer.

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