Induction Machine Parameter Identification Using LMS Algorithm Associated with a Nonlinear Adaptive Observer: ICEERE 2018, 15–17 April 2018, Saidia, Morocco

Chapter · January 2019

DOI: 10.1007/978-981-13-1405-6_68

5 authors, including:

Mohammed Belkheiri
Université Amar Telidji Laghouat

Ahmed Belkheiri
Université Amar Telidji Laghouat

Mourad Boufadene
Université Amar Telidji Laghouat

Hamou Ait Abbas
Université de Bouira

Induction machine parameter identification using LMS algorithm associated with a nonlinear adaptive observer

Mohammed Belkheiri[1], Ahmed Belkheiri[1] , Boufaden Mourad[2], Ait Abbas Hamou[2], and Abdlhamid Rabhi[3]

[1] Laboratoire de Télécommunications, Signaux et Système
University Amar Telidji of Laghouat, PB. 37G, Ghardia Road, Laghouat, 03000, Algeria
[2] Ecole Supérieure en Sciences Appliquées à Alger, Place des Martyrs, Alger 16001,Algérie
3 Laboratoire Modélisation Information et Systèmes, 33 rue Saint Leu - 80039 Amiens- France
m.belkheiri@lagh-univ.dz

Abstract. In this paper, we describe and evaluate a method for estimating the induction motor parameters. It is fast, efficient, and does not require special test signals or machine configuration. In addition, this method is adequate for the continuous updating of the parameters of the normal operation of the machine, so that the monitoring of the variations of the parameters is possible, we do not consider the problem of estimating the speed, but rather to simplify the problem by assuming that the speed is known. On the other hand, the speed is assumed variable, showing how the rotor flux estimates can be constructed at the same time. The Results of simulation show the effectiveness of the proposed identifier associated with the observer.

Keywords: Induction machine, parameter identification, flux observer.

1 Introduction

The induction motor has become very used in various industrial applications thanks to its low cost and robustness. This type of machine has been proposed to replace hydraulic actuators in aerospace applications and internal combustion engines [1]. Solving problems related to the regulation and / or tracking of the speed of induction motors has attracted the automatic community through recent nonlinear control techniques such as input/output linearization, backstepping and theory of passivity. Whatever control method is used, a significant problem must be first solved which is a precise machine model with exact parameters. The uncertainties in the parameters may affect the performance of the designed control laws [2,6]. The problem is usually complicated by the fact that some state variables (i.e. the rotor flux components) are not measured or require expensive sensors for their measurement. If the flux is measured, it would be relatively simpler to design a recursive identifier to estimate the motor parameters [1, 3]. Nevertheless, if the parameters of the machine are known exactly, then it would be possible to design an observer to estimate the flux. However, the common problem is much more complicated. It does not fall directly into the adaptive identification framework because of the non-linearity of the dynamic model of the induction motor.

The standard methods of estimating the parameters of the induction motor include the locked rotor test, the open circuit test, and the stop frequency response test, a procedure is described automatically in which a sequence of these tests is performed. Each test is designed to isolate and measure a specific parameter [4].

Another procedure is described, based mainly on the identification of the transfer function of the motor at standstill. The model is then refined to account for magnetic saturation and adaptation is included to compensate for the effects of heating [5,6].

In this paper, we describe and evaluate a method for estimating induction motor parameters. It is fast, efficient, and does not require special test signals or machine configuration. In addition, the method is adequate for the continuous updating of the parameters of the normal operation of the machine, so that the monitoring of the variations of the parameters is possible, we do not consider the problem of the estimate of the speed, but rather to simplify the problem by assuming that the speed is known. On the other hand, the speed is assumed variable, showing how the rotor flux estimates can be constructed at the same time.

The paper is organized as follows. Section II presents the standard asynchronous machine modeling. The least squares identification is applied for the estimation of the electric and mechanical parameters of the motor in section III. The method for rebuilding flux is also detailed. Simulation and Results are presented in section IV.

2 Mathematical modelling of the induction motor

Standard models of induction machines are widely developed in the literature see [1] for example, where a suitable model for control applications is discussed. Some complex effects such as hysteresis, eddy currents, magnetic saturation are generally neglected in establishing Induction motor model for controller design. The identification algorithm presented here is based on the model expressed in a coordinate frame rotating with the rotor.

$$\frac{di_{sx}}{dt} = \frac{1}{\sigma L_s} v_{sx} - \gamma i_{sx} + \frac{\beta}{T_r}\psi_{rx} + n_p \beta\omega\psi_{ry} + n_p\omega i_{sy} \tag{1}$$

$$\frac{di_{sy}}{dt} = \frac{1}{\sigma L_s} v_{sy} - \gamma i_{sy} + \frac{\beta}{T_r}\psi_{ry} - n_p\beta\omega\psi_{rx} - n_p\omega i_{sx} \tag{2}$$

$$\frac{d\psi_{rx}}{dt} = \frac{M}{T_r} i_{sx} - \frac{1}{T_r}\psi_{rx} \tag{3}$$

$$\frac{d\psi_{ry}}{dt} = \frac{M}{T_r} i_{sy} - \frac{1}{T_r}\psi_{ry} \tag{4}$$

$$\frac{d\varpi}{dt} = \frac{2Mn_p}{JL_r\, n_{ph}} \left(i_{sy}\psi_{rx} - i_{rx}\psi_{ry}\right) - \frac{\tau_L}{J} \tag{5}$$

In the above model, the angular velocity of the rotor is denoted as ω and N_{ph} is the number of phases. The unknown parameters of the model are the five electrical parameters, R_s and R_r (stator and rotor resistors), M (the mutual inductance), L_s and L_r (stator and rotor inductors), and the two mechanical parameters, J (rotor inertia) and τ_L (load torque).

The symbols $T_r = \frac{L_r}{R_r}$, $\sigma = 1 - \frac{M^2}{L_a L_r}$, $\beta = \frac{M}{\sigma L_s L_r}$, and $\gamma = \frac{R_s}{\sigma L_s} + \frac{M^2 R_r}{\sigma L_s L_r^2}$ have been used to simplify expressions. T_r is the constant rotor time and σ is the total leakage-factor. Manipulating the induction motor model (1 to 5) to get a simplified model where the unknown parameters can be linearly isolated as follows:

$$\frac{di_{sx}}{dt} + \gamma i_{sx} - \frac{\beta}{T_r}\psi_{rx} - n_p\beta\omega\psi_{ry} - n_p\omega i_{sy} = \frac{1}{\sigma L_s}v_{sx} \quad (6)$$

$$\frac{di_{sy}}{dt} + \gamma i_{sy} - \frac{\beta}{T_r}\psi_{ry} - n_p\beta\omega\psi_{rx} + n_p\omega i_{sx} = \frac{1}{\sigma L_s}v_{sy} \quad (7)$$

Taking the first derivatives of equations (6) and (7) and after some mathematical manipulations we can get

$$\frac{1}{\sigma L_s}\frac{dv_{sx}}{dt} + \frac{1}{T_r\sigma L_s}v_{sx} - n_p\omega\left(\frac{1}{T_r} + \frac{\beta M}{T_r}\right)i_{sy} = \frac{d^2 i_{sx}}{dt^2} + \left(\gamma + \frac{1}{T_r}\right)\frac{di_{sx}}{dt} + \left(\frac{\gamma}{T_r} - \frac{\beta M}{T_r^2}\right)i_{sx} - n_p\left(i_{sy} + \beta\psi_{ry}\right)\frac{d\omega}{dt} - n_p\omega\frac{di_{sy}}{dt} \quad (8)$$

$$\frac{1}{\sigma L_s}\frac{dv_{sy}}{dt} + \frac{1}{T_r\sigma L_s}v_{sy} = \frac{d^2 i_{sy}}{dt^2} + \left(\gamma + \frac{1}{T_r}\right)\frac{di_{sy}}{dt} + \left(\frac{\gamma}{T_r} - \frac{\beta M}{T_r^2}\right)i_{sy} + n_p\omega\left(\frac{1}{T_r} + \frac{\beta M}{T_r}\right)i_{sx} + n_p(i_{sx} + \beta\psi_{rx})\frac{d\omega}{dt} + n_p\omega\frac{di_{sx}}{dt} \quad (9)$$

This model can be written as:

$$\frac{d^2 i_{sx}}{dt^2} + \theta_1\frac{di_{sx}}{dt} + \theta_2 i_{sx} - \theta_3 n_p\omega i_{sy} - n_p\omega\frac{di_{sy}}{dt} = \theta_4\frac{dv_{sx}}{dt} + \theta_5 v_{sx} \quad (10)$$

$$\frac{d^2 i_{sy}}{dt^2} + \theta_1\frac{di_{sx}}{dt} + \theta_2 i_{sy} + \theta_3 n_p\omega i_{sx} + n_p\omega\frac{di_{sx}}{dt} = \theta_4\frac{dv_{sy}}{dt} + \theta_5 v_{sy} \quad (11)$$

where

$$\theta_1 = \gamma + \frac{1}{T_r}, \theta_2 = \frac{\gamma}{T_r} - \frac{\beta M}{T_r^2}, \theta_3 = \frac{1}{T_r} + \frac{\beta M}{T_r}, \theta_4 = \frac{1}{\sigma L_s}, \theta_5 = \frac{1}{\sigma L_s T_r}$$

To estimate the physical parameters, we can use

$$R_s = \frac{\theta_2}{\theta_5}, L_s = \frac{\theta_3}{\theta_5}, \sigma = \frac{\theta_5}{\theta_3\theta_4}, T_r = \frac{\theta_4}{\theta_5}$$

The model can also be expressed in matrix as shown below:

$$\begin{pmatrix} -\frac{di_{sx}}{dt} & -i_{sx} & n_p\omega i_{sy} & \frac{dv_{sx}}{dt} & v_{sx} \\ -\frac{di_{sy}}{dt} & -i_{sy} & -n_p\omega i_{sx} & \frac{dv_{sy}}{dt} & v_{sy} \end{pmatrix}\begin{pmatrix}\theta_1\\ \theta_2\\ \theta_3\\ \theta_4\\ \theta_5\end{pmatrix} = \begin{pmatrix}\frac{d^2 i_{sx}}{dt^2} - n_p\omega\frac{di_{sy}}{dt}\\ n_p\omega\frac{di_{sx}}{dt} + \frac{d^2 i_{sy}}{dt^2}\end{pmatrix} \quad (12)$$

This linear form of the motor model allows direct application of a least squares identification algorithm to estimate electrical parameters.

Using equation (12) and defining the error vector as

$$\boldsymbol{\varepsilon}(k) = \boldsymbol{y}(k) - \boldsymbol{\varphi}^{\mathrm{T}}(k)\boldsymbol{\theta} \quad (13)$$

where $\boldsymbol{\varphi}(k)$ represents the regressor vector, $\boldsymbol{\theta}$ the vector parameters to be identified and $\varepsilon(k)$ the error of equation written in the general form of prediction error.

$$\boldsymbol{\varphi}^{\mathrm{T}}(k)=\begin{pmatrix} -\frac{di_{sx}}{dt} & -i_{sx} & n_p\omega i_{sy} & \frac{dv_{sx}}{dt} & v_{sx} \\ -\frac{di_{sy}}{dt} & -i_{sy} & -n_p\omega i_{sx} & \frac{dv_{sy}}{dt} & v_{sy} \end{pmatrix}$$

$$\boldsymbol{\theta}=\begin{pmatrix}\theta_1\\ \theta_2\\ \theta_3\\ \theta_4\\ \theta_5\end{pmatrix},\boldsymbol{y}(k)=\begin{pmatrix}\frac{d^2 i_{Sx}}{dt^2}-n_p\omega\frac{di_{Sy}}{dt}\\ n_p\omega\frac{di_{Sx}}{dt}+\frac{d^2 i_{sy}}{dt^2}\end{pmatrix}$$

By accumulating *N* measurements, for example at the discrete instants *k = 1, ... N*, the equation (13) gives in matrix form:

$$\begin{pmatrix}\varepsilon(1)\\ \varepsilon(2)\\ \vdots\\ \vdots\\ \varepsilon(N)\end{pmatrix}=\begin{pmatrix}y(1)\\ y(2)\\ \vdots\\ \vdots\\ y(N)\end{pmatrix}-\begin{pmatrix}\boldsymbol{\varphi}^T(1)\\ \boldsymbol{\varphi}^T(2)\\ \vdots\\ \vdots\\ \boldsymbol{\varphi}^T(N)\end{pmatrix}\boldsymbol{\theta} \tag{14}$$

$$\mathcal{E}=\boldsymbol{Y}-\Phi\boldsymbol{\theta} \tag{15}$$

The quadratic prediction error is as follows:

$$\min J=\sum_{k=1}^{N}\varepsilon^2(k)=\mathcal{E}^{\mathrm{T}}\mathcal{E}$$

The minimization of the quadratic error gives

$$\widehat{\boldsymbol{\theta}}=(\Phi^T\Phi)^{-1}\Phi^T Y \tag{16}$$

3 Flux Adaptive Observer Design

Note that the need to have flux measurements is avoided by the assumption that the speed varies slowly. This is an advantage because flux measurements, which require sensors near the gap, are not practical to obtain. A disadvantage is that derivatives from there currents are needed. These can be reconstructed by filtered differentiation. In this paper an observer is designed to reconstruct the flux from the available current and the parameters identified in the precedent section.

First an observer is designed for the stator subsystem:

$$\begin{pmatrix}\frac{di_{Sx}}{dt}\\ \frac{d\psi_{Sx}}{dt}\end{pmatrix}=\begin{pmatrix}-\gamma & \frac{\beta}{T_R}\\ 0 & \frac{-1}{T_R}\end{pmatrix}\begin{pmatrix}i_{Sx}\\ \psi_{Sx}\end{pmatrix}+\begin{pmatrix}\frac{1}{\sigma L_s}\\ 0\end{pmatrix}u_{Sx}+\begin{pmatrix}\eta_p\beta\omega\psi_{Ry}+\eta_p\omega i_{Sy}\\ 0\end{pmatrix} \tag{17}$$

$$y_{sx}=(1\ \ 0)\begin{pmatrix}i_{Sx}\\ \psi_{Sx}\end{pmatrix}$$

Let us parametrize the above subsystem considering the linear part and a nonlinear function f linearly parametrized with unknown parameters as follows:

$$A = \begin{pmatrix} -\gamma & \frac{\beta}{T_R} \\ 0 & \frac{-1}{T_R} \end{pmatrix},\ B = \begin{pmatrix} \frac{1}{\sigma L_s} \\ 0 \end{pmatrix},\ f = \begin{pmatrix} \eta_p \beta \omega \psi_{Ry} + \eta_p \omega i_{Sy} \\ 0 \end{pmatrix},\ C = (1\ \ 0)$$

The adaptive observer is designed to take the measured stator current to reconstruct the state vector using:

$\dot{\hat{x}} = A\hat{x} + f(u,y) + B\varphi\hat{\theta} + L(y - C\hat{x})$

where $\hat{x}$ is the estimated state vector and the $\hat{\theta}$ is the estimated parameters and L is a tuning gain of the linear part of the observer.

$$\dot{x} = Ax + B(u,y) + f$$
$$\dot{\hat{x}} = A\hat{x} + Bu + \hat{f} + L(Cx - C\hat{x})$$

Defining $e = x - \hat{x}$ as the error between the actual and the estimated state vector; and $\tilde{\theta} = \theta - \hat{\theta}$ as the parameter estiation error,

Using the Lyapunov candidate:

$V = e^T P e + \tilde{\theta}^T \gamma^{-1} \tilde{\theta}$

Where γ is a diagonal positive definite adaptation gain matrix, and P, Q are semi-positive definite matrices satisfying the algebraic Lyapunov matrix equation:

$$A^T P + PA = -Q \tag{18}$$

Defining the closed loop matrix $A_c = A - LC$ and based on equation (17), the error dynamics can be expressed as:

$$\dot{e} = A_c e + B\varphi\tilde{\theta}$$

The derivative of the Lyapunov equation can be given as:

$$\dot{V} = \dot{e}^T P e + e^T P \dot{e} + \dot{\tilde{\theta}}^T \gamma^{-1} \tilde{\theta} + \tilde{\theta}^T \gamma^{-1} \dot{\tilde{\theta}} \tag{19}$$

Applying the parametrization for the stator system we can derive the stator subsystem observer as:

$$\frac{d\hat{i}_{Sx}}{dt} = \frac{u_{Sx}}{\sigma L_s} - \gamma i_{Sx} + \frac{\beta}{T_R}\hat{\psi}_{Rx} + \eta_p \beta \hat{\omega} \psi_{Ry} + \eta_p \hat{\omega} i_{Sy} \tag{20}$$

$$\frac{d\hat{\psi}_{Rx}}{dt} = \frac{M}{T_R} i_{Sx} - \frac{1}{T_R}\hat{\psi}_{Rx} \tag{21}$$

and the error dynamics

$\dot{e} = \dot{x} - \dot{\hat{x}} =$

$$\begin{pmatrix} \frac{di_{Sx}}{dt} - \frac{d\hat{i}_{Sx}}{dt} \\ \frac{d\psi_{Sx}}{dt} - \frac{d\hat{\psi}_{Sx}}{dt} \end{pmatrix} = \begin{pmatrix} \frac{u_{Sx}}{\sigma L_s} - \gamma i_{Sx} + \frac{\beta}{T_R}\psi_{Rx} + \eta_p \beta \omega \psi_{Ry} + \eta_p \omega i_{Sy} - \frac{d\hat{i}_{Sx}}{dt} \\ \frac{M}{T_R} i_{Sx} - \frac{1}{T_R}\psi_{Rx} - \frac{d\hat{\psi}_{Sx}}{dt} \end{pmatrix}$$

4 Simulation Results

In order to test the identification method presented in this chapter, a model of the machine was constructed in the Simulation environment Matlab / 2015b. The figure summarizes the simulation scheme

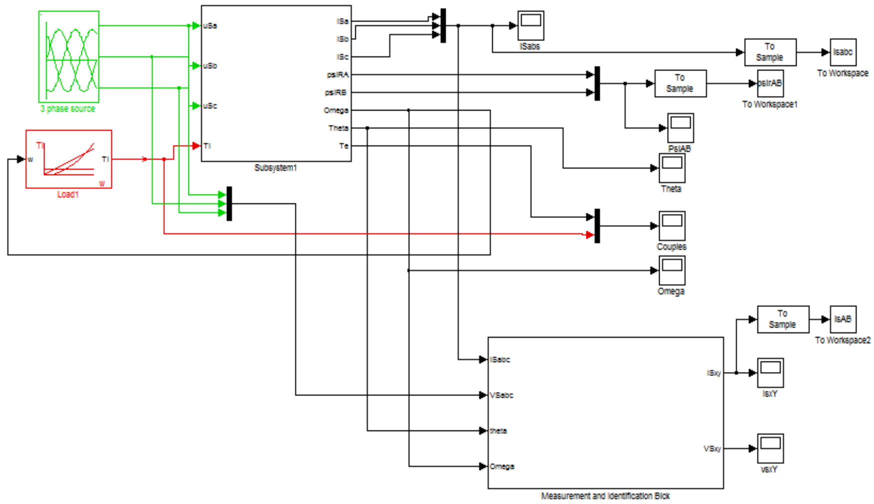

Figure 1. Simulation of the Induction machine

The machine was simulated in the rotor coordinate system where the system dynamics were divided into three interconnected subsystems (mechanical system, rotor flow system and stator current)

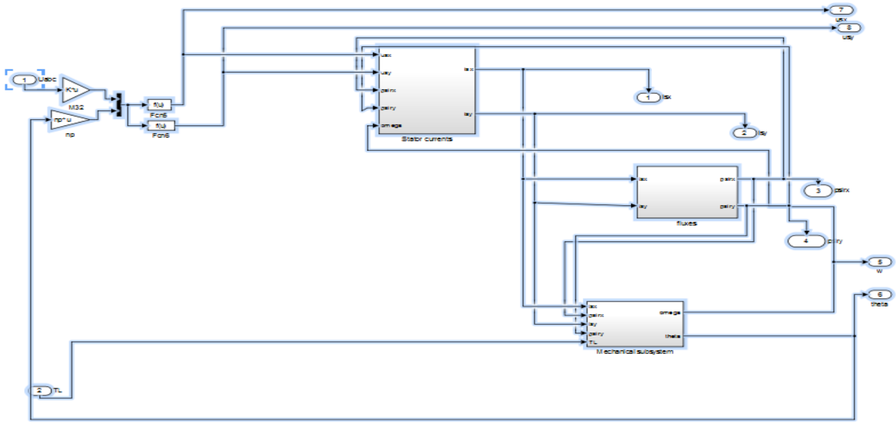

Figure 2. Schéma interne de bloc identification

We considered a 1/2 KW squirrel cage asynchronous motor with following parameters [1]:

Vmax = 466.7; fr = 50; f = 0 np = 2; ph = 3; Rr = 8.6 Rs = 9.7; Lr = 0.67
Ls = 0.67; M = 0.64 Lm = M; sigma = 0.0875 J = 0.011, f = 0.001; TL = 3.7

The applied voltages are a balanced three phase voltage with a frequency of 50 Hz.

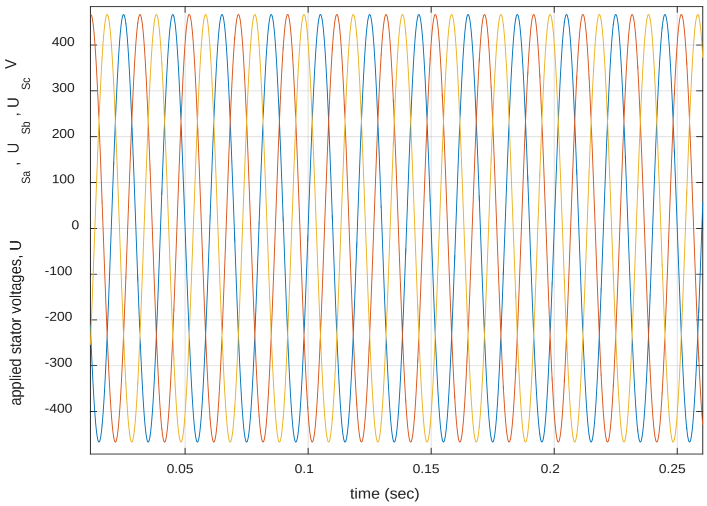

Figure 3. Applied voltages

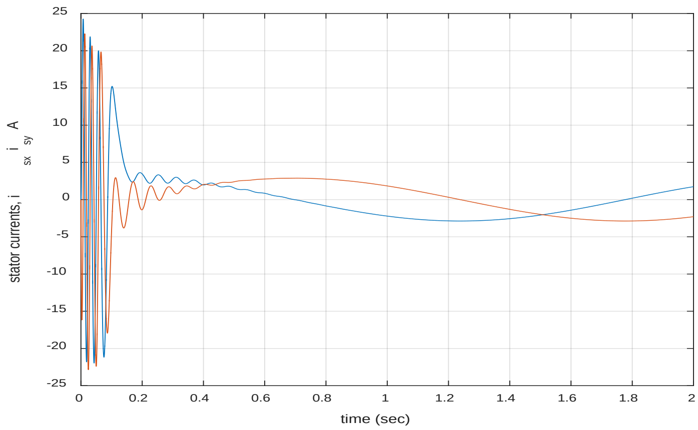

Figure 4 : Measured currents

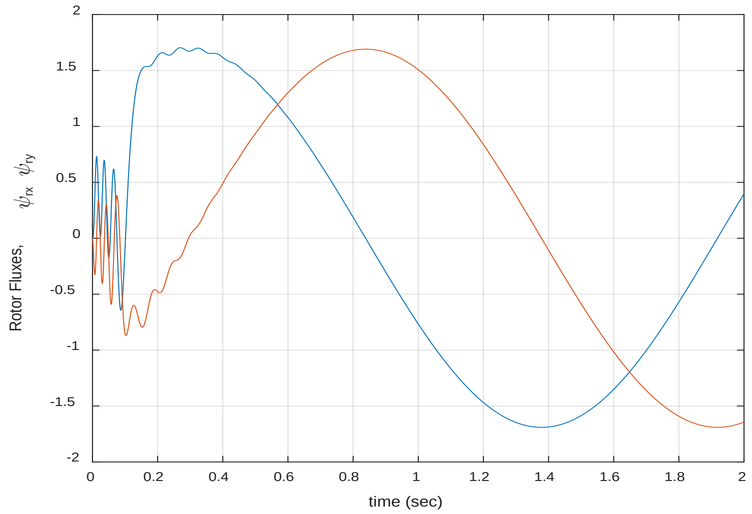

Figure 5 Estimated flux

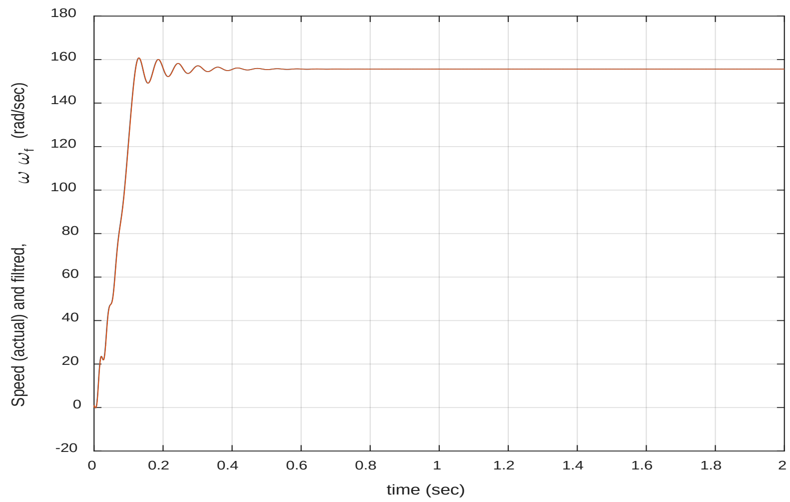

Figure 5 : Angular velocity (actual and identified)

The identified mathematical parameters are:

$$\boldsymbol{\theta} = \begin{pmatrix} \theta_1 = 263{,}980 \\ \theta_2 = 115.701 \\ \theta_3 = 66.9488 \\ \theta_4 = 15.69561 \\ \theta_5 = 99.09449 \end{pmatrix}$$

Table 1 shows that the identified parameters are very close to the real values. The differences may be due to the conditions of use for the identification of the parameters of the IM are different from those defined by the manufacturer.

Table 1. The actual and identified electrical parameters.

Parameter	Current value	Estimated value
Rs	9.6999 Ω	11.675 Ω
Ls	0.6700 mH	0.6756 mH
Sigma	0.0875	0.0943
Tr	0.1491	0.1583

5 Conclusion

The aim of this paper is to propose a simple parametric identification method for the induction machine. through Simulink simulation under MATLAB, the model identified by the proposed approache combined with flux estimator were verified and validated. This study shows that: - The parameters of the machine depend on the operating point and therefore the measurement conditions, - The identification results are satisfactory for a simulation of the behavior of the machine, conversely, they are insufficient for its control and diagnosis.

References

1. Chiasson, John. “Modeling and High-Performance Control of Electric Machines”, in: John Wiley & Sons, New Jersey, 2005.
2. Rebaia Chergui, Identification des paramètres d’un moteur asynchrone , Master thesisin electrotechnical engineering, University of Batna – Dec. 2014.
3. Mourad Boufadene , Mohammed Belkheiri , “Abdelhamid Rabhi, Adaptive nonlinear observer augmented by radial basis neural network for a nonlinear sensorless control of an induction machine”, International Journal of Automation and Control, Vol 12.
4. J. Stephan, M. Bodson and J. Chiasson, "Real-time estimation of the parameters and fluxes of induction motors," Conference Record of the 1992 IEEE Industry Applications Society Annual Meeting, Houston, TX, 1992, pp. 578-585 vol.1. N° 1, Jan 2018.
5. Stephan, M. Bodson and J.Chiasson, “Real-time estimation of the parameters and fluxes of induction Motor”, IEEE Transactions on industry applications 30 (3), 746-759, 1994.
6. Hamou Ait Abbas, Mohammed Belkheiri and Boubakeur Zegnini, “Feedback linearisation control of an induction machine augmented by single-hidden layer neural networks”, International Journal of Control, Volume 89, Issue 1, 2016.