PARAMETER ESTIMATION OF A CLOSED LOOP THREE-PHASE INDUCTION MOTOR USING THE METHOD OF LEAST SQUARES

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Abstract. *When is used vector control in three phase induction motor, the mathematical model is considered as a set of linear equations, therefore the control is more effective only over an operation point. However, when we change that point, the control can pass to respond inappropriately, causing unwanted errors of speed, position or even instability. Such behavior are due to the real model of the motor, which is a highly nonlinear and time variant system. Thus, parametric identification techniques allow that the motor parameters be determined through the online method, tracking its time variation. Additionally, in a following step, use the data in combination with the predictive control algorithms adjusting the speed controller of the vector control. Is intended with this paper to present a general background of the parameter identification techniques and show the results obtained using the studied approaches, more specifically exploring the method of least squares to fit the control for different operating points of the induction motor.*

Keywords: *Parameter Estimation, Vector Control, Predictive Control, Three-Phase Induction Motor*

1. INTRODUCTION

The present control techniques seek to meet a better dynamic response in order to increase the performance of the system. It is usual to assume that all electrical parameters of the motor are known. Furthermore, the controllers development, observers and data for simulation also require such knowledge. Another important feature about systems identification is that different kinds of working problems in motors applications can be observed through changing a few parameters, so its estimation can be a part of an electrical motor condition monitoring.

There are mainly two ways to identify the parameters of the motor: *online* and *offline* approaches. The *offline* approach is basically done with the rotor in a static condition (standstill). Hence, there is a simplified model of the motor, once the uncertainties inherent speed measurement are eliminated, and then the *offline* identification techniques may be employed (Kwon *et al.*, 2009). On the other hand, the *online* approach is done with the motor at full operation, which increases the complexity of the model and the parameter identification.

A possible implementation of the algorithm is made with a preliminary parameters estimation with the motor parked (*offline*) or using the known values of the parameters to be estimated, generating initial conditions for them. Then, the method *online* takes care of updating the data with the motor in operation, increasing the convergence speed of the mathematical model.

The mathematical model is obtained in order to be able to represent the motor through its electrical parameters, making visible the relationship of each parameter with the operation of the induction motor. This paper shows the relationships that describes the motor, such as the implementation of control techniques to be adopted. Finally, is analyzed the strategy of implementation of the estimation algorithms.

2. MODELING THE MOTOR AND DEVELOPMENT OF CONTROL ALGORITHMS

The models obtained in this paper are related to the electrical circuit of the induction motor in order to verify the dependence of the parameter with the measurement variable, such as shown by Marques (1996). Therefore, the state

equations of the motor are given by,

$$
\begin{bmatrix} \dot{i}_\alpha^s \\ \dot{i}_\beta^s \\ \dot{\phi}_\alpha^s \\ \dot{\phi}_\beta^s \end{bmatrix} = \begin{bmatrix} -(\alpha+\beta) & -\upsilon\omega_r & \frac{\beta}{L_s} & \frac{\upsilon\omega_r}{\sigma L_s} \\ \upsilon\omega_r & -(\alpha+\beta) & -\frac{\upsilon\omega_r}{\sigma L_s} & \frac{\beta}{L_s} \\ -R_s & 0 & 0 & 0 \\ 0 & -R_s & 0 & 0 \end{bmatrix} \begin{bmatrix} i_\alpha^s \\ i_\beta^s \\ \phi_\alpha^s \\ \phi_\beta^s \end{bmatrix} + \begin{bmatrix} \frac{1}{\sigma L_s} & 0 \\ 0 & \frac{1}{\sigma L_s} \\ 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} v_\alpha^s \\ v_\beta^s \end{bmatrix}
\tag{1}
$$

where, $\alpha = \frac{R_s}{\sigma L_s}$, $\beta = \frac{R_r}{\sigma L_r}$ and $\sigma = 1 - \frac{L_{sr}^2}{L_r L_s}$. And also, L_s is the stator inductance, L_r is the rotor inductance, L_{sr} is the mutual inductance, R_r is the rotor resistance and R_s is the stator resistance.

For the mechanical system, is shown that

$$
\dot{\omega}_r = \frac{\upsilon}{J}\left(i_\beta^s \phi_\alpha^s - i_\alpha^s \phi_\beta^s\right) - \frac{b}{J}\omega_r - \frac{\tau}{J},
\tag{2}
$$

where υ is the pairpoles number, b is the viscous friction coefficient, J is the momentum inertia coefficient and τ is the load constant.

2.1 Vector control and its dependency with the parameters of the motor

The theoretical principle of vector control technique allows the alignment of the motor flux linkage with the direct-axis synchronous coordinate system, resulting in uncoupling torque and flux. Thus, the direct component of stator current controls the flux linkage, and the quadrature component of stator current controls the torque.

There are basically two ways to implement the vector control.

- *Direct Vector Method*: The rotor flux linkage is obtained by direct measurement with the aid of coil exploitative or hall effect sensors.

- *Indirect Vector Method*: The measurement is performed by using the slip ratio to estimate the position of the flux linkage.

This work uses the indirect vector method, since is utilized the slip ratio to obtain the flux position to perform the alignment of the system.

An important information about the vector control is its dependency about the knowledge of the motor parameters to be implemented. In order to study these dependencies, it will be used some equations obtained through the induction motor state model in synchronous reference frame. The electromagnetic torque inside this context of vector control is given by

$$
\tau_m = \frac{\upsilon L_{sr}}{L_r} i_q^s \phi_d^r
\tag{3}
$$

and the rotor flux linkage, in steady state is,

$$
\phi_d^r = L_{sr} i_d^s
\tag{4}
$$

The Equations (3) and (4) were obtained considering the direct-axis alignment of the rotor flux linkage with the direct-synchronous reference frame. It makes the rotor flux linkage quadrature-axis null. Such as explained before, it is possible to verify the uncoupling of flux and torque in these equations.

To perform the alignment of the rotor flux linkage in vector control, is used the slip ratio considering the electric slip speed definition $\omega_{sl} = \omega_s - \upsilon\omega_r$, so

$$
\omega_{sl} = \frac{L_{sr} i_d^s}{\tau_r \phi_d^r}
\tag{5}
$$

where, $\tau_r = \frac{L_r}{R_r}$ is the rotor time constant.

The Equations (3), (4) and (5) are well known and formulate the main expressions for vector control. According to these three equations, we can see their dependencies with three parameters of the motor: the mutual inductance (L_{sr}), the rotor inductance (L_r) and the (R_r) rotor resistance.

3. DISTORTION ANALYSIS

In practical situations, the direct-axis of the coordinate system almost never will be perfectly aligned with the rotor flux linkage. Such mismatches causes some distortions in the system due to the transformations of coordinate and the mismatch of the motor parameters (Cortajanera *et al.*, 2010).
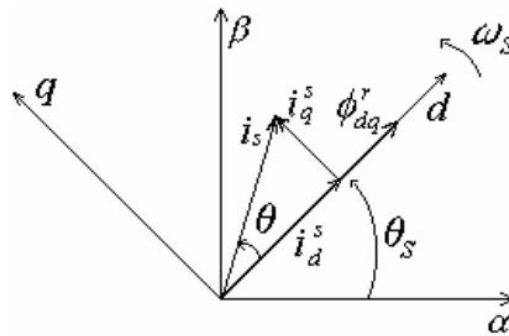
Figure 1: Spacial representation of the vector control principle
Retrieved from Ferrari (2005).

3.1 Phase distortion analysis

The components i_d^s and i_q^s will not have amplitude errors, because of the nature of the coordinate transformations (see Fig. 1).

The slip speed estimative in steady state may be obtained by (4) and (5) so,

$$\hat{\omega}_{sl} = \frac{\hat{L}_{sr}\hat{i}_q^s}{\hat{\tau}_r\hat{\phi}_d^r} = \frac{\hat{i}_q^s}{\hat{\tau}_r\hat{i}_d^s}. \tag{6}$$

The hat over the variables means that they are estimated parameters.

Once the proposed system is orthogonal, In Fig. 1 we can formulate the following trigonometric relations, where $\hat{\theta}$ is the estimated phase of the stator current i_s, regarding the synchronous reference frame, so

$$\hat{\theta} = \arctan\left(\frac{\hat{i}_q^s}{\hat{i}_d^s}\right) \quad , \quad \sin\hat{\theta} = \frac{\hat{i}_q^s}{\hat{i}_s} \quad , \quad \cos\hat{\theta} = \frac{\hat{i}_d^s}{\hat{i}_s}. \tag{7}$$

replacing the Equation (5) in (7), it can be rewritten by

$$\hat{\theta} = \arctan(\hat{\omega}_{sl}\hat{\tau}_r) \quad , \quad \sin\hat{\theta} = \frac{\hat{\omega}_{sl}\hat{\tau}_r}{\sqrt{1+(\hat{\omega}_{sl}\hat{\tau}_r)^2}} \quad , \quad \cos\hat{\theta} = \frac{1}{\sqrt{1+(\hat{\omega}_{sl}\hat{\tau}_r)^2}}. \tag{8}$$

for the motor, is shown that:

$$\theta = \arctan(\omega_{sl}\tau_r) \tag{9}$$

Therefore, the relation between θ and $\hat{\theta}$, is given by:

$$\frac{\hat{\theta}}{\theta} = \frac{\arctan(\hat{\omega}_{sl}\hat{\tau}_r)}{\arctan(\omega_{sl}\tau_r)}. \tag{10}$$

By the Equation (10), it is possible to conclude that the phase distortion caused by the coordinate transformations depends only on the rotor time constant τ_r. According to Ferrari (2005), such relation is due to the constructive factor $\hat{\omega}_{sl} = \omega_{sl}$.

3.2 Control torque distortion analysis

Replacing the Equation (4) in (3), is shown that

$$\hat{\tau}_m^* = \frac{\upsilon\hat{L}_{sr}}{\hat{L}_r}\hat{i}_q^s\hat{\phi}_d^r = \frac{\upsilon(\hat{L}_{sr})^2}{\hat{L}_r}\hat{i}_q^s\hat{i}_d^s. \tag{11}$$

Using the Equations (7) and (8) in (11) yields,

$$\hat{\tau}_m^* = \frac{\upsilon\hat{L}_{sr}(i_s)^2}{\hat{L}_r}\frac{\hat{\omega}_{sl}\hat{\tau}_r}{1+(\hat{\omega}_{sl}\hat{\tau}_r)^2} \tag{12}$$

and for the motor,

$$\tau_m = \frac{\upsilon L_{sr}(i_s)^2}{L_r} \frac{\omega_{sl}\tau_r}{1 + (\omega_{sl}\tau_r)^2}. \tag{13}$$

However, $|\hat{i}_s| = |i_s|$ due to the fact there is not amplitude distortion in the system. Therefore, the distortion torque ratio between the real torque of the motor and the reference torque is

$$\frac{\tau_m}{\hat{\tau}_m^*} = \left(\frac{L_{sr}}{\hat{L}_{sr}}\right)^2 \left(\frac{\hat{L}_r}{L_r}\right) \left(\frac{\tau_r}{\hat{\tau}_r}\right) \frac{(1 + \omega_{sl}\hat{\tau}_r)}{(1 + \omega_{sl}\tau_r)}. \tag{14}$$

Through the Equation (14) it is observed that:

- The term $\left(\frac{L_{sr}}{\hat{L}_{sr}}\right)^2 \left(\frac{\hat{L}_r}{L_r}\right)$ represent the direct distortion over the torque.

- The term $\left(\frac{\tau_r}{\hat{\tau}_r}\right) \frac{(1+\omega_{sl}\hat{\tau}_r)}{(1+\omega_{sl}\tau_r)}$ represent the distortion torque due to the phase distortion.

3.3 Rotor flux linkage distortion analysis

Using the same methodology previously done, for $\hat{\phi}_d^{r*} = \hat{L}_{sr}\hat{i}_d^s$ and $\phi_d^r = L_{sr}i_d^s$ being the, reference flux linkage and the rotor flux linkage respectively. The rotor distortion ratio is given by

$$\frac{\phi_d^r}{\hat{\phi}_d^{r*}} = \left(\frac{L_{sr}}{\hat{L}_{sr}}\right) \sqrt{\frac{1 + (\omega_{sl}\hat{\tau}_r)}{1 + (\omega_{sl}\tau_r)}}, \tag{15}$$

where the Equation (15) and the Fig. 1 shows that:

- The term $\left(\frac{L_{sr}}{\hat{L}_{sr}}\right)$ represents the direct distortion over the flux.

- The term $\sqrt{\frac{1+(\omega_{sl}\hat{\tau}_r)}{1+(\omega_{sl}\tau_r)}}$ represents the flux distortion due to the phase distortion.

3.4 Current distortion analysis

The deviation of the parameters may cause a current distortion in the system . It is called *uncoupling distortion*.

$$i_d^s = \frac{\cos\theta}{\cos\hat{\theta}}\hat{i}_d^s = \sqrt{\frac{1 + (\omega_{sl}\hat{\tau}_r)^2}{1 + (\omega_{sl}\tau_r)^2}}\hat{i}_d^s \tag{16}$$

and

$$i_q^s = \frac{\sin\theta}{\sin\hat{\theta}}\hat{i}_q^s = \frac{\hat{\tau}_r}{\tau_r}\sqrt{\frac{1 + (\omega_{sl}\hat{\tau}_r)^2}{1 + (\omega_{sl}\tau_r)^2}}\hat{i}_q^s. \tag{17}$$

Note that they are caused by the voltage uncoupling equations introduced in both d-q current loops. The Fig. 2 illustrate this issue.

Theses relations shows the dependency of the currents with the correct values of σ, L_s, i_d^s and i_q^s. Δ_1 correspond to the estimative error of the product $\sigma L_s i_q^s$, and Δ_2 is the estimative error of the product $L_s i_d^s$. These errors decrease the performance of control, whereas they are considered as perturbations in the system (Carli and Cava, 1976; Novotny and Lipo, 1996; Tajima *et al.*, 2002).

In steady state operation, the controllers must correct these perturbations in the respective loops, even in the vector control, where its transient performance is more complicated (Coirault *et al.*, 1996; Krishnan and Doran, 1987; Krishnan and Bharadwaj, 1990).

4. PARAMETER ESTIMATION USING METHOD OF LEAST SQUARES

Based on several literatures, (Aguirre, 2004; Coelho and Coelho, 2004; Marques, 1996; Ferrari, 2005), it is possible to describe a discrete system by the following relation

$$y_k = \phi_k^T \theta + e_k, \tag{18}$$

where y_k is the output signal, $\phi_k^T = [x_{k1} \quad x_{k2} \ldots x_{kn}]^T$ is the known deterministic vector, called regression vector, $\theta = [\theta_1 \; \theta_2 \ldots \theta_n]^T$ is the parameters vector to be estimated and e_k is an error model vector.
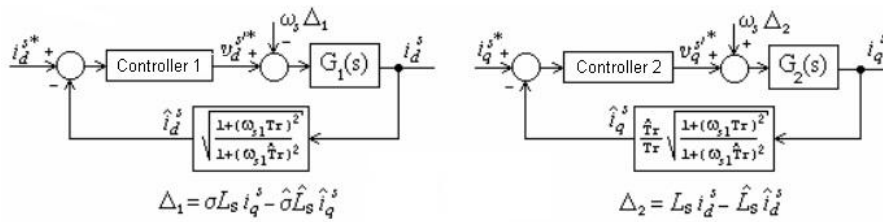
Figure 2: Currents control loops and the uncoupling distortions
Adapted from Ferrari (2005)

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4.1 Batch Estimator

According to Aguirre (2004) and using the Equation (18) is easy to show that

$$\hat{\theta} = \left[\mathbf{\Phi}^T\mathbf{\Phi}\right]^{-1}\mathbf{\Phi}^T\mathbf{Y} \tag{19}$$

The Equation (19) is known as batch estimator, because the information are stored in the memory, and then all data is used to estimate θ. Therefore, it is also usually called of *off-line* estimator.

Using this method to estimate the parameters, the algorithm becomes not biased, that is, the noise interference is minimized while the data number utilized to process the estimation tends to infinite, which is unpractical. However, if is intended to make the process robust enough, it is necessary a high quantity of available memory. On the other hand, it turns the regression matrix, $\mathbf{\Phi}$ with $[N_A \times (N + 1)]$ dimension, where N_A is the number of parameters to be estimated and N are the total stored data.

The proposed solution presented in this paper for this disadvantage, is considering the matrix $\mathbf{\Phi}^T\mathbf{\Phi}$ and the matrix $\mathbf{\Phi}^T\mathbf{Y}$ as a single matrices each one, and update them in every sample period. And then, after some time previously defined, estimate the vector θ.

Note that, in the following relation,

$$\mathbf{\Phi}^T\mathbf{\Phi} = \mathbf{\Phi}_{[N_A \times 1]}\mathbf{\Phi}_{[1 \times N_A]} = \mathbf{P}_{[N_A \times N_A]}, \tag{20}$$

the matrix $\mathbf{P}_{[N_A \times N_A]}$ can be updated every sample period.

For the second case, the analog analysis is done, and the matrix multiplication $\mathbf{\Phi}^T\mathbf{Y}$ results in the following matrix $\mathbf{B}_{[N_A \times 1]}$, which one may be updated such as the P matrix. We can conclude that, if there are few parameters to estimate, the batch mode is an easy implementation and a good solution, even in a *DSP* hardware with low available memory.

4.2 Recursive Least Squares Estimator

The development of the recursive least squares (RLS) matches the adopted procedures in Coelho and Coelho (2004). The main relations of the RLS are:

$$\begin{array}{rcl} \hat{\theta}_\lambda(k) &=& \hat{\theta}(k-1) + \frac{\mathbf{G}(k)}{\mathbf{H}_\lambda(k)}\mathbf{e}(k) \\ P_\lambda(k) &=& \frac{1}{\lambda}\left[P(k-1) + \frac{\mathbf{G}(k)}{\mathbf{H}_\lambda(k)}\mathbf{J}(k)\right], \end{array} \tag{21}$$

where, k represents the current sample time, $\hat{\theta}_\lambda(k)$ is the actual estimated parameter vector, $\mathbf{e}(k)$ is the predicted error vector, $P_\lambda(k)$ is covariance matrix, and

$$\begin{array}{rcl} \mathbf{H}_\lambda &=& \lambda + \mathbf{\Phi}_k^T\mathbf{P}(k-1)\mathbf{\Phi}(k) \\ \mathbf{G}(k) &=& \mathbf{P}(k-1)\mathbf{\Phi}(k-1) \\ \mathbf{e}(k) &=& \mathbf{y}(k) - \mathbf{\Phi}^T(k)\hat{\theta}(k-1) \end{array} \tag{22}$$

where, $\mathbf{\Phi}(k)$ is the current regression vector and $\mathbf{y}(k)$ is the last output system sampled.

Here λ is the forgetting factor, and its use is important because all the oldest data are exponentially forgotten, it means that their effects over the estimation become negligible as soon as new acquisitions are available. In this case, if $\lambda = 1$, it becomes the standard RLS. In practice, for motor control is used values in range $0.99 \leq \lambda \leq 1$.

The algorithm to perform the recursive estimation is exposed in the following steps:

1. Update the measured vector $\mathbf{\Phi}(k)$ (the input-output signals system);

2. Compute the estimated parameter vector $\hat{\theta}_\lambda(k)$;

3. Compute the covariance matrix $\mathbf{P}_\lambda(k)$;

4. Return to step 1 when new acquisitions are available.

5. *ONLINE* THREE-PHASE INDUCTION MOTOR IDENTIFICATION

The three-phase model of the induction motor is a non-linear and time variant system, however in the rotor reference frame, the parameters of the motor are related to a linear model. Therefore, it is used a linear transfer function of the motor to perform the parameter identification (Ferrari, 2005).

$$\frac{\psi_{ab}^s}{I_{ab}^s} = \frac{(L_s L_r - L_{sr}^2) + L_s R_r}{L_r s + R_r} \tag{23}$$

The Equation (23) contains two variables which can be measured or observed (current and stator flux linkage), and also almost all the important parameters to be estimated, with exception of R_s that will be obtained separately. Note that they are refereed to the a-b reference frame, in this paper this nomenclature means that the system is in the rotor reference frame.

The current is easily obtained with direct measurement, however the stator flux linkage can not be measured directly. There are several algorithms to calculate the stator flux linkage, such as those shown in Lascu and Boldea (2000); Holtz (2002). In this paper will be implemented the stator flux linkage observer with respect to the voltage model equation, then

$$\psi_{\alpha\beta}^s = \int_0^t [V_{\alpha\beta}^s(\tau) - R_s(\tau) I_{\alpha\beta}^s(\tau)] d\tau, \tag{24}$$

In Equation (24) is evident the requirement of the stator resistance (R_s), which is a time dependent parameter, therefore its identification is important. Nevertheless, the stator voltage is not sinusoidal, it is a pulsed signal due to the PWM (Pulse Width Modulation) switching. In this case, the reference output stator voltage of the control will be used.

5.1 Parameter Identification Using the Homopolar Model

An approach to acquire the stator resistance, is using the following transfer function.

$$\frac{I_0^s}{V_0^s} = \frac{1}{L_{s\sigma} s + R_s} \tag{25}$$

The Equation (25) shows the relation between the stator homopolar voltage and the stator homopolar current, measuring these two signals it is possible to estimate the stator resistance R_s and the leakage stator inductance $L_{s\sigma}$ through the least squares method.

Therewith, the estimated resistance is used to update the stator flux observer and estimate the other parameters using the transfer function exposed in (23).

5.2 Parameter Identification Using the Motor Class Model

In many cases, it is impossible to perform the homopolar method commented previously, due to the fact that the PWM modulation strategies frequently have used the spacial vectors, which by hardware action, do not allow the generation of the homopolar component, it means that the relation (25) can not be used.

The IEEE-512 (1996), classify the induction motors according to their characteristics torque $\times$ speed, by the following expression

$$L_{s\sigma} = k L_{r\sigma} \tag{26}$$

where:

- $k = 1$ for motors class A,D and wound rotor;

- $k = \frac{2}{3}$ for motors class B;

- $k = \frac{3}{7}$ for motors class C.

The Equation (23) can be rewritten using the above concepts, then

$$\frac{\psi_{ab}^s}{I_{ab}^s} = \frac{[(L_s - L_{sr})(L_s + kL_{sr})]s + kL_s R_r}{[L_s + (k-1)L_{sr}]s + kR_r}, \tag{27}$$

hence, the parameters L_r, L_s, L_{sr} and R_r can be estimated. Note that the stator current R_s can not be calculated *a priori*. However, the direct current injection technique can be used to perform the estimation, but it will not be implemented in this paper.

6. RESULTS

The results of the implementation techniques was developed in C++ language regarding the following characteristics of the motor: rated power = $3.0Hp$, rated speed = $1710rpm$, rated voltage = $380V$, rated current = $4,68A$, polepairs number = 2, class A. The main reference parameters of the motor are shown in Tab. 1.

The Fig. 3 shows the stator current Fig. 3(a) and stator flux linkage Fig.3(b) in rotor reference frame, these variables are used to calculate the parameters of the motor according to (23) and (27). Note that they are used for both Homopolar and motor class models. On the other hand, the homopolar stator current and voltage, Fig. 3(c) and Fig. 3(d) respectively, are used to identify the stator resistance and the leakage stator inductance for the homopolar model.

Table 1: Reference Parameters of the Motor

PARAMETER	VALUE
Stator Resistance (R_s)	2.50 Ω
Rotor Resistance (R_r)	2.24 Ω
Stator Inductance (L_s)	0.288 H
Rotor Inductance (L_r)	0.288 H
Mutual Inductance (L_r)	0.270 H
Dispersion Stator Inductance ($L_{s\sigma}$)	0.018 H
Dispersion Rotor Inductance ($L_{r\sigma}$)	0.018 H

Simulation parameters: time simulation = $500ms$, sample period = $200\mu s$, batch estimation time = $200ms$, speed reference $1070rpm$, rotor flux linkage reference $0.5Wb$ and load $\tau = 0.8Nm$.

The Tab. 2 summarizes the mechanical parameters used in the simulation.

Table 2: Mechanical Parameters of the Motor

PARAMETER	Value
Inertia Coefficient (J)	0.0135 $\frac{N.m.s^2}{rad}$
Viscous Friction Coefficient (b)	0.0027 $N.m.s$

6.1 Recursive Method

Using the signals shown in Fig. 3 it is possible to design the homopolar and motor class models to identify the motor parameters using (22), (23), (25) and (27).

For this paper was chosen a constant $\lambda = 0.9995$, its value was set considering the better transient performance and fastest speed of convergence.

6.1.1 Homopolar Model Using RLS Method

- R_s and $L_{s\sigma}$:

By using (22) and (25) it is possible to estimate R_s and $L_{s\sigma}$. The Fig. 4 shows the implementation results of the RLS algorithm in the homopolar model, it is possible to check the stabilization time around $100ms$ with a minimum error in the estimation after this time.

- R_r, L_s, L_r and L_{sr}:

The parameters R_r, L_s, L_r and L_{sr}, can be obtained by (22) and (23). The Fig. 5 shows the results. It is noted that the algorithm reached the stabilization in around $300ms$.

6.1.2 Motor Class Model Using RLS Method

In this case there is no necessity to compute nor the stator resistance (R_s) neither the leakage stator inductance ($L_{s\sigma}$), instead of calculating it, we can use the motor class model. As the motor is class A, then $k = 1$. So, using (27) to calculate

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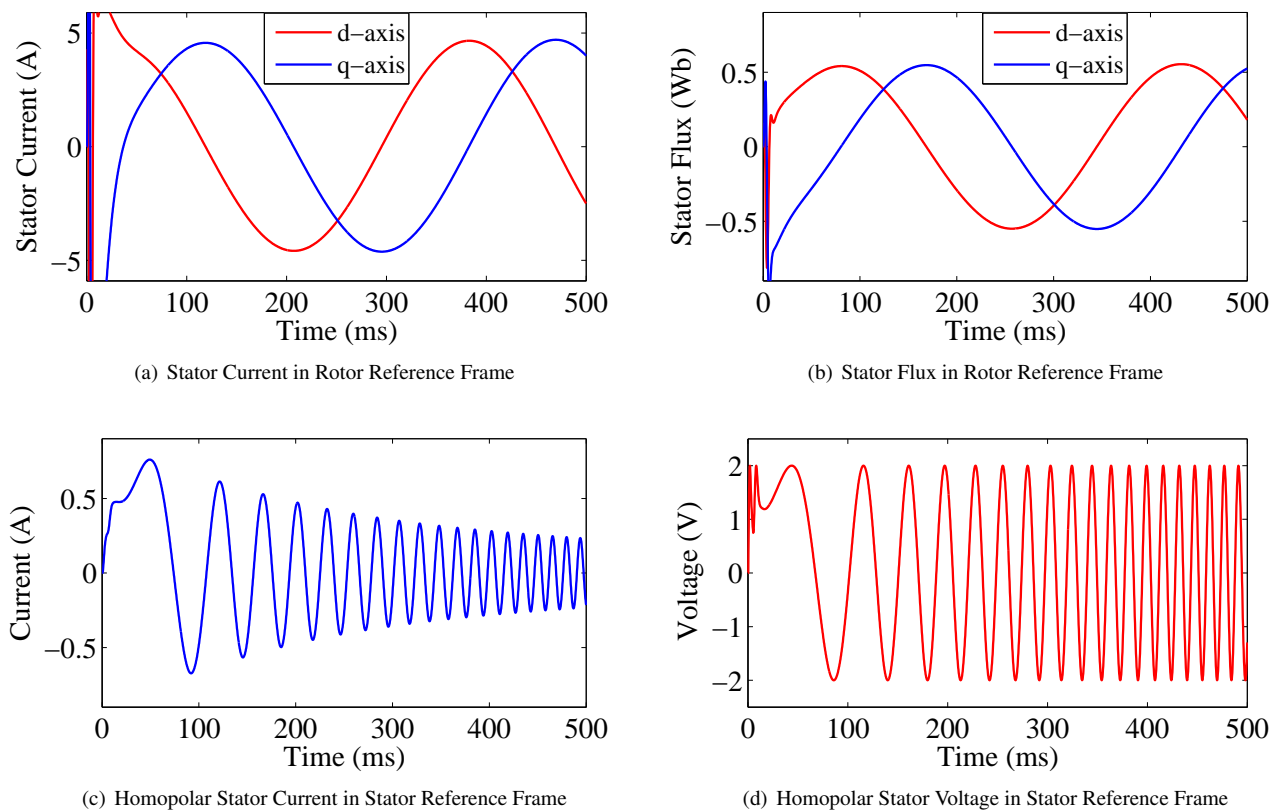(Closed Loop Induction Motor Parameter Identification)

(a) Stator Current in Rotor Reference Frame

(b) Stator Flux in Rotor Reference Frame

(c) Homopolar Stator Current in Stator Reference Frame

(d) Homopolar Stator Voltage in Stator Reference Frame

Figure 3: Motor Variables used in closed loop parameter identification

(a) Stator Resistance Ω

(b) Leakage Stator Inductance $L_{s\sigma}$
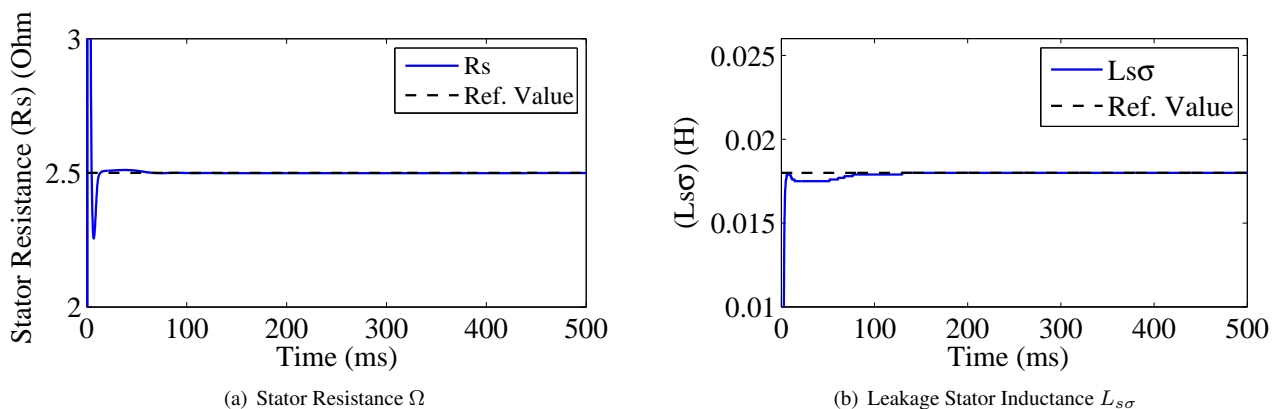
Figure 4: R_s and $L_{s\sigma}$ computation using the RLS method in Homopolar Model

the R_r, L_s, L_r and L_{sr} parameters. The Fig. 6 shows the result for the estimation, it is observed a stabilization time of $300ms$ in this case.

The difference of the time convergence, observed between the (Rs and $L_s\sigma$) and the R_r, L_s, L_r and L_{sr} parameters, are caused by the behavior of the measured variables of the motor. As the stator flux linkage and stator current are in the rotor reference frame, they vary slowly than the homopolar stator current and voltage, which are rotating in the synchronous reference frame. However, the least squares algorithms, requires that the signals measured vary frequently to avoid their matrices be non-singular. As soon the matrices are becoming nonsingular, its performance convergence decreases.
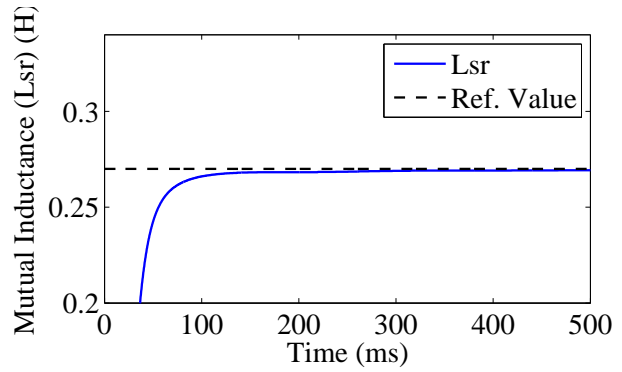
6.2 Batch Method

The procedure to perform the estimation, is similar to the RLS method. But, instead of using (22), will be used (19). The computation time for the Batch algorithm was set in $200ms$. It means, every $200ms$ the algorithm update the estimated parameters.
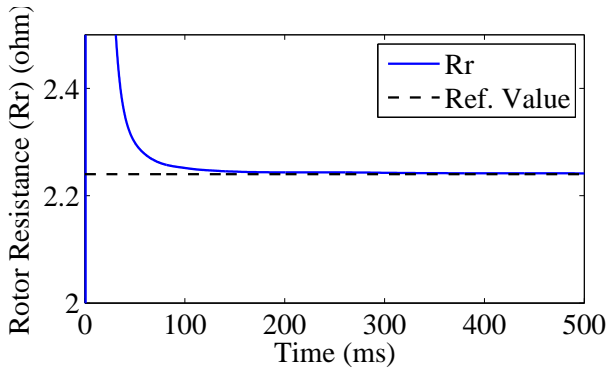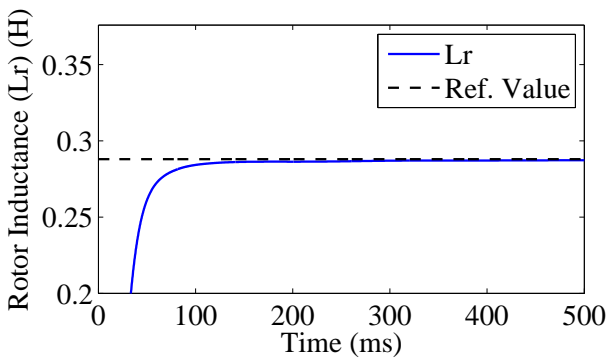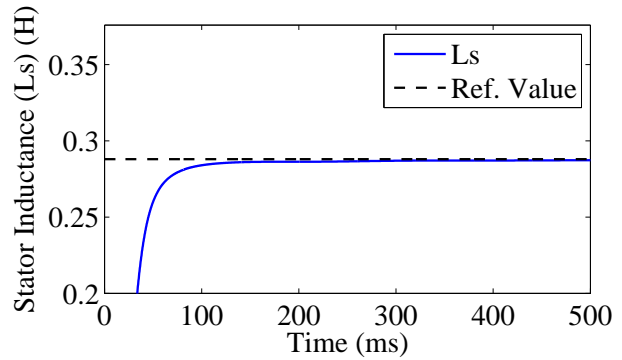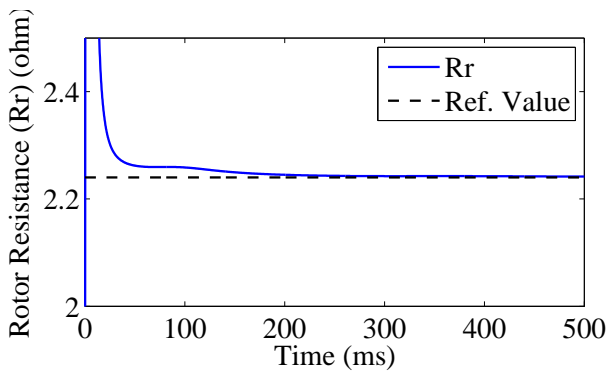
(a) Rotor Resistance Ω
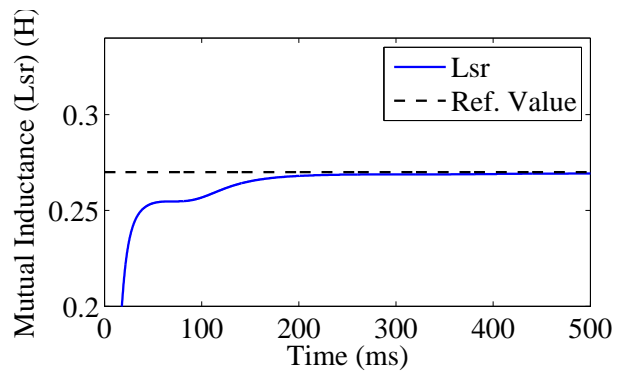
(b) Mutual Inductance H

(c) Rotor Inductance H

(d) Stator Inductance H

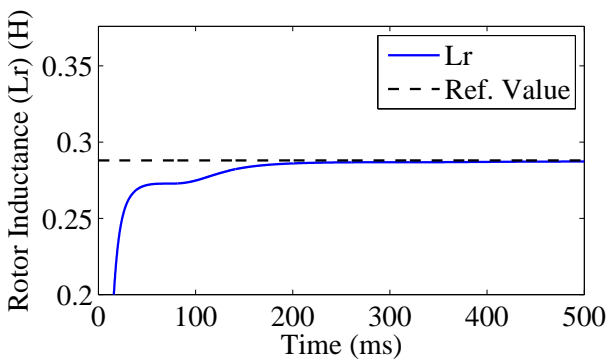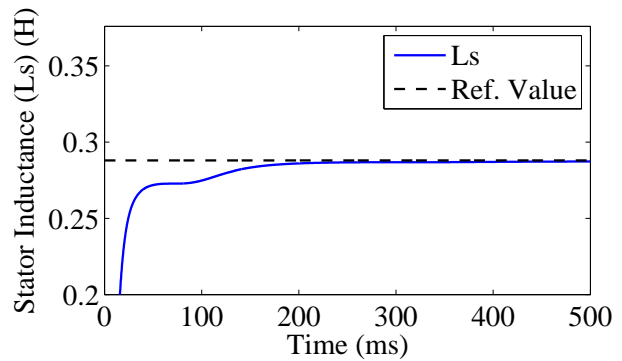Figure 5: The R_r, L_s, L_r and L_{sr} computation using the RLS method in Homopolar Model

(a) Rotor Resistance Ω

(b) Mutual Inductance H

(c) Rotor Inductance H

(d) Stator Inductance H

Figure 6: The R_r, L_s, L_r and L_{sr} computation using the RLS method in Motor Class Model

6.2.1 Homopolar Model Using Batch Method

- R_s and $L_{s\sigma}$:

By combining the expressions (19) and (25), the Fig. 7 shows their results. For the Batch computation is observed that $200ms$ was enough for the algorithm estimate the parameter with low error rate in steady state.

(a) Stator Resistance Ω
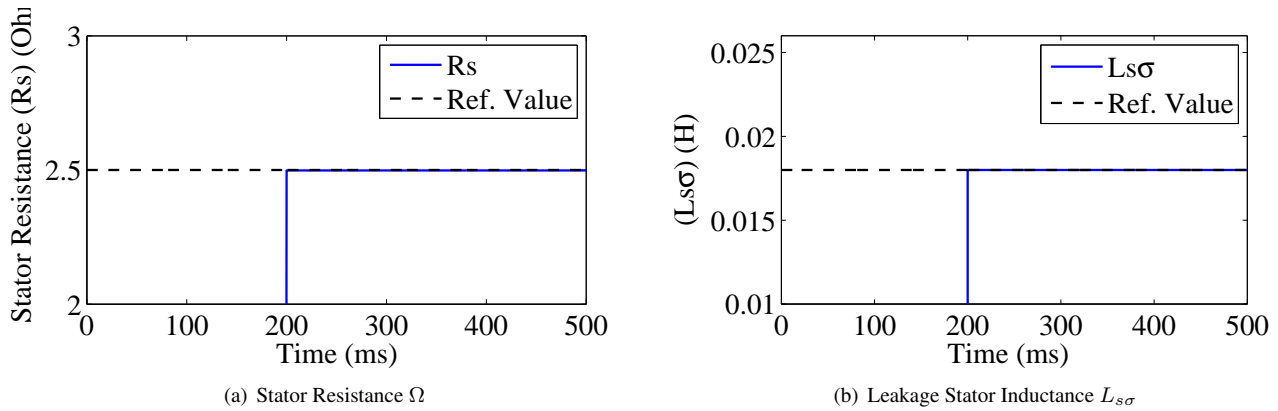
(b) Leakage Stator Inductance $L_{s\sigma}$

Figure 7: R_s and $L_{s\sigma}$ computation using the Batch method in Homopolar Model

- R_r, L_s, L_r and L_{sr}:

In Fig. 8 is noted that the algorithm has achieved the reference value in the first computation, for all the parameters.

(a) Rotor Resistance Ω

(b) Mutual Inductance H
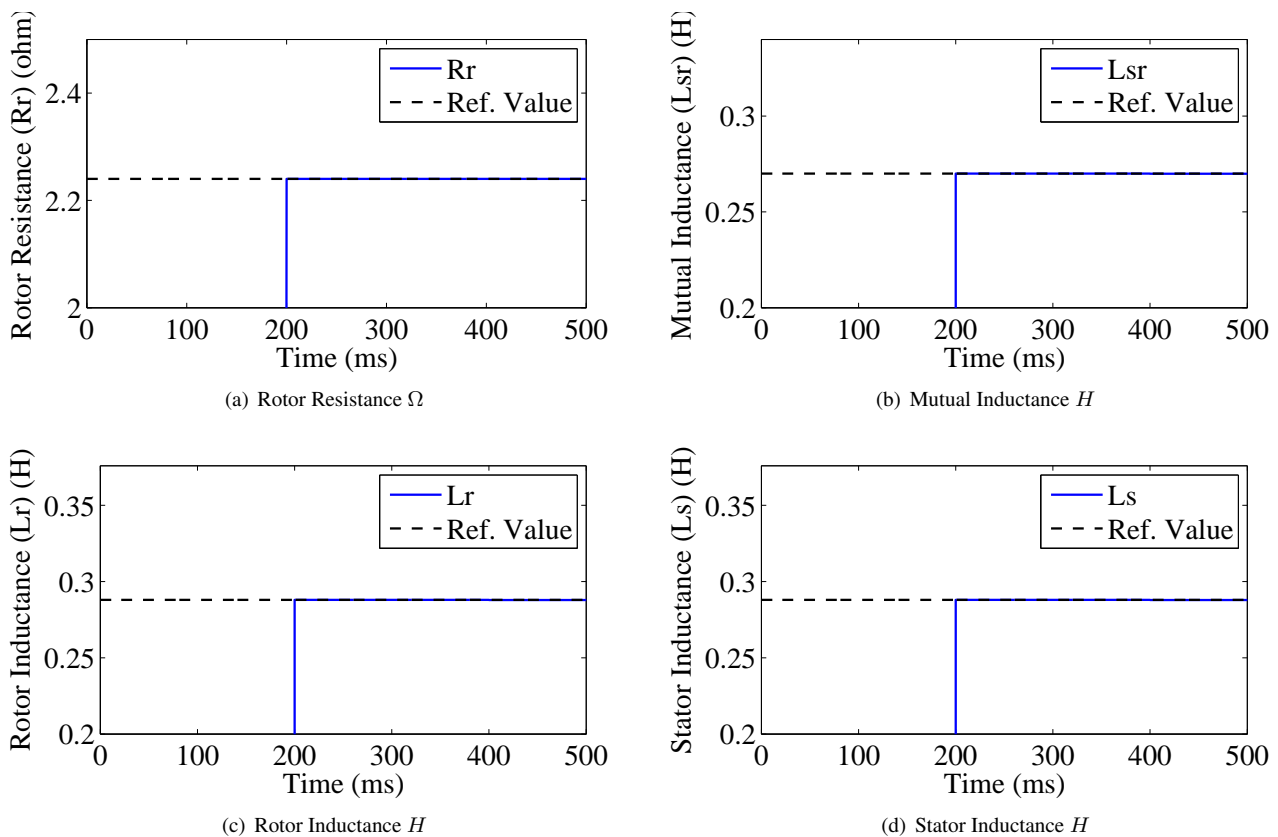
(c) Rotor Inductance H

(d) Stator Inductance H

Figure 8: The R_r, L_s, L_r and L_{sr} computation using the Batch method in Homopolar Model

6.2.2 Motor Class Model Using Batch Method

In Fig. 9 is observed that, also in this case, the algorithm quickly has achieved the reference value.
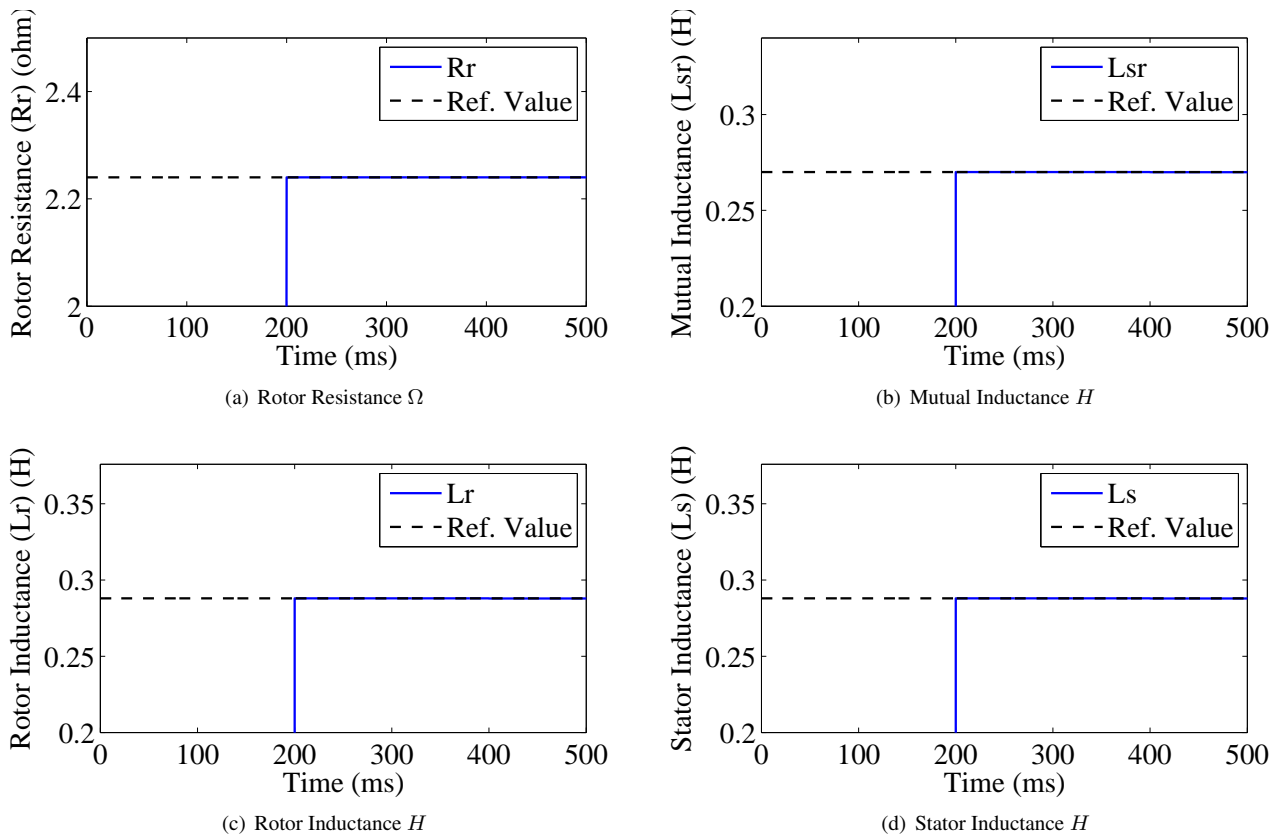

(a) Rotor Resistance Ω

(b) Mutual Inductance H

(c) Rotor Inductance H

(d) Stator Inductance H

Figure 9: The R_r, L_s, L_r and L_{sr} computation using the Batch method in Motor Class Model

7. CONCLUSION

The recent papers have shown several techniques of parameter identification, however, in most of them, it is necessary to compute either the derivative of current signals, which in general, it adds a significant amount of noise or use the stator voltage applied to the motor, which is a pulsed signal (Bianchunyuan *et al.*, 2012; He *et al.*, 2012; Pilevahrani and Dehghani, 2011; Lin *et al.*, 2012).

In this paper have been analyzed the performance of the method of least squares (MLS) for parameter identification of the closed loop induction motor using discretized models without calculating the derivative signals. We have evaluated the distortions caused by the mismatch between the real parameters of the motor and the parameters used in the vector control. The main contribution presented in this paper was the efficient approach to use the batch method of MLS using *DSP* in the parameter identification. The simulation results have shown an improved performance in relation to the RLS algorithm. As commented before, the batch method needs a lot of available memory and more time to process the algorithm. However, using the method presented in this paper, it has noticed that the used memory and processing power were considered normals. Such the Recursive method as the batch method, proved to be good choices for implementation in parametric identification. Additionally, the motor class model can be easily included in the program of induction motors drives. Moreover, it has a relatively low computational effort and excitation signals of the estimator are sinusoidal signals easily found in the industrial environment.

8. ACKNOWLEDGEMENTS

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