ARPN Journal of Engineering and Applied Sciences


www.arpnjournals.com

# PARAMETER IDENTIFICATION OF SQUIRREL CAGE INDUCTION MACHINE USING LINEAR KALMAN FILTER

Mokhlis Salah-Eddine, Sadki Said, Barra Adil and Bensassi Bahloul
Department of Physics, GITIL Laboratory, Faculty of Sciences Ain Chock Hassan II University, Casablanca, Morocco
E-Mail : mokhlis.id@gmail.com

## ABSTRACT

In the industrial environment, the induction machine is generally the most used, given its low cost, its efficiency, and its reliability. To obtain optimal operation, it is essential to collect values of its parameters (stator and rotor resistances and inductions). This data can be used to prevent breakdowns and ensure these machines' rational use. In this context, this article proposes a new method to estimate the internal parameters of these machines using the KALMAN FILTER. Simulations under the MATLAB environment have been developed. Their results show that the estimated parameters are close to the nominal ones.

**Keywords:** KALMAN filter, system identification, recursive least square, squirrel cage induction machine.

Manuscript Received 13 October 2022; Revised 13 May 2023; Published 30 May 2023

## 1. INTRODUCTION

The Induction Machine (IM) is used in different applications such as conveyors and wind turbines [1], and their demand will increase with the massive orientation towards electric vehicles. Despite the well-known qualities of these machines, they are subjected during their operation to electrical, magnetic, mechanical, and thermal constraints, which cause changes in the internal parameters of the motor. These changes, and their effects, are reflected in their magnitudes, mainly on flux, currents, speed, and torque, which can be used for parameter estimation. Note that having the exact values of the internal parameters of the IM will improve the control performance [2] [3], and help monitor the health of the IM [4].

The parameters of the IM are traditionally estimated using three well-known offline methods. The DC test, the no-load test, and the locked rotor test [5]. These offline methods are straightforward but highly approximate. In addition, since the machine is coupled to a mechanical load, proceeding with those tests in an industrial environment is quite challenging. Furthermore, the service must be interrupted while these tests are being carried out [6]. To overcome these challenges, a wide range of techniques for determining induction motor parameters can be found in the literature [7]. Based on [8], these techniques can be categorized into five classes:

- Parameter calculation using construction data,
- Parameter estimation based on the steady-state model of the IM.
- Frequency-domain parameter estimation,
- Time-domain parameter estimation
- real-time parameter estimation.

Because it is fast, efficient, and easy to implement, the recursive least square (RLS) is a popular identification technique. Several studies for estimating IM parameters based on the RLS algorithm have been developed in this area. In [9], the RLS is used to estimate the parameters in the steady state of the IM. In [10], a Butterworth filter is used to reduce the effect of noise and improve the estimation. In [11] and [12][13], the RLS algorithm is used with the FOC controller to estimate the time-varying parameters of the IM and improve the control performance. Those methods provide good results. However, the RLS algorithm is known for its sensitivity to noise, and these studies are performed in the steady state of the IM while the speed is considered constant.

This work is devoted to the estimation of the internal parameters of the IM which includes, stator resistance $R_s$, rotor resistance $R_r$, stator leakage induction $L_s$, rotor leakage induction $L_r$ and magnetizing inductance $M$. Compared to the previous works, the present study aims to estimate the parameters of the IM while the speed is variable using a linear Kalman Filter (KF). In the first section, we were interested in modeling the IM in the αβ frame in by considering the different simplifying hypotheses. This model is used to develop a new regression equation for the estimation of parameters. In the second section, the KF used for the estimation of parameters is introduced. The third section contains the results of the performed method. A conclusion will end the paper.

## 2. MODEL OF SQUIRREL CAGE IM FOR PARAMETER ESTIMATION

The first step of the estimation is to define a suitable system model. This model will have to reflect as accurately as possible all the phenomena that the designer seeks to highlight, to predict the behavior of the physical system in dynamic and static regimes. However, electrical machines are too complex to be able to take into account in modelling all the physical phenomena that they undergo. Thus, it is then essential to introduce some conventional simplifying assumptions which do not alter the validity of the machine model. In this manner, we model the squirrel cage IM, in the $\alpha\beta$ stator frame, in a

ARPN Journal of Engineering and Applied Sciences



healthy operation, neglecting the effect of magnetic saturation, Foucault's current, and the skin effect according to the following equations [14].

The electrical dynamics of the IM are described by the equations (1) and (2):

$$\frac{d\varphi_{s\alpha}}{dt} = V_{s\alpha} - R_s i_{s\alpha} \quad (1.1)$$

$$\frac{d\varphi_{s\beta}}{dt} = V_{s\beta} - R_s i_{s\beta} \quad (1.2)$$

$$V_{r\alpha} = 0 = R_r i_{r\alpha} - \dot{\omega}_r \varphi_{r\beta} + \frac{d\varphi_{r\alpha}}{dt} \quad (1.3)$$

$$V_{r\beta} = 0 = R_r i_{r\beta} + \dot{\omega}_r \varphi_{r\alpha} + \frac{d\varphi_{r\beta}}{dt} \quad (1.4)$$

were

$$\varphi_{s\alpha} = L_s i_{s\alpha} + M i_{r\alpha} \quad (2.1)$$

$$\varphi_{s\beta} = L_s i_{s\beta} + M i_{r\beta} \quad (2.2)$$

$$\varphi_{r\alpha} = M i_{s\alpha} + L_r i_{r\alpha} \quad (2.3)$$

$$\varphi_{r\beta} = M i_{s\beta} + L_r i_{r\beta} \quad (2.4)$$

$(\varphi_{s\alpha}\varphi_{s\beta})$ are the stator flux in $\alpha\beta$ frame.
$(\varphi_{r\alpha}, \varphi_{r\beta})$ are the rotor flux in $\alpha\beta$ frame.
$(i_{s\alpha}, i_{s\beta})$ are stator currents in $\alpha\beta$ frame.
$(i_{r\alpha}, i_{r\beta})$ are rotor currents in $\alpha\beta$ frame.
$\omega_r$ is the rotor pulsation.

From (2.1) and (2.2), we have

$$i_{r\alpha} = \frac{\varphi_{s\alpha} - L_s i_{s\alpha}}{M} \quad (3.1)$$

$$i_{r\beta} = \frac{\varphi_{s\beta} - L_r i_{s\beta}}{M} \quad (3.2)$$

replacing (3.1) in (2.3) and (3.2) in (2.4), we obtain.

$$\varphi_{r\alpha} = \frac{L_r}{M}\varphi_{s\alpha} + \left(M - \frac{L_r L_s}{M}\right) i_{s\alpha} \quad (4.1)$$

$$\varphi_{r\beta} = \frac{L_r}{M}\varphi_{s\beta} + \left(M - \frac{L_r L_s}{M}\right) i_{s\beta} \quad (4.2)$$

replacing (4.1) and (4.2) in (1.3):

$$\frac{di_{s\alpha}}{dt} = -\frac{R_r L_s + R_s L_r}{\sigma L_s L_r} i_{s\alpha} - p\Omega_r i_{s\beta} + \frac{R_r}{\sigma L_s L_r}\varphi_{s\alpha} + \frac{p\Omega_r}{\sigma L_s}\varphi_{s\beta} + \frac{V_{s\alpha}}{\sigma L_s} \quad (5)$$

Replacing (4.1) and (4.2) in (1.4):

$$\frac{di_{s\beta}}{dt} = p\Omega_r i_{s\alpha} - \frac{R_r L_s + R_s L_r}{\sigma L_s L_r} i_{s\beta} - \frac{p\Omega_r}{\sigma L_s}\varphi_{s\alpha} + \frac{R_r}{\sigma L_s L_r}\varphi_{s\beta} + \frac{V_{s\beta}}{\sigma L_s} \quad (6)$$

With:

$$\sigma = \left(1 - \frac{M^2}{L_s L_r}\right)$$
$$\omega_r = p\Omega_r$$

$\Omega_r$Is the rotor speed, and $\sigma$ is the leakage factor.

By integrating (2.1) et (2.2), one has

$$\varphi_{s\alpha} = -R_s \int_0^T i_{s\alpha} dt + \int_0^T V_{s\alpha} dt + C_1 \quad (7.1)$$

$$\varphi_{s\beta} = -R_s \int_0^T i_{s\beta} dt + \int_0^T V_{s\beta} dt + C_2 \quad (7.2)$$

And using (7.1) and (7.2) in (5):

$$\frac{di_{s\alpha}}{dt} = -\frac{R_r L_s + R_s L_r}{\sigma L_s L_r} i_{s\alpha} - p\Omega_r i_{s\beta} - \frac{R_r R_s}{\sigma L_s L_r}\int_0^T i_{s\alpha} dt + \frac{R_r}{\sigma L_s L_r}\int_0^T V_{s\alpha} dt - \frac{pR_s}{\sigma L_s}\Omega_r \int_0^T i_{s\beta} dt + \frac{p}{\sigma L_s}\Omega_r \int_0^T V_{s\beta} dt + \frac{1}{\sigma L_s} V_{s\alpha} + \frac{pC_2}{\sigma L_s}\Omega_r + C_1 \quad (8)$$

By integrating equation (8), we have

$$i_{s\alpha} = -\frac{R_r L_s + R_s L_r}{\sigma L_s L_r}\int_0^T i_{s\alpha} dt - p\int_0^T \Omega_r i_{s\beta} dt - \frac{R_r R_s}{\sigma L_s L_r}\int_0^T\int_0^T i_{s\alpha} dt^2 + \frac{R_r}{\sigma L_s L_r}\int_0^T\int_0^T V_{s\alpha} dt - \frac{pR_s}{\sigma L_s}\int_0^T\left(\Omega_r \int_0^T i_{s\beta} dt\right) dt + \frac{p}{\sigma L_s}\int_0^T\left(\Omega_r \int_0^T V_{s\beta} dt\right) dt + \frac{1}{\sigma L_s}\int_0^T V_{s\alpha} dt + \frac{pC_2}{\sigma L_s}\int_0^T \Omega_r dt + C_1 \cdot t + C_2 \quad (9)$$

Equation (9) doesn't use the rotor flux signals, which are considered hard to measure, and it is linear in the coefficients $\theta$ and can be expressed in the form of the equation (10).

This motor model's liner form enables the KF identification procedure discussed in section 3 to calculate the motors' electrical parameters.

$$Y = \Psi \cdot \theta \tag{10}$$

Where:

$$\psi = [\Psi_1 \quad \Psi_2 \quad \Psi_3 \quad \Psi_4 \quad \Psi_5 \quad \Psi_6 \quad \Psi_7 \quad \Psi_9 \quad \Psi_9 \quad \Psi_{10}]$$
$$\theta = [-\theta_1 \quad -\theta_2 \quad -\theta_3 \quad \theta_4 \quad -\theta_5 \quad \theta_6 \quad \theta_7 \quad \theta_9 \quad \theta_9 \quad \theta_{10}]^T$$
$$Y = i_{s\alpha} \tag{11}$$

Were

$$\theta_1 = \left(\frac{R_s}{\sigma L_s} + \frac{R_r}{\sigma L_r}\right) \tag{12.1}$$

$$\theta_2 = p \tag{12.2}$$

$$\theta_3 = \frac{R_s R_r}{\sigma L_s L_r} \tag{12.3}$$

$$\theta_4 = \frac{R_r}{\sigma L_s L_r} \tag{12.4}$$

$$\theta_5 = \frac{p R_s}{\sigma L_s} \tag{12.5}$$

$$\theta_6 = \frac{p}{\sigma L_s} \tag{12.6}$$

$$\theta_7 = \frac{1}{\sigma L_s} \tag{12.7}$$

$$\theta_8 = \frac{p C_2}{\sigma L_s} \tag{12.8}$$

$$\theta_9 = C_1 \tag{12.9}$$

$$\theta_{10} = C_2 \tag{12.10}$$

And

$$\psi_1 = \int_0^T i_{s\alpha} dt \tag{13.1}$$

$$\psi_2 = \int_0^T \Omega_r i_{s\beta} dt \tag{13.2}$$

$$\psi_3 = \int_0^T \int_0^T i_{s\alpha} dt^2 \tag{13.3}$$

$$\psi_4 = \int_0^T \int_0^T V_{s\alpha} dt^2 \tag{13.4}$$

$$\psi_5 = \int_0^T \left(\Omega_r \int_0^T i_{s\beta} dt\right) dt \tag{13.5}$$

$$\psi_6 = \int_0^T \left(\Omega_r \int_0^T V_{s\beta} dt\right) dt \tag{13.6}$$

$$\psi_7 = \int_0^T V_{s\alpha} dt \tag{13.7}$$

$$\psi_8 = \int_0^T \Omega_r dt \tag{13.8}$$

$$\psi_9 = t \tag{13.9}$$

$$\psi_{10} = 1 \tag{13.10}$$

Finally, we can obtain the formulas for the motor parameters, stator and rotor resistances $\hat{R}_s$ and $\hat{R}_r$, leakage inductance $\hat{L}_s, \hat{L}_r$ and the mutual inductance $\hat{M}$ and magnetic leakage coefficient $\hat{\sigma}$ by assuming $L_s = L_r$And using the above coefficients$\theta$ relationship formulas.

$$\hat{p} = \hat{\theta}_2 \tag{14.1}$$

$$\hat{R}_s = \frac{\hat{\theta}_5}{\hat{\theta}_6} \tag{14.2}$$

$$\hat{R}_r = \frac{\hat{\theta}_1}{\hat{\theta}_7} - \frac{\hat{\theta}_5}{\hat{\theta}_6} \tag{14.3}$$

$$\hat{L}_s = \hat{L}_r = \hat{L}_{sr} = \frac{\hat{\theta}_1\hat{\theta}_6 - \hat{\theta}_5\hat{\theta}_7}{\hat{\theta}_4\hat{\theta}_6} \tag{14.4}$$

$$\hat{\sigma} = \frac{\hat{\theta}_4\hat{\theta}_6\hat{\theta}_7}{\hat{\theta}_1\hat{\theta}_6 - \hat{\theta}_5\hat{\theta}_7} \tag{14.5}$$

$$M^2 = (1-\sigma)\hat{L}_{sr}^2 \tag{14.6}$$

## 3. KALMAN FILTER FOR REGRESSION MODELS

Parameter estimation is the mathematical process of estimating the parameters of a system from its measurements. This is done by minimizing or maximizing a criterion using an estimation algorithm based on the figure below.

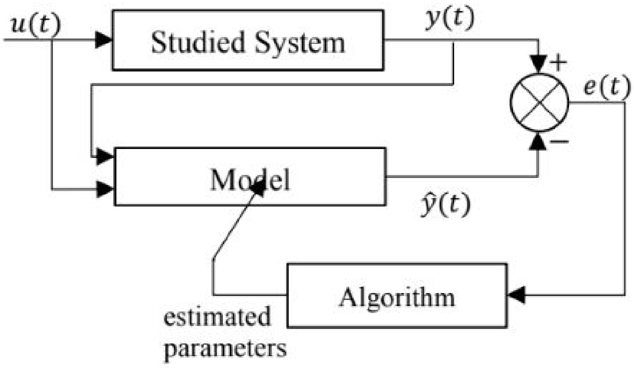


**Figure-1.** Parameter estimation method.

In this section, we describe the KF algorithm used for the estimation as follows:

We consider a stochastic system defined by:

$$y(k) = \psi^T(k)\theta + v(k) \tag{15}$$

Where $y(k)$is the observation, $v(k)$isthe noise signals, $\psi(k)$ is the regressor, $\theta(k)$are the parameters of the system.

To estimate the unknown parameters $\hat{\theta}$ we introduce the following recursive KALMAN filter [15] [16].

VOL. 18, NO. 7, APRIL 2023 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

$$\hat{\theta}(k) = \hat{\theta}(k-1) + \frac{P(k-1)\psi^T(k)}{R+\psi(k)P(k-1)\psi^T(k)}\left(y(k) - \psi(k)\hat{\theta}(k-1)\right) \quad (16)$$

$$P(k) = P(k-1) - \frac{P(k-1)\psi_k^T\psi(k)P(k-1)}{R+\psi(k)P(k-1)\psi^T(k)} + Q \quad (17)$$

- $Q = E\,w(k)w^T(k)$is obtained by considering the following model of the system's parameters

$$\theta(k) = \theta(k-1) + w(k) \quad (18)$$

- $R = E\,v^2(k)$

Where $Q$ >0, $R$ > 0, $\hat{\theta}(0)$ and $P(0)$ are deterministic and can be arbitrarily chosen. Based on [16], we can estimate the time-varying parameters by estimating $Q$ and $R$. However, in this paper, we supposed that the parameters are constant.

Note if $Q = 0$ and $R = 1$, we obtain the recursive least square algorithm.

## 4. SIMULATION AND RESULTS

The simulation of the proposed estimation method is carried out with MATLAB by using the numerical values of the parameters as follows:

**Table-1.** Nominal parameter values of the IM.

| Parameter | Nominal value |
|---|---|
| $R_s$ | 0.436 |
| $R_r$ | 0.8160 |
| $M$ | 0.0693 |
| $L_s = L_r$ | 0.0713 |

Next, the inputs ($V_{s\alpha}$,$V_{s\beta}$) and the outputs ($i_{s\alpha}, i_{s\beta}$, $\Omega_r$) of the IM were measured with a simple time of $10^{-4}$s and polluted with a white noise signal. The obtained signals are illustrated in Figures 3, 4, and 5. Those signals are used to construct the regressor Ψ described by equation (9) using the trapezoidal integration.

Afterward, the Linear Kalman Filter algorithm, which is discussed in section 3, is used to estimate the IM coefficients. A description of the estimation technique is given in Figure-2. The obtained results are displayed in Figures 6 to 12.

The simulation results for the estimated and nominal values of coefficients $\theta_1$ to $\theta_7$ values are shown respectively in Figures 6 to 12. This later indicates that the estimates converge to the nominal values at steady-state with little estimation error.

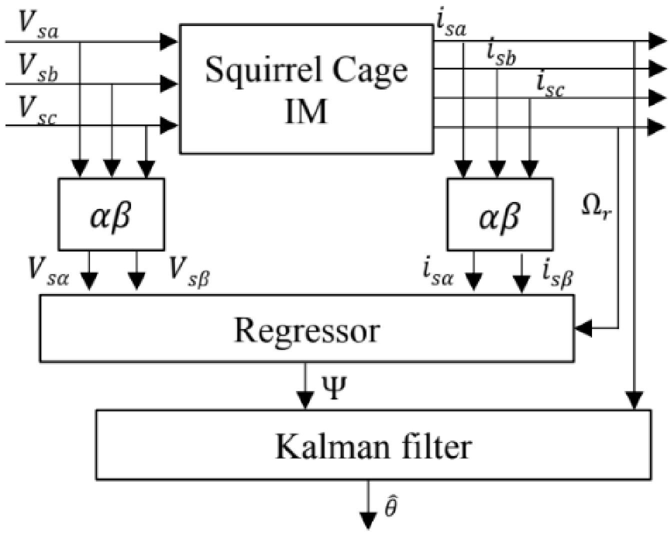


**Figure-2.** The principle of the estimation of the machine parameters

By estimating the coefficients θ, we obtain the estimated parameters $\hat{R}_s, \hat{R}_r, \hat{L}_s, \hat{L}_r$ and $M$ by using the equations in section 2. The obtained results can be seen in the table below.

**Table-2.** Comparison between the estimated and nominal parameters of the IM.

| Parameter | Nominal value | Estimated value | Estimation Error |
|---|---|---|---|
| $R_s$ | 0.436 | 0.4342 | 0.4128 % |
| $R_r$ | 0.8160 | 0.8166 | 0.0735 % |
| $L_s = L_r$ | 0.0713 | 0.07433 | 4.2496 % |
| $M$ | 0.0693 | 0.7229 | 4.3290 % |

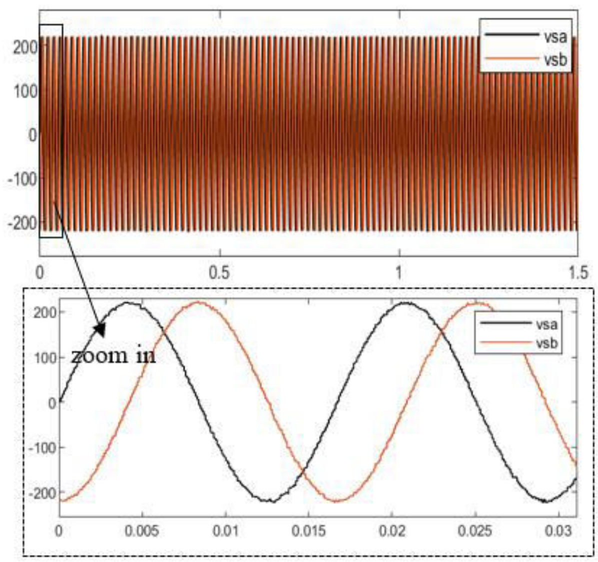


**Figure-3.** Measured voltage (V) in alpha-beta frame.

VOL. 18, NO. 7, APRIL 2023 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences



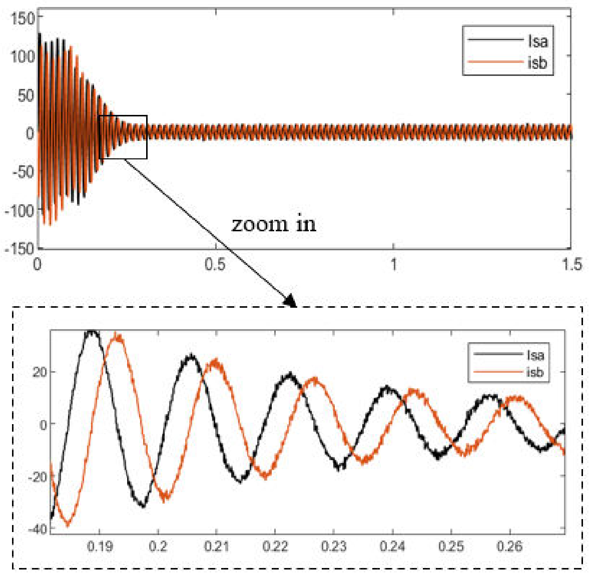


**Figure-4.** Measured currents $i_{s\alpha}, i_{sb}$ (A) in alpha-beta frame.

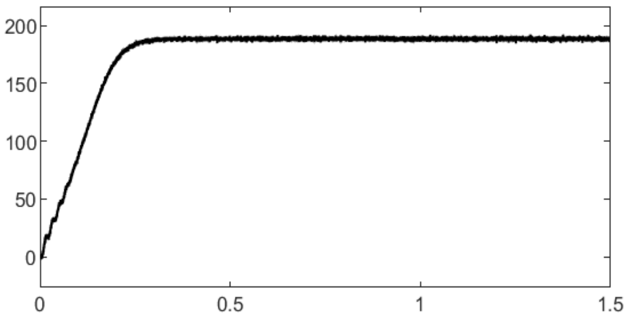

**Figure-5.** Measured speed in rad/s.

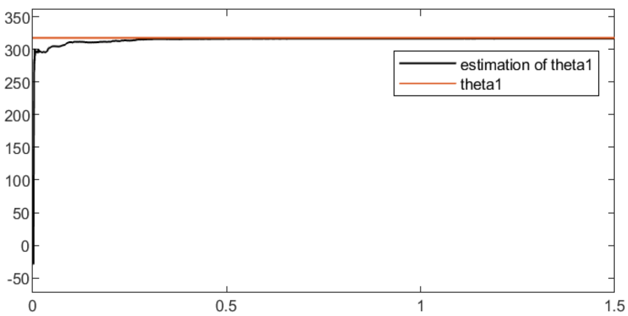


**Figure-6.** Comparison between the estimated and nominal parameter $\theta_1$.

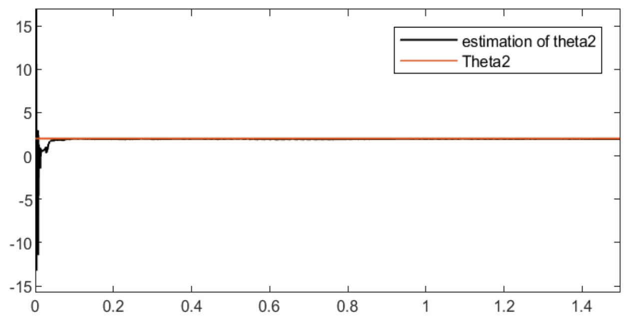


**Figure-7.** Comparison between the estimated and nominal parameter $\theta_2$.

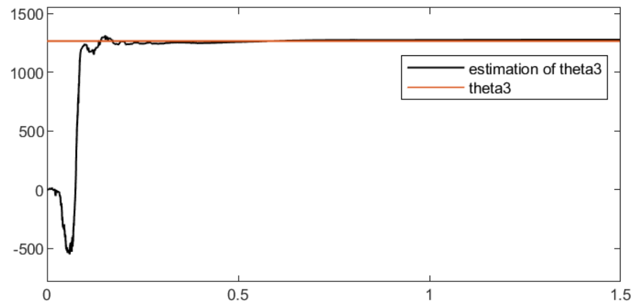


**Figure-8.** Comparison between the estimated and nominal parameter $\theta_3$.

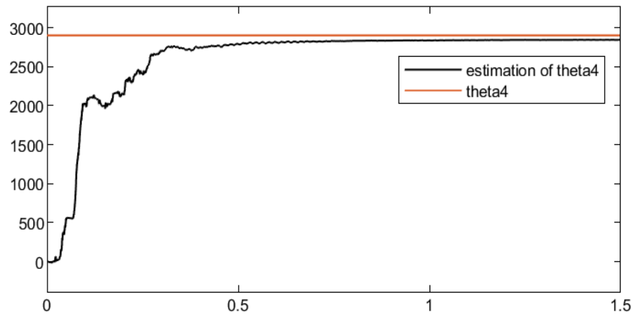


**Figure-9.** Comparison between the estimated and nominal parameter $\theta_4$.

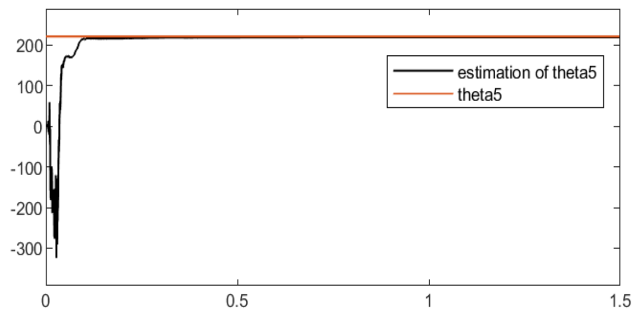


**Figure-10.** Comparison between the estimated and nominal parameter $\theta_5$.

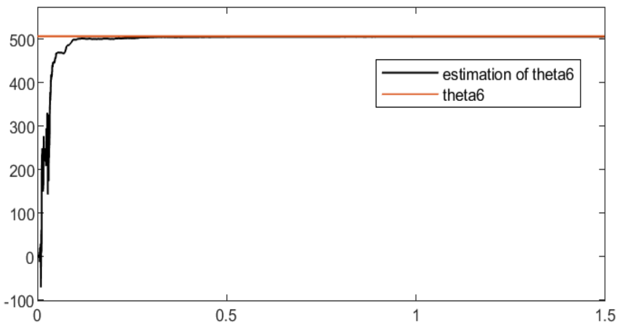


**Figure-11.** Comparison between the estimated and nominal parameter $\theta_6$.

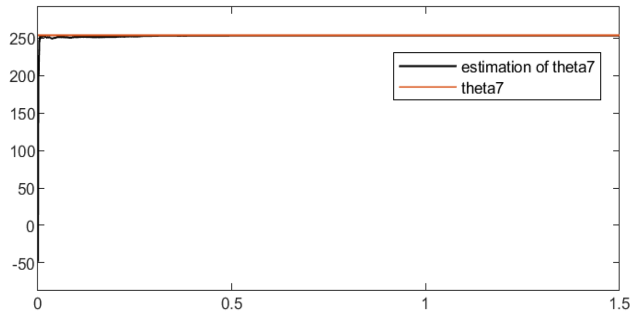


**Figure-12.** Comparison between the estimated and nominal parameter $\theta_7$.

**5. CONCLUSIONS**

In this work, the electrical parameters of an induction motor were effectively identified using an approach based on the KALMAN Filter algorithm, using stator currents, voltages, and the rotor speed. The linear regression equation that is constructed from the dynamical machine model in the alpha-beta frame serves to estimate the model coefficients, those later, are used to estimate the electrical parameters. The results demonstrate that the obtained estimated parameters are close to the references of the considered IM. This shows that the suggested identification method for estimating induction motor parameters is accurate.

**REFERENCES**

[1] H. Ouadi, A. Barra and K. El Majdoub. 2017. Nonlinear Control for Grid-Connected Wind Energy System with Multilevel Inverter. 12(4), Accessed: Oct. 05, 2022. [Online]. Available: www.arpnjournals.com

[2] R. Padilha, R. Zelir, C. Cauduro and H. Abilio. 2012. Electrical Parameter Identification of Single-Phase Induction Motor by RLS Algorithm. Induction Mot. - Model. Control, 2012, doi: 10.5772/37664.

[3] B. Reddy, G. Poddar and B. P. Muni. 2022. Parameter Estimation and Online Adaptation of Rotor Time Constant for Induction Motor Drive. IEEE Trans. Ind. Appl., 58(2): 1416-1428, doi: 10.1109/TIA.2022.3141700.

[4] F. Karami, J. Poshtan and M. Poshtan. 2010. Detection of broken rotor bars in induction motors using nonlinear Kalman filters. ISA Trans., 49(2): 189-195, doi: 10.1016/j.isatra.2009.11.005.

[5] H. R. Mohammadi and A. Akhavan. 2014. Parameter Estimation of Three-Phase Induction Motor Using Hybrid of Genetic Algorithm and Particle Swarm Optimization. J. Eng. (United Kingdom), vol. 2014, doi: 10.1155/2014/148204.

[6] Y. S. Mohamed, B. M. Hasaneen, A. A. Elbaset and A. E. Hussein. 2011. Recursive Least Square Algorithm for Estimating Parameters of an Induction Motor. J. Eng. Sci., 39(1): 87-98.

[7] J. Tang, Y. Yang, F. Blaabjerg, J. Chen, L. Diao and Z. Liu. 2018. Parameter identification of inverter-fed induction motors: A review. Energies, 11(9): 1-21, doi: 10.3390/en11092194.

[8] Y. Koubaa. 2004. Recursive identification of induction motor parameters. Simul. Model. Pract. Theory, 12(5): 363-381, doi: 10.1016/J.SIMPAT.2004.04.003.

[9] P. Dipanjali Behera *et al*. 2019. On-Line Parameter Identification of a Squirrel Cage Induction Motor. J. Phys. Conf. Ser., 1302(2): 022054, doi: 10.1088/1742-6596/1302/2/022054.

[10] H. Zhang, S. J. Gong and Z. Z. Dong. 2013. On-line parameter identification of induction motor based on RLS algorithm. in 2013 International Conference on Electrical Machines and Systems, ICEMS 2013, pp. 2132-2137. doi: 10.1109/ICEMS.2013.6713208.

[11] L. Yang, X. Peng and Z. Li. 2010. Induction motor electrical parameters identification using RLS estimation. 2010 Int. Conf. Mech. Autom. Control Eng. MACE2010, pp. 3294-3297, doi: 10.1109/MACE.2010.5535653.

[12] T. Kostal and P. Kobrle. 2021. Induction machine on-line parameter identification for resource-constrained microcontrollers based on steady-state voltage model. Electron. 10(16), doi: 10.3390/electronics10161981.

[13] F. Debbabi, A. L. Nemmour, A. Khezzar and S. E. Chelli. 2020. An approved superiority of real-time induction machine parameter estimation operating in

self-excited generating mode versus motoring mode using the linear RLS algorithm: Ideas and applications. Int. J. Electr. Power Energy Syst., 118(November 2019): 105725, doi: 10.1016/j.ijepes.2019.105725.

[14] M. Boufadene. 2018. Modeling and Control of AC Machine using MATLAB®/SIMULINK. Model. Control AC Mach. using MATLAB®/SIMULINK, (December 2018): 1-50, doi: 10.1201/9780429029653.

[15] L. Guo. 1990. Estimating time-varying parameters by the kaiman filter based algorithm: Stability and convergence. IEEE Trans. Automat. Contr., 35(2): 141-147, doi: 10.1109/9.45169.

[16] A. Isaksson. 1987. Identification of Time Varying Systems through Adaptive Kalman Filtering. IFAC Proc. 20(5): 305-310, doi: 10.1016/s1474-6670(17)55517-2.