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Unknown Input Observer design for fault sensor estimation applied to Induction Machine

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Abstract

The paper focuses on the estimation of the sensor faults and the state variables, using an unknown inputs observer (UIO), applied to an induction machine. A model based on LPV (linear parameter varying) systems of the machine is used where the rotation speed is considered as a variable parameter. Then based on Lyapunov theory, a feasible algorithm is explored to ensure the stability of the proposed approach. Furthermore, the observer efficiency is investigated in presence of the current sensor faults. It's done by using the calculation of the observer gains based on the LMI (Linear Matrix Inequalities). The contribution of this study lies on the development of an extended unknown inputs observer (UIO) to estimate the sensors faults. In addition, an augmented system is constructed, using a first filter, to transform the sensor faults to actuator faults and the noise to disturbance. The performance of this method is compared either in terms of state observation errors or in terms of fault estimation. The results obtained by simulation illustrate the effectiveness of the proposed approach.

Keywords: Induction motor; unknown inputs observer; linear

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parameter varying (LPV); Linear Matrix Inequalities (LMI); sensor faults.

1 Introduction

The induction cage machine (IM) is well known since a long period in leading position in applications requiring very high dynamic and static performance, due its the simplicity, low manufacturing cost and low maintenance[1]. A
5 low starting torque accompanies this simplicity and at constant frequency, it transmits a fixed speed. The induction motor has become the most widely used in complex system, especially due to the development of power electronics devices, which have brought the notion of true frequencies. In addition, the flux control allows the induction motor to provide high torque especially at the
10 machine start and working at variable speed[2].

Due to the nonlinearity of the induction machine dynamic model and the influence of parametric variations, the control of this machine is not easy. Therefore, the IM control becomes an attractive topic, several works dealing with IM control can be found in the literature. The indirect field oriented
15 control (IFOC) technique is the mostly used, [[3],[4],[5]] applied this technique in their investigation, as is also the Direct Torque Control (DTC) command used in [6], in [7], the authors have improved the performance of IM control using this technique based on fuzzy logic. In addition, the approach of control by sliding mode was developed in [8]. In [9] a combination of the sliding mode and
20 the DTC with an observation of the magnetizing reluctance has been studied. On the other hand, the approaches without sensor speed were developed. The stability of an estimation based on a back Electromotive Morce- Model Reference Adaptive System (EMF-MRAS) observers apply to an induction machine has been analyzed. [10].

25 In order to improve efficiency, the reliability can be achieved by fault tolerant control (FTC) [[11],[12],[13]].The first step of tolerant controls is the detection and location of faults. Fault detection uses up to now signal process-

ing techniques [14], for operating phases, which highlights and localizes faults. Moreover, we can find other techniques based on observers [15] or analytical
30 redundancy based on parity space space approach [16] and the modelless ap-
proaches such as the use of neural networks in [17] and fuzzy logic in [18]. The
second step is named the faults estimation, as presented by [19]. On other hand,
in [20] diagnosis problems of the induction motors were developed, with neural
detectors, in the case of rotor, stator and rolling bearing faults. In this case, in
35 [21] the authors present an accurate transient model of squirrel cage induction
machines under current stator failures.

Linear Parameter Varying (LPV) approach can be used to convert a nonlinear
system into a multiple model form. LPV systems can be seen as nonlinear
systems that are linearized along a trajectory determined by the parameter
40 vector, this approach is developed in several works, in [22] a control system of a
LPV system is designed, , López-Estrada et al [23] studied the stability of the
double feed induction machine (DFIG) using LPVs. In addition, and Bokor et
al [[24]] used the LPV system to investigate the fault detection and isolation
by using an approach for linear invariant systems and extended to LPV ones.
45 Moreover, to eliminate the nonlinear character of the system, the authors of
[25] use a Takagi-Sugeno approach for the design of a nonlinear state observer.

There are several methods developed for fault diagnosis and estimation. The
most effective method use unknown observers input, and it is used in [26] to
develop a detection and diagnostic system for the induction machine. . Rotondo
50 et al [27] propose a diagnosis of actuator faults and icing in unmanned aerial
vehicles (UAVs) based on a unknown input observer which use linear parameter
varying model. Despite of its advantages, the UIO is only used for actuator
faults and unknown input such as rotor resistance, also an extended version is
necessary and a first order filter is used for building an augmented system. In
55 the proposed method, the sensor fault and noise can be converted into actuator
fault and disturbance.

In this context, this article investigates an estimation of the sensor faults and
the output states of the IM by an extended observer with unknown input based

on an LPV model. Then, this problem will be solved using the Linear Matrix
60 Inequalities (LMI) tools.

The rest of this paper is organized as follows. Section 2, gives the dynamic
presentation of the induction machine and its nonlinear state representation.
In section 3, the development of the variable parameter linear model of IM is
presented. The model obtained is used in Section 4 to synthesis and design an
65 augmented unknown inputs observer UIO for IM sensor fault estimation. The
results demonstrate effectiveness of the proposed approach are given in Section
5, followed by some conclusions and future works in section 6.

Notation:

Throughout the paper, the following useful notation is used:

- 70 • T^T denotes the transpose of the matrix T .
- $T > 0$ means that T is a symmetric positive definite matrix.
- $\|T\|$ represents the norm for matrix T and the symbol $*$ denotes the trans-
pose elements in the symmetric positions.
- Sometimes to simplify the calculation, we will write the variables that
75 depend on the time without : (t)

2 Dynamic model of induction machine

The current modeling approach of the asynchronous machine is based on
the transformation of the three-phase system into a bi-phase system equivalent
to Park. It can also be asserted that the model is nonlinear as shown by the

80 following equations [[2],[6],[8],[11],[16],[28]]:

$$\left\{ \begin{array}{l} \frac{d}{dt} i_{ds} = \left(\frac{1}{\sigma L_s} \right) \left(-R_{sm} i_{ds} + \sigma L_s \omega_s i_{qs} + \frac{L_m}{L_r T_r} \phi_{dr} + \frac{L_m P}{L_r} \phi_{qr} \omega_r + V_{ds} \right) \\ \frac{d}{dt} i_{qs} = \left(\frac{1}{\sigma L_s} \right) \left(-R_{sm} i_{qs} - \sigma L_s \omega_s i_{ds} + \frac{L_m}{L_r T_r} \phi_{qr} + \frac{L_m P}{L_r} \phi_{dr} \omega_r + V_{qs} \right) \\ \frac{d}{dt} \phi_{dr} = \frac{L_m}{T_r} i_{ds} - \frac{1}{T_r} \phi_{dr} + (\omega_s - P \omega_r) \phi_{qr} \\ \frac{d}{dt} \phi_{qr} = \frac{L_m}{T_r} i_{qs} - \frac{1}{T_r} \phi_{qr} + (\omega_s - P \omega_r) \phi_{dr} \\ \frac{d}{dt} \omega_r = \left(\frac{P L_m}{J T_r} \right) (i_{qs} \phi_{dr} - i_{ds} \phi_{qr}) + \frac{1}{J} (-C r - K f \omega_r) \end{array} \right. \quad (1)$$

The systems shown in equation (1) can be written in the general nonlinear form, equation (2):

$$\left\{ \begin{array}{l} \dot{x} = A(x).x(t) + B.u \\ y = C.x(t) \end{array} \right. \quad (2)$$

Where A is the state function matrix and g is the input function matrix.

The state variables are the stator and rotor current components with flux and speed velocity, in addition, the inputs are the stator voltage components, but the outputs are stator current components and speed velocity as given in Equations (3) to (7). Then the equation (1) of a squirrel-cage asynchronous machine rewritten in state space form (2) becomes:

$$\left\{ \begin{array}{l} \dot{x}_1 = -\gamma x_1 + \omega_s x_2 + \alpha k x_3 + P k x_4 x_5 + u_1 \\ \dot{x}_2 = -\omega_s x_1 - \gamma x_2 + \alpha k x_4 - P k x_3 x_5 + u_2 \\ \dot{x}_3 = \alpha L_m x_1 - \alpha x_3 + (\omega_s - P x_5) x_4 \\ \dot{x}_4 = \alpha L_m x_2 - \alpha x_4 - (\omega_s - P x_5) x_3 \end{array} \right. \quad (3)$$

The state vector x is given by:

$$x = \left[\begin{array}{cccc} x_1 & x_2 & x_3 & x_4 \end{array} \right]^T \quad (4)$$

where : $x_1 = i_{ds}$; $x_2 = i_{qs}$; $x_3 = \phi_{ds}$; $x_4 = \phi_{qs}$; $x_5 = \omega_r$

By replacing x_1, x_2, x_3, x_4 in equation (1) we obtain the speed velocity given by equation(5)

$$\dot{\omega} = \psi(x_2x_3 - x_1x_4) + \frac{1}{J}(-c_r - K_f\omega) \quad (5)$$

And: $\alpha = \frac{1}{T_r}$, $\beta = \frac{1}{\sigma L_s}$, $\gamma = \beta.R_{sm}$, $k = \frac{L_m}{\sigma L_s L_r}$, $\psi = \frac{PL_m}{JT_r}$.

85 The model equation (3) is under the polynomial form and allows the non-measurable state variables can be eliminated. $x \in \mathbb{R}^n$ is the state vector, $u \in \mathbb{R}^p$ is the vector of control inputs and $y \in \mathbb{R}^m$ is the output vector and variables are functions of time t . All vectors are in appropriate dimensions. The output vector is:

$$y = \begin{bmatrix} y_1 & y_2 \end{bmatrix}^T = \begin{bmatrix} x_1 & x_2 \end{bmatrix}^T \quad (6)$$

90 The input vector is:

$$u = \begin{bmatrix} u_1 & u_2 \end{bmatrix}^T = \begin{bmatrix} V_{ds} & V_{qs} \end{bmatrix}^T \quad (7)$$

The input function matrix g in equation 2 is:

$$B = \begin{bmatrix} \frac{1}{\sigma L_s} & 0 & 0 & 0 & 0 \\ 0 & \frac{1}{\sigma L_s} & 0 & 0 & 0 \end{bmatrix}^T \quad (8)$$

As mentioned in the introduction, the work will be devoted to the estimation of the sensor fault and the state estimation. The scheme presented in figure 1, gives a presentation of the principle of the observer with unknown input, where 95 U represents the command, f_s is the sensor fault, \hat{f}_s and \hat{x} are respectively the estimate of the fault and the estimate of the state, and y the output (sensor) of the machine.

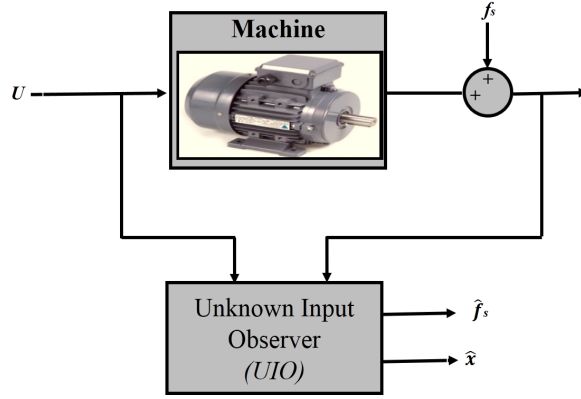


Figure 1: Schematic block of the approach.

3 Linear parameters variable (LPV) model of induction machine

In order to transform the nonlinear state-space model of Induction Machine considered in equation 3 to an LPV system, the speed rotation is considered as varying parameter and equation (9) gives the the LPV model, it can also be asserted that the model is nonlinear.

The equations (9- 18) show the different steps of the development of the LPV model for the induction machine.

$$\dot{x} = A(x).x(t) + B.u \quad (9)$$

Where:

$$A(x) = \begin{bmatrix} -\gamma & \omega_s & \alpha k & Pk\omega \\ -\omega_s & -\gamma & -Pkx_3\omega & \alpha k \\ \alpha L_m & 0 & -\alpha & \omega_s - P\omega \\ 0 & \alpha L_m & -(\omega_s - P\omega) & -\alpha \end{bmatrix} \text{ and } u = \begin{bmatrix} u_1 \\ u_2 \\ 0 \\ 0 \end{bmatrix} \quad (10)$$

If the rotor speed is considered as a varying parameter $\rho = \omega$, the equation

(9) can be written in the usual form:

$$\begin{cases} \dot{x}(t) = A[\rho(t)]x(t) + Bu(t) \\ y(t) = Cx(t) \end{cases} \quad (11)$$

where :

$$A(\rho) = A_0 + \sum_{i=1}^r \rho_i A_i \quad (12)$$

With:

$$A_0 = \begin{bmatrix} -\gamma & \omega_s & \frac{k}{T_r} & 0 \\ -\omega_s & -\gamma & 0 & \frac{k}{T_r} \\ \frac{L_m}{T_r} & 0 & -\frac{1}{T_r} & \omega_s \\ 0 & \frac{L_m}{T_r} & -\omega_s & -\frac{1}{T_r} \end{bmatrix} \quad (13)$$

$$A_i = \begin{bmatrix} 0 & 0 & 0 & Pk\omega_i \\ 0 & 0 & Pk\omega_i & 0 \\ 0 & 0 & 0 & -Pk\omega_i \\ 0 & 0 & P\omega_i & 0 \end{bmatrix} \quad (14)$$

And :

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \quad (15)$$

We assume for physical limits that all the current and speed are measurable and this allowed us to say that:

$$\omega_{min} \leq \omega \leq \omega_{max} \quad (16)$$

For this purpose, the following variation interval is obtained:

$$\begin{cases} A_1 = A_{\omega_{min}} \Rightarrow \rho_1 = \frac{\omega - \omega_{min}}{\omega_{max} - \omega_{min}} \\ A_2 = A_{\omega_{max}} \Rightarrow \rho_2 = \frac{\omega_{max} - \omega}{\omega_{max} - \omega_{min}} \end{cases} \quad (17)$$

So we will have :

$$\sum_{i=1}^r \rho_i A_i = \rho_1 A_1 + \rho_2 A_2 \quad (18)$$

And: $\sum_{i=1}^r \rho_i = 1$ is verified

4 Design of unknown input observer for sensor fault estimation

Knowing that the unknown input observers are designed for the evaluation of the actuator faults, so, it is necessary to build the extended version in order to estimate the sensor faults. In this section, based on the system of equation (19), an observer will be developed to estimate the sensor faults. In addition, from this equation the noise will be considered in the system :

$$\begin{cases} \dot{x} = A(\rho).x(t) + B.u \\ y = C.x(t) + Ww(t) + F_s f_s(t) \end{cases} \quad (19)$$

110 Where x is the state vector, u the input, y the output and w the noise and f_s the sensor fault vector. A , B , F and D are matrix of appropriate dimension. Based on LPV and by substituting in equation of A , The system (19) can be rewritten as follows:

$$\begin{cases} \dot{x} = \sum_{i=1}^r \rho_i A_i .x(t) + B.u(t) \\ y = C.x(t) + Ww(t) + F_s f_s(t) \end{cases} \quad (20)$$

The construction of the augmented system is based on filtering $y(t)$ by a first
115 order filter such that:

$$\begin{cases} \dot{x}_s = A_s .x_s(t) + B_s .u_s(t) \\ y = x_s(t) \end{cases} \quad (21)$$

Where: A_s is negative.

Knowing that the filter control will be done by the observer output, so we obtain :

$$\dot{x}_s = A_s .x_s(t) + B_s .[C.x(t) + Ww(t) + F_s f_s(t)] \quad (22)$$

120 By combining the system (20) with (22) we have the following equation:

$$\begin{cases} \dot{x} = \sum_{i=1}^r \rho_i A_i .x(t) + B.u(t) \\ \dot{x}_s = A_s .x_s(t) + B_s .C.x(t) + B_s .W.w(t) + B_s .F_s .f_s(t) \end{cases} \quad (23)$$

Therefore, the following matrix system can be deduced:

$$\begin{bmatrix} \dot{x} \\ \dot{x}_s \end{bmatrix} = \begin{bmatrix} A_i & 0 \\ B_s.C & A_s \end{bmatrix} \begin{bmatrix} x \\ x_s \end{bmatrix} + \begin{bmatrix} B \\ 0 \end{bmatrix} u + \begin{bmatrix} 0 \\ B_s.F_s \end{bmatrix} f_s + \begin{bmatrix} 0 \\ B_s.W \end{bmatrix} w \quad (24)$$

Denote :

$$\dot{\bar{x}} = \begin{bmatrix} \dot{x}^T(t) & \dot{x}_s^T(t) \end{bmatrix} \quad \text{and} \quad \bar{x} = \begin{bmatrix} x^T(t) & x_s^T(t) \end{bmatrix} \quad (25)$$

Therefore, equation (26) gives the expression of the augmented system

$$\begin{cases} \dot{\bar{x}} = \bar{A}_i(\rho).\bar{x}(t) + \bar{B}.u(t) + \bar{D}w(t) + \bar{F}f_s(t) \\ y = \bar{C}.\bar{x}(t) \end{cases} \quad (26)$$

Where the expression of the matrices are:

$$\bar{A}_i = \begin{bmatrix} A_i & 0 \\ B_s.C & A_s \end{bmatrix}, \bar{B} = \begin{bmatrix} B \\ 0 \end{bmatrix}, \bar{D} = \begin{bmatrix} 0 \\ B_s.W \end{bmatrix}, \bar{F} = \begin{bmatrix} 0 \\ B_s.F_s \end{bmatrix}, \bar{C} = \begin{bmatrix} 0 \\ C \end{bmatrix},$$

In this case, the system (26) makes it possible to treat the sensor faults as actuator faults.

125

Consider the system (26), which describes our system of continuous descriptor (LPV) affected by perturbations and apply the following assumptions to determine the gains of the observer:

130

- \bar{A}_i Is an invariant matrix over time.
- (\bar{A}_i, \bar{C}) is observable.
- \bar{C} is full rank and also \bar{D} is full row of columns.
- $w(t)$ and $f_s(t)$ are derived and bounded functions

Based on the system ((26)), the unknown observer can be written as :

$$\begin{cases} \dot{z}(t) = \sum_{i=1}^r \rho_i N_i z(t) + Gu(t) + Ly(t) + T \hat{f}_s \\ \hat{x}(t) = z(t) - Ex(t) \end{cases} \quad (27)$$

where :

- $z(t)$ state vector related to $x(t)$
- N_i, G, L, T and E , are matrices of appropriate dimension.

The error is defined such that:

$$\begin{aligned} e(t) &= \bar{x}(t) - \hat{x}(t) \\ &= (I_2 + E\bar{C})\bar{x}(t) - z(t) \end{aligned} \quad (28)$$

Then the expression of the error becomes:

$$\dot{e}(t) = M\dot{\bar{x}}(t) - \dot{z}(t) \quad (29)$$

where : $M = I_2 + E\bar{C}$ and I_2 is an identity matrix with appropriate dimensions.

Therefore, the dynamic error can be rewritten as:

$$\begin{aligned} \dot{e} &= [M \sum_{i=1}^r \rho_i \bar{A}_i - \sum_{i=1}^r \rho_i N_i M - L\bar{C}]x(t) + M\bar{D}\omega(t) + [M\bar{B} - G]u(t) \\ &\quad + M\bar{F}\hat{f}_s(t) - T\hat{f}_s + \sum_{i=1}^r \rho_i N_i e \end{aligned} \quad (30)$$

Based on the following change of variable $\tilde{f}_s(t) = f_s(t) - \hat{f}_s(t) \Rightarrow f_s(t) = \tilde{f}_s(t) + \hat{f}_s(t)$, and if the conditions in equation(31) hold :

$$\left\{ \begin{array}{l} M \sum_{i=1}^r \rho_i \bar{A}_i - \sum_{i=1}^r \rho_i N_i M - L\bar{C} = 0 \\ M\bar{B} - G = 0 \\ M\bar{D} = 0 \\ T = M\bar{F} \end{array} \right. \quad (31)$$

The dynamic error becomes:

$$\dot{e} = \sum_{i=1}^r \rho_i N_i e + T\tilde{f}_s \quad (32)$$

Note the dynamic error is only related to \tilde{f}_s , then the error tends to zero if the N_i is Hurwitz and estimation converges to zero.

Knowing that $r_e = y(t) - \hat{y}(t)$ and based on equation of y in (26) , the following relationship is obtained:

$$\begin{aligned} \Rightarrow r_e &= \bar{C}e(t) \\ \Rightarrow \dot{r}_e &= \bar{C}\dot{e}(t) \end{aligned} \quad (33)$$

The formula chosen to estimated the fault is equation (34), its stability is
 140 studied using Lyapunov function equation (35):

$$\dot{\hat{f}}(t) = QS(\dot{r}_e + \sigma r_e) \quad (34)$$

$$V = e^T P e + \frac{1}{\sigma} \tilde{f}_s^T Q^{-1} \tilde{f}_s \quad (35)$$

By deriving the equation , the equation (36) is obtained :

$$\dot{V} = \dot{e}^T P e + e^T P \dot{e} + \frac{1}{\sigma} \dot{\tilde{f}}_s^T Q^{-1} \tilde{f}_s + \frac{1}{\sigma} \tilde{f}_s^T Q^{-1} \dot{\tilde{f}}_s \quad (36)$$

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

$$\dot{V} = \dot{e}^T P e + e^T P \dot{e} + \frac{2}{\sigma} \tilde{f}_s^T Q^{-1} \dot{\tilde{f}}_s \quad (37)$$

By replacing equations (34) and (32) in equation (37), the final expression of
 the stability derivative expression obtained, equation (38):

$$\dot{V} = \sum_{i=1}^r \rho_i e^T (N_i^T P + P N_i) e + \frac{2}{\sigma} \tilde{f}_s^T Q^{-1} \dot{\tilde{f}}_s - \frac{2}{\sigma} \tilde{f}_s^T S C \sum_{i=1}^r \rho_i N_i e - \frac{2}{\sigma} \tilde{f}_s^T S \bar{C} T \tilde{f}_s \quad (38)$$

To study system stability, lemma 01 theorem, is used to transform equation
 (38) to inequality, equation (41).

Lemma 1

Given a scalar μ and a positive positive symmetric matrix P1, the following
 equality is true [29]

$$2x^T y \leq \frac{1}{\mu} x^T P_1 x + \mu y^T P_1^{-1} y \quad (39)$$

Based on lemma 01, we can deduce the following inequality:

$$\frac{2}{\sigma} \tilde{f}_s^T Q^{-1} \dot{\tilde{f}}_s \leq \frac{2}{\sigma} \left(\frac{1}{\mu} \tilde{f}_s^T P_1 \tilde{f}_s + \mu Q^{-1 T} \dot{\tilde{f}}_s^T P_1^{-1} Q^{-1} \dot{\tilde{f}}_s \right) \quad (40)$$

According to the proposed hypothesis, we have the derivative of the fault f_s
 145 is bounded then : $\|\dot{f}_s\| < \alpha_1$, Such as $0 < \alpha_1 < \infty$ and $\|\dot{f}_s\| + \|\dot{f}_s^T\|$

By combining the equation (32) and equation (40), the inequality (38) is obtained:

$$\dot{V} \leq \sum_{i=1}^r \rho_i e^T (N_i^T P + P N_i) e + \frac{1}{\mu\sigma} \tilde{f}_s^T P_1 \tilde{f}_s + \phi - \frac{2}{\sigma} \tilde{f}_s^T T^T \sum_{i=1}^r \rho_i N_i e - \frac{2}{\sigma} \tilde{f}_s^T S \bar{C}^T \tilde{f}_s \quad (41)$$

Note that: $\phi = \frac{\mu}{\sigma} \alpha_1^2 \lambda_{max} Q^{-1T} P_1^{-1} Q^{-1}$

The vector ϵ is defined as :

$$\epsilon = \begin{bmatrix} e \\ \tilde{f} \end{bmatrix}^T \quad (42)$$

Now the vector \dot{V} can be written as follows:

$$\dot{V} \leq \sum_{i=1}^r \rho_i \epsilon^T \psi_i \epsilon + \phi \quad (43)$$

Where :

$$\psi = \begin{bmatrix} N_i^T P + P N_i & * \\ \frac{1}{\sigma} T^T P N_i & \frac{1}{\mu\sigma} P_1 - \frac{2}{\sigma} T^T P^T \end{bmatrix} \leq 0 \quad (44)$$

From the convergence conditions (31), H can be written as follows :

$$H = [M, E] = [M, E] = [I, 0] \begin{bmatrix} I & D \\ -C & 0 \end{bmatrix} \quad (45)$$

Denote:

$$K_i = L_i - N_i E$$

by the substitution of (45) to (31), the gains of the observers can be calculated as :

$$\begin{aligned} N_i &= M A_i - K_i C \\ L_i &= K_i (I + C E) - M A_i E \\ T &= M F \end{aligned} \quad (46)$$

Replacing the N_i of equation (46) in equation (44) and taking $\bar{k}_i = P.k_i$, the solution of the LMI can be obtained by YALMIP or MATLAB editor. The figure

150 (2) shows the different computing steps of the observer algorithm :

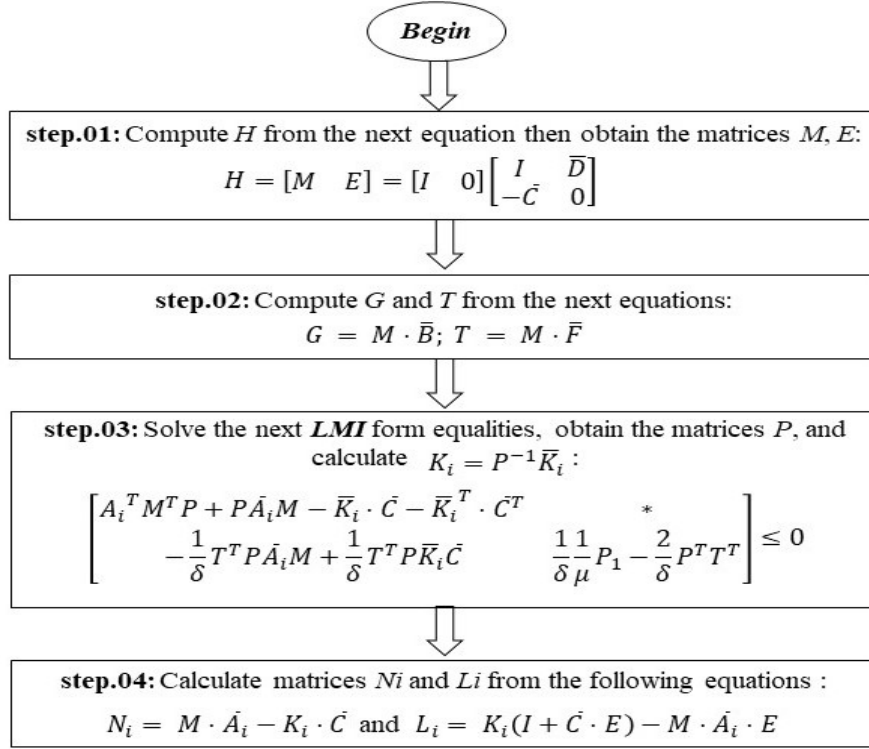


Figure 2: Algorithm of Unknown Input Observer design

According to the parameters of the induction machine mentioned in tables
APPENDIX(A) :

$$A_1 = \begin{bmatrix} -264.7163 & 314.1593 & 420.9129 & 606.2030 \\ -314.1593 & -264.7163 & -606.2030 & 420.9129 \\ 3.5828 & 0 & -13.8869 & 294.1593 \\ 0 & 3.5828 & -294.1593 & -13.8869 \end{bmatrix}$$

$$A_2 = 1.0e + 03 * \begin{bmatrix} -0.2647 & 0.3142 & 0.4209 & 9.5174 \\ -0.3142 & -0.2647 & -9.5174 & 0.4209 \\ 0.0036 & 0 & -0.0139 & 0.0002 \\ 0 & 0.0036 & -0.0002 & -0.0139 \end{bmatrix}$$

Where : A_1, A_2 are matrix given by equation 14.

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

The parameters of UIO can be obtained following the steps of the observer algorithm of figure (2) and solving the LMIs using the Yalmip:

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

$$N1 = \begin{bmatrix} -29.4716 & 45.9571 & 256.7790 & 46.3225 \\ 29.4896 & -46.0233 & -256.7790 & -46.3225 \\ 4.7653 & 4.9220 & -13.8869 & 294.1593 \\ -6.1519 & -12.8996 & -294.1593 & -13.8869 \end{bmatrix}; L1 = \begin{bmatrix} 31.2179 & 125.8617 \\ -31.2390 & -125.8407 \\ 3.6220 & -0.0392 \\ -1.6869 & 5.2697 \end{bmatrix}$$

$$N2 = 1.0e+03* \begin{bmatrix} -0.3973 & -0.1162 & 2.4846 & 2.2741 \\ 0.3968 & 0.1159 & -2.4846 & -2.2741 \\ 0.0017 & 0.0008 & -0.0139 & 0.0002 \\ 0.0013 & 0.0006 & -0.0002 & -0.0139 \end{bmatrix}; L2 = \begin{bmatrix} 82.6350 & 74.4447 \\ -82.6017 & -74.4779 \\ 3.3621 & 0.2207 \\ -0.1777 & 3.7605 \end{bmatrix}$$

$$G = \begin{bmatrix} 8.0475 & -8.0475 \\ -8.0475 & 8.0475 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}; T = \begin{bmatrix} 0.2500 & -0.2500 \\ -0.2500 & 0.2500 \\ 0 & 0 \\ 0.0000 & -0.0000 \end{bmatrix}; S = 1.0e+03* \begin{bmatrix} -2.0171 & -2.3658 \\ 2.0171 & 2.3658 \end{bmatrix}$$

5 Results and discussion of the application on induction machine

In order to demonstrate the effectiveness of the proposed approach, it has been applied to the induction machine, where we have considered current outputs of the IM as inputs variables of the observer.

The observer has been tested for three different cases :

- Case 01: without fault.
- Case 02: quasi-square fault between 3s and 7s.
- 160 • Case 03: a variable fault between 0s and 8s.

under the condition below and for two sensor faults, the results are given by the figures (3-7):

- The speed varies between a minimum value $\omega_{min} = 0$, and a maximum value $\omega_{max} = 157$ [rad/s].
- 165 • We will simulate only one sensor fault at a time, which will be of the order of 15 % of the nominal values.

Figure 3 shows the evolution of the estimation faults and the state variable (I_{ds} and I_{qs}) in the absence of faults. It is noteworthy in these figures that the estimated fault value and variable state converges to the reference value.

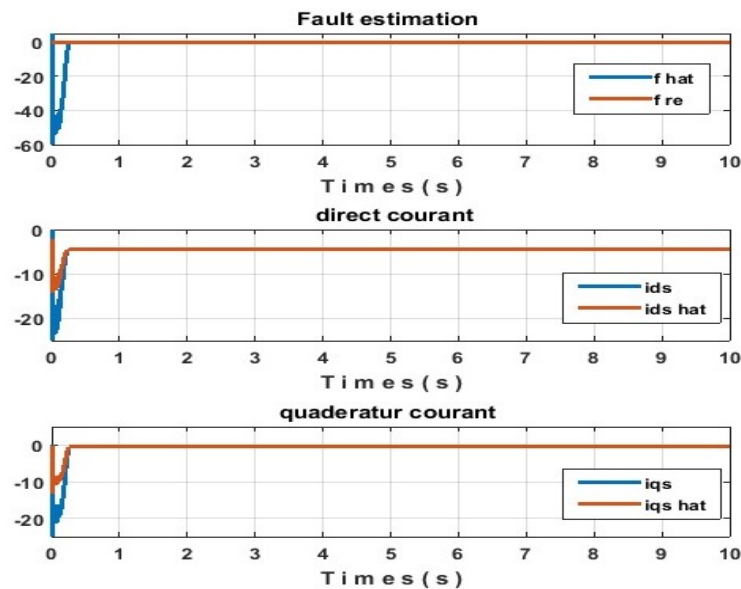


Figure 3: Free system (without sensor faults).

170 The Figures 4 and 5, present the evolution of the reference, fault estimation, fault estimation error and estimation error of state variables, with square sensor faults in I_{ds} and I_{qs} respectively. We can see also that fault simulated converges to the reference fault which demonstrates the effectiveness of the proposed algorithm.

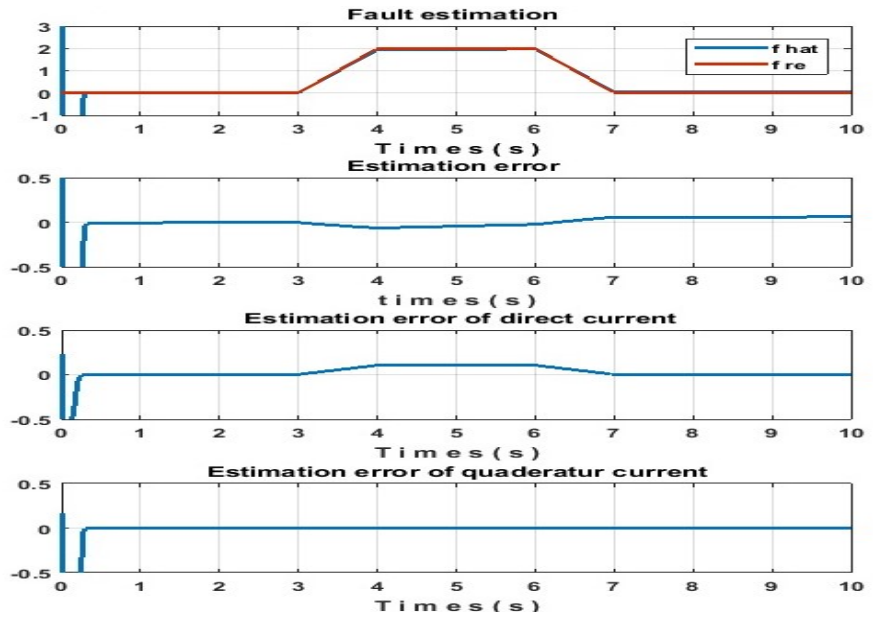


Figure 4: Estimation of square sensor faults in I_{ds} .

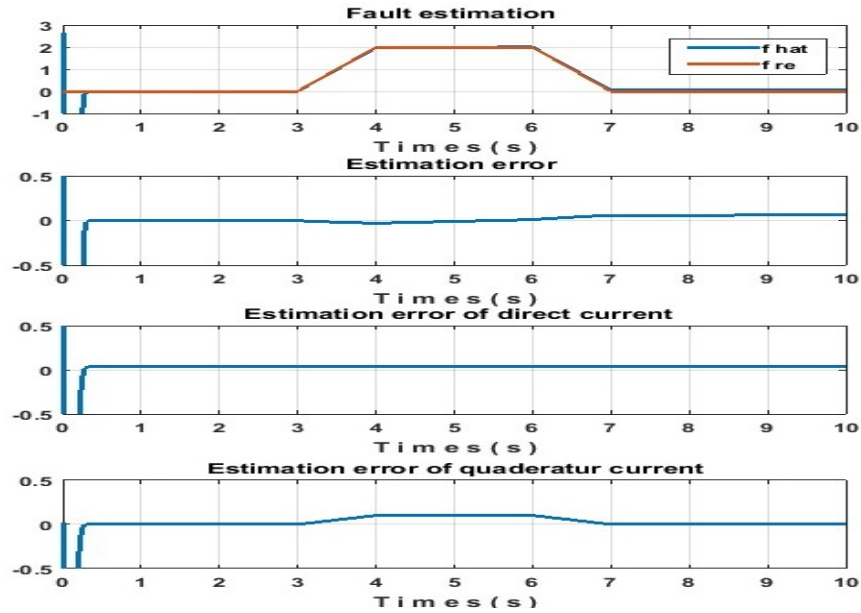


Figure 5: Estimation of square sensor faults in I_{qs} .

175 The results shown on figures 6 and 7, give the estimation of the sensor faults and the error of the estimation of the state variables, in the prsence of variable sensor faults where this variation is between 0 and 2A.

We can see that the fault well be estimated and the error estimation tends to zero. This is confirms the effectiveness of the algorithim.

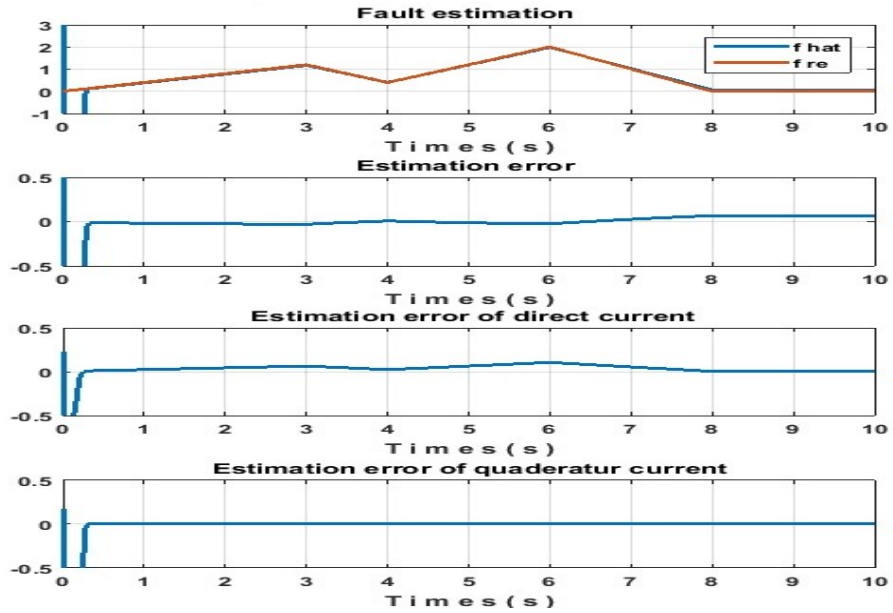


Figure 6: Estimation of variable sensor faults in I_{ds} .

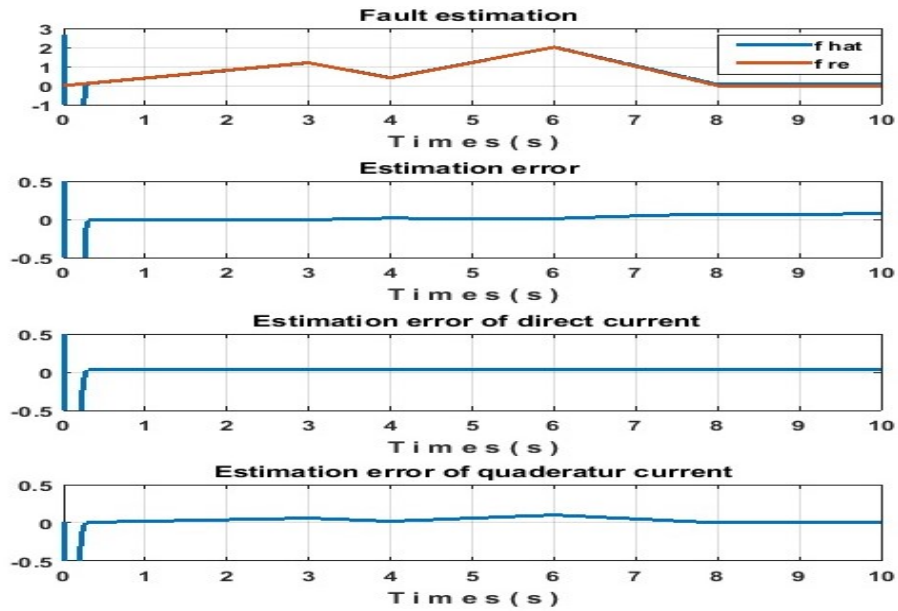


Figure 7: Estimation of variable sensor faults in I_{qs} .

180 From the above simulation, it's possible to test the performance of the proposed method.

In the light of the results shown in figures 3-7, the observer estimates the state values which converge to the faults references and the estimation error
185 tends to zero. It can be noticed that the output currents of the observer follow those of the machine and the error is almost zero. Therefore, the estimation by this method gives good results. The results show that the unknown inputs observer can be augmented to estimate the sensor faults and the twinning between the UIO and LPV gives system with satisfactory performance.

190 6 CONCLUSION

In this paper an augmented unknown inputs observer has been developed for sensor faults estimation and the noise for an induction machine, this last is represented by a Linear Parameter Varying model (LPV).

As a result, the application of the proposed estimation approach of sensor
195 faults and states gives good results despite the complexity of the system. The augmented observer would allow to deal with the sensor faults as same as actuator faults. Based on the results obtained, it can be said also that this approach could find a large field of applications in fault-tolerant control design, which will be the subject of future work, as its implementation on a real induction
200 machine.

7 APPENDIX A

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

Rated power	1.5 Kw.	P_N
Nominal voltage	220/380 V.	V_N
Rated power factor	0.8.Rated.	$\cos\phi$
Speed	1420 rev/ min	ω
Nominal frequency	50 Hz.	f
Stator resistance	4.85 Ω .	R_s
Rotor resistance	3.805 Ω .	R_r
Stator cyclic inductance	0.274 H.	L_s
Cyclic inductance of Rotor	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

8 APPENDIX B

Synchronous Pulsation [rad/s].	ω_s
Electrical angular Pulsation [rad/s].	ω_r
Electromagnetic torque [N.m].	$C_e m$
Resistive torque [N.m].	C_r
Rotor time constant [s].	T_r
The direct stator voltage	V_{ds}
The stator quadrature voltage	V_{qs}
The direct stator current	i_{ds}
The stator quadrature current	i_{qs}
The direct stator flow	$\phi_{i_{ds}}$
The stator quadrature flow	$\phi_{i_{qs}}$

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