Advances in Communication Technology, Computing and Engineering
***Editors*:** Mariyam Ouaissa, Mariya Ouaissa, Sarah El Himer, Zakaria Boulouard
pp. 702 – 717, Copyright © 2021 RGN Publications

Sensorless Backstepping Control Using a Extended Kalman Filter for Double Star Induction Motor

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Abstract. An approach by the Backstepping control of a double stator asynchronous machine DSIM with resistant torque estimation is presented in this article. The Backstepping technique is used to construct a recursively stable law control for speed and flux, in industry. This control law poses a major problem which is the need to use a mechanical value sensor (speed, flux, load torque), and imposes an extra cost and increases the complexity of the process. To ovoid this problem, an Extended Kalman filter EKF estimator has been detailed for the objective of reducing costs (no sensor to implement) or presented as a degraded but functional solution to applications with sensors in case of malfunction. The simulation results are presented to illustrate the performance of the proposed control approach associated with the Kalman filter.

Keywords and phrases: Dual Star Induction Motor DSIM, Direct Filed Oriented Control (DFOC), Backstepping Control, Sensorless Control, Extended Kalman Filter EKF.

1 Introduction

The double star induction motor DSIM has been widely used in various industrial applications due to its high reliability, low cost, segment the power and easy maintenance requirements [1]. However, its nonlinear structure requires decoupled torque and flux control. Several methods of control are used to control the double star induction motor among which the field oriented control (FOC) allows a decoupling between the flux and the torque in order to obtain an independent control of the flux and the torque like DC motors [1].

Because the dynamic structure DSIM is strongly non-linear and coupled. The situation changes with the appearance of the theory of non-linear systems in control theory where the researchers are interested in new control as Backstepping control. This method allows to approach large

systems with a systematic approach, which was introduced during the 1990s by several researchers, Kokotovic is quoted [2]. The application of the latter is found, for example, in the field of aeronautics in [2], and in the field of robotics in [3], and electrical machines [4], and also for power network regulation in [5].

The majority of the control laws of asynchronous machines such as vector and non-linear commands require the measurement not only of the stator currents (possibly stator voltages) but also of the mechanical speed. Moreover, the load torque is a measurable disturbance but the price of the sensor often makes this measurement unrealistic. The control without mechanical sensor (speed, flux, load torque) has become a major concern in industry.

Among several approaches without mechanical sensor of the asynchronous machine use neural networks [6], sliding mode [7], another approach widely used based on a model of behavior of the machine which using observation techniques from the extended Luenberger filters in [8, 9, 10]. However, with the presence of noise, the error of estimations can't be equal to zero. This one decreases the performance of the observer. It is even possible to filter the output in order to eliminate the noise. But this filter can also eliminate its information of the dynamic of the system, in addition to the sensitivity to random disturbances and to variations in the parameters. Moreover, in the nonlinear version, the Luenberger observer is considered generally difficult to realize and presents the noises and error of estimations which can't be equal to zero [8]. The sliding observer with real adjustment didn't give satisfactory result when operating in low speed [11]. So the extended Kalman filter remains the most method since it gives a well optimal estimate of the states or parameters for noisy nonlinear systems compared with other observers [11-12].

From this point of view, the objective of this paper consists of Backstabbing control based on contribution of extended Kalman filter to determine quantities (speed and flux, load torque) of the double stator asynchronous machine DSIM in noisy environments, where using only measurements of electrical quantities. These techniques used to replace the information given by the mechanical sensors either in case of failure or the sensors or not implanted (reduce the number of sensors).

In this paper, first, we use Backstepping recursive control algorithm to synthesize a stabilizing control for the double stator asynchronous machine DSIM to control the speed and flux. After a short exposition of the vector control equations by orientation of the direct rotor flux DFOC which will be use to define low of Backstebbing control. The Kalman filter is proposed to reconstruct the speed, the flux, and the essentially as the resistive torque. In fact, the resistive torque is very necessary for the implementation of the all controls law, and in practice the value of the resistive torque (load) is unknown.

The simulations results are presented in the end of paper with efficiency of this control and efficiency of replacing the sensors by the proposed EKE estimation approach.

2 Indirect Field Oriented Control of DSIM

The vector control is based on the decoupling of flux and torque. The principle of the vector control called control by flux orientation, obtained by the adjustment of torque by a component of the current and the flux by the other component [8-13-14]. Vector control leads to high industrial performance of asynchronous drives. If we make the rotor flux coincide with the axis (d) of the frame linked to the rotating field. The rotor flux orientation by:

$$\phi_{qr} = 0; \phi_{dr} = 0 \tag{1}$$

So the main objective of vector control is to produce reference voltages for the static voltage converters supplying the DSIM. Note X^* for reference quantities, (torque, flux, voltages and currents). Applying the orientation of the rotor flux on the system of equations of the machine leads to [8-13, 14-15] has been presented by: ω_{sr}^* : the slip angular frequency with : $\mu = \frac{L_m}{L_m + L_r}$; $\alpha = \frac{R_r}{L_m + L_r}$; $\alpha = \frac{L_r}{R_r}$

$$\begin{cases} T_e = p \dfrac{L_m}{L_m + L_r}\left(I_{qs1}^* + I_{qs2}^*\right)\Phi_r^* \\ \omega_{sr}^* = \dfrac{R_r L_m}{\left(L_m + L_r\right)\Phi_r^*}\left(I_{qs1}^* + I_{qs2}^*\right) \\ \omega_s^* = \omega_{sr}^* + \omega_r \\ \Phi_r^* = L_m\left(I_{ds1}^* + I_{ds2}^*\right) \end{cases} \tag{2}$$

$$\begin{cases} V_{ds1}^* = R_s I_{ds1} + L_s \dfrac{d}{dt} I_{ds1} - \omega_s^*(L_s I_{qs1} + T_r \Phi_r^* \omega_{sr}^*) \\ V_{ds2}^* = R_s I_{ds2} + L_s \dfrac{d}{dt} I_{ds2} - \omega_s^*(L_s I_{qs2} + T_r \Phi_r^* \omega_{sr}^*) \\ V_{qs1}^* = R_s I_{qs1} + L_s \dfrac{d}{dt} I_{qs1} + \omega_s^*(L_s I_{ds1} + \Phi_r^*) \\ V_{qs2}^* = R_s I_{qs2} + L_s \dfrac{d}{dt} I_{qs2} + \omega_s^*(L_s I_{ds2} + \Phi_r^*) \end{cases} \tag{3}$$

Equations (3) constituted the reference equation voltage system.

3 THE STEP OF BACKSTEPPING CONTROL

The Backstepping control technique provides a systematic method for designing a controller for nonlinear systems [2-4-8]. The idea is to compute a control law in order to guarantee, for a certain positive definite (Lyapunov) function, an always negative derivative. The method consists in breaking up the system into a set of decreasing nested subsystems. The calculation of the Lyapunov function is then performed recursively from the inside of the loop. The objective of this technique is to calculate, at each stage of the process, a virtual command is thus generated to ensure the convergence of the system towards its equilibrium state. This can be achieved from the functions of Lyapunov which ensure step by step the stabilization of each synthesis step. Unlike most other methods, Backstepping has no nonlinearity constraints.

3.1 First step "speed loop, flux loop"

In this step, the objective is to force the rotation speed ω, to follow at best a given reference ω^*. The first error variable e_1 is defined as the error between the speed of rotation and the speed desired by:

$$e_1 = \omega^* - \hat{\omega} \tag{4}$$

By derivation, we obtain: $\dot{e}_1 = \dot{\omega}^* - \dot{\hat{\omega}}$

To ensure the operation of the machine in the linear regime (out of saturation), a flow control is also carried out such that Φ_r follows an imposed trajectory Φ_r^* .

To achieve this goal we pose:

$$e_2 = \Phi_r^* - \hat{\Phi}_r \tag{5}$$

By derivation, we obtain: $\dot{e}_2 = \dot{\Phi}_r^* - \dot{\hat{\Phi}}_r$

The first Lyapunov candidate function is defined by:

$$V_1 = \frac{1}{2}\left(e_1^2 + e_2^2\right) \tag{6}$$

By derivation, we obtain: $\dot{V}_1 = e_1\dot{e}_1 + e_2\dot{e}_2$

$$\dot{V}_1 = e_1\left[\omega^* - \frac{1}{J}\left(p\mu(I_{qs1} + I_{qs2})\Phi_r^* + \beta_\omega\omega + \hat{T}_l\right)\right] + e_2\left[\Phi_r^* + \alpha\hat{\Phi}_r - L_m\alpha(I_{ds1} + I_{ds2})\right] \tag{7}$$

According to Lyapunov stability, the origin $e_1 = 0$ and $e_2 = 0$ of system (7) is asymptotically stable when $\dot{V}_1$ is defined negative.

We then define $(I_{qs1} + I_{qs2})$ and $(I_{ds1} + I_{ds2})$ as the virtual command. Indeed, for an expert in the field of electrical machines, this choice of virtual command is normal, that is to say, one looks for the value that the virtual command must take so that the origin is stable, so the stabilizing virtual function is determined so that:

$\dot{V}_1 = -k_1 e_1^2 - k_2 e_2^2 \prec 0$ with $k_1 \succ 0$, $k_2 \succ 0$. We find:

$$\begin{cases} I_{qs1}^* + I_{qs2}^* = \dfrac{j}{p\mu\Phi_r^*}\left[\omega^* + \dfrac{\beta_\omega}{j}\hat{\omega} + \dfrac{\hat{T}_l}{j} + k_1 e_1\right] \\ I_{ds1}^* + I_{ds2}^* = \dfrac{1}{\alpha L_m}\left[\alpha\hat{\Phi}_r + \dot{\Phi}_r + k_2 e_2\right] \end{cases} \tag{8}$$

With: $(I_{qs1}^* = I_{qs2}^*)$, and $(I_{ds1}^* = I_{ds2}^*)$ represent the references of the components of the current.

3.2 Second step "currents loop"

For this step, our goal is the elimination of the current regulators by the calculation of the control voltages. Other errors concerning the components of the stator current and their references are defined:

$$\begin{cases} e_3 = I_{qs1}^* - I_{qs1} \\ e_4 = I_{ds1}^* - I_{ds1} \\ e_5 = I_{qs2}^* - I_{qs2} \\ e_6 = I_{ds2}^* - I_{ds2} \end{cases} \tag{9}$$

The dynamics of errors is given by:

$$\begin{cases} \dot{e}_3 = \dot{I}^*_{qs1} - \dfrac{1}{L_s}\left[V_{qs1} + \delta_1\right] \\ \dot{e}_4 = \dot{I}^*_{ds1} - \dfrac{1}{L_s}\left[V_{ds1} + \delta_2\right] \\ \dot{e}_5 = \dot{I}^*_{qs2} - \dfrac{1}{L_s}\left[V_{qs2} + \delta_3\right] \\ \dot{e}_6 = \dot{I}^*_{ds2} - \dfrac{1}{L_s}\left[V_{ds2} + \delta_4\right] \end{cases} \tag{10}$$

With:

$$\begin{cases} \delta_1 = -R_s I_{qs1} - \omega^*_s\left[L_s I_{ds1} + \Phi^*_r\right] \\ \delta_2 = -R_s I_{ds1} - \omega^*_s\left[L_s I_{qs1} + T_r \Phi^*_r \omega^*_{sr}\right] \\ \delta_3 = -R_s I_{qs1} - \omega^*_s\left[L_s I_{ds2} + \Phi^*_r\right] \\ \delta_4 = -R_s I_{qs2} - \omega^*_s\left[L_s I_{ds2} + T_r \Phi^*_r \omega^*_{sr}\right] \end{cases} \tag{11}$$

The new function of Lyapunov is given by:

$V_2 = \dfrac{1}{2}\left[V_1 + e_3^2 + e_4^2 + e_5^2 + e_6^2\right]$ Then: $\dot{V}_2 = \dot{V}_1 + e_3\dot{e}_3 + e_4\dot{e}_4 + e_5\dot{e}_5 + e_6\dot{e}_6$

We look for the value that must be taken by the reference command $\left[V^*_{ds1}, V^*_{qs1}, V^*_{ds2}, V^*_{qs2}\right]$ for the origin be stable. So the stabilizing virtual function is determined so that:

$$\dot{V}_2 = \dot{V}_1 + \left[-k_3 e_3^2 - k_4 e_4^2 - k_5 e_5^2 - k_6 e_6^2\right] \prec 0$$

With k_3, k_4, k_5, k_6 positive gains. For this one poses:

$$\begin{cases} V^*_{qs1} = L_s\left[k_3 e_3 - \delta_1 + \dot{I}^*_{qs1}\right] \\ V^*_{ds1} = L_s\left[k_4 e_4 - \delta_2 + \dot{I}^*_{ds1}\right] \\ V^*_{qs2} = L_s\left[k_5 e_5 - \delta_3 + \dot{I}^*_{qs2}\right] \\ V^*_{ds2} = L_s\left[k_6 e_6 - \delta_4 + \dot{I}^*_{ds2}\right] \end{cases} \tag{12}$$

4 PROPOSED KALMAN FILTER FOR SPEED, FLUX, AND LOAD TORQUE SENSORLESS

The extended Kalman filter is a mathematical tool capable of determining state values, immeasurable or parameters of the state system from measurable physical values. It allows estimating the state of a nonlinear system. This filter is based on a number of assumptions, including noise. Indeed, that supposes that the noises which affect the model are centered and white and that these are decorrelated from the estimated states. In addition, state noise must be decorrelated from measurement noise [16, 17].

The algorithm of the extended Kalman filter is the same as the standard Kalman filter which has two steps:

- A prediction step: consists in evaluating the state variables from the system model.
- Correction step: consists in correcting the prediction error on the variables using the existing differences between the observed and measured variables.
- These steps are preceded by an initialization of state vector and of covariance matrices [17]. This filter formulated by the following equation:

$$\begin{aligned} X(k+1) &= \hbar\left[X(k), U\right] + \Psi(k) \\ &= \mathrm{A}_d X(k) + \beta_d U(k) + \Psi(k) \end{aligned} \tag{13}$$

$$\begin{aligned} y(k) &= \hbar\left[X(k) + \Gamma(k)\right] \\ &= C_d X(k) + \Gamma(k) \end{aligned} \tag{14}$$

- The discrete extended noises $\left(\Psi(k);\Gamma(k)\right)$ are white, Gaussian and of zero mean, and the covariance matrices $\left(\square(k);\Re(k)\right)$ are defined positive and symmetrical.

4.1 Equation of the kalman observers

- The extended Kalman observer is generally defined by the following equations [16, 17]:
- Estimate of the initial state: $\hat{X}(0)$
- Variance the initial state $P(0)$, whit:

$$P(k) = A_d(k)P(k-1)A_d^T + \Psi \tag{15}$$

- KALMAN GAIN:

$$g(k) = P(k)C_d^T\left[C_d P(k-1)C_d^T + \Re\right]^{-1} \tag{16}$$

- STATE ESTIMATES BY (UPDATE):

$$\hat{X}(k+1) = \hat{X}(k) + g(k)\left[y(k) - C_d\hat{X}(k-1)\right] \tag{17}$$

- UPDATING THE COVARIANCE MATRIX:

$$P(k+1) = (\mathrm{I} - g(k))C_d P^{-1}(k) \tag{18}$$

4.2 Application of the kalman filter to DSIM

The application of the extended Kalman filter is based on reducing the DSIM model. The ideal case consists in choosing a reduced model of the DSIM in [1-15] established in the reference frame d-q linked to the rotor. In this case, the extended Kalman filter is applied to a system whose estimated state vector is extended to the mechanical speed of rotation $\hat{\omega}(k)$, the flux of the rotor $\hat{\phi}_r(k)$ and to the load torque $\hat{T}_L(k)$.

If it clears the estimation of constant resistance torque T_L , we assume that it changes slowly. So we can use for load torque the following model [8]:

$$\frac{dT_l}{dt} \cong 0 \tag{19}$$

So, we choose the extended state model of the system described by:

$$\begin{cases} \dot{X} = AX + BU \\ y = CX \end{cases} \tag{20}$$

With: $X = [\vartheta \quad \omega \quad \Phi_r \quad T_L]^T$; $U = [I_{ds1} \quad I_{ds2} \quad I_{qs1} \quad I_{qs2}]^T$; $C = [1 \quad 0 \quad 0 \quad 0]$

$$A = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & -\frac{\beta_\omega}{j} & 0 & -\frac{1}{j} \\ 0 & 0 & -\alpha & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \qquad B = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{\mu\Phi_r^*}{j} & \frac{\mu\Phi_r^*}{j} \\ \alpha L_m & \alpha L_m & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

The discrete system which determines the behavior of the continuous filter at discrete times is necessary for the implementation of the Kalman filter in real time.

Considering the process noise and the measurement noise $\psi(k)$, and $\Gamma(k)$, assume the sampling time T_c . The discrete DSIM model can expressed by the following equation:

$$\begin{cases} X(k+1) = A_d X(k) + B_d U(k) + \psi(k) \\ y(k) = C_d X(k) + \Gamma(k) \end{cases} \tag{21}$$

With:

$$A_d = \begin{bmatrix} 0 & T_c & 0 & 0 \\ 0 & 1-T_c\dfrac{\beta_\omega}{j} & 0 & -\dfrac{T_c}{j} \\ 0 & 0 & 1-\alpha T_c & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} B_d = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & T_c\dfrac{\mu\Phi_r^*}{j} & T_c\dfrac{\mu\Phi_r^*}{j} \\ T_c\alpha L_m & T_c\alpha L_m & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} C_d = \begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix}$$

we can say that, the critical step in the EKF is the search for the best covariance matrices and $\Re$ to be established based on the stochastic properties of the corresponding noise are chosen by simulation tests to achieve a desired evaluation performance. Finally we can present the flow chart of status estimating algorithm based on EKF with M iteration by Figure 1.

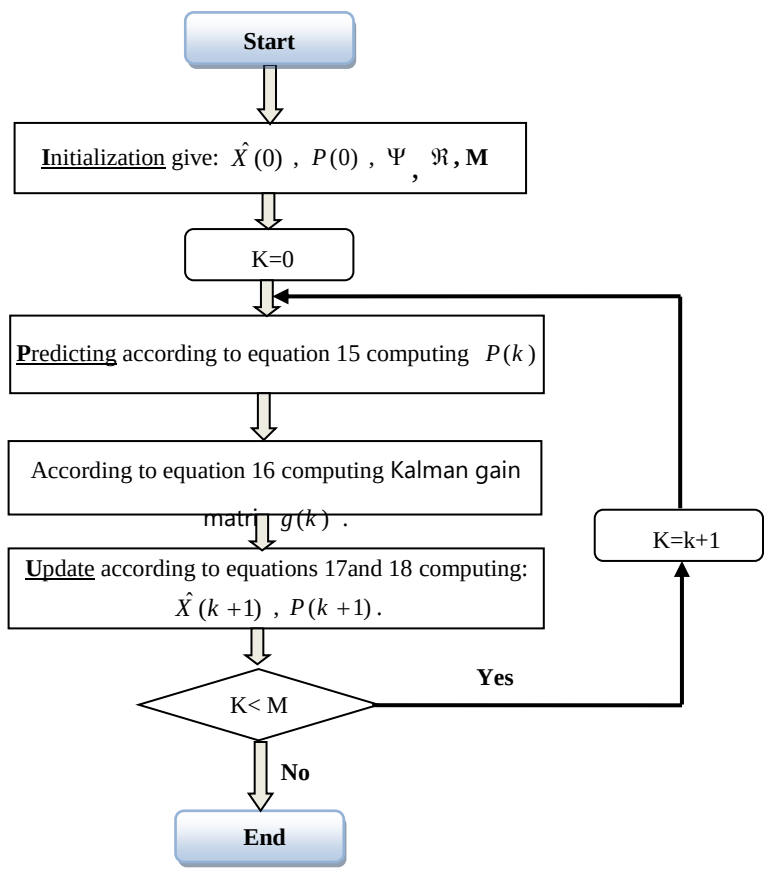

Figure 1: Flow chart of status estimating algorithm based on EKF.

5 SIMULATION AND INTERPRETATION OF RESULTS

In order to validate the control strategies as discussed, associate the parts of the paper and achieve a numerical simulation using the system described in Figure 2. Simulations have been realized under Matlab. The parameters of dual star induction motor used are indicated in Table I.

The results presented in this paper were made with the following synthesis parameters: $\Phi_r^* = 1wb$ $K_1 = 500$; $K_2 = 650$; $K_3 = 170$; $K_4 = 380$; $K_5 = 240$; $K_6 = 20$; $T_c = 10^{-4}$ sec.

It assumes that the noises that affect the model are centered and white, the research of the best matrices of covariance ψ and $\Re$ at summer based the tests of series simulation to take the performance desired where are set by: $P(0) = 0.2 * I_4$, $\Psi = 0.7 * I_4$, $\Re = 0.1$

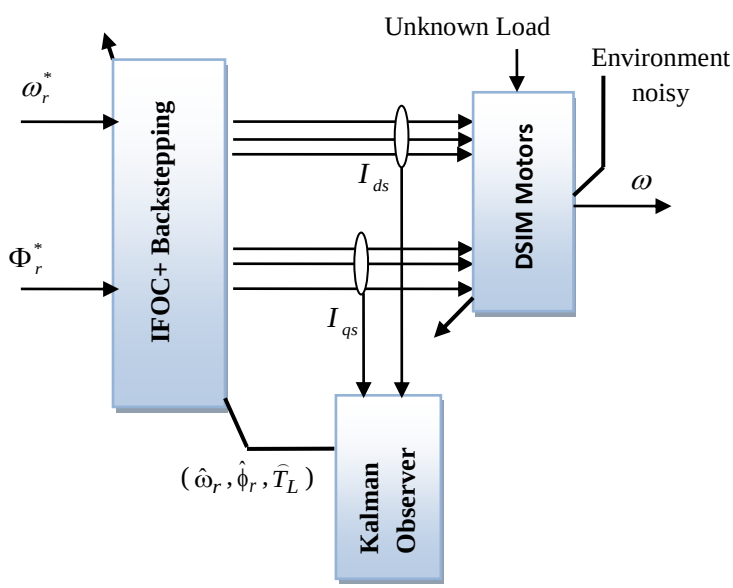

Figure 2: Diagram of the speed control of the DSIM motors combined with an observer under a noise.

The angular speed is estimated by the Kalman observer. It should be noted that the source voltage and the stator currents are measured and used in the senseless control algorithm, the simulations are made with reference speed of 200 rad /s. For the speed step, a load disturbance $T_l = 15N.m$ applied in 1s and 2s, Figure 3, illustrates the real and estimated speed, rotor flux, load torque, of a senseless vector control equipped Kalman to a DSIM under a noise.

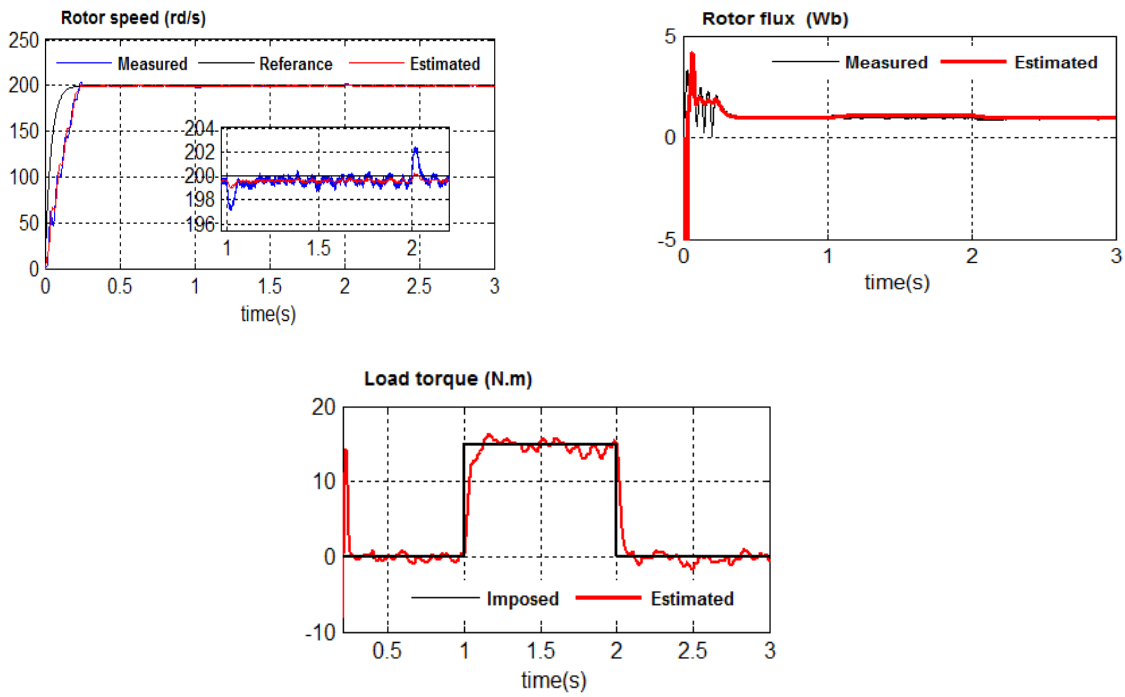

Figure 3: Illustrate the real and estimated speed, rotor flux, the load torque, with deferent the reference speed, and $T_l = 15N.m$ at t= [1 2]s, under a noise.

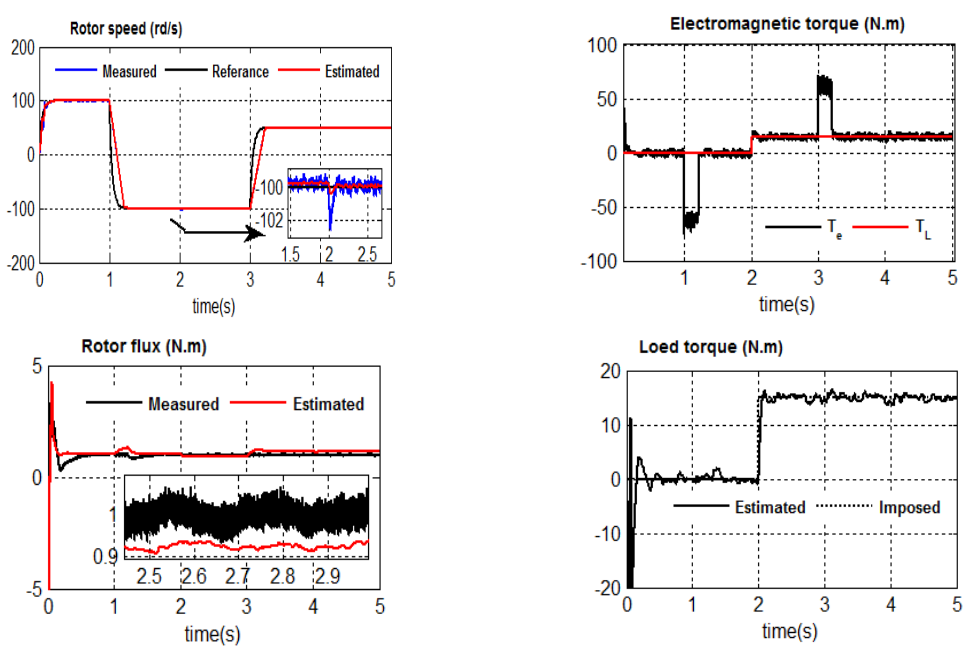

Figure 4: Illustrate the real and estimated speed, rotor flux, the load torque, with deferent the

reference speed (100,-100, 50) rad/s, and $T_l = 15N.m$ at t=2s, under a noise.

In order to test the robustness with respect to a significant variation of the speed reference, a 100rad/s speed reference change is introduced at -100rad/s and +50 rad/s. It can be seen from Figure 4. That the electromagnetic torque peak during reversal of the direction of rotation and then stabilize in steady state. The decoupling still persists, which shows the robustness with wide variations in speed. Finally we study the robustness of the Backstepping control based Kalman observer by the variation of the rotor parameters of the DSIM and with a variable load torque (+15, +5, 0) N.m, where the process noisy. The robustness tests presented in Figure. 5, 6 ,7.

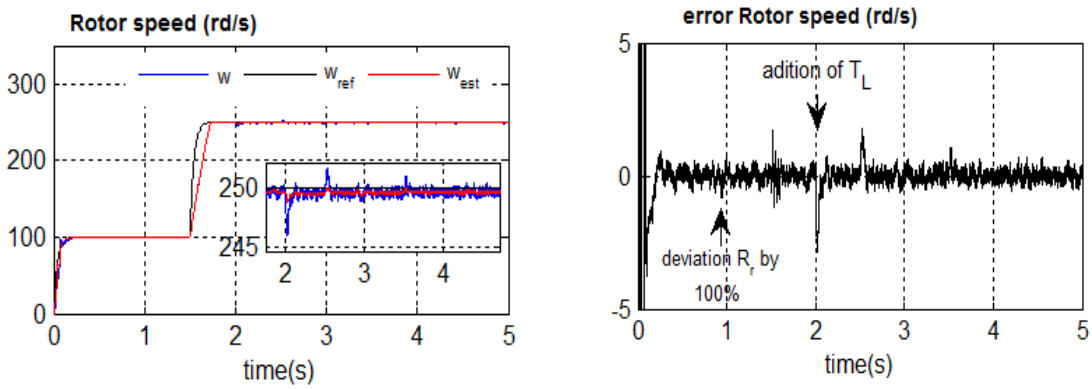

Figure 5: Dynamic the speed and error speed behavior with the increase in rotor resistance at 100% of nominal value at t=1s) under noise.

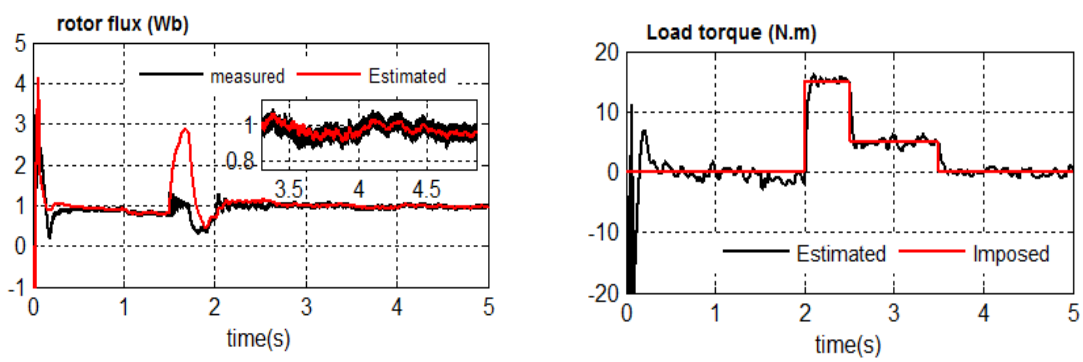

Figure 6: Dynamic the load torque and rotor flux behavior with the increase in rotor resistance at 100% of nominal value at t=1s) by a Backstepping control associated with the Kalman filter under noise.

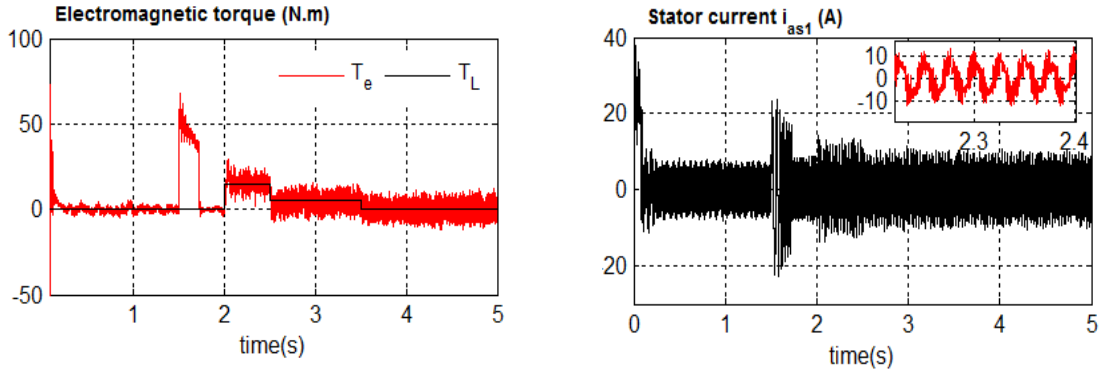

Figure 7: Dynamic of the electromantique torque and stator current behavior with the increase in rotor resistance at 100% of nominal value at t=1s) under noise.

We note the insensitivity of the Backstepping control with the Kalman observer facing the variation of the rotor resistance R_r of the dual star asynchronous machine.

From the simulation results, the rotor speed and load torque can be estimated in different working modes. The flux is insensitive to disturbances and it tracks the reference value. The observer used has a good tracking of speed and flux, all test the system is under noise, generally estimation error is not important and a static error practically zero.

Consequently, the global control scheme introduces high performances of robustness, stability and precision, particularly, pending inversing the speed, parameters variation under noise.

Conclusion

The speed control scheme of a dual stator induction machine DSIM with the Backstepping control has been proposed. The principles of Lyapunov stability theory have been applied for determined stability of control.

The detailed design procedure for the extended Kalman filter EKF has been presented and used for the speed, flux and load torque senseless direct vector control of an double star induction motor DSIM.

The different simulations results demonstrate a good performance of estimation. The global system drive (Backstepping control+ EKF) show the high robustness in presences of the parameters variations as the rotor resistance, the load, and the reference speed. The control of the speed gives fast response. On conclusion, we can say that the EKF is more superior to all the traditional observers who encouraged us to include experimental validation of the proposed algorithm at the following paper in future work.

APPENDIX A

DSIM motor parameters

Parameter name	Symbol	Value	Unit
DSIM Mechanical power	P_n	4.5	kW
Nominal tension	V_n	220	V
Nominal Currants	I_n	5.6	A
Nominal speed	N	2970	rpm
Stator resistances	$R_{s1} = R_{s2} = R_s$	3.72	Ω
Rotor resistance	R_r	3.72	Ω
Stator self inductances	$L_{s1} = L_{s2} = L_s$	0.022	H
Rotor self inductance	L_r	0.006	H
Mutual inductance	L_m	0.3672	H
Moment of inertia	j	0.0662	$kg.m^2$
Viscous friction coefficient	B_ω	0.001	N.m/rad
Supply frequency	f	50	Hz
pole pairs number	P	1	/

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