ROTOR FLUX AND SPEED ESTIMATION IN INDUCTION MOTORS BASED ON SLIDING MODE OPERATING IN LOW SPEED CONDITIONS

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Abstract – **This work proposes a modification to a robust state observer based on the concept of sliding mode for rotor flux and motor speed estimation. The sliding mode observer characteristics are refined by proposing a new procedure for rotor flux integration, allowing appropriate estimation in a wide speed range. The flux and speed estimates are employed in the direct field oriented control system and they are evaluated considering transient behavior, static accuracy, robustness to noise, parametric variation and different operation speeds. The performance is also compared with that provided by the extended Kalman filter flux estimator proposed by [1] associated with an adaptive speed estimator [2].**

KEYWORDS

Induction motors; Velocity control; Sliding mode; Extended Kalman Filter; Estimation algorithms; Field oriented control.

I. INTRODUCTION

The field-oriented control technique has been widely used for high-performance applications. The rotor flux and speed determination is the main implementation problem. The two basic approaches are: a) direct sensing; b) estimators and observers systems.

The use of sensors brings severe disadvantages in cost terms, reliability and immunity the noise, degrading the drive system performance. The estimation techniques based on the mathematical model of the induction motor (IM) are affected by parametric variations, mainly the rotor resistance, due to changes in the IM operating temperature [3].

Speed estimation systems that use Reference Model Adaptive Systems (MRAS) presents stability and robustness to parametric variations on a large speed operation range, but its performance is deficient in low speeds [2]. Aiming at removing this, in the present article a speed sensor-less system is presented using a robust flux and speed rotor observer based on sliding mode. These techniques have been explored for providing good properties, as insensitivity to parametric variations and noises, external disturbance rejection and fast dynamic response [4].

The procedure based on sliding mode considered in [5], although efficient, presents problems in low operation speeds due to the approach used for the pure integrator in the determination of the rotor flux estimation. In this work we blend the approach presented in [5] combined with a strategy inspired by [6], resulting in a good performance.

Simulations and performance comparisons between the proposed algorithm and the works developed for [1] and [2] are presented.

In section II the mathematical model of the induction motor is presented. Section III deals with the configuration of the direct field-oriented control system. A summary of the rotor flux and speed simultaneous estimators is presented in section IV. The results and performance comparisons are found in section V, and the conclusions in section VI.

II. IM MATHEMATICAL MODEL

The dynamic model of an IM in the stationary reference frame ($\alpha - \beta$), using the nomenclature based on [7], can be described as

$$\begin{bmatrix} \dot{i}_{s\alpha} \\ \dot{i}_{s\beta} \end{bmatrix} = \begin{bmatrix} -\left(\dfrac{R_s}{\sigma L_s} + \dfrac{1-\sigma}{\sigma T_r}\right) & 0 \\ 0 & -\left(\dfrac{R_s}{\sigma L_s} + \dfrac{1-\sigma}{\sigma T_r}\right) \end{bmatrix} \begin{bmatrix} i_{s\alpha} \\ i_{s\beta} \end{bmatrix} + \frac{1}{\sigma L_s} \begin{bmatrix} V_{s\alpha} \\ V_{s\beta} \end{bmatrix} + \begin{bmatrix} \dfrac{L_m}{\sigma L_s L_r' T_r} & \dfrac{L_m}{\sigma L_s L_r'} w_r \\ -\dfrac{L_m}{\sigma L_s L_r'} w_r & \dfrac{L_m}{\sigma L_s L_r' T_r} \end{bmatrix} \begin{bmatrix} \phi_{r\alpha}' \\ \phi_{r\beta}' \end{bmatrix} \tag{1}$$

$$\begin{bmatrix} \dot{\phi}_{r\alpha}' \\ \dot{\phi}_{r\beta}' \end{bmatrix} = \begin{bmatrix} -\dfrac{1}{T_r} & -w_r \\ w_r & -\dfrac{1}{T_r} \end{bmatrix} \begin{bmatrix} \phi_{r\alpha}' \\ \phi_{r\beta}' \end{bmatrix} + \frac{L_m}{T_r} \begin{bmatrix} i_{s\alpha} \\ i_{s\beta} \end{bmatrix} \tag{2}$$

III. INDUCTION MOTOR DRIVE SYSTEM

The block diagram of the IM drive system with rotor flux reference field-oriented control, and rotor flux and speed estimation, is presented in Figure 1.

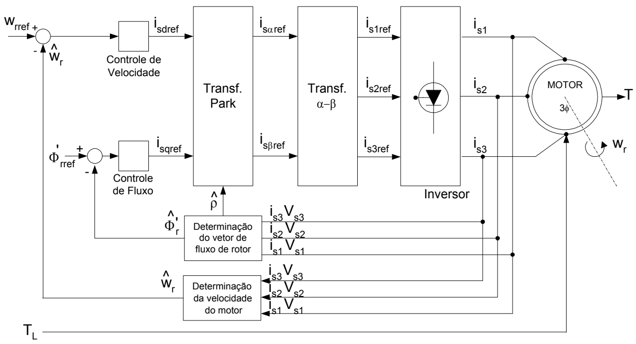

Figure 1. Direct field-oriented drive system.

By means of Park's transformation [7], the equations used for the control loop design are determined,

$$\Phi'_r = \frac{L_m}{(T_r p + 1)} i_{sd} \tag{3}$$

$$\frac{d\rho}{dt} = w_{\Phi' r} = w_r + \frac{L_m}{T_r \Phi'_r} i_{sq} \tag{4}$$

$$w_r = \frac{n}{(Jp + D)}(T - T_L) \tag{5}$$

$$T = \frac{n L_m}{L'_r} \Phi'_r i_{sq} \tag{6}$$

The rotor flux and speed control loop (Fig. 1) is implemented through a proportional-integral (PI) controller, and each of them is adjusted by means of the optimal performance index ITAE [8]. The IM nominal parameters and gains of the PI controller are presented in appendix A.

IV. FLUX AND SPEED ESTIMATORS

The flux and speed estimation algorithms considered in this work are robust observers based on sliding mode techniques, Kalman filters and MRAS. The main characteristics are summarized as follows.

4.1 Robust flux and speed observer based on sliding mode theory

The work proposed by [5] aims at bringing robustness to the parametric variations and external disturbance using sliding mode techniques. The flux and speed estimation system comprises a current observer, a rotor flux observer and a rotor speed estimator.

From (1) the dummy variables V_α and V_β are

$$\begin{bmatrix} V_\alpha \\ V_\beta \end{bmatrix} = \frac{1}{K_B} \begin{bmatrix} \dfrac{L_m}{\sigma L_s L'_r T_r} & \dfrac{L_m}{\sigma L_s L'_r} w_r \\ -\dfrac{L_m}{\sigma L_s L'_r} w_r & \dfrac{L_m}{\sigma L_s L'_r T_r} \end{bmatrix} \begin{bmatrix} \phi'_{r\alpha} \\ \phi'_{r\beta} \end{bmatrix} \tag{7}$$

$$= \frac{1}{K_B} \left\{ \begin{bmatrix} \dot{i}_{s\alpha} \\ \dot{i}_{s\beta} \end{bmatrix} + \begin{bmatrix} \left(\dfrac{R_s}{\sigma L_s} + \dfrac{1-\sigma}{\sigma T_r}\right) & 0 \\ 0 & \left(\dfrac{R_s}{\sigma L_s} + \dfrac{1-\sigma}{\sigma T_r}\right) \end{bmatrix} \cdot \begin{bmatrix} i_{s\alpha} \\ i_{s\beta} \end{bmatrix} - \frac{1}{\sigma L_s} \begin{bmatrix} V_{s\alpha} \\ V_{s\beta} \end{bmatrix} \right\}$$

The current and flux observer are proposed in the following

$$\begin{bmatrix} \dot{\hat{i}}_{s\alpha} \\ \dot{\hat{i}}_{s\beta} \end{bmatrix} = \begin{bmatrix} -\left(\dfrac{R_s}{\sigma L_s} + \dfrac{1-\sigma}{\sigma T_r}\right) & 0 \\ 0 & -\left(\dfrac{R_s}{\sigma L_s} + \dfrac{1-\sigma}{\sigma T_r}\right) \end{bmatrix} \begin{bmatrix} \hat{i}_{s\alpha} \\ \hat{i}_{s\beta} \end{bmatrix} + \frac{1}{\sigma L_s} \begin{bmatrix} V_{s\alpha} \\ V_{s\beta} \end{bmatrix} + K_B \begin{bmatrix} \hat{V}_\alpha \\ \hat{V}_\beta \end{bmatrix} + k \begin{bmatrix} \operatorname{sgn}(\hat{i}_{s\alpha} - i_{s\alpha}) \\ \operatorname{sgn}(\hat{i}_{s\beta} - i_{s\beta}) \end{bmatrix} \tag{8}$$

$$\begin{bmatrix} \dot{\hat{\phi}}'_{r\alpha} \\ \dot{\hat{\phi}}'_{r\beta} \end{bmatrix} = \frac{L_m}{T_r} \begin{bmatrix} \hat{i}_{s\alpha} \\ \hat{i}_{s\beta} \end{bmatrix} - \begin{bmatrix} \hat{V}_\alpha \\ \hat{V}_\beta \end{bmatrix} \tag{9}$$

where $\hat{V}_\alpha, \hat{V}_\beta, \hat{i}_{s\alpha}$ e $\hat{i}_{s\beta}$ are the observed value of $V_\alpha, V_\beta, i_{s\alpha}$ e $i_{s\beta}$, respectively, and the switching surface are defined as follows

$$s = \begin{bmatrix} \hat{i}_{s\alpha} - i_{s\alpha} \\ \hat{i}_{s\beta} - i_{s\beta} \end{bmatrix} \tag{10}$$

Subtracting (1) from (8) the following error dynamic is obtained,

$$\begin{bmatrix} \dot{e}_\alpha \\ \dot{e}_\beta \end{bmatrix} = \begin{bmatrix} -\left(\dfrac{R_s}{\sigma L_s} + \dfrac{1-\sigma}{\sigma T_r}\right) & 0 \\ 0 & -\left(\dfrac{R_s}{\sigma L_s} + \dfrac{1-\sigma}{\sigma T_r}\right) \end{bmatrix} \begin{bmatrix} e_\alpha \\ e_\beta \end{bmatrix} + K_B \begin{bmatrix} \hat{V}_\alpha - V_\alpha \\ \hat{V}_\beta - V_\beta \end{bmatrix} + k \begin{bmatrix} \operatorname{sgn}(\hat{i}_{s\alpha} - i_{s\alpha}) \\ \operatorname{sgn}(\hat{i}_{s\beta} - i_{s\beta}) \end{bmatrix} \tag{11}$$

The switching gain is designed via Lyapunov method, implying an error dynamic globally asymptotically stable, equation (11), if this gain is defined as [5]

$$k = \min \left\{ \begin{array}{l} \left(\dfrac{R_s}{\sigma L_s} - \dfrac{1-\sigma}{\sigma T_r}\right) \left|\hat{i}_{s\alpha} - i_{s\alpha}\right| - K_B (\hat{V}_\alpha - V_\alpha) \operatorname{sgn}(\hat{i}_{s\alpha} - i_{s\alpha}), \\ \left(\dfrac{R_s}{\sigma L_s} - \dfrac{1-\sigma}{\sigma T_r}\right) \left|\hat{i}_{s\beta} - i_{s\beta}\right| - K_B (\hat{V}_\beta - V_\beta) \operatorname{sgn}(\hat{i}_{s\beta} - i_{s\beta}) \end{array} \right\} - \delta \tag{12}$$

Based on the concept of the equivalent control, the system dynamic can be described as

$$\dot{s} = 0 \tag{13}$$

and, with an appropriate gain *k*, equation (12), the system described in (11) is asymptotically stable, and in sliding mode condition

$$\begin{bmatrix} \dot{e}_\alpha \\ \dot{e}_\beta \end{bmatrix} = \begin{bmatrix} e_\alpha \\ e_\beta \end{bmatrix} = 0 \tag{14}$$

According to (11) and (13), $\hat{V}_\alpha$, $\hat{V}_\beta$ can be obtained by

$$\begin{bmatrix} \hat{V}_\alpha \\ \hat{V}_\beta \end{bmatrix} = \frac{K}{K_B} \begin{bmatrix} V_\alpha \\ V_\beta \end{bmatrix} \tag{15}$$

where K is the switching function defined as

$$K = -k \begin{bmatrix} \mathrm{sgn}(\hat{i}_{s\alpha} - i_{s\alpha}) \\ \mathrm{sgn}(\hat{i}_{s\beta} - i_{s\beta}) \end{bmatrix} \tag{16}$$

Using equation (7) and results from equations (9) and (15), the speed estimator can be derived as follows

$$\hat{w}_r = \frac{\hat{V}_\alpha \hat{\phi}'_{r\beta} - \hat{V}_\beta \hat{\phi}'_{r\alpha}}{\hat{\phi}'^2_{r\alpha} + \hat{\phi}'^2_{r\beta}} \tag{17}$$

Figure 2 shows a block diagram of the rotor flux and speed estimator.

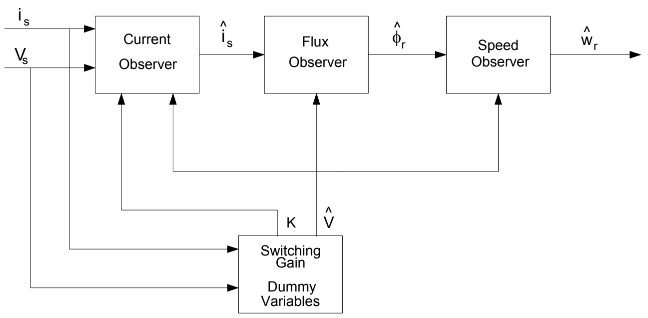

Figure 2. Block diagram of the speed observer system.

To reduce the chattering phenomena, the sign function is replaced by

$$\frac{s}{s+r}$$

$$r = \begin{cases} 0, & |s| \geq \xi \\ r_0, & |s| < \xi \end{cases} \tag{18}$$

where ξ e r_0 are positive constants. However, the precision and stability is not guaranteed when $|s| < \xi$. Therefore, looking for a behavior closer to that established by equation (12), ξ is set as small as possible, and the value of r_0 should be large enough to reduce the chattering phenomena effectively [5].

4.2 Robust flux and speed observer based on sliding mode theory with a programmable LPF

The rotor flux estimate is obtained through a pure integrator in (9), implying in drift and saturation problems. Thus, the pure integrator is usually replaced by a low pass filter (LPF). However, when the motor frequency is lower than the cutoff frequency of the LPF, an estimation error will be produced. On the other hand, setting a very low cutting frequency there still remains the drift problems due to the very large LPF time constant.

In this work we propose to replace the LPF with a fixed pole for a programmable LPF with variables pole and gain, with phase compensation, similar to the procedure used in [6] but in the rotor flux reference frame. At first, the pure integrator in (9) is replaced by a LPF, i.e.,

$$\frac{\hat{\phi}'_{rl}}{v_e} = \frac{1}{s+a} \tag{19}$$

where ϕ'_{rl} is the estimated rotor flux, a is the LPF pole and v_e is the integration term in equation (9). The LPF gain and phase compensation is derived from Figure 3 (Table I), where $\hat{w}_e$ is the estimated angular frequency of the signal v_e.

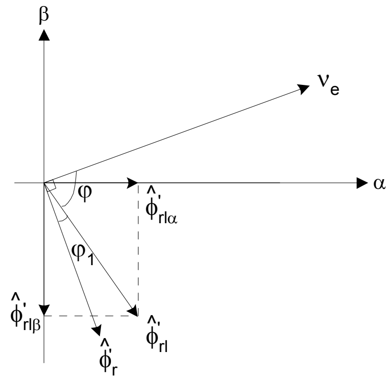

Figure 3. Programmable LPF and pure integrator diagrams.

Table I.
Pure integrator and LPF phase and gain compensation.

	Phase	Gain
Pure Integrator	90^o	$1/\hat{w}_e$
LPF	$-\tan^{-1}(\hat{w}_e/a)$	$1\Big/\sqrt{\hat{w}_e^2 + a^2}$
Compensation	$\exp(-j\varphi_1)$	$\sqrt{\hat{w}_e^2 + a^2}\Big/\lvert\hat{w}_e\rvert$

To solve drift and attenuation problems the pole a is allocated proportionally to the motor speed, that is

$$a = \frac{\hat{w}_e}{k_L} \tag{20}$$

where k_L is a positive constant.

Therefore, from (19) and (20)

$$\frac{\hat{\phi}'_{rl}}{v_e} = \frac{1}{s + (|\hat{w}_e|/k_L)} \frac{\sqrt{\hat{w}_e^2 + (\hat{w}_e/k_L)^2}}{|\hat{w}_e|} \exp(-j\varphi_1) \tag{21}$$

where

$$\exp(-j\varphi_1) = \frac{|\hat{w}_e| - j(\hat{w}_e/k_L)}{\sqrt{\hat{w}_e^2 + (\hat{w}_e/k_L)^2}} \tag{22}$$

The estimated value $\hat{w}_e$ is the angular frequency of the rotor flux components, $w_{\Phi r}$, obtained from (4). Figure 4 shows the programmable LPF.

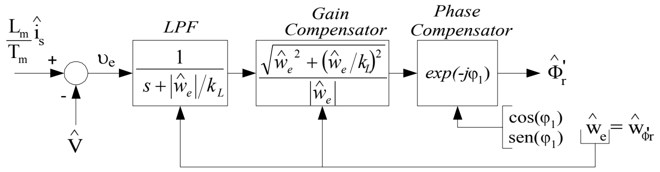

Figure 4. Block diagram for the programmable LPF

4.3 *Extended Kalman filter for rotor flux and speed estimation using MRAS technique*

The rotor flux estimation issue can also be dealt with by using a Kalman filter algorithm. The parameter identification problem can also be considered, by including the rotor resistance in the state vector and then using an extended Kalman filter [1].

The model of the estimation process, equation (2), is discretized and expressed as

$$\begin{bmatrix} \phi'_{r\alpha}(n+1) \\ \phi'_{r\beta}(n+1) \end{bmatrix} = \begin{bmatrix} 1-\dfrac{T_a R_r(n)}{L'_r} & -T_a w_r(n) \\ T_a w_r(n) & 1-\dfrac{T_a R_r(n)}{L'_r} \end{bmatrix} \begin{bmatrix} \phi'_{r\alpha}(n) \\ \phi'_{r\beta}(n) \end{bmatrix} \tag{23}$$

$$+\frac{T_a L_m R_r(n)}{L'_r} \begin{bmatrix} i_{r\alpha}(n) \\ i_{r\beta}(n) \end{bmatrix} + \begin{bmatrix} w_{r\alpha}(n) \\ w_{r\beta}(n) \end{bmatrix}$$

where $w_{r\alpha\beta}(n) = [w_{r\alpha}(n) w_{r\beta}(n)]^t$ represents the state noise and T_a is the sample time.

To determine the observation equation associated with the estimation process, (23), the voltage model, defined as

$$\begin{bmatrix} V_{s\alpha} \\ V_{s\beta} \end{bmatrix} = R_s \begin{bmatrix} i_{s\alpha} \\ i_{s\beta} \end{bmatrix} \frac{L_s L'_r - L_m^2}{L'_r} \begin{bmatrix} \dot{i}_{s\alpha} \\ \dot{i}_{s\beta} \end{bmatrix} + \frac{L_m}{L'_r} \begin{bmatrix} \dot{\phi}'_{r\alpha} \\ \dot{\phi}'_{r\beta} \end{bmatrix} \tag{24}$$

is discretized as follows

$$\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \phi'_{r\alpha}(n) \\ \phi'_{r\beta}(n) \end{bmatrix} - \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \phi'_{r\alpha}(n-1) \\ \phi'_{r\beta}(n-1) \end{bmatrix} =$$

$$\frac{T_a L'_r}{L_m} \left\{ \begin{bmatrix} V_{s\alpha}(n-1) \\ V_{s\beta}(n-1) \end{bmatrix} - R_S \begin{bmatrix} i_{s\alpha}(n-1) \\ i_{s\beta}(n-1) \end{bmatrix} \right\} - \sigma L_m \left\{ \begin{bmatrix} i_{s\alpha}(n) \\ i_{s\beta}(n) \end{bmatrix} - \begin{bmatrix} i_{s\alpha}(n-1) \\ i_{s\beta}(n-1) \end{bmatrix} \right\} \tag{25}$$

Therefore, the observation process is defined as

$$\begin{bmatrix} y_{r\alpha}(n) \\ y_{r\beta}(n) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \phi'_{r\alpha}(n) \\ \phi'_{r\beta}(n) \end{bmatrix} - \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \phi'_{r\alpha}(n-1) \\ \phi'_{r\beta}(n-1) \end{bmatrix} + \begin{bmatrix} Z_{r\alpha}(n) \\ Z_{r\beta}(n) \end{bmatrix} \tag{26}$$

where $Z_{r\alpha\beta}(n) = [Z_{r\alpha}(n) Z_{r\beta}(n)]^t$ represents the measurement noise. The state and measurement noise are assumed not correlated, with zero mean and covariance *Q* and *N*, respectively.

By defining the system state vector as $x(n) = \lfloor \phi'_{r\alpha}(n) \phi'_{r\beta}(n) R'_r(n) \rfloor$, the prediction and estimation equations proposed in [1] are written as

$$\hat{x}(n+1 \mid n) = f(\hat{x}(n \mid n), n) \tag{27}$$

$$\hat{x}(n+1 \mid n+1) = \hat{x}(n+1 \mid n) + K_{3x2}(y_r(n+1) - \hat{y}_r(n+1)) \tag{28}$$

The function $f(\hat{x}(n \mid n), n)$ represents the dynamic relation between states and input system variables, equation (23), $y_r(n+1)$ the output vector and K_{3x2} the gain matrix of the filter.

The estimated measurement vector, equation (26), is given by

$$\hat{y}_r(n) = H\hat{x}(n \mid n) + J\hat{x}(n-1 \mid n) \tag{29}$$

where *H* e *J* are defined as

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

The algorithm called delayed state filter [9] is used to obtain the filter gain matrix, in such form that the elements of the main diagonal of the covariance matrices are minimized.

The speed estimation is performed through the algorithm considered by [2], applying the MRAS technique, Fig. 5. The voltage model, (24), is regarded as a reference model and the current model, (1), as an adjustable model. The error between the states of the two models is then used to drive a suitable adaptation mechanism that generates the estimate $\hat{w}_r$,

$$\hat{w}_r = \left(k_1 + \frac{k_2}{p}\right)\varepsilon \tag{30}$$

where

$$\varepsilon \triangleq \hat{\phi}'_{r\alpha}\phi'_{r\beta} - \phi'_{r\alpha}\hat{\phi}'_{r\beta} \tag{31}$$

The filters applied to the MRAS solve the drift and initial conditions problems, but they bring attenuation problems in low speed operation. The gains k_1 and k_2 are calculated in accordance with the procedure described in [2].

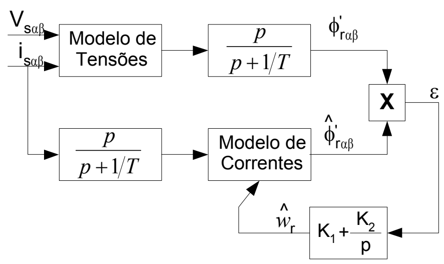

Figure 5. Block diagram of the speed estimation using MRAS technique.

V. SIMULATION RESULTS

The simulations of the direct field-oriented control and drive systems (Fig. 1) and the estimation algorithms were performed via, MATLAB®/SIMULINK. The estimation algorithms and the IM model are started simultaneously. The speed reference is a square wave with period 2 seconds and amplitude from 100 to –100 rad/s or 100 to 0 rad/s.

A low pass filter with cutoff frequency 5 Hz is used to smooth the estimated speed, due the presence of measurement noises.

The noise co variances applied on current and voltage measurement are $\sigma_{Vs}^2 = 4.0\,V^2$, $\sigma_{is}^2 = 0.25\,A^2$, and $\sigma_{wr}^2 = 1.0\,rad^2/s^2$ for the rotor speed measurement. The IM initial conditions are setting different from zero. In all cases the load torque is fixed in 10 Nm, and the reference value of the rotor flux is kept in 1.13 Wb. The rotor resistance is fixed at 50% of its nominal value.

5.1 Comparisons between LPF with fixed pole and programmable LPF

At first, a comparison is made between the application of the LPF with fixed pole and the programmable LPF, both employed for flux and speed estimator (Fig. 6).

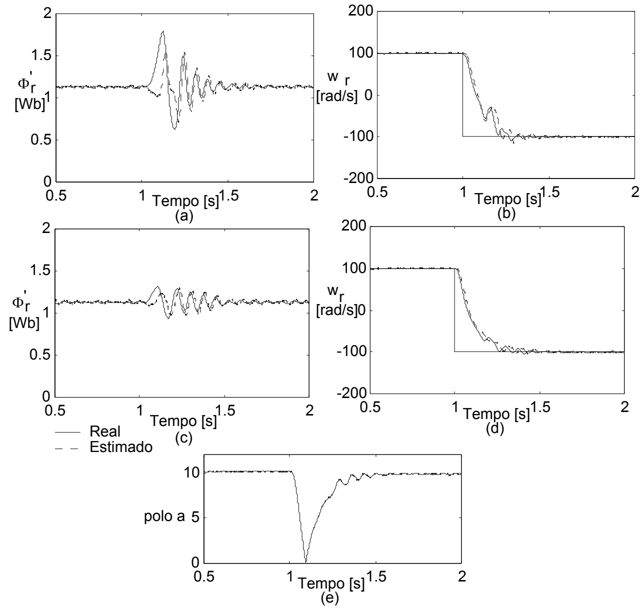

Figure 6. Robust rotor flux and speed observer with LPF (a)-(b) and programmable LPF (c)-(e).

The pole is fixed in 10, the constant k_L is adjusted to 10 and parameters r_0 and ξ setting in 2 e 0.05, respectively. A speed reference signal from 100 to -100 rad/s is applied.

5.2 Flux and speed estimation using a robust observer based on sliding mode

The robust observer with the programmable LPF of section 5.2 is used with the same setting parameters, and a speed reference signal of 100 to 0 rad/s, to evaluate its behavior in low speeds (Fig. 7).

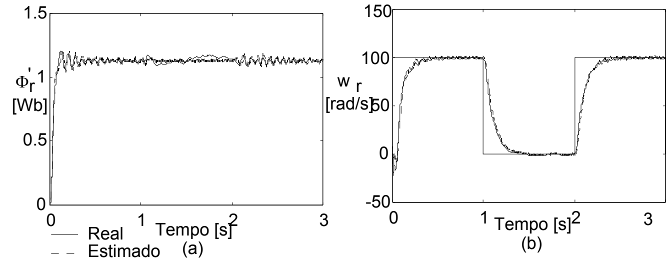

Figure 7. Robust rotor flux and speed observer based on sliding mode.

5.3 Flux and speed estimation using an extended Kalman filter associated with MRAS technique

The EKF setting parameters are: initial error covariance matrix $P(0) = diag(0.5, 0.5, 0.5)$; state noise covariance matrix, $Q = diag(1e-6, 1e-6, 1e-6)$; measurement noise covariance matrix $N = diag(1e-3, 1e-3)$ (Fig. 8).

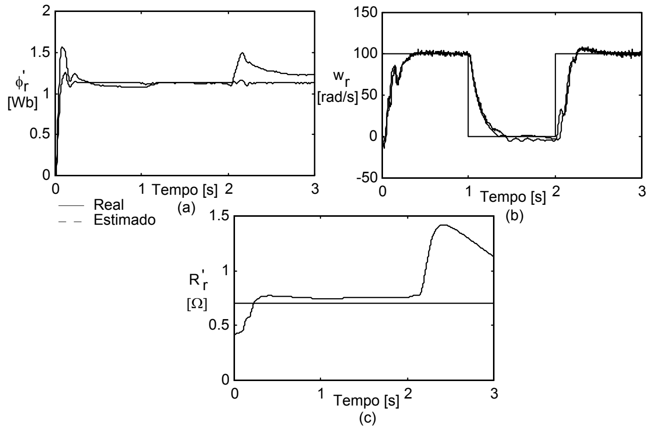

Figure 8. Extended Kalman filter for rotor flux and speed estimation associated with MRAS technique.

Figure 6 shows the effectiveness of the programmable LPF in speed reversion (100 to –100 rad/s), compared to the use of the LPF with fixed pole. The programmable LPF solves the drift and initial conditions problems, performing phase and gain compensation, alleviating the effects of the LPF (Fig.6 (a)-(b)), improving the quality of the estimate rotor flux (Fig. 6 (c)-(d)).

The two estimators considered in Figures 7 and 8 present satisfactory steady state performance, with average operation speed. The observer based on sliding mode theory presents a faster dynamic response and is more robust to the rotor resistance variation. The variation of the gain k in accordance with (12) brings stability and robustness to the parametric variations and external disturbances.

Figure 8 shows that the speed control is not affected by the incorrect rotor flux estimate, from 2 seconds (Fig. 8 (a)-(b)) onwards. It is also important to note that the rotor resistance estimation error degrades the flux estimation, interval 2-3 seconds, degrading the control system performance.

In the region of zero-speed operation, the MRAS system presents some difficulties (Fig. 8), and can even became unstable [2]. The use of the programmable LPF allows a better performance for the observer based on sliding mode in this region of operation (Fig. 7).

The rotor flux and speed estimator based on Kalman filter, as expected, presents low sensibility to the noise when compared to the robust observer with programmable LPF [2].

VI. CONCLUSIONS

In the present work it was evaluated the application of a low pass filter with variable pole, with phase and gain compensation, in a robust rotor flux and speed observer based on sliding mode.

The sliding mode based techniques provide robustness to the parametric variation and external disturbance, and a fast dynamic response. The application of the programmable LPF reduces the effects of the standard LPF, allowing a better performance of the algorithm in lower speeds of operation. Moreover, comparisons are made with the proposal in [1], where an extended Kalman filter combined with MRAS technique is used to estimate both rotor flux and speed.

APPENDIX A

TABLE II
IM nominal parameters.

R_S	L_S	R'_R	L'_R	L_m	J	n
0.728 Ω	0.0996 H	0.706 Ω	0.0996 H	0.0969 H	0.062 kg m^2	4

TABLE III
IM nominal conditions

380 V	16.5A	7.5kW	50 Hz

TABLE IV
IM Loop control parameters

$k_{p\Phi}$	$k_{i\Phi}$	$G_{p\Phi}$
66.11	2047.40	$\frac{30.97}{p+30.97}$
k_{pw}	k_{iw}	G_{pw}
0.25	2.29	$\frac{8.92}{p+8.92}$

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