

Actuator Fault Estimation Based on LPV Unknown Input Observer for Induction Machine

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Abstract: This paper presents an unknown inputs observer (UIO) applied to an induction machine (IM) in order to estimate the actuator faults and the state variables. Knowing that the machine used is highly nonlinear, a model based on LPV (linear parameter varying) system of the machine is used. Indeed, using the induction machine based on LPV model, we develop the structure of an observer where the actuator faults are the unknown inputs. The conditions for convergence are based on the Lyapunov theory that will ensure the stability. Based on the LMI (Linear Matrix Inequalities), the gains of the UIO subject to actuator faults are confirmed and then ensure the efficiency of our approach. The obtained results through simulations demonstrate the effectiveness of the proposed approach.

Keywords: Induction motor, Unknown inputs observer, Linear parameter varying (LPV), Linear Matrix Inequalities (LMI), Actuator faults.

1. Introduction

Due to its simplicity, low manufacturing cost and low maintenance, the induction cage machine has earned its leading position in applications requiring very high dynamic and static performance [24]. On the other hand, this simplicity is accompanied by a low starting torque and at constant frequency, it transmits a constant speed. Power electronics has recently emerged as a complex and multidisciplinary technology which brought the variable frequency, and also flow control to provide high torque [26]. Thanks to this, the asynchronous motor was able to take a step ahead.

This machine is not easy to control due to the nonlinearity of its dynamic model. Moreover, its state variables are not all measurable and it is under the influence of parametric variations. Therefore, a good control is necessary to guaranty the stability of its proper functioning. In the literature, most of the works deal with steady state vector control [8-10, 21, 25], Direct Torque Control (DTC) [19], Sliding Mode Control (SMC) [13,27]. In addition, nonlinear control applied to induction machine has been developed such in [14].

The advantages of such approaches are their robustness to disturbances and their simplicity of implementation. The major disadvantage of the set-up is that all controls rely on the reliability of the measurement provided by sensors,

which makes these commands vulnerable. The occurrence of an output sensor fault and especially the actuator faults which directly affect them, hence the development of fault-tolerant controls is needed [6,11,15].

The first step of active fault tolerant control is the detection and the location of faults. Fault detection uses up to now signal processing techniques [17], for operating phases, which highlights and localizes a dysfunction. Moreover, most of the techniques are based on observers [1, 23] or analytical redundancy based on parity space [3].

The second step, is the estimation of faults. Several works have been presented such us [2, 20]. However, the nonlinearity of the IM model makes the estimator's synthesis difficult. This problem is solved by separating the system into two subsystems, performing a linearization to obtain a linear model whose parameters depend on the rotation speed. Then a Linear Parameter Varying model (LPV) has been obtained and developed in several works. Reference [21] is dedicate to design a nonlinear method for a fault diagnosis method based on a polytypic linear parameter varying (LPV) formulation, and [12] is interested in a stability analysis of the double feed induction machine using LPVs. On the other hand, in [4] a design of a linear parameter varying model is used to control the speed of the shaft angle of

an induction motor. Moreover, to eliminate the nonlinear character of the model, the authors of [16] use a Takagi-Sugeno approach for the design of an unmeasurable premise variable nonlinear observer for determining parameters inside a PEM Fuel Cell which is able to estimate the pressures and mass flow rates.

There are several methods developed for fault diagnosis and estimation, and the large challenge resides in the pairing between the LPV model and the estimator. A solution has been made by using observers with unknown input, which is considered one of the most effective observers, and it is used in [7] for state estimation applied to particular class of uncertain systems. Reference [22] deals with a nonlinear unknown input observer based on linear matrix inequality approach and propose an observer for the fault actuator detection and isolation scheme. Reference [5] deals with a nonlinear observer to detect for actuator fault (Exhaust Gas Recirculation) of diesel engines.

In this context, the main objective of this study is to put in place an observer with unknown input based on an LPV model that can efficiently estimate the faults of the actuators and the output states of the IM. This problem will then be translated into a convex optimization problem that will be solved using the Linear Matrix Inequalities (LMI) tools.

Section 2 deals with the presentation of the dynamic model of IM. The model given in section 2 is transformed in LPV model where the rotation speed represents the nonlinearity of LPV model. The LPV model will be used, in Section 4, to perform the synthesis and design of an observer with unknown inputs (faults and disturbance). In Section 5, simulation results shown the performance and the effectiveness of the proposed approach. Finally, section 6 concludes this study and presents the future works.

2. Dynamic model of induction machine

The current modelling approach of the asynchronous machine is based on the transformation of the three-phase system into a bi-phase system equivalent to Park.

Thus, in order to study the diagnosis of the asynchronous machine, both the stator variables

and the rotor variables of the Park transformations are generally applied under assumptions on the magnetic circuits. It can also be asserted that the model is nonlinear as shown by the following equations [9,11,19,21,26]:

Here, the stator and rotor current components with Flux and speed velocity are considered as state variables, the stator voltage components are considered as inputs, stator current components and rotation speed are considered as outputs as given in Equations (1)-(7). Then the induction machine model written in state space form is:

$$\begin{cases} \dot{x}_1 = -\gamma x_2 + \omega_s x_2 + \alpha k x_3 + p k x_4 \omega + u_1 \\ \dot{x}_2 = -\omega_s x_1 - \gamma x_2 + \alpha k x_4 - p k x_3 \omega + u_2 \\ \dot{x}_3 = -\alpha L_m x_1 - \alpha x_3 + (\omega_s - p\omega) x_4 \\ \dot{x}_4 = -\alpha L_m x_2 - \alpha x_4 - (\omega_s - p\omega) x_3 \end{cases} \quad (1)$$

In addition, the equation of the rotor speed is the following:

$$\dot{\omega} = -\frac{K_f}{J} \omega + \psi (x_2 x_3 - x_1 x_4) + -\frac{1}{J} C_r,$$

where the state vector x is given by:

$$x = [x_1 \quad x_2 \quad x_3 \quad x_4]^T \quad (2)$$

and:

$$x_1 = i_{ds}; x_2 = i_{qs}; x_3 = \phi_{dr}; x_4 = \phi_{qr}.$$

$$\beta = \frac{1}{\sigma L_s}, \gamma = \beta R_{sm}, k = \frac{L_m}{\sigma L_r L_s}, \psi = \frac{p L_m}{J T_r}, \alpha = \frac{1}{T_r}$$

$x \in \mathfrak{R}^n$ is the state vector, $u \in \mathfrak{R}^p$ is the vector of control inputs and $y \in \mathfrak{R}^m$ is the output vector and variables are functions of time t . All vectors are in appropriate dimensions. The output vector is:

$$y = [y_2 \quad y_1]^T = [x_2 \quad x_1]^T \quad (3)$$

The input vector is:

$$u = [u_1 \quad u_2]^T = [V_{ds} \quad V_{qs}]^T \quad (4)$$

The input function matrix B can be written as:

$$B = \begin{bmatrix} B_1 \\ B_2 \end{bmatrix} = \begin{bmatrix} \frac{1}{\sigma L_s} & 0 & 0 & 0 \\ 0 & \frac{1}{\sigma L_s} & 0 & 0 \end{bmatrix}^T \quad (5)$$

All parameters with their values can be found in the Nomenclature Table.

3. Linear Parameter Varying (LPV) model of induction machine

Reference is made to the nonlinear state–space model of a squirrel–cage IM considered in equation 1 [4, 18]. Under the assumption of linear magnetic circuits, the electrical and mechanical state equations turn out to be:

$$\dot{x} = A(x).x(t) + B.u(t) \quad (6)$$

where:

$$A(x) = \begin{bmatrix} -\gamma & \omega_s & \alpha k & pk\omega \\ -\omega_s & -\gamma & -pk\omega & 0 \\ -\alpha L_m & 0 & -\alpha & (\omega_s - p\omega) \\ 0 & -\alpha L_m & -(\omega_s - p\omega) & -\alpha \end{bmatrix}$$

The rotor speed is considered as a varying parameter $\rho = \omega$, the equation (6) can be interpreted as the state equation of an LPV system with state $x = [x_1 \ x_2 \ x_3 \ x_4]^T$. This state equation (6) can be rewritten in the usual form:

$$\begin{cases} \dot{x}(t) = A(\rho).x(t) + B.u(t) \\ y = C.x(t) \end{cases} \quad (7)$$

where:

$$A(\rho) = A_0 + \omega A_i \quad (8)$$

with:

$$A_0 = \begin{bmatrix} -\gamma & \omega_s & \alpha k & 0 \\ -\omega_s & -\gamma & 0 & \alpha k \\ -\alpha L_m & 0 & -\alpha & \omega_s \\ 0 & -\alpha L_m & -\omega_s & -\alpha \end{bmatrix} \quad (9)$$

and:

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \quad (10)$$

Due to physical limits, we assume that all the components of the state are measurable or estimable and this allowed us to say that:

$$\rho_{\min} \leq \rho \leq \rho_{\max} \quad (11)$$

For this purpose the following variation interval is obtained:

$$\begin{cases} A_1 = A_{\omega_{\min}} \Rightarrow \rho_1 = \frac{\omega - \omega_{\min}}{\omega_{\max} - \omega_{\min}} \\ A_2 = A_{\omega_{\max}} \Rightarrow \rho_2 = \frac{\omega_{\max} - \omega}{\omega_{\max} - \omega_{\min}} \end{cases} \quad (12)$$

with:

$$A_{\omega_{\min}} = \begin{bmatrix} 0 & 0 & 0 & pk\omega_{\min} \\ 0 & 0 & -pk\omega_{\min} & 0 \\ 0 & 0 & 0 & -p\omega_{\min} \\ 0 & 0 & p\omega_{\min} & 0 \end{bmatrix}$$

and:

$$A_{\omega_{\max}} = \begin{bmatrix} 0 & 0 & 0 & pk\omega_{\max} \\ 0 & 0 & -pk\omega_{\max} & 0 \\ 0 & 0 & 0 & -p\omega_{\max} \\ 0 & 0 & p\omega_{\max} & 0 \end{bmatrix}$$

So we will have:

$$A(\rho) = \sum_{i=1}^r \rho_i A_i = \rho_1 A_{\omega_{\min}} + \rho_2 A_{\omega_{\max}} \quad (13)$$

and $\sum_{i=1}^r \rho_i = 1$ is verified.

4. UIO design for a nonlinear system (LPV model)

4.1 Description and preliminaries on the observer

The method adopted in this article is related to the work carried out in [3] which deals with the design of fault detection and isolation (FDI) for an induction machine using Non-Linear Analytical Redundancy (NLAR) and the residuals are generated by analytical redundancy relation. As mentioned in the introduction, this work will focus on the estimation of the actuator fault and

the state estimation. The scheme presented in Figure 1, gives a presentation of the principle of the observer with unknown input, where U represents the command, f the actuator fault, d the perturbation, \hat{f} and \hat{x} are respectively the estimate of the fault and the estimate of the state, and y the output of the machine [5,7,22].

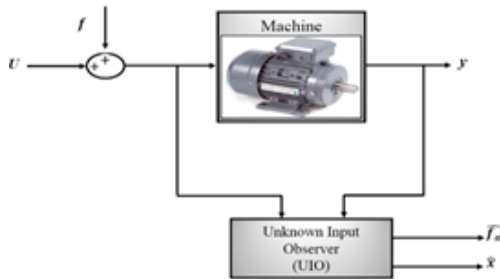


Figure 1. Schematic block of the approach

4.2 Design of unknown input observer for IM

Consider the variable system of linear parameters, described by an LPV model affected by actuator faults as follows:

$$\begin{cases} \dot{x}(t) = A(\omega(t)).x(t) + B.u(t) + Ff(t) \\ y = C.x(t) \end{cases} \quad (14)$$

Where f represents the faults vector. $A(\omega)$, B and F are matrix of appropriate dimension.

The equation (14) can be rewritten as follows:

$$\begin{cases} \dot{x}(t) = \sum_{i=1}^r \rho_i A_i .x(t) + B.u(t) + Ff(t) \\ y = C.x(t) \end{cases} \quad (15)$$

Where r is the number of varying parameter.

In this paper, in order to compute the unknown observer the following assumptions should be checked:

- A_i is an invariant matrix over time.
- (A_i, C) is observable.
- C is full row rank.
- $f(t)$ are derived and bounded functions.

Based on the system (15), the unknown observer can be written as follows:

$$\begin{cases} \dot{z}(t) = \sum_{i=1}^r \rho_i N_i .z(t) + G.u(t) + L.y(t) + T\hat{f}(t) \\ \hat{x}(t) = z(t) - E.x(t) \end{cases} \quad (16)$$

where:

- $z(t)$ is the state vector related to $x(t)$.
- N_i, G, L, T and E are matrices of appropriate dimension and they satisfy the following conditions:

Knowing that the error $e(t)$ is defined such that:

$$e(t) = x(t) - \hat{x}(t) \quad (17)$$

then:

$$e(t) = (I_2 + EC)x(t) - z(t)$$

Where I_2 is an identity matrix with appropriate dimensions.

Let $M = I_2 + EC$ Then the expression of the error becomes:

$$e(t) = M.x(t) - z(t) \quad (18)$$

Therefore the dynamic error can be determined such that:

$$\begin{aligned} \dot{e}(t) &= M\dot{x}(t) - \dot{z}(t) \\ \dot{e}(t) &= \left[M \sum_{i=1}^r \rho_i A_i - \sum_{i=1}^r \rho_i N_i M - LC \right] x(t) + MFf(t) \\ &\quad + [MB - G]u(t) - T\hat{f}(t) + \sum_{i=1}^r \rho_i N_i e(t) \end{aligned}$$

In order to compute the observer, the following conditions which guarantee the convergence of the estimation error should be hold:

$$\begin{cases} M \sum_{i=1}^r \rho_i A_i - \sum_{i=1}^r \rho_i N_i M - LC = 0 \\ MB - G = 0 \\ MF = T \end{cases} \quad (19)$$

On the basis of the convergence conditions equation (19) one obtains:

$$\dot{e}(t) = \sum_{i=1}^r \rho_i N_i e(t) + MFf(t) - T\hat{f}(t) \quad (20)$$

The following change of variable is made:

$$\tilde{f}(t) = f(t) - \hat{f}(t) \Rightarrow f(t) = \hat{f}(t) + \tilde{f}(t) \quad (21)$$

Knowing that $M.F = T$ and based on equation (21), the dynamic error given in (20) becomes:

$$\dot{e}(t) = \sum_{i=1}^r \rho_i N_i e(t) + T\tilde{f}(t) \quad (22)$$

Based on the residual calculations, the following relationship is obtained:

$$r_e = y(t) - \hat{y}(t) = Cx(t) - C\hat{x}(t) = Ce(t) \quad (23)$$

The equation (24) gives the fault estimation:

$$\hat{f}(t) = QS \left[r_e - \int \delta r_e dt \right] \quad (24)$$

where Q is defined positive with appropriate dimension.

In order to make the LMIs feasible, the stability is checked by the following Lyapunov function which depends on the error of fault estimation:

$$V = e^T P e + \frac{1}{\delta} \tilde{f}^T Q^{-1} \tilde{f} \quad (25)$$

By deriving the equation (25), the equation (26) is obtained:

$$\dot{V} = \dot{e}^T P e + e^T P \dot{e} + \frac{1}{\delta} \dot{\tilde{f}}^T Q^{-1} \tilde{f} + \frac{1}{\delta} \tilde{f}^T Q^{-1} \dot{\tilde{f}} \quad (26)$$

Knowing that $\dot{\tilde{f}}^T \tilde{f} = \tilde{f}^T \dot{\tilde{f}}$, we can obtain the following derivative Lyapunov function:

$$\dot{V} = \dot{e}^T P e + e^T P \dot{e} + \frac{2}{\delta} \tilde{f}^T Q^{-1} \dot{\tilde{f}} \quad (27)$$

Replacing the value of the derivative of the error in equation (27):

$$\begin{aligned} \dot{V} = & \sum_{i=1}^r \rho_i e^T [N_i^T P + P N_i] e + 2 \tilde{f}^T T^T P e \\ & + \frac{2}{\delta} \tilde{f}^T Q^{-1} \dot{\tilde{f}} \end{aligned} \quad (28)$$

By replacing equation (25) in the last equation, the expression of the derivative of the stability equation is obtained us follow:

$$\begin{aligned} \dot{V} = & \sum_{i=1}^r \rho_i e^T [N_i^T P + P N_i] e + \frac{2}{\delta} \tilde{f}^T Q^{-1} \dot{\tilde{f}} \\ & - \frac{2}{\delta} \tilde{f}^T S C \dot{e} \end{aligned} \quad (29)$$

Replacing equations (22) in the last equation:

$$\begin{aligned} \dot{V} = & \sum_{i=1}^r \rho_i e^T [N_i^T P + P N_i] e + \frac{2}{\delta} \tilde{f}^T Q^{-1} \dot{\tilde{f}} \\ & - \frac{2}{\delta} \tilde{f}^T S C \sum_{i=1}^r \rho_i N_i e - \frac{2}{\delta} \tilde{f}^T S C T \tilde{f} \end{aligned} \quad (30)$$

Lemma 01:

Given a scalar μ and a positive symmetric matrix P_1 , the following equality is true [28]:

$$2x^T y \leq \frac{1}{\mu} x^T P_1 x + \mu y^T P^{-1} y \quad (31)$$

On the basis of lemma 01, we can deduce the following inequality:

$$\frac{2}{\delta} \tilde{f}^T Q^{-1} \dot{\tilde{f}} \leq \frac{1}{\delta} \left[\frac{1}{\mu} \tilde{f}^T P_1 \tilde{f} + \mu Q^{-1T} \dot{\tilde{f}}^T P^{-1} Q^{-1} \dot{\tilde{f}} \right] \quad (32)$$

According to the proposed hypothesis, the derivative of the fault f is bounded then: $\|\dot{f}\| \leq \alpha_1$

Such as $0 < \alpha_1 < \infty$ and $\|\dot{f}\| \leq \|\dot{f}^T\|$

Then we have the following inequality

$$\frac{2}{\delta} \tilde{f}^T Q^{-1} \dot{\tilde{f}} \leq \frac{1}{\delta} \frac{1}{\mu} \tilde{f}_a^T P_1 \tilde{f}_a + \frac{\mu}{\delta} \alpha_1^2 \lambda_{\max} Q^{-1T} P^{-1} Q^{-1} \quad (33)$$

In order to not charge the notation, we put:

$$B = \frac{\mu}{\delta} \alpha_1^2 \lambda_{\max} Q^{-1T} P^{-1} Q^{-1}$$

Replacing the latest results in equation (30):

$$\begin{aligned} \dot{V} \leq & \sum_{i=1}^r \rho_i e^T [N_i^T P + P N_i] e + \frac{1}{\delta} \frac{1}{\mu} \tilde{f}^T P_1 \tilde{f} + B \\ & - \frac{2}{\delta} \tilde{f}^T T^T \sum_{i=1}^r \rho_i N_i e - \frac{2}{\delta} \tilde{f}^T S C T \tilde{f} \end{aligned} \quad (34)$$

We define the vector:

$$\varepsilon = \begin{bmatrix} e \\ \tilde{f} \end{bmatrix}^T \quad (35)$$

We can write now the vector \dot{V} as follows:

$$\dot{V} \leq \sum_{i=1}^r \rho_i \varepsilon^T \psi_i \varepsilon + B \quad (36)$$

Such as:

$$\varepsilon = \begin{bmatrix} N_i^T P + P N_i & * \\ \frac{1}{\delta} T^T P N_i & \frac{1}{\delta} \frac{1}{\mu} P_1 - \frac{2}{\delta} P^T T^T \end{bmatrix}$$

Algorithm of Unknown Input Observer design

Step 1: Compute H from the next equation then obtain the matrices M, E :

$$H = [M \ E] = [I \ 0] \begin{bmatrix} I \\ -C \end{bmatrix}^+ \quad (37)$$

Step 2: Compute G and T from the next equations:

$$G = MB; \quad T = MF \quad (38)$$

Step 3: Solve the next **LMI** form equalities, obtain the matrices P , and calculate K_i :

$$\begin{bmatrix} N_i^T P + P N_i & * \\ -\frac{1}{\delta} T^T P N_i & \frac{1}{\delta} \frac{1}{\mu} P_1 - \frac{2}{\delta} P^T T^T \end{bmatrix} \leq 0 \quad (39)$$

In order to resolve the **LMI** let: $\bar{K}_i = P \cdot K_i$ and we replace N_i by the following equation:

$$N_i = M \cdot A_i - K_i \cdot C \quad (40)$$

Then we have the following inequality to solve:

$$\begin{bmatrix} A_i^T M^T P + P A_i M - \bar{K}_i \cdot C - \bar{K}_i^T \cdot C^T & * \\ -\frac{1}{\delta} T^T P A_i M + \frac{1}{\delta} T^T P \bar{K}_i C & \frac{1}{\delta} \frac{1}{\mu} P_1 - \frac{2}{\delta} P^T T^T \end{bmatrix} \leq 0$$

Step 4: Compute matrices N_i, L_i and S_i from the equations (40), (41) and (42) respectively:

$$L_i = K_i (I + C \cdot E) - M \cdot A_i \cdot E \quad (41)$$

$$S = T^T P C^{-1} \quad (42)$$

5. Application to Induction Machine

We will simulate the model of the induction machine whose current outputs are considered as input variables for the observer has unusual inputs and the rotor speed is chosen as time variable as given in the section (3).

The computation will be done with the toolbox YALMIP, according to the equations of the observer and with the following conditions:

- The speed varies between a minimum value $\omega_{\min} = 0$, and a maximum value $\omega_{\max} = 157 \text{ rad/s}$.

- We take $\mu = 100$ and $\delta = 10^{-4}$.

In order to demonstrate the effectiveness of the study method, a simulation of the dynamic behaviour of the machine are performed and the observer has been tested for two faults possible of the actuator, i.e. a fault in the stator direct voltage (V_{ds}) and (V_{qs}), the results are given in the figures (2-6) and this for the following conditions:

- We will simulate only one actuator fault at a time, which will be around of 15% of the nominal values.
- Test 1: state without fault.
- Test 2: state with a quasi-square fault between 3s and 7s.
- Test 3: state with a variable fault between 0s and 8s.

The matrix values obtained are as follows:

$$A_1 = \begin{bmatrix} -264.71 & 314.15 & 420.91 & 0 \\ -314.15 & -264.71 & 0 & 420.91 \\ 3.58 & 0 & -13.89 & 314.15 \\ 0 & 3.58 & 314.15 & -13.89 \end{bmatrix}$$

$$A_2 = \begin{bmatrix} -264.71 & 314.15 & 420.91 & 9517.4 \\ -314.15 & -264.71 & 9517.4 & 420.91 \\ 3.58 & 0 & -13.89 & 0.2 \\ 0 & 3.58 & 0.2 & -13.89 \end{bmatrix}$$

$$B = \begin{bmatrix} 32.1898 & 0 \\ 0 & 32.1898 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}; \quad C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}; \quad F = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

$$M = \begin{bmatrix} 0.25 & 0.25 & 0 & 0 \\ -0.25 & 0.25 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}; \quad E = \begin{bmatrix} -0.75 & -0.25 \\ -0.25 & -0.75 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

$$N_1 = \begin{bmatrix} -330.65 & 307.15 & 105.23 & -105.23 \\ 330.58 & -308.40 & -105.23 & 105.23 \\ 1.357 & -15.793 & -18.887 & 314.16 \\ -34.656 & 6.8448 & -314.16 & -13.887 \end{bmatrix}$$

$$N_2 = \begin{bmatrix} -747.4 & 759.9 & 2484.6 & 2274.1 \\ 747.2 & -763 & -2484.6 & -2274.1 \\ 0.9 & -2.4 & -13.9 & 0.2 \\ 0.7 & 1.9 & 0.2 & -13.9 \end{bmatrix}$$

$$L_1 = \begin{bmatrix} 171.81 & -14.73 \\ -172.11 & 15.03 \\ -0.705 & 4.288 \\ 10.375 & -6.79 \end{bmatrix}; L_2 = \begin{bmatrix} 389.19 & -232.11 \\ -389.91 & 232.84 \\ 2.756 & 0.826 \\ -0.644 & 4.226 \end{bmatrix}$$

$$G = \begin{bmatrix} 8.0475 & -8.0475 \\ -8.0475 & 8.0475 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}; T = \begin{bmatrix} 0.25 & -0.25 \\ -0.25 & 0.25 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

$$S = 10^3 \cdot \begin{bmatrix} -2.0171 & -2.3658 \\ 2.0171 & 2.3658 \end{bmatrix}; Q = \begin{bmatrix} 0.33 & 0.06 \\ 0.06 & 0.33 \end{bmatrix}$$

Figure 2 shows the evolution of currents (I_{ds} and I_{qs}) and the estimation of fault in the case of free system.

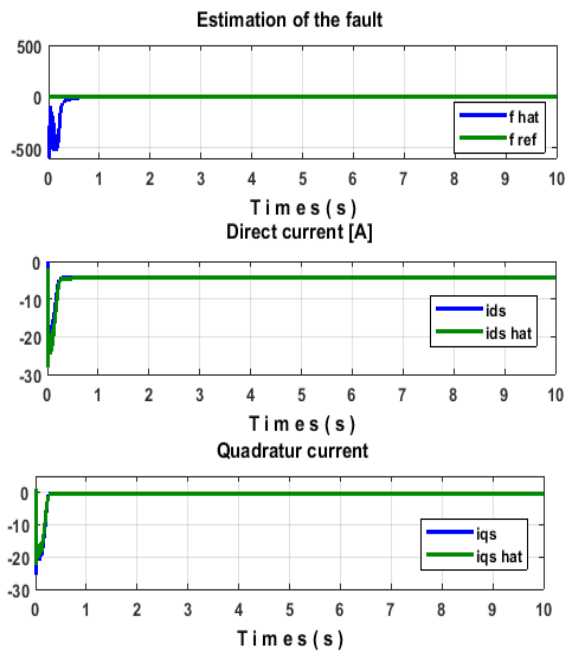


Figure 2. Free system: Estimation without actuator faults

Since the machine is initially stopped, a transient state less than half second is noted. Subsequently, a permanent regime is established and the observer follows the evolutions of the state variables and the fault.

Figure 3 shows the evolution of the reference and estimated fault, as well as the errors of estimating the states and the fault with actuator faults in V_{ds} . The results show that the errors converge to zero, which makes it possible to obtain good estimation results.

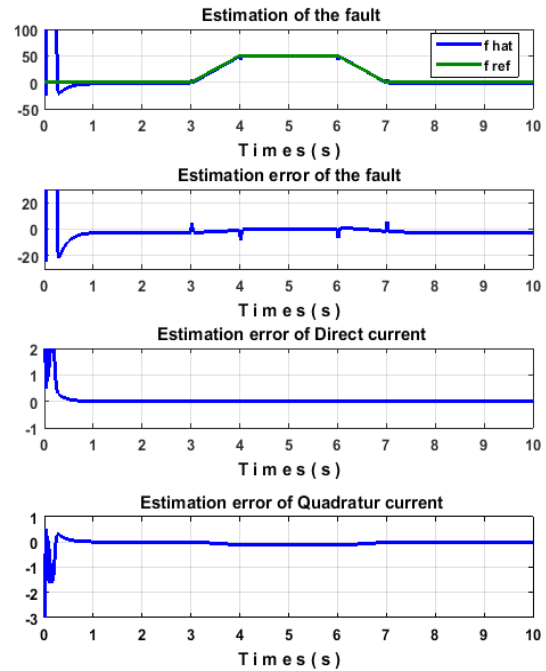


Figure 3. Estimation of square actuator faults in V_{ds}

The results obtained for a square error on V_{qs} are presented in Figure.4, and it is noted that the error is well estimated and the estimation errors are around zero.

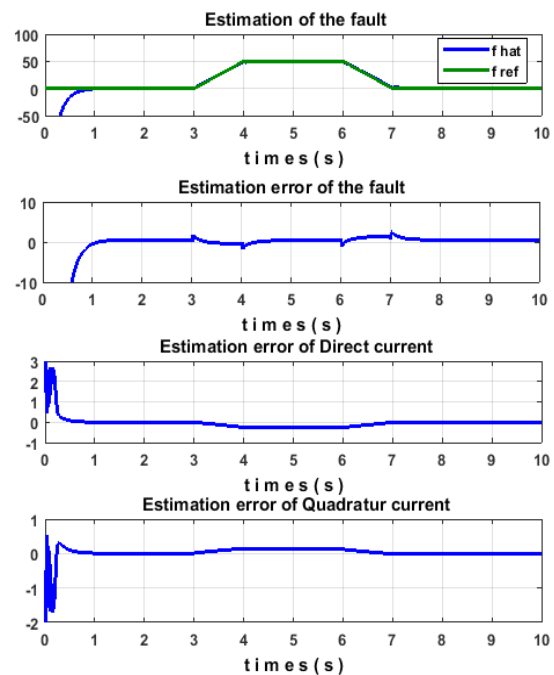


Figure 4. Estimation of square actuator faults in V_{qs}

From the results shown in Figures 5 and 6, it can be noted that for a variable fault on V_{ds} and V_{qs} we can say that there is no difference between the square fault and the variable fault. This confirms the results obtained in the preceding figures.

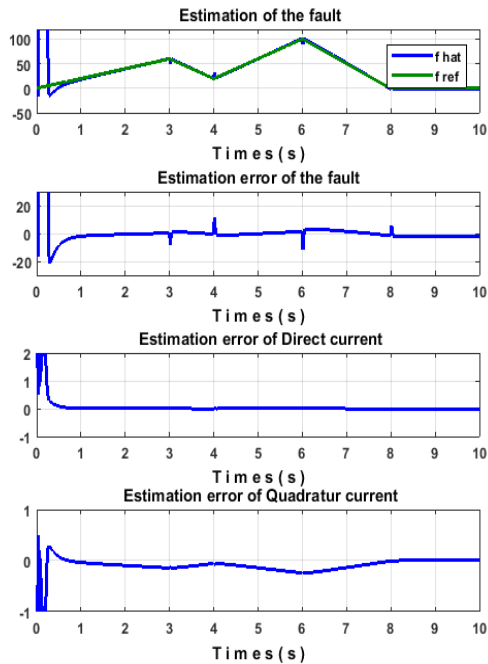


Figure 5. Estimation of variable actuator faults in V_{ds}

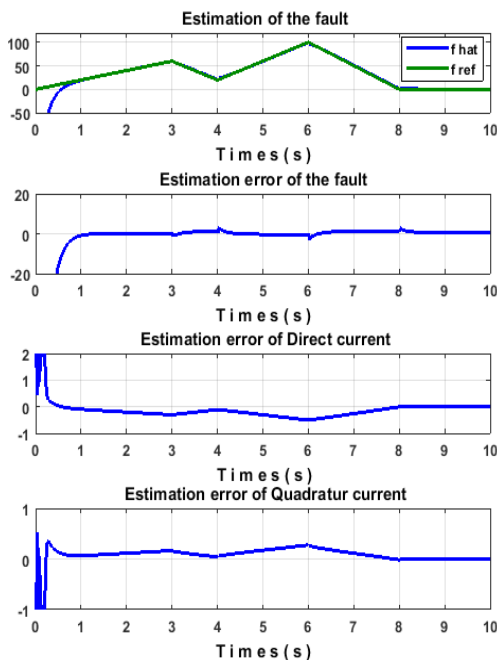


Figure 6. Estimation of variable actuator faults in V_{qs}

In the previous figures, we observe that the observer's estimated error values converge towards their steady-state references with short transitional regime and the estimation error tends to zero. We also notice that the output currents of the observer follow those of the machine and

the error is almost zero. So the estimation by this method gives almost good results.

From these results, also we can say that the unknown inputs observer applied to an induction machine has very satisfactory performance.

7. Conclusion

The results obtained show our contribution to the problem of state and fault actuator of the induction machine modelled by a linear parameter varying model.

In order to obtain the observer gain by the resolution of LMIs, we choose a Lyapunov function which depends not only the error of estimation but also the error of fault estimation.

The estimation of faults and states has been reached despite the complexity of the system. On the basis of the results obtained, we can conclude that the approach also presents an interesting application in the field of fault-tolerant control design which will be the subject of future work in addition to the application of this study on a real machine.

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Appendix A

The parameters of the induction machine cage used are shown below:

| | | |
|--------------------------|-----------------------------|----------|
| Rated power | 1.5 Kw | P_N |
| Nominal voltage | 220/380 V. | V_N |
| Speed | 1420 rad/ min | ω |
| Nominal frequency | 50 Hz | f |
| Stator resistance | 4.85 Ω | R_s |
| Rotor resistance | 3.805 | R_r |
| Stator cyclic inductance | 0.274 H. | L_s |
| Rotor Cyclic inductance | 0.274 H | L_r |
| Cyclic mutual inductance | 0.258 H. | L_m |
| Number of pole pairs | 2 | P |
| Moment of Inertia | 0,031 Nms ² /rad | J |
| Friction | 0.008 Nm s/rad | K_f |

Appendix B

| | |
|---------------------------------------|-------------|
| Synchronous Pulsation [rad/s]. | ω_s |
| Electrical angular Pulsation [rad/s]. | ω_r |
| Electromagnetic torque [N.m]. | C_{em} |
| Resistive torque [N.m]. | C_r |
| Rotor time constant [s]. | T_r |
| The direct stator voltage | V_{ds} |
| The quadrature stator voltage | V_{qs} |
| The direct stator current | i_{ds} |
| The stator quadrature current | i_{qs} |
| The direct stator flow | Φ_{dr} |
| The stator quadrature flow | Φ_{qr} |

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