Observability Analysis Of The Induction Motor State Space Models

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Abstract— **The implementation of direct field oriented control techniques usually employs nonlinear estimate algorithms that should consider parametric variations as well as different operation conditions [4]. In the present work, the local nonlinear observability of discrete observer algorithms (complete and reduced order), based on the current and voltage models of the induction motor, are analyzed in a detailed form. Different operation conditions, dependent of the instantaneous speed, load torque, parametric variations and addition of a small perturbation signals in the rotor flux reference, are considered. Simulations using two suitable deterministic observers based on the extended Kalman Filter [9] are also presented to ilustrate the usefulness of the proposed observability analysis.**

Keywords— **Nonlinear Observability Analysis, Extended Kalman Observers; Nonlinear Systems; Induction Motor; Field Oriented Control.**

I. Introduction

One of the most useful techniques, with the aim of electric machines variables estimation, is the extended Kalman Filter (EKF). Once the states and parameters simultaneous estimation can be naturally considered as a nonlinear filtering problem, and given the inherent nonlinearties of the electric and mechanic induction motor (IM) models, the EKF becomes a suitable option in the electric drives field, see [1], [2] and [3].

Regarding the robustness requirements that power applications demand, it is extremely important to accomplish a rigorous convergence analysis of the control system and the estimation algorithms used. In the extended Kalman filter case, besides considering the flux variables estimation (necessary for flux magnitude and torque decouple in field oriented control), several works add electric and mechanical variables to the state vector, thereby solving a parameter identification problem, [2], [1] and [4]. On the other hand, practically none of this works consider the stability analysis, as a function of the nonlinear servo-drive characteristics, of the estimation algorithm.

The convergence proof of the nonlinear deterministic filter is based on two fundamental conditions [5]:

a) The estimation error covariance matrix is observable in the wide sense [6], i.e., limited error covariance matrices.

b) The filter converges locally, i.e., the state estimation vector converge to the real one as long as $t \to \infty$.

The present work main contribution is the determination and evaluation of the observability matrices of the IM state space models in well defined operation conditions of a motor drive system, condition (a). This analysis are not, as far as the authors are aware, available in the literature.

For both, complete and reduced order models, a deterministic version of the Kalman filter is used to estimate the rotor flux and identify the rotor resistance simultaneously. The estimation algorithms, one proposed by [7] and [8], the other by [9], whose convergence analysis is a function of the linear matrix inequalities (LMI) supplied by the condition of a decreasing Lyapunov function, condition (b).

In section 2, the IM state space models are presented as well as the estimation algorithms and the proper observability matrices. The observability matrices evaluation in different operation conditions (considering operation speed, load torque, parametric variations and addition of disturbance signals in the flux reference) is detailed in the section 3. Simulations where the theoretical conclusions are verified and where different characteristics of a real implementation are considered (voltage inverter with PWM algorithms and antialiasing filters) are presented in section 4. The main conclusions of the work are described in the section 5.

II. IM State Space Models

In the present section the IM models used in the state space observers, complete order (COO) and reduced order (ROO), are presented. Once rotor resistance variation is assumed, deterministic observers based on the extended Kalman filter are used to estimate the electromagnetic variables and for the resistance identification. The observability matrices are also presented for the analysed models. Stator coordinates, $\alpha - \beta$, are used as reference coordinates in the models.

A. Complete Order

The IM state equation, used for the COO design, is given by the following discrete domain expression,

$$\begin{bmatrix} i_{S\alpha\beta(k+1)} \\ \Phi_{R\alpha\beta(k+1)} \end{bmatrix} =$$
$$\begin{bmatrix} \left[1 - \frac{(R_S L_R^2 + R_R L_m^2) T_a}{\sigma L_S L_R^2}\right] I & \frac{L_m T_a}{\sigma L_S L_R} \left(\frac{R_R}{L_R} I - w_m J_c\right) \\ \frac{R_R L_m T_a}{L_R} I & \left(1 - \frac{R_R T_a}{L_R}\right) I + w_m T_a J_c \end{bmatrix}$$
$$\begin{bmatrix} i_{S\alpha\beta(k)} \\ \Phi_{R\alpha\beta(k+1)} \end{bmatrix} + \begin{bmatrix} \frac{1}{\sigma L_S} I \\ 0_{2\times2} \end{bmatrix} v_{S\alpha\beta} \tag{1}$$

The observation process is represented by the stator current vector, more precisely

$$y_{(k)} = \begin{bmatrix} I & 0_{2\times2} \end{bmatrix} \begin{bmatrix} i_{S\alpha\beta(k)} \\ \Phi_{R\alpha\beta(k+1)} \end{bmatrix} \tag{2}$$

where $\Phi_{R\alpha\beta(k)} = \left[\phi_{R\alpha(k)}, \phi_{R\beta(k)}\right]^T$, $i_{S\alpha\beta(k)} = \left[i_{S\alpha(k)}, i_{S\beta(k)}\right]^T$ and $v_{S\alpha\beta(k)} = \left[v_{S\alpha(k)}, v_{S\beta(k)}\right]^T$ represent the rotor flux, stator currents and voltages vectors, respectively. T_a represent the sampling time, I represent the dimension 2 identity matrix, J_c the matrix defined as $J_c = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$ and $0_{2\times2}$ the null matrix. The parameter values used in the simulations are presented in the Appendix.

Once the complete order state space model, equations (1)-(2), presents standard dynamic and output equations (i.e. they only depend on the actual states), the deterministic observer proposed in [8] is used for the IM rotor flux estimation. The algorithm design matrices are defined as,

$$R_{k+1} > 0 \tag{3}$$
$$Q_k = \zeta e_k^T e_k I_n + \delta I_n \tag{4}$$

where $\zeta > 0$ should be chosen sufficiently high, particularly for inadequate initializations, and $\delta > 0$ sufficiently small to avoid the matrix Q_k assuming singular values in steady state. As for matrix R_{k+1}, once that no nonlinearty exists in the system observation process, equation (2), it is only necessary that this matrix be positive defined to guarantee the algorithm convergence, [5], [8].

Once the complete order model output equation presents a standard format, equation (2), and defining the estimate state vector (order 5) as

$$\widehat{x} = \left[\widehat{i}_{S\alpha\beta}^T \; \widehat{\Phi}_{R\alpha\beta}^T \; \widehat{R}_R\right]^T \tag{5}$$

the observability matrix is given by [8]

$$O_{k-N+1} = \begin{bmatrix} H_{k-N+1} \\ H_{k-N+2} F_{k-N+1} \\ \vdots \\ H_k F_{k-1} F_{k-2} \ldots F_{k-N+1} \end{bmatrix} \tag{6}$$

For the IM particular case, equations (1)-(2), the linearized dynamic matrix, F_k, and the output matrix, H_k, are given by

$$F_k = \begin{bmatrix} F_k^{11} & F_k^{12} & F_k^{13} \\ F_k^{21} & F_k^{22} & F_k^{23} \\ 0_{1\times2} & 0_{1\times2} & 1 \end{bmatrix} \tag{7}$$

and

$$H_k = \begin{bmatrix} I & 0_{2\times2} & 0_{2\times1} \end{bmatrix} \tag{8}$$

where

$$F_k^{11} = \left(1 - \frac{\left(R_S L_R^2 + \widehat{R}_{R(k)} L_m^2\right) T_a}{\sigma L_S L_R^2}\right) I \tag{9}$$

$$F_k^{12} = \frac{L_m T_a}{\sigma L_S L_R} \left(\frac{\widehat{R}_{R(k)}}{L_R^2} I - w_{m(k)} J_c\right) \tag{10}$$

$$F_k^{13} = \frac{L_m T_a \left(\widehat{\Phi}_{R\alpha\beta(k)} - L_m i_{S\alpha\beta(k)}\right)}{\sigma L_S L_R^2} \tag{11}$$

$$F_k^{21} = \left(\frac{\widehat{R}_{R(k)} L_m T_a}{L_R}\right) I \tag{12}$$

$$F_k^{22} = \left(1 - \frac{\widehat{R}_{R(k)} T_a}{L_R}\right) I + w_{m(k)} T_a J_c \tag{13}$$

$$F_k^{23} = -\frac{T_a \left(\widehat{\Phi}_{R\alpha\beta(k)} - L_m i_{S\alpha\beta(k)}\right)}{L_R} \tag{14}$$

B. Reduced Order

For the ROO design we consider the second order discrete version of the usually denominated IM "current model", more precisely

$$\Phi_{R\alpha\beta(k+1)} = \left[\left(1 - \frac{T_a R_R}{L_R}\right) I + T_a w_{m(k)} J_c\right] \Phi_{R\alpha\beta(k)} + \frac{T_a Lm R_R}{L_R} i_{S\alpha\beta(k)} \tag{15}$$

The observation process is based on the "voltage model", and it is represented by the following discrete equation

$$\begin{aligned} y_{(k)} &= \Phi_{R\alpha\beta(k)} - \Phi_{R\alpha\beta(k-1)} \\ &= \frac{T_a L_R}{Lm} \left\{v_{S\alpha\beta(k-1)} - R_S i_{S\alpha\beta(k-1)}\right\} \\ &- \sigma L_m \left\{i_{S\alpha\beta(k)} - i_{S\alpha\beta(k-1)}\right\} \end{aligned} \tag{16}$$

or in a general way

$$y_k = H_k \; x_k + J_k \; x_{k-1} \tag{17}$$

As we can see in the observation process, equation (16), the system output depends on the actual and previous state. The *Delayed State Kalman Filter (DSKF)* [10], deal with this particularity modifying the standard Kalman filter algorithm in way to consider the unitary delay in the minimization procedure of the estimation error covariance matrix. In [9], the convergence analysis proposed in [7] and [8], is extended for this particular type of systems, proposing the *Delayed State Extended Kalman Observer (DSEKO)*. The design matrices of this new deterministic version of the DSKF are

$$R_{k+1} = J_{k+1}\left(P_k^{-1} + F_k^T Q_k^{-1} F_k\right)^{-1} J_{k+1}^T \quad (18)$$

$$Q_k = \zeta e_k^T e_k I_n + \delta I_n \quad (19)$$

where ζ and δ are chosen in the same way that in complete order model case.

Once the reduced order observer presents an output equation with an unit delay, equation (17), and defining the following state vector estimate (order 3),

$$\widehat{x} = \left[\widehat{\Phi}_{R\alpha\beta}^T \ \widehat{R}_R\right]^T \quad (20)$$

the observability matrix is given by [9]

$$O_{k-N+1} = \begin{bmatrix} H_{k-N+1} + J_{k-N+1}F_{k-N+1}^{-1} \\ \left(H_{k-N+2} + J_{k-N+2}F_{k-N+2}^{-1}\right) F_{k-N+1} \\ \vdots \\ \left(H_k + J_k F_k^{-1}\right) F_{k-1}F_{k-2}...F_{k-N+1} \end{bmatrix} \quad (21)$$

For the particular case of the IM model, equations (15)-(16), the linearized dynamic matrix, F_k, and the output matrices, H_k and J_k, are given by

$$F_k = \begin{bmatrix} F_k^{11} & F_k^{12} \\ 0_{1\times 2} & 1 \end{bmatrix} \quad (22)$$

and

$$H_k = \begin{bmatrix} I & 0_{2\times 1} \end{bmatrix} \quad (23)$$

$$J_k = \begin{bmatrix} -I & 0_{2\times 1} \end{bmatrix} \quad (24)$$

where

$$F_k^{11} = \left(1 - \frac{\widehat{R}_{R(k)}T_a}{L_R}\right) I + w_{m(k)} T_a J_c \quad (25)$$

$$F_k^{12} = -\frac{\left(\widehat{\Phi}_{R\alpha\beta(k)} - L_m i_{S\alpha\beta(k)}\right)}{L_R} \quad (26)$$

It should be stressed that the extended Kalman filter presents appropriate convergence characteristics when the initial estimates are close of the real state and when the nonlinearties are smooth. The choice represented in equations (3)-(4) and (18)-(19) attempts to enlarge the interval in which the linearization is efficient. In this way it is possible to make a rigorous convergence analysis of the algorithms and verify an increase of the system robustness to high nonlinearties and bad initial conditions, [8] and [9].

III. IM Observability Analysis

Once deterministics observers are used for state estimation and parametric identification, the models local uniform observability can be verified determining the observability matrix rank value, equations (6) and (21) [8]. In the IM specific case, the observability analysis should be accomplished for the different operation conditions in which the servo-drive is operated.

In the present work, three important operation conditions are considered in the observability characteristics evaluation of the IM, when applied in servo-drives,

i) Steady state in all magnitudes (electromagnetic and mechanic) and fine tuned field oriented control (i. e. constant speed and constant flux magnitude).

ii) Different operation speed and load torque values, including null ones.

iii) Disturbance signal addition in the rotor flux magnitude reference.

Observations:

a) With regard to condition i), once the present work intends to evaluate in a rigorous way the estimation algorithms, steady state is assumed to avoid electromagnetic transients that could increase the persistent excitation of the input signals.

b) Once the field oriented control is the main application of the estimation algorithms being analysed, it is important to assume speed and flux magnitude appropriately regulated.

c) Concerning condition iii), the disturbance signal addition aims the observability properties recovery.

Now, the simplifications that each one of the operation conditions imposes into the observability matrix, for each one of the models, are presented. The effect produced in the observability matrix rank value is also exhibited in different result tables.

A. Steady State With Non Null Speed Values

Assuming steady state and balanced sine wave input signals, the rotor flux vector can be approximate by[11]

$$\phi_{R\alpha(k)} = |\Phi_R| \cos(w_s k) \quad (27)$$

$$\phi_{R\beta(k)} = |\Phi_R| \sin(w_s k) \quad (28)$$

where w_s represents the synchronous frequency and the flux vector magnitude is defined as $|\Phi_R| =$

$\sqrt{\phi^2_{R\alpha(k)} + \phi^2_{R\beta(k)}}$. Assuming a constant rotor flux vector magnitude , i.e., fine tuned field oriented control, and differentiating the equations (27)-(28), we obtain

$$\dot{\phi}_{R\alpha(k)} = -w_s \phi_{R\beta(k)} \tag{29}$$

$$\dot{\phi}_{R\beta(k)} = w_s \phi_{R\beta(k)} \tag{30}$$

Replacing the equations (29)-(30) into the IM current model, it is possible to determine the steady state stator current equations, more precisely

$$i_{S\alpha\beta(k)} = \frac{1}{L_m}\left[I + \frac{L_R}{R_R}\left(w_s - w_{m(k)}\right) J_c\right] \Phi_{R\alpha\beta(k)} \tag{31}$$

The observability characteristics, assuming steady state and non null operation speeds, are evaluated substituting the equations (31) into the observability matrices and determining the correspondent rank value.

It is important to note that the synchronous frequency, w_s, assumes the same values that the rotor speed at steady state and null load torque [12]. In table I the simplifications accomplished in the observability matrix and the correspondent rank values are presented.

TABLE I

Observability matrix rank in steady state and non null speeds.

Observability matrix, assuming:	COO	ROO
Equation (31)	5	3
Constant speed($w_{m(k)} = w_m$)	5	3
Null load torque($T_l = 0$, $w_s = w_m$)	5	3
Constant estimates($\widehat{R}_{R(k)} = \widehat{R}_R$)	5	3

As it is possible to observe in table I, assuming steady state and non null speeds, the complete and reduced order observers maintains the observability properties.

B. Steady State and Null Operation Speeds

In the null operation speeds case, the observability characteristics are evaluated replacing the equation (31) in the corresponding observability matrices and equating the speed variable to zero. Once the synchronous speed is governed by the following equation [12]:

$$w_s = w_m + \frac{d\delta}{dt} \tag{32}$$

where δ represents the torque angle, it is possible to verify that for steady state, null operation speeds and null load torque, the synchronous speed also presents null values. Therefore, in this conditions, the components of the rotor flux, equations (27)-(28), are give by

$$\phi_{R\alpha(k)} = |\Phi_R| \tag{33}$$

$$\phi_{R\beta(k)} = 0 \tag{34}$$

where $|\Phi_R|$ represents the rotor flux magnitude.

In the following table we present the simplifications accomplished in the observability matrix as well as the corresponding rank value.

TABLE II

Observability matrix rank in steady state and null speed.

Observability matrix, assuming:	COO	ROO
Equation (31)	5	3
Null speed($w_{m(k)} = 0$)	5	3
Null load torque ($T_l = 0$, $w_s = 0$, $\phi_{R\alpha(k)} = \lvert\Phi_R\rvert$, $\phi_{R\beta(k)} = 0$)	5	3
Constant estimates ($\widehat{R}_{R(k)} = \widehat{R}_R$, $\widehat{\phi}_{R\alpha\beta(k)} = \widehat{\phi}_{R\alpha\beta}$)	4	2

As table II shows, assuming steady state, null speed and null load torque, both complete and reduced order observers loose observability properties. It is important to note that the constant estimates case depends on steady state operation and no persistent excitation.

C. Disturbance Signal Addition in the Flux Reference

Assuming a time varying rotor flux magnitude and differentiating the equations (27)-(28), we obtain

$$\dot{\phi}_{R\alpha(k)} = \frac{d\,|\Phi_R|}{dt}\cos\left(w_s t\right) - w_s \phi_{R\beta(k)} \tag{35}$$

$$\dot{\phi}_{R\beta(k)} = \frac{d\,|\Phi_R|}{dt}\sin\left(w_s t\right) + w_s \phi_{R\alpha(k)} \tag{36}$$

Replacing the equations (35)-(36) into the IM current model, equation (15), the stator current steady state equations are obtained, more precisely,

$$\begin{aligned} i_{S\alpha(k)} &= \frac{d\,|\Phi_R|}{dt}\frac{L_R\cos\left(w_{s(k)}\right)}{L_m R_R} + \frac{\phi_{R\alpha(k)}}{L_m} \\ &\quad - \frac{L_R}{L_m R_R}\left(w_s - w_{m(k)}\right)\phi_{R\beta(k)} \end{aligned} \tag{37}$$

$$\begin{aligned} i_{S\beta(k)} &= \frac{d\,|\Phi_R|}{dt}\frac{L_R\sin\left(w_{s(k)}\right)}{L_m R_R} + \frac{\phi_{R\beta(k)}}{L_m} \\ &\quad + \frac{L_R}{L_m R_R}\left(w_s - w_{m(k)}\right)\phi_{R\alpha(k)} \end{aligned} \tag{38}$$

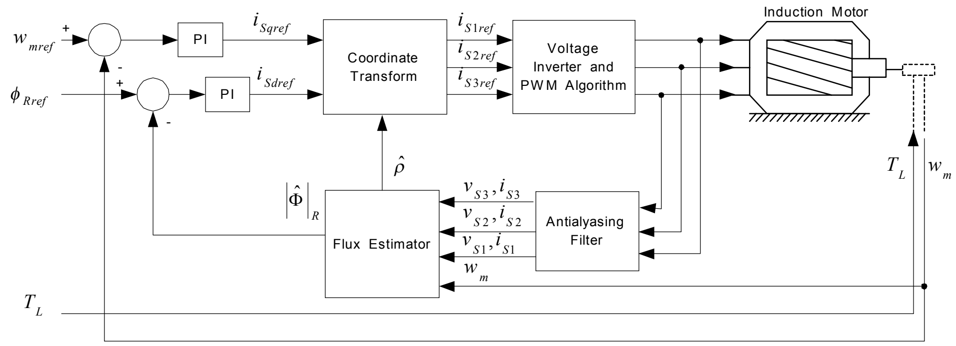

Fig. 1. Direct Field Oriented Control.

As in the previous sections, the observability is analysed by replacing the stator current, equations (37)-(38), in the observability matrices and determining the corresponding rank value. In table III we present the results obtained as well as the simplifications accomplished in the observability matrices.

TABLE III
OBSERVABILITY MATRIX RANK IN STEADY STATE, NULL SPEED AND PERTURBATION SIGNAL.

Observability matrix, assuming:	COO	ROO
Equations (37)-(38)	5	3
Null speed($w_{m(k)} = 0$)	5	3
Null load Torque ($T_l = 0$, $w_s = 0$, $\phi_{R\alpha(k)} = \lvert\Phi_R\rvert$, $\phi_{R\beta(k)} = 0$)	5	3
Constant estimates ($\widehat{R}_{R(k)} = \widehat{R}_R$, $\widehat{\phi}_{R\alpha\beta(k)} = \widehat{\phi}_{R\alpha\beta}$)	5	3

As we can see in table III, the addition of a limited magnitude and limited frequency perturbation signal, recovers the observability characteristics in the case of null operation values of speed and load torque, so much in the complete and reduced order observers. As the equations (37)-(38) show, the only characteristic that the disturbance signal should present is a not null derivative.

Once the algorithms observability were theoretically evaluated, considering all the possible operation conditions of a IM based servo-drive, in the next section are presented some simulations where the observers are applied in the field oriented control technique.

IV. Simulation Results

The examples in this section consider the IM operating under field oriented control, see Fig. 1. In order to avoid the flux estimate influence in the control system, in all simulations the real flux components are feedback. In such case, the observability conditions are determined independently of any transient of the current and tension motor variables (estimation algorithms input).

A voltage inverter with a PWM generation algorithm, as well as antialiasing filters, were implemented in all simulations. Therefore, high frequency signals effect are also considered in the estimation algorithms and observability characteristics.

Note that the estimation algorithms are initialized when the real variables are in steady state. In figures 2 and 3, the observers are tested in different operation conditions, the dashed line represents the complete order observer estimate, the dotted line the reduced order observer estimate, finally the continuous line represents the real variables. The initial values are fixed in $\Phi_R = 1.13Wb$, $\widehat{\Phi}_R = 50$ and $\widehat{R}_R = 3.53\Omega$. The observers initial conditions and design matrices, are given as

COO: $P_{(0)} = I_5$, $R_{k+1} = 2H_{k+1}P_{k+1/k}H_{k+1}^T + 10^{-3}I_2$ and $Q_k = 10^4 e_k^T e_k I_5 + 10^{-3}I_5$

ROO: $P_{(0)} = diag(2 \cdot 10^3, 2 \cdot 10^3, 1)$, $R_{k+1} = 8H_{k+1}P_{k+1/k}H_{k+1}^T + 10^{-2}I_2$ and $Q_k = 10^4 e_k^T e_k I_3 + 10^{-2}I_3$

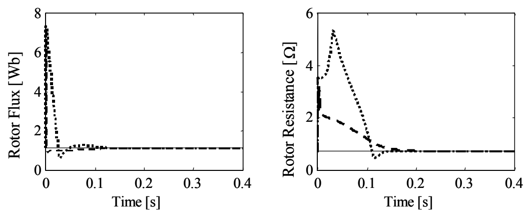

Fig. 2. Simulation under observability conditions, i.e., $w_m = 100rad/s$ and $T_L = 50nm$.

As figure 2 shows, the observers performance is suitable when the observability conditions are satisfied, i.e., when the motor speed and load torque don't present null values simultaneously. Both observers present a convergence time smaller than 0.2

s. for the resistance and flux estimates, even with an non favorable initialization.

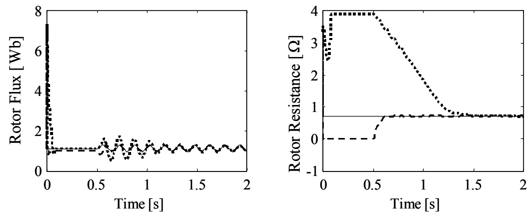

Fig. 3. Simulation without observability conditions (i.e., $w_m = 0rad/s$ and $T_L = 0nm$) and disturbance signal addition in the flux reference.

In figure 3, the simulation is accomplished without observability conditions ($w_m = 0$ and $T_L = 0$) in the interval $0 < t < 0.5$. As we can see, the estimates (flux and resistance) converge in values (equilibrium points) different from the real ones. When a disturbance signal is added in the rotor flux reference, $t = 0.5s.$, the observability conditions are recovered and the estimates converge in the real values, validating the theoretical results presented in the table III. It is verified that the high frequency signals, generated by the PWM algorithm, are filtered by the intrinsic inductive dynamics of the motor and by the antialiasing filters.

As shown in figures 2 and 3, the complete observer convergence time is smaller than the reduced order observer one. We should note that in the ROO case (based in the *Delayed State Kalman Filter*) the design variable R_{k+1}, equation 18, needs to be chosen in order to guarantee the algorithm convergence and not only in function of the transient performance [9]. However, the main advantage that the ROO presents in relation to the COO, is a smaller computational cost.

V. Conclusions

This work dealt with the determination and evaluation of the IM models observability matrices, for both complete and reduced order observers, under several operation conditions. For the numeric evaluation of the observability characteristics, two deterministic robust observers were implemented, both based on the extended Kalman filter and proposed in [8] and [9], respectively. In all simulations voltage inverters with PWM generation algorithms and antialiasing filters were considered. It was verified that the high frequency signals that feed the IM are not significant in the estimators performance.

Three different operation conditions were defined, considering electromagnetic and mechanics variables, for the observability characteristics analysis. It is verified that a loss of observability exists in the simultaneous presence of null speeds and null load torque (null slip frequencies). It is verified, also, that the observability can be recovered by the addition of disturbing signals, of limited magnitude and frequency, in the flux reference.

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Appendix

The induction motor used in the simulations has the following nominal parameters: $n = 2$ (pole pairs number)

$$L_S = 0.0996\,[H] \quad L_R = 0.0996\,[H] \quad L_m = 0.0969\,[H]$$
$$R_S = 0.728\,[\Omega] \quad R_R = 0.706\,[\Omega] \quad J = 0.062\,[kg\,m^2]$$

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