New State Observer Based On Takai-Sugeno Fuzzy Controller of Induction Motor

Mohamed Yacine Hammoudi, Mohamed Benbouzid, N Rizoug, A Allag

New State Observer Based On Takai-Sugeno Fuzzy Controller of Induction Motor

M.Y Hammoudi, M.E.H Benbouzid, Senior Member, IEEE, N. Rizoug, A. Allag

Abstract— **This paper presents a nonlinear observer-based on Takagi-Sugeno(T-S)fuzzy controller design approach for induction motor (IM). The peculiarity of this paper is the synthesis of a mono- Luenberger observer for highly coupled system. The TS fuzzy model is firstly used to approximate the nonlinear IM systems. Next, based on the differential mean value theorem combined to the sector nonlinearity transformation, a nonlinear fuzzy observer is designed to estimate the system states in order to implement the fuzzy controller. Then, the parallel distributed compensator (PDC) scheme is used to design the fuzzy controller for the overall system. Fuzzy Controller and observer gains are obtained by solving a set of Linear Matrix Inequality (LMI).Finally, illustrative simulation results represented to validate the performance of the proposed approach.**

Index Terms— **Observer design, Differential mean value theorem, Sector nonlinearity transformation, Linear matrix inequalities (LMI), Induction motor, Parallel distributed compensator, T-S Fuzzy Model.**

I. Introduction

The induction motor (IM) has many excellent performance features such as rugged, high reliability, low cost and simple hardware structure. Due to the advantages mentioned above, the induction motor has been used widely in the field of industrials driving systems and their applications [1]-[2].

Due to the intrinsic nonlinear coupling between the dynamics of the electrical part and of the mechanical part, inaccessibility for the rotor flux, and system-parameter variations, many modern control techniques have been designed to overcome the tracking problem. Adaptive control methods are proposed in [3]; Fuzzy adaptive control has been studied in [4] and, sliding mode control has been adopted by [5].

In [3] an adaptive controller for speed regulation of induction motor was designed based on the input-output decoupled technique.

An adaptive fuzzy MIMO control of induction motors is studied in [4]. M. Rodicand all [5] proposed Speed-sensorless sliding-mode torque control of an induction motor. Fuzzy control design methods for induction motor with a guaranteed H model reference tracking performance is proposed by [6].

The Takagi-Sugeno fuzzy approach has been extensively used to the nonlinear systems [7], [2]. This kind of model is described by a group of fuzzy IF-THEN rules which describe the local inputoutput relationships of original nonlinear system. The basic idea is to decompose the model of a nonlinear system into a set of linear subsystems with associated nonlinear weighting functions [6].

The PDC offers a procedure to design a fuzzy controller from a given T-S fuzzy model. The main idea of the PDC technique is the partition of a nonlinear system dynamics into a number of linear subsystems, design a number of local controllers for each linear subsystem, and finally generate the overall controller by the fuzzy blending of such local controllers [8].

All states of IM systems are not measurable. Hence, we envision that a nonlinear observer would be important in fuzzy control. Over the past few years, various observers have been considered to the state of IM system.

In [9], a robust adaptive observer for sensorless induction motor was designed based on the linearized dynamic equation and linear matrix inequality method. Sliding mode observers to estimate rotor flux were proposed in [10]-[11]. In [12] an extended Kalman filter method was adapted to estimate the rotor flux of induction motor. Nonlinear Luenberger observers [13] have been proposed for Sensorless Vector Control of Induction Motors. In [14], a new non-linear observer structure based on the backstepping principle for sensorless IM drive is proposed. A nonlinear observer based control of induction motors is proposed by [15].

In [16] an adaptive resilient observer for a Lipschitz nonlinear system was designed, the authors [17] proposed an observer based on DMVT for a nonlinear system. Another LMI-based observer design for a class of Lipschitz nonlinear dynamical systems can be found in [18].

The design procedure in this paper aims at designing stable nonlinear observer based fuzzy controllers for Induction motor. Firstly, the Takagi-Sugeno approach is used to approximate the nonlinear system of induction motor. Once the fuzzy model is obtained, the control design is carried out via the PDC scheme. The basic idea is that for each local linear model, there is an associated linear feedback control [19]. Secondly, the DMVT fuzzy observer is also designed independently for the controller according to the separation property. Controller and observer gains may be computationally solved from stability criteria formulated into linear matrix inequalities. The stability of the overall control

This work was not supported by any organization

M.Y Hammoudi is with MSE Laboratory, University of Biskra, 07000, Algeria dr.hammoudi@gmail.com

M.E.H. Benbouzid is with the University of Brest, EA 4325 LBMS, Rue de Kergoat, CS 93837, 29238 Brest Cedex 03, France Mohamed.Benbouzid@univ-brest.fr

N. Rizoug is with the Ecole Suprieure des Techniques Aronautiques et de Construction Automobile, 53061 Laval, France nassim.rizoug@estaca.fr

A. Allag is with the University of Biskra, MSE Laboratory, Department of Electrical Engineering, BP 145, Biskra, Algeria abdelkarim_allag@yahoo.fr

system including a fuzzy regulator and a fuzzy observer is guaranteed.

This paper is organised as follows: the TS fuzzy modeling is performed in Section 2, Sections 3 provide the controller design and the observer design respectively. The dynamic model of IM system is illustrated in Section 4. In Section 5, simulation results are represented to illustrate the effectiveness of proposed methods. Finally, conclusions are drawn in Section 6.

II. Nonlinear Observer Based Fuzzy Controller Design

Consider a nonlinear system described by

$$\begin{cases} \dot{x}(t) = f(x(t),u(t)) \\ y(t) = h(x(t)) \end{cases} \tag{1}$$

Where $x \in \mathbb{R}^n$, $u \in \mathbb{R}^p$ and $y \in \mathbb{R}^m$ are the state, the input and the output measurement vectors, and $C \in \mathbb{R}^{n\times m}$ are appropriate matrices. In addition, the function $f(x)$ and $h(x)$ are assumed to be differentiable.

A. Takagi-Sugeno fuzzy model

The TS fuzzy model is described by fuzzy if-then rules which represent local linear input-output relations of a nonlinear system. The i^{th} rule of the T-S fuzzy model is of the following form:

Plant Rule i

IF $z_1(t)$ is F_{i1} and $z_2(t)$ is F_{i2} $\ldots$ $z_p(t)$ is F_{ip}

THEN

$$\begin{cases} \dot{x}(t) = A_i x(t) + B_i u(t)) \quad i = 1,2,\ldots,r \\ y(t) = C_i x(t) \end{cases} \tag{2}$$

The above fuzzy model is represented as

$$\begin{cases} \dot{x}(t) = \sum_{i=1}^{r} h_i(z(t))(A_i x(t) + B_i u(t)) \\ y(t) = C_i x(t) \end{cases} \tag{3}$$

Where $h_i(z(t))$ are the weighting functions depending on the variables $z_i(t)$ and satisfy the convexity property:

$$h_i(\xi(t)) = \frac{\mu_i(\xi(t))}{\sum_{i=1}^{r} \mu_i(\xi(t))} \tag{4}$$

$$\sum_{i=1}^{r} h_i(\xi(t)) = 1 \quad and \quad 0 \le h_i(\xi(t)) \le 1 \tag{5}$$

B. Observer Design

1) Problem statement: This section presents an efficient methodology for designing observers for the class of nonlinear systems [20]: The proposed observer is described by:

$$\dot{\hat{x}}(t) = \sum_{i=1}^{r} h_i(\hat{x}(t))(A_i \hat{x}(t) + B_i u(t) + L_0(y(t) - \hat{y}(t)) \tag{6}$$

Let us introduce the following matrices

$$A_0 = \frac{1}{r}\sum_{i=1}^{r} A_i, B_0 = \frac{1}{r}\sum_{i=1}^{r} B_i, \bar{A}_i = A_i - A0, \bar{B}_i = B_i - B0 \tag{7}$$

Then, it is easy to rewrite the system (2) in the following Lipchitzien form

$$\dot{x}(t) = A_0 x(t) + B_0 u(t) + \sum_{i=1}^{r} h_i(x(t))(\bar{A}_i x(t) + \bar{B}_i u(t)) \tag{8}$$

We denote that the matrices A_0 and B_0 play the role of nominal values of the system. The state equation of the observer (6) can also be presented in the following form

$$\begin{aligned} \dot{\hat{x}}(t) = A_0 \hat{x}(t) + B_0 u(t) + L_0(y(t) - \hat{y}(t)) \\ + \sum_{i=1}^{r} h_i(\hat{x}(t))(\bar{A}_i \hat{x}(t) + \bar{B}_i u(t) \end{aligned} \tag{9}$$

Let us defined a new function $\varphi(x)$ Where

$$\Phi(x,u) = \sum_{i=1}^{r} h_i(x(t))(\bar{A}_i x(t) + B_i u(t)) \tag{10}$$

The dynamic of the state estimation error $e(t)$ is given by:

$$\begin{cases} e(t) = x(t) - \hat{x}(t) \\ \dot{e}(t) = (A_0 - L_0 C)e(t) + (\Phi(x,u) - \phi(\hat{x},u)) \end{cases} \tag{11}$$

2) Differential mean value theorem: In this section, we present the mean value theorem for vector functions in order to develop the observer gain in the next section [21].

Lemma 1*:*

Let a vector function $(x) : \mathbb{R}^n \to \mathbb{R}^q$, we can write f as follow:

$$f(x) = \sum_{i=1}^{q} e_q(i) f_i(x) \tag{12}$$

Where f_i is the i^{th} component of f. And e_q defined by:

$$\begin{cases} e_q(i) = [0 \ldots 0 \quad 1 \quad 0 \quad \ldots \ 0]^T \\ \qquad\qquad 1 \quad i-1 \quad i \quad i+1 \qquad q \end{cases} \tag{13}$$

Theorem 1*:*

Consider$f_i(x) : \mathbb{R}^n \to \mathbb{R}$ Let ,$b \in \mathbb{R}^n$. We assume that f_i is differentiable on $[a,b]$. Then there exists a constant vector $\xi \in]a,b[$, such that

$$f_i(a) - f_i(b) = \frac{\partial f_i(\xi)}{\partial x}(a-b) \tag{14}$$

Applying the theorem on (12), it is obtained for$a,b \in \mathbb{R}^n$

$$f(a) - f(b) = \sum_{i=1}^{n}\sum_{j=1}^{n} e_n(i) e_i^T \frac{\partial f_i(\xi)}{\partial x}(a-b) \tag{15}$$

The observation problem consists in finding a gain L_0 such that the observer error converges exponentially and asymptotically towards zero. Comparing (9) with (10), we find

$$\phi(x,u) = (f(x) - A_0 x) + (g(x)u - B_0 u) \tag{16}$$

From (16), and By the DMVT, there exists $\xi(t) \in]x,\hat{x}[$,such that:

$$\varphi(x) - \varphi(\hat{x}) = \frac{\partial \varphi(\xi)}{\partial x}(x - \hat{x}) \tag{17}$$

Then, (17) could be written as:

$$\varphi(x) - \varphi(\hat{x}) = \sum_{i=1}^{n}\sum_{j=1}^{n} e_n(i)e_n^T(j)\frac{\partial \varphi_i(\xi)}{\partial x_j}(x - \hat{x}) \tag{18}$$

The expression (18) into (11), the dynamics of the observer error becomes:

$$\dot{e}(t) = (A_0 - L_0C + \sum_{i=1}^{n}\sum_{j=1}^{n} e_n(i)e_n^T(j)\frac{\partial \varphi_i(\xi)}{\partial x_j}).e \tag{19}$$

C. Fuzzy regulator design via parallel distributed compensation:

The parallel distributed compensation (PDC) [19] is employed to design a fuzzy controller from the T-S fuzzy model. The main idea of the PDC is to design each local control rule so as to compensate each local rule of a fuzzy system. Each control rule is distributively designed from the corresponding rule of the T-S fuzzy model in the PDC. The PDC provides the fuzzy rule structure (20) for the fuzzy model.

Plant Rule i

IF $z_1(t)$ is F_{i1} and $z_2(t)$ is F_{i2} $\ldots$ $z_p(t)$ is F_{ip}

THEN

$$u(t) = -K_i x(t) \qquad i = 1,2,\ldots,r \tag{20}$$

The fuzzy control rules have linear state feedback laws in the consequent parts. The overall fuzzy controller is represented by

$$u(t) = -\sum_{i=1}^{n} \mu_i(\hat{x}(t))K_i(\hat{x}(t) - x_c(t)) \tag{21}$$

The feedback gains of the controller $K_i$are determined by an LMI-based design technique, the desired states $x_c(t)$in our application are determined by the field oriented control (FOC). By substituting (20) into (3), we obtain

$$\begin{cases} \dot{x}(t) = A_0x(t) - B_0\sum_{i=1}^{r} \mu_i(\hat{x}(t))K_i\hat{x}(t) + \varphi(x) \\ \dot{e}(t) = (A_0 - L_0C + \sum_{i=1}^{n}\sum_{j=1}^{n} e_n(i)e_n^T(j)\frac{\partial \varphi_i(\xi)}{\partial x_j}).e(t) \end{cases} \tag{22}$$

1) Assumption : We assume that the functions $\varphi(x)$is a differentiable function satisfying

$$\alpha_i j < \varphi_i(x) < \beta_i j \tag{23}$$

We assume that the functions $\frac{\partial \varphi_i(\xi)}{\partial x_j}$ is a differentiable function satisfying

$$\frac{\partial \varphi_i(\xi)}{\partial x_j} = \lambda_{ij}^1(\xi).\alpha_{ij} + \lambda_{ij}^2(\xi).\beta_{ij} \tag{24}$$

Where

$$\begin{cases} 0 \le \lambda_{ij}^1 = \dfrac{\frac{\partial \varphi_i(\xi)}{\partial x_j} - \alpha_{ij}}{\beta_{ij} - \alpha_{ij}} \le 1 \\ 0 \le \lambda_{ij}^2 = \dfrac{\beta_{ij} - \frac{\partial \varphi_i(\xi)}{\partial x_j}}{\beta_{ij} - \alpha_{ij}} \le 1 \\ \lambda_{ij}^1 + \lambda_{ij}^2 = 1 \end{cases} \tag{25}$$

We replace (24) in (22):

$$\dot{e}(t) = ((A_0 - L_0C) + \sum_{i=1}^{n} h_iA_i).e \tag{26}$$

Then

$$\begin{bmatrix} \dot{x}(t) \\ \dot{e}(t) \end{bmatrix} = \sum_{i=1}^{r}\sum_{j=1}^{r} \mu_i(z(t))h_i(z(t))\times \begin{bmatrix} A_0 - B_0K_i + A_i & -B_0K_i \\ 0 & A_0 - L_0C + A_j \end{bmatrix} \cdot \begin{bmatrix} x(t) \\ e(t) \end{bmatrix} \tag{27}$$

Now the main problem consists in finding the gains K_i and L_0 such that the system (27) is asymptotically stable. Due to the coupling of the observer and controller equations, we cannot calculate directly the gains by solving the LMI's, however, we exploit the separation principle holds to getting the observer and controller gains, and therefore one can make use of the results and relaxations techniques in literature [13].

D. LMI based designs for augmented system

In this section, we propose LMI-based designs for the augmented system containing the nonlinear the observer and the fuzzy regulator. From the above discussions, the whole system which consists of the fuzzy regulator and the DMVT observer are required to satisfy:

$$\begin{cases} Reg & x(t) \to x_c(t) \quad when\ t \to \infty \\ Obs & \hat{x}(t) \to x(t) \quad when\ t \to \infty \end{cases}$$

The stability analysis of the system (27) is studied in order to find the gains (K_i and L_0).This analysis is performed by using the Lyapunov theorem and a tow quadratic Lyapunov function, defined by:

$$\begin{cases} Reg & V(x(t)) = x^T(t)Px(t) \\ Obs & W(e(t)) = e^T(t)Se(t) \end{cases}$$

Theorem 2*:*

The state estimation error asymptotically converges to ward zero if there exist a symmetric positive definite matrix P and a matrix M such that the following linear matrix inequalities hold $i = 1,\ldots,q$

$$A_0P + PA_0^T + A_iP + PA_i^T - B_0G_i - G_i^TB_0^T < 0 \tag{28}$$

$$A_0^TS + SA_0 + A_i^TS + SA_i - NC - C^TN^T < 0 \tag{29}$$

Where the observer gain and the controller gains are given by

$$\begin{cases} K_i = G_iP^{-1} \\ L_0 = S^{-1}N \end{cases} \tag{30}$$

***Proof**:*

Considering the Lyapunov functions (28), therefore, there derivative is given as follows:

$$\dot{V}(x(t)) = x^T(t)(A_0^T P + PA_0 - K_i^T B_0^T P - PB_0 K_i + A_i^T P + PA_i).x(t) < 0 \quad (31)$$

$$\dot{W}(e(t)) = e^T(t)(A_0^T S + SA_0 - C^T L_0^T S - SL_0 C + A_i^T S + SA_i).e(t) < 0 \quad (32)$$

The stability of the state and state estimation error are ensured if the time derivative of the Lyapunov equations (31) and (32) are negative definite, which leads to the LMIs (26-27), for more details of the proof of the theorem see [19].

***Remark**:*

Note that the dynamics of the observer is very fast as the controller; consequently, it does not affect the stability of the latter.

III. Dynamical Model of Induction Motor

Let$(i_{sd}, i_{sq}), (\phi_{rd}, \phi_{rq}), \omega_s$ and (u_{sd}, u_{sq})denote the components of the stator currents, rotor fluxes, electrical speed of stator, and the stator voltages, respectively. The electromagnetic dynamic model of the induction motor in the synchronous $d-q$ reference frame can be described in [6]:

$$\dot{x} = f(x(t)) + g(x(t))u(t) + v(t) \quad (33)$$

$$f(x) = \begin{bmatrix} -\gamma i_{sd} + \varpi_s i_{sq} + \frac{K_s}{\tau_r}\phi_{rd} + K_s n_p \omega_m \phi_{rq} \\ -\varpi_s i_{sd} - \gamma i_{sq} - K_s n_p \omega_m \phi_{rd} + \frac{K_s}{\tau_r}\phi_{rq} \\ \frac{M}{\tau_r} i_{sd} - \frac{1}{\tau_r}\phi_{rd} + (\varpi_s - n_p\omega_m)\phi_{rq} \\ \frac{M}{\tau_r} i_{sq} - (\varpi_s - n_p\omega_m)\phi_{rd} - \frac{1}{\tau_r}\phi_{rq} \\ \frac{n_p M}{J L_r}(\phi_{rd} i_{sq} - \phi_{rq} i_{sd}) - \frac{f}{J}\omega_m \end{bmatrix}$$

$$g(x) \begin{bmatrix} \frac{1}{L_s} & 0 & 0 & 0 & 0 \\ 0 & \frac{1}{L_s} & 0 & 0 & 0 \end{bmatrix}^T$$

$x = \begin{bmatrix} i_{sd} & i_{sq} & \phi_{rd} & \phi_{rq} & \omega_m \end{bmatrix}^T, u = \begin{bmatrix} u_{sd} & u_{sq} \end{bmatrix}^T$ *and* $y = \begin{bmatrix} 0 & 0 & 0 & 0 & \frac{-Cr}{J} \end{bmatrix}^T$

$$\tau_r = \frac{L_r}{R_r}, \quad \tau_s = \frac{L_s}{R_s}, \quad K_s = \frac{M_{sr}}{\sigma L_s L_r}$$
$$\sigma = 1 - (\frac{M_{sr}^2}{L_s L_r}), \quad \gamma = (\frac{1}{\sigma\tau_s} + \frac{1-\sigma}{\sigma\tau_r})$$

The motor parameters are: stator resistance and inductance(R_s, L_s), rotor resistance and inductance(R_r, L_r), moment of inertia, mutual inductance M, friction coefficient f and number of poles pairs n_p. The electrical speed of the stator defined in the synchronous $d-q$ frame is proved in [6]:

$$w_{sc} = n_p\omega_c + \frac{M}{\tau_r \phi_{rdc}} i_{sqc} \quad (34)$$

In order to determine the desired states $x_c(t)$,we exploit the theory of Field Orientated Control (FOC). The Field Orientated Control (FOC) [20] consists of controlling the stator currents represented by a vector. This control is based on projections which transform a three phase time and speed dependent system into a two co-ordinate (d and q co-ordinates) time invariant system. These projections lead to a structure similar to that of a DC machine control. After replacing the state variables of the induction motor by the reference signals

$$x = \begin{bmatrix} i_{sdc} & i_{sqc} & \phi_{rdc} & 0 & \omega_{mc} \end{bmatrix}^T$$

in (33) we obtain the following equations lead to the stator current reference:

$$\begin{cases} i_{sdc} = \frac{\phi_{rdc}}{M} + \frac{\tau_r}{M}\frac{d}{dt}\phi_{rdc} \\ i_{sqc} = \frac{JL_r}{n_p M \phi_{rdc}}(\frac{C_r}{J} + \frac{f}{J}\omega_{mc} + \frac{d}{dt}\omega_{mc}) \end{cases} \quad (35)$$

A. TS fuzzy model representation of Induction Motor

The method based on nonlinear sector transformation allows to exactly transform the system (33) into the T-S model with 8 sub models [2]. The chosen premise variables are given by:

$$\begin{cases} z_1(t) = i_{sd}(t) \\ z_2(t) = i_{sq}(t) \\ z_3(t) = \omega_m(t) \end{cases} \quad (36)$$

Then the TS fuzzy model can be written as follow [6] :

$$\begin{cases} \dot{x}(t) = \sum_{i=1}^{r} h_i(z(t))(A_i x(t) + B_i u(t) + v(t)) \end{cases} \quad (37)$$

Where $h_i(z(t))$are the weighting functions depending on the variables $z_i(t)$ and satisfy the convexity property:

$$\begin{cases} \dot{x}(t) = \sum_{i=1}^{r} h_i(z(t)) = 1 \forall i \in \{1, 2, \ldots, n\} \\ \leq h_i(z(t)) \leq 1 \end{cases} \quad (38)$$

B. Fuzzy controller and fuzzy Observer for induction motor

We design a fuzzy controller and a fuzzy DMVT observer for induction motor In order to estimate the unknown states of the induction motor we use the fuzzy observer. We assume that the components of the stator currents are measured The basic design steps for the mean value theorem observer are summarized below. Calculate the matrix A_0 from the T-S representation. Forming the matrix $\frac{\partial f}{\partial x}(\xi)$. Calculate the matrices ψ . Solving the linear matrix inequality. Next, we design a fuzzy regulator and a nonlinear observer from the fuzzy model using the procedure proposed in this paper. Using the convex optimization technique involving LMIs, we find K_i and L_0. Therefore, the augmented system is stable.

$$K_1 = \begin{bmatrix} 59.002 & -41.998 & 11735 & -7270 & 0.6959 \\ 18.291 & 59.324 & 1828.5 & 10631 & -0.16108 \end{bmatrix}$$

$$K_2 = \begin{bmatrix} 0.13 & 17.79 & 1079 & 1751.9 & 0.237 \\ -42.01 & 58.19 & -7320.6 & 11560 & -0.67 \end{bmatrix}$$

$$K_3 = \begin{bmatrix} 59.502 & -41.883 & 11793 & -7265.9 & 0.85021 \\ 18.151 & 58.84 & 1818 & 10576 & -0.15997 \end{bmatrix}$$

$$K_4 = \begin{bmatrix} 60.634 & 17.78 & 10852 & 1741.9 & 0.39255 \\ -42.023 & 57.708 & -7316.8 & 11504 & -0.6678 \end{bmatrix}$$

$$K_5 = \begin{bmatrix} 59.005 & -41.741 & 11732 & -7242.5 & 0.69208 \\ 18.029 & 59.324 & 1800.2 & 10634 & -0.3176 \end{bmatrix}$$

$$K_6 = \begin{bmatrix} 60.135 & 17.789 & 10792 & 1751 & 0.23509 \\ -42.011 & 58.194 & -7320.2 & 11561 & -0.82468 \end{bmatrix}$$

$$K_7 = \begin{bmatrix} 59.502 & -41.889 & 11793 & -7266.6 & 0.84773 \\ 18.153 & 58.843 & 1818.1 & 10576 & -0.315 \end{bmatrix}$$

$$K_8 = \begin{bmatrix} 60.634 & 17.779 & 10852 & 1741.8 & 0.39004 \\ -42.026 & 57.711 & -7317.2 & 11505 & -0.82286 \end{bmatrix}$$

$$L_0 = \begin{bmatrix} -1095.7 & -895.3 \\ -403.04 & 102.19 \\ -9.4541 & 7.721 \\ -32.049 & -45.56 \\ 16150 & 17254 \end{bmatrix}$$

The Overall scheme of the nonlinear observer based fuzzy controller is shown by figure 1.

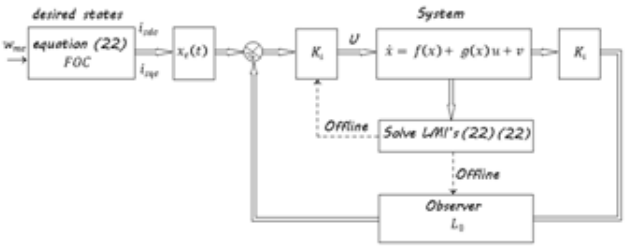

Fig. 1. Overall diagram of the proposed observer based controller

IV. Simulation Results

Numerical simulations were carried out in order to verify the efficiency of the approach. We used the following motor parameters:

Mutual inductance $M = 0.4475H$
Moment of inertia $J = 0.0293Kg.m^2$
Stator resistance $R_s = 9.65\Omega$
Rotor resistance $R_r = 4.3047\Omega$
Stator inductance $L_s = 0.4718H$
Rotor inductance $L_r = 0.4718H$
Pole Pair $n_p = 2$
The premise variables are bounded as:

$$\begin{cases} -200rd/s \leq \omega(t) \leq 200rd/s \\ -6A \leq i_{sd}(t) \leq 6A \\ -6A \leq i_{sq}(t) \leq 6A \end{cases}$$

Simulation results are presented for step change in speed. The actual and estimated speed responses of induction motor are shown in Fig.2, where the rotor Speed of IM is increased from $60rd/s$ to $120rd/s$ to $157\ rd/s$ at $t = 1s$ and $t = 2s$ respectively. Fig.3, show the error rotor speed. Initially, the load is zero and motor, at $t = 3s$, a balanced load of $5Nm$is applied to induction motors. Always, the system is still at stable state. The motor and load torque responses are shown in Fig.4 .

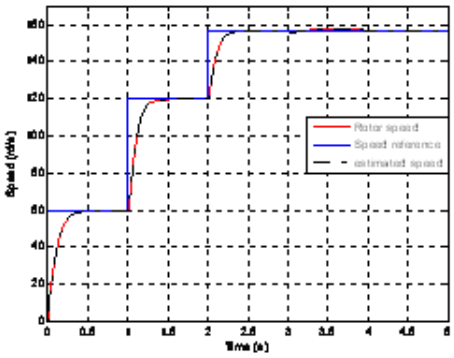

Fig. 2. Rotor speed and their estimated

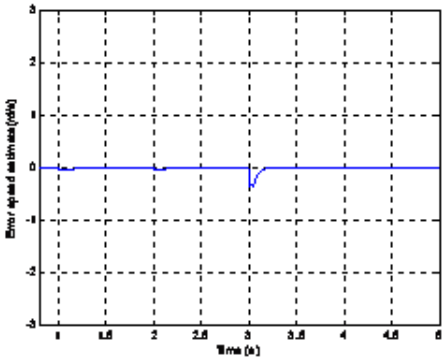

Fig. 3. Error speed

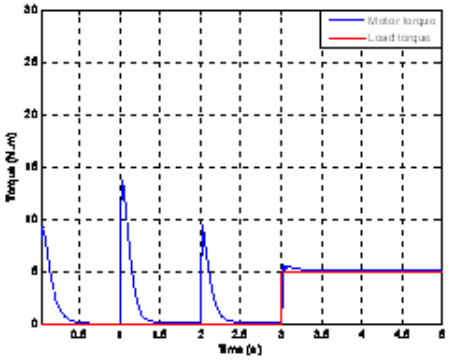

Fig. 4. Motor Torque

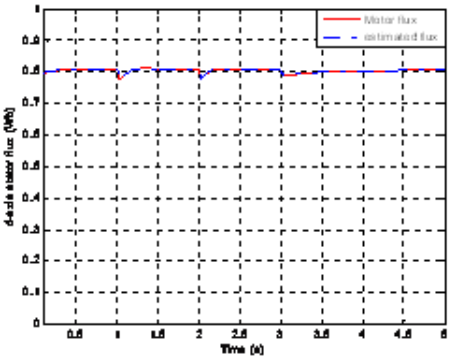

Fig. 5. d-axis stator flux and their estimate

The d-axis stator flux and their estimate are depicted in Fig.5.

Fig.2 and Fig.5, show a less tracking errors is observed for the speed and the d-axis ux in spite of the load torque, but it remains close to its reference value.

These results demonstrate and confirm the highlight effectiveness of the proposed observer based controller. However, low cost and fast Digital Signal Processors capable of implementing relatively complex algorithms are available in the market that makes this method suitable for high performance applications.

V. Conclusion

In this paper, a fuzzy regulator and fuzzy observer based on differential mean value theorem for induction motor is developed. First, we transform the nonlinear model of induction motor into a T-S fuzzy representation, which derived from the sector nonlinearity approach. Then, LMI based design procedures for fuzzy controller have been constructed using the parallel distributed compensation. Next, we used the differential mean value theorem which allows writing the dynamics of the observer error as a LPV system for concept the fuzzy observer. The stability conditions are expressed in terms of Linear Matrix Inequalities. Finally, a design algorithm of fuzzy control system containing fuzzy regulator and fuzzy observer has been constructed. The simulation results are provided to verify the validity of the proposed approach.

References

[1] Y. Wang, T. Chai, and Y. Zhang, "State observer-based adaptive fuzzy output-feedback control for a class of uncertain nonlinear systems," *Information Sciences*, vol. 180, no. 24, pp. 5029–5040, 2010.

[2] K. Tanaka and H. O. Wang, *Fuzzy control systems design and analysis: a linear matrix inequality approach*. John Wiley & Sons, 2004.

[3] R. Marino, P. Tomei, and C. Verrelli, "Adaptive control for speed-sensorless induction motors with uncertain load torque and rotor resistance," *International Journal of Adaptive Control and Signal Processing*, vol. 19, no. 9, pp. 661–685, 2005.

[4] H. A. Yousef and M. A. Wahba, "Adaptive fuzzy mimo control of induction motors," *Expert systems with applications*, vol. 36, no. 3, pp. 4171–4175, 2009.

[5] M. Rodic and K. Jezernik, "Speed-sensorless sliding-mode torque control of an induction motor," *Industrial Electronics, IEEE Transactions on*, vol. 49, no. 1, pp. 87–95, 2002.

[6] M. Allouche, M. Chaabane, M. Souissi, D. Mehdi, and F. Tadeo, "State feedback tracking control for indirect field-oriented induction motor using fuzzy approach," *International Journal of Automation and Computing*, vol. 10, no. 2, pp. 99–110, 2013.

[7] T. Takagi and M. Sugeno, "Fuzzy identification of systems and its applications to modeling and control," *Systems, Man and Cybernetics, IEEE Transactions on*, no. 1, pp. 116–132, 1985.

[8] M. Seidi and A. H. Markazi, "Performance-oriented parallel distributed compensation," *Journal of the Franklin Institute*, vol. 348, no. 7, pp. 1231–1244, 2011.

[9] M. Hasegawa, "Robust-adaptive-observer design based on γ-positive real problem for sensorless induction-motor drives," *Industrial Electronics, IEEE Transactions on*, vol. 53, no. 1, pp. 76–85, 2006.

[10] A. B. Proca and A. Keyhani, "Sliding-mode flux observer with online rotor parameter estimation for induction motors," *Industrial Electronics, IEEE Transactions on*, vol. 54, no. 2, pp. 716–723, 2007.

[11] S. Hongyu and F. Yong, "A hybrid sliding mode flux observer for induction motor drive," in *Control Conference (CCC), 2011 30th Chinese*, pp. 762–767, IEEE, 2011.

[12] S. H. Jeon, K. K. Oh, and J.-Y. Choi, "Flux observer with online tuning of stator and rotor resistances for induction motors," *Industrial Electronics, IEEE Transactions on*, vol. 49, no. 3, pp. 653–664, 2002.

[13] A. Savoia, M. Mengoni, L. Zarri, and D. Casadei, "A nonlinear luenberger observer for sensorless vector control of induction motors," in *Electrical Machines and Power Electronics and 2011 Electromotion Joint Conference (ACEMP), 2011 International Aegean Conference on*, pp. 544–549, IEEE, 2011.

[14] H. Rasmussen, P. Vadstrup, and H. Borsting, "Full adaptive backstepping design of a speed sensorless field oriented controller for an induction motor," in *Industry Applications Conference, 2001. Thirty-Sixth IAS Annual Meeting. Conference Record of the 2001 IEEE*, vol. 4, pp. 2601–2606, IEEE, 2001.

[15] C.-W. Park and S. Lee, "Nonlinear observer based control of induction motors," *Electrical Engineering*, vol. 90, no. 2, pp. 107–113, 2007.

[16] M. Pourgholi and V. J. Majd, "A nonlinear adaptive resilient observer design for a class of lipschitz systems using lmi," *Circuits, Systems, and Signal Processing*, vol. 30, no. 6, pp. 1401–1415, 2011.

[17] A. Zemouche, M. Boutayeb, and G. I. Bara, "Observer design for nonlinear systems: An approach based on the differential mean value theorem.," in *Decision and Control, 2005 and 2005 European Control Conference. CDC-ECC'05. 44th IEEE Conference on*, pp. 6353–6358, IEEE, 2005.

[18] A. Zemouche, M. Boutayeb, and G. I. Bara, "Observers for a class of lipschitz systems with extension to h performance analysis," *Systems & Control Letters*, vol. 57, no. 1, pp. 18–27, 2008.

[19] K. Tanaka and H. O. Wang, "Fuzzy regulators and fuzzy observers: a linear matrix inequality approach," in *Decision and Control, 1997., Proceedings of the 36th IEEE Conference on*, vol. 2, pp. 1315–1320, IEEE, 1997.

[20] D. Ichalal, H. Arioui, and S. Mammar, "Observer design for two-wheeled vehicle: A takagi-sugeno approach with unmeasurable premise variables," in *Control & Automation (MED), 2011 19th Mediterranean Conference on*, pp. 934–939, IEEE, 2011.

[21] D. Ichalal, B. Marx, J. Ragot, and D. Maquin, "State estimation of takagi–sugeno systems with unmeasurable premise variables," *IET Control Theory & Applications*, vol. 4, no. 5, pp. 897–908, 2010.