Observer Design for Takagi-Sugeno Descriptor System with Lipschitz Constraints

Kilani Ilhem¹, Jabri Dalel², Bel Hadj Ali Saloua¹ and Abdelkrim¹

Mohamed Naceur

¹MACS Unit - National Engineering School of Gabès Tunisia, University of Gabès, kilani.ilhem@gmail.com
²University of Reims Champagne-Ardenne CReSTIC EA3804, Moulin de la Housse BP 1039, 51687 Reims Cedex 2, France, dalel.jabri@yahoo.fr

ABSTRACT

This paper investigates the design problem of observers for nonlinear descriptor systems described by Takagi–Sugeno (TS) system; Depending on the available knowledge on the premise variables two cases are considered. First a TS descriptor system with measurables premises variables are proposed. Second, an observer design which satisfying the Lipschitz condition is proposed when the premises variables are unmeasurables. The convergence of the state estimation error is studied using the Lyapunov theory and the stability conditions are given in terms of Linear Matrix Inequalities (LMIs). Examples are included to illustrate those methods.

KEYWORDS

Descriptor TS system, Lipschitz Condition, Unmeasurable Premise Variable & Observer Design.

1. INTRODUCTION

Since more than two decades ago, Takagi–Sugeno (T–S) fuzzy models have attracted wide attention from scientists and engineers, essentially because the well-known fuzzy models can effectively approximate a wide class of nonlinear systems. Relaxed sufficient conditions for fuzzy controllers and fuzzy observers are proposed in via a multiple Lyapunov function approach [1].

System modeling by descriptor method has an important use in the literature since it represents many class of non linear system. The enhancement of the modeling ability is due to the structure of the dynamic equation which encompasses not only dynamic equations, but also algebraic relations [2]. Since both TS and descriptor formalism are attractive in the field of modeling, the TS representation has been generalized to descriptor systems. The stability and the design of state-feedback controllers for T-S descriptor systems are characterized via LMI in [3], [4].

System modeling by descriptor method has an important use in the literature since it represents many class of non linear system.

In other hand, many problems in decision making, control and monitoring require a state estimation based on a dynamic system model. A generic method for the observer design, valid for all types of nonlinear systems, has not yet been developed. This problem received considerable attention in the last three decades; it is of great importance in theory and practice, since there are many situations where premise variable are inaccessible.

In this paper, we propose to design a state observer to estimate exactly the descriptor’s states. For a TS fuzzy model, well-established methods and algorithms can be used to design observers that estimate measurable states. Several types of such observers have been developed for TS fuzzy systems, among which: fuzzy Thau–Luenberger observers reduced-order observers and
sliding-mode observers. In general, the design methods for observers also lead to an LMI feasibility problem [5], [6], [7], [8].

For the unmeasurable variables many searchers studied the observer design for nonlinear descriptor system with lipschitz constraint [9] [10][11][12]. The fuzzy TS systems are studied in [13]. The main objective of this paper is to develop an observer design for TS descriptor system with lipschitz constraint. Under some sufficient conditions, the design of the observer is reduced to the determination of a matrix. The choice of this parameter is performed by solving strict LMIs (linear matrix inequalities).

The outline of the paper is as follows. First, the class of studied systems and observer are given. Second problem formulation for observer with measurable variables is dealt. Third the Lipschitz observer will be studied. Finally we present an example to illustrate the effectiveness of the proposed method. Concluding remarks finish this paper.

2. SYSTEM DESCRIPTION AND PRELIMINARIES

2.1. Descriptor System

Let us consider the class of nonlinear descriptor system which is defined as:

\[
\begin{align*}
E(x(t))\dot{x}(t) &= A(x(t))x(t) + B(x(t))u(t) \\
y(t) &= C(x(t))x(t)
\end{align*}
\]

Where \( x(t) \in \mathbb{R}^n \), \( u(t) \in \mathbb{R}^q \) and \( y(t) \in \mathbb{R}^m \) represent respectively the state, the control input and the output vectors; \( A(x(t)) \), \( E(x(t)) \) \( \in \mathbb{R}^{n \times n} \), \( B(x(t)) \) \( \in \mathbb{R}^{n \times m} \) and \( C(x(t)) \) \( \in \mathbb{R}^{m \times n} \) are nonlinear matrices functions. For simplicity, we should always consider that \( E(x(t)) \) is regular for each \( x(t) \in \mathbb{R}^n \).

Then the TS descriptor system is given as:

\[
\sum_{k=1}^{l} v_k(z(t)) \sum_{i=1}^{r} h_i(z(t)) (A_i x(t) + B_i u(t)) = C x(t)
\]

Where \( z \) represent the premise variable; \( h_i(z(t)) \) and \( v_k(z(t)) \) represent respectively the right and the left activating function; \( r \) and \( l \) is respectively the right and the left number of fuzzy rules ; \( E_k, A_i, B_i \) and \( C \) are constant matrices;

Where

\[
h_i(z(t)) = \frac{w_i(z(t))}{\sum_{i=1}^{r} h_i(z(t))}, \quad w_i(z(t)) = \prod_{j=1}^{k} F_j(z_j(t))
\]

\( h_i(z(t)) \) has also the same characteristic as \( v_k(z(t)) \) and it satisfies:

\[
h_i(z) = 1 \quad \text{and} \quad h_i(z) > 0 \quad \text{for} \quad i = 1,...,r
\]

The passage from the nonlinear system to the TS descriptor system is obtained by the sector nonlinearity approach. In this case, the TS descriptor matches exactly the nonlinear model in a compact set of the state variables.

2.2. Descriptor observer

In general a TS observer is defined by the interconnection between many locals Luenberger observers [14], [15]. It is written as:
\[
\dot{x}(t) = \sum_{j=1}^{r} h_j(z(t)) \left[ A_i \dot{x}(t) + B_i u(t) L_i \left( y(t) - \dot{y}(t) \right) \right]
\]
\[
\dot{y}(t) = \frac{\partial z(t)}{\partial x(t)} \dot{x}(t)
\]

Where \( \dot{x}(t) \) and \( z(t) \) represent respectively the estimate state and the estimate premise variable; \( L_i \) are the observer gain matrices.

In this study, the proposed observer is in the descriptor form. Using the general TS descriptor form, it is possible to suppose a nonlinear observer based on this form:

\[
\sum_{k=1}^{i} v_k(z(t)) E_k \dot{x}(t) = \sum_{j=1}^{r} h_j(z(t)) \left[ A_i \dot{x}(t) + B_i u(t) L_i \left( y(t) - \dot{y}(t) \right) \right]
\]

There are two cases to define which related to the accessibility of the premises variables. In the first time we assume that the variables \( z(t) \) are real time available \( \dot{z}(t) = z(t) \) and thus so are the weighting functions \( h_i(\dot{z}(t)) = h_i(z(t)) \) and \( v_k(\dot{z}(t)) = v_k(z(t)) \). But, in many practical situations, these premise variables depend on the state variables that are not always accessible. Then two cases are considered.

- measurables premises variables
- unmeasurables premises variables.

3. OBSERVER DESIGN

3.1. Measurables Premises Variables

This section is devoted to the state estimation. In fact a descriptor form of observer will be considered. The following theorem presents the main result.

Theorem 1: The convergence of the error estimation between the system (2) and the observer (6) is ensured if there exist: \( P_i = P_i^T > 0 \) and \( P_3, L_i, Y_3 \) for \( i = 1,\ldots,r \) and \( k = 1,\ldots,l \) such that:

\[
\begin{bmatrix}
A_i^T P_3 - C_i^T Y_3 + P_3^T A_i - Y_3 C_i & (\ast) \\
P_i - E_k^T P_3 + P_3^T A_i - Y_3 C_i & -E_k^T P_3 - P_3^T E_k
\end{bmatrix}
< 0
\]

As usual, a star (\( \ast \)) indicates a transpose quantity in a symmetric matrix.

Proof:

Away to obtain sufficient convergence conditions for descriptor fuzzy observer is to consider the error estimation as:

\[ e(t) = x(t) - \hat{x}(t) \]

Its time derivative is given by:

\[ \dot{e}(t) = \dot{x}(t) - \dot{\hat{x}}(t) \]

According to equation (2) equation (6) becomes:

\[
\sum_{k=1}^{i} v_k(z(t)) E_k \dot{x}(t) = \sum_{j=1}^{r} h_j(z(t)) \left( (A_i \dot{x}(t) + B_i u(t)) + L_i (C x(t) - C \hat{x}(t)) \right)
\]

The difference between this last equations and equation (2) is given by:
\[
\sum_{\ell=r}^{l}v_{\ell}(z(t))E_{\ell}\dot{x}(t) = \sum_{i=1}^{r}h_{i}(z(t))(A_{i}-L_{i}C)x(t)
\]  
(11)

Let us consider the augmented error vector is given by:
\[
\vec{e}(t) = \begin{bmatrix} e^{T}(t) & \dot{e}^{T}(t) \end{bmatrix}^{T}
\]  
(12)

Equations (11) can be written:
\[
\vec{E}\vec{e} = \vec{A}_{ik}\vec{e}(t)
\]  
(13)

With
\[
\vec{E} = \begin{bmatrix} I & 0 \\ 0 & 0 \end{bmatrix} \quad \text{and} \quad \vec{A}_{ik} = \begin{bmatrix} 0 & I \\ A_{i}-L_{i}C & -E_{k} \end{bmatrix}
\]  
(14)

In order to find an asymptotic convergence error, we consider the Lyapunov candidate function
\[
V(\vec{e}(t)) = \vec{e}(t)^{T}\vec{P}\vec{e}(t), P = P^{T}, P \in \mathbb{R}^{n \times n}
\]  
with:
\[
\vec{E}\vec{P} = \vec{P}\vec{E} > 0, P = \begin{bmatrix} P_{1} & P_{2} \\ P_{3} & P_{4} \end{bmatrix}, P_{1} = P_{1}^{T} > 0 \text{ and } P_{2} = 0
\]  
(15)

The negativity of the Lyapunov function is assumed by:
\[
\dot{V}(\vec{e}(t)) = \vec{e}(t)^{T}\vec{P}\vec{e}(t) + \vec{e}(t)^{T}\vec{P}\dot{\vec{e}}(t) < 0
\]  
(16)

In others words, obviously, with (14), the condition (16) becomes:
\[
\vec{e}(t)^{T}(\vec{A}_{ik}^{T}P + P^{T}\vec{A}_{ik})\vec{e}(t) < 0
\]  
(17)

Then for \( i = 1, \ldots, r \) and for \( k = 1, \ldots, l \) we obtain:
\[
\begin{bmatrix} 0 & (A_{i}-L_{i}C)^{T} \end{bmatrix} \begin{bmatrix} P_{1} & 0 \\ P_{3} & P_{4} \end{bmatrix} \begin{bmatrix} 0 & I \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 0 & I \\ A_{i}-L_{i}C & -E_{k} \end{bmatrix} < 0
\]  
(18)

\[
\begin{bmatrix} A_{i}^{T}P_{3} - C^{T}L_{i}^{T}P_{3} + P_{3}^{T}A_{i} - P_{3}^{T}L_{i}C & (*) \\ P_{1} - E_{k}^{T}P_{3} + P_{3}^{T}A_{i} - P_{3}^{T}L_{i}C & -E_{k}^{T}P_{2} - P_{2}^{T}E_{k} \end{bmatrix} < 0
\]  
(19)

In order to solve strict LMIs, we suppose that \( P_{4} = P_{3} \), then
\[
\begin{bmatrix} A_{i}^{T}P_{3} - C^{T}L_{i}^{T}P_{3} + P_{3}^{T}A_{i} - P_{3}^{T}L_{i}C & (*) \\ P_{1} - E_{k}^{T}P_{3} + P_{3}^{T}A_{i} - P_{3}^{T}L_{i}C & -E_{k}^{T}P_{2} - P_{2}^{T}E_{k} \end{bmatrix} < 0
\]  
(20)

To have terms of Linear Matrix Inequalities we consider a bijectif changement \( Y_{\ell i} = P_{2}^{T}E_{k} \):
\[
\begin{bmatrix} A_{i}^{T}P_{3} - C^{T}Y_{\ell i} + P_{3}^{T}A_{i} - Y_{\ell i}C & (*) \\ P_{1} - E_{k}^{T}P_{3} + P_{3}^{T}A_{i} - Y_{\ell i}C & -E_{k}^{T}P_{2} - P_{2}^{T}E_{k} \end{bmatrix} < 0
\]  
(21)

### 3.2 Unmeasurables Premises Variables

This part addresses the issues of observer design for a class of descriptor systems with Lipschitz constraint. The general form for the TS descriptor system is in the form of equation (2). To avoid to have a complex equation, we will suppose that all the \( E_{k} = E \) for \( k = 1, \ldots, l \). Then we have a new form of TS descriptor system given as below:
\[ E\dot{x}(t) = \sum_{j=1}^{r} h_j(z(t)) \left( A_j x(t) + B_i u(t) \right) \]
\[ y(t) = C \dot{x}(t) \]  

(22)

Then the observer corresponds to this extension of TS descriptor system will be defined as:
\[ E\hat{\dot{x}}(t) = \sum_{j=1}^{r} h_j(\hat{z}(t)) \left[ A_j \hat{x}(t) + B_i u(t) L_1 \left( y(t) - \hat{y}(t) \right) \right] \]
\[ \hat{y}(t) = C' \hat{x}(t) \]  

(23)

In this section, the purpose is to suggest a method for the design of observer for TS descriptor system. The following hypotheses and lemma will be used in the development.

Hypothesis 1: The activating function is lipschitz:
\[ \left| h_i(x(t)) - h_i(\hat{x}(t)) \right| \leq \gamma_i |x(t) - \hat{x}(t)| \]  

(24)

\[ \left| h_i(x(t)) x(t) - h_i(\hat{x}(t)) \hat{x}(t) \right| \leq m_i |x(t) - \hat{x}(t)| \]  

(25)

Where \( \gamma_i \) and \( m_i \) positives scalars Lipschitz constants.

Hypothesis 2: The control input \( u(t) \) is bounded:
\[ \left\| u(t) \right\| \leq \beta_1, \beta_i > 0 \]  

(26)

Lemma 1
For all matrices \( X \) and \( Y \), \( \lambda \) a positive scalar, the following property is given as:
\[ X^T Y + Y^T X \leq \lambda X^T X + \lambda^{-1} Y^T Y, \ \lambda > 0 \]  

(27)

The following theorem shows the most important result.

Theorem 2: The convergence of the error estimation between the system (22) and the observer (23) tend asymptotic to zero is ensured if there exist: \( P \in R^{nn} \) and \( Q \in R^{nn} \) symmetric positive defined, the matrix \( K_0 \in R^{nn} \) and positives scalars \( \lambda_1, \lambda_2 \) such that:

\[ A_0^T P + PA_0 - C^T K_0^T - K_0 C < -Q \]  

(28)

\[
\begin{bmatrix}
-Q + \lambda m \xi I & P A_i & P B_i & n \gamma I \\
A_i^T P & -\lambda_1 I & 0 & 0 \\
B_i^T P & 0 & -\lambda_2 I & 0 \\
n \gamma I & 0 & 0 & -\lambda_2 I \\
\end{bmatrix} < 0
\]  

(29)

\[ \gamma - \beta_i \lambda \geq 0 \]  

(30)

\[ EP = P^T E > 0 \]  

(31)

The gain of the observer is given by:
\[ L_1 = P^{-1} K_1 \]  

(32)

Proof:
The basic idea is to concept a descriptor observer which verifies Lipschitz condition by introducing some change in the system. Hence, the matrices \( A, B, and C \) will be written as:
The system (23) will be written as:

\[
A_0 = \sum_{i=1}^{r} A_i, \quad \bar{A}_i = A_i - A_0 \\
B_0 = \sum_{i=1}^{r} B_i, \quad \bar{B}_i = B_i - B_0 \\
C_0 = \sum_{i=1}^{r} C_i, \quad C_i = C_i - C_0
\]

(33)

(34)

(35)

The system (23) will be written as:

\[
\dot{E}\hat{x}(t) = A_0 x(t) + B_0 u(t) + \sum_{i=1}^{r} h_i (x(t)) (\bar{A}_i x(t) + \bar{B}_i u(t)) \\
y(t) = C x(t)
\]

(36)

Then the observer equation will be changed as:

\[
\dot{\hat{y}}(t) = C \hat{x}(t)
\]

(37)

The estimation error is given as:

\[
e(t) = x(t) - \hat{x}(t)
\]

(38)

Consequently, the augmented state estimation error obeys to the following nonlinear system:

\[
\dot{E}e(t) = \sum_{i=1}^{r} h_i (\hat{x}(t)) (A_i - L_i C_e(t)) e(t) + \sum_{i=1}^{r} \bar{A}_i (h_i (x(t)) x(t) - h_i (\hat{x}(t)) \hat{x}(t)) + \bar{B}_i (h_i (x(t)) - h_i (\hat{x}(t))) u(t)
\]

(39)

To show the effecteness of hypotheses we suppose as below:

\[
\left\{
\begin{array}{l}
\delta_i (t) = h_i (x(t)) x(t) - h_i (\hat{x}(t)) \hat{x}(t) \\
\Delta_i (t) = h_i (x(t)) - h_i (\hat{x}(t)) \\
\Phi_i (t) = A_i - L_i C
\end{array}
\right.
\]

(40)

Then the dynamic error will be defined as:

\[
\dot{E}e(t) = \sum_{i=1}^{r} h_i (\hat{x}(t)) \Phi_i (t) e(t) + \sum_{i=1}^{r} \bar{A}_i \delta_i (t) + \bar{B}_i \Delta_i (t) u(t)
\]

(41)

In order to find an asymptotic convergence error, we consider the quadratic Lyapunov function

\[
V (e(t)) = e(t)^T E P e(t), P = P^T, P \in \mathbb{R}^{n \times n}, \quad EP = P^T E > 0
\]

Then the time derivative of the Lyapunov function will be written as:

\[
\dot{V} (e(t)) = \dot{e}(t)^T E P e(t) + e(t)^T E P \dot{e}(t)
\]

(42)

Then

\[
\dot{V} (e(t)) = \sum_{i=1}^{r} \delta_i (t)^T A_i^T P e(t) + e(t)^T P \bar{A}_i \delta_i (t) + \Delta_i (t)^T B_i^T P e(t) + e(t)^T P \bar{B}_i \Delta_i (t) \\
+ h_i (\hat{x}(t)) (e(t)^T \Phi_i^T P e(t) + e(t)^T P \Phi_i e(t))
\]

(43)
The derivative of the Lyapunov function is composed of quadratic terms in $e(t)$ and of terms crossed in $e(t)$, $\gamma_i(t)$ and $\Delta_i(t)$. In order to express $V(e(t))$ in a quadratic form in $e(t)$, we proceed as follows:

$$\left| \delta_i(t) \right| \leq m_i |e(t)|$$
$$\left| \Delta_i(t) \right| \leq n_i \beta_i |e(t)|$$
$$\left| \psi_i(t) \right| \leq \gamma_i |e(t)|$$

(44)

By applying the lemma 1 we lead to the following inequalities:

$$\delta_i(t)^T \bar{A}^T Pe(t) + e(t)^T P\bar{A} \delta_i(t) \leq \lambda_i \delta_i(t)^T \delta_i(t) + \lambda_i^{-1} e(t)^T \bar{P} \bar{A} \delta_i(t)$$
$$\leq \lambda_i m_i^2 e(t)^T e(t) + \lambda_i^{-1} e(t)^T \bar{P} \bar{A} \delta_i(t)$$

(45)

$$\Delta_i(t)^T \bar{B}^T Pe(t) + e(t)^T \bar{P} \bar{B} \Delta_i(t) \leq \lambda_2 \Delta_i(t)^T \Delta_i(t) + \lambda_2^{-1} e(t)^T \bar{P} \bar{B} \Delta_i(t)$$
$$\leq \lambda_2 n_i^2 \beta_i^2 e(t)^T e(t) + \lambda_2^{-1} e(t)^T \bar{P} \bar{B} \Delta_i(t)$$

(46)

The derivative of the Lyapunov function became:

$$\dot{V}(e(t)) = \sum_{i=1}^{r} \delta_i(t)^T \bar{A}^T Pe(t) + e(t)^T P\bar{A} \delta_i(t) + \Delta_i(t)^T \bar{B}^T Pe(t) + e(t)^T \bar{P} \bar{B} \Delta_i(t)$$
$$+ h_i(\hat{x}(t))(\bar{t}(t))^T \Phi_i^T Pe(t) + e(t)^T P\Phi_i e(t)$$

(47)

$$\dot{V}(e(t)) \leq \sum_{i=1}^{r} e(t)^T \left( h_i(\hat{x}(t))(\Phi_i^T P + P\Phi_i) + \left( \lambda_i m_i^2 + \lambda_2 n_i^2 \beta_i^2 \right) I + \lambda_i^{-1} P\bar{A} \bar{A}^T P + \lambda_2^{-1} P\bar{B} \bar{B}^T P \right) e(t) < 0$$

(48)

The stability of this last equation is assured, for $i = 1, ..., r$:

$$e(t)^T \left( h_i(\hat{x}(t))(\Phi_i^T P + P\Phi_i) + \left( \lambda_i m_i^2 + \lambda_2 n_i^2 \beta_i^2 \right) I + \lambda_i^{-1} P\bar{A} \bar{A}^T P + \lambda_2^{-1} P\bar{B} \bar{B}^T P \right) e(t) < 0$$

(49)

This leads to the following conditions:

$$\left( A_0 - L(C)^T P + P(A_0 - L(C) < -Q \right)$$

(50)

$$-Q + \left( \lambda_i m_i^2 + \lambda_2 n_i^2 \beta_i^2 \right) I + \lambda_i^{-1} P\bar{A} \bar{A}^T P + \lambda_2^{-1} P\bar{B} \bar{B}^T P < 0$$

(51)

Then we suppose variable change $K_i = PL_i$ and the complement Schur. Then it will be defined as below:

$$A_0^T P + PA_0 - C^T K_i - K_i C < -Q$$

(52)

To have an effective choice we can take the input as a variable to be determined which one will call $\rho$.

By using the complement Schur, inequality (52) will be written:
The presence of the product $\lambda_2 \rho$ leads to a nonlinear inequality. To rewrite it in form LMI, we pose $\gamma = \lambda_2 \rho$:

$$A_0^T P + P A_0 - C^T K_i^T - K_i C < -Q$$

(55)

$$\begin{bmatrix}
-Q + \lambda_2 m \gamma^2 I & PA_i & PB_i & n_i \lambda_2 \rho I \\
\lambda_2^T P & -\lambda_2 I & 0 & 0 \\
\lambda_2^T P & 0 & -\lambda_2 & 0 \\
n_i \lambda_2 \rho I & 0 & 0 & -\lambda_2 I
\end{bmatrix} < 0 \quad \lambda_1 > 0 \text{ et } \lambda_2 > 0$$

(54)

Knowing $\gamma$ and $\lambda_2$, we can deduce the value $\rho = \frac{\gamma}{\lambda_2}$

4. DESIGN EXAMPLES

4.1. Example 1

This section is dedicated to illustrate the efficiency of the proposed approach. We consider the following example with illustrate the first theorem:

$$\sum_{k=1}^{2} y_k(z(t)) E_i x(t) = \sum_{i=1}^{2} h_i(z(t)) (A_i x(t) + B_i u(t))$$

$$y(t) = C x(t)$$

With $x_0 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$, $A_1 = \begin{bmatrix} -3 & 1 \\ 1 & -1 \end{bmatrix}$, $A_2 = \begin{bmatrix} -2 & 1 \\ 1 & 0 \end{bmatrix}$, $B_1 = \begin{bmatrix} -2 \\ 1 \end{bmatrix}$, $B_2 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$, $C = \begin{bmatrix} 1 & 1 \end{bmatrix}$.

$$E_i = \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix} \text{ and } E_2 = \begin{bmatrix} 1 & 0 \\ 0 & 2.01 \end{bmatrix}.$$  

And the activating functions:

$$h_i = \left(1 - \tanh(x_i)\right)/2, \quad h_2 = 1 - h_1 \quad \text{and} \quad v_1 = \cos(x_1)\cos(x_2), \quad v_2 = 1 - v_1.$$  

According to the given procedure, we design the descriptor observer based on theorem 1 via the Matlab LMI toolbox. Then we obtain $P_1$ and $P_3$:

$$P_1 = \begin{bmatrix} 0.9875 & -0.0266 \\ -0.0266 & 1.2489 \end{bmatrix}, \quad P_3 = \begin{bmatrix} 0.2561 & -0.0373 \\ 0.0394 & 0.3161 \end{bmatrix}.$$  

The corresponding observer gain matrices are:

$$L_1 = \begin{bmatrix} -0.4898 \\ 0.4323 \end{bmatrix}, \quad L_2 = \begin{bmatrix} 0.5255 \\ -0.1566 \end{bmatrix}.$$
We conclude from the simulation results that the observe design shows the essential aims of this method. The estimation error of $x_1 - \hat{x}_1$ is shown in Figure 1 and the error of $x_2 - \hat{x}_2$ in Figure 2 are close to zero quickly.
4.2. Example 2

The theorem 2 is illustrated by this example:

\[
\dot{x}(t) = \sum_{i=1}^{3} h_i(z(t))(A_i x(t) + B_i u(t)) \\
y(t) = C\dot{x}(t)
\]

With \( x_0 = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}, A_1 = \begin{bmatrix} -2 & 1 & 1 \\ 1 & -3 & 0 \\ 2 & 1 & -6 \end{bmatrix}, A_2 = \begin{bmatrix} -3 & 2 & -2 \\ 5 & -3 & 0 \\ 0.5 & 0.5 & -4 \end{bmatrix}, B_1 = \begin{bmatrix} 1 \\ 0.5 \end{bmatrix}, B_2 = \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix}, C = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & 1 \end{bmatrix}\)

and

\[
E = \begin{bmatrix} 1 & 2 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 1 \end{bmatrix}
\]

And the activating functions:

\[ h_1 = \left(1 - \tanh(x_1)\right)/2, \quad h_2 = 1 - h_1. \]

According to the given procedure, we design the descriptor observer based on theorem 2 via the Matlab LMI toolbox. Then we obtain:

\[
P = \begin{bmatrix} 1.2594 & 0.2698 & 0.4471 \\ 0.2698 & 1.4447 & -0.0991 \\ 0.4471 & -0.0991 & 0.7367 \end{bmatrix} \quad \text{and} \quad Q = \begin{bmatrix} 1.5534 & -0.0000 & -0.0300 \\ -0.0000 & 1.5235 & -0.0000 \\ -0.0300 & -0.0000 & 1.5534 \end{bmatrix}
\]

Figure 3. Error estimation for x1
The corresponding observer gain matrices are:

\[
L_1 = \begin{bmatrix} 118.4894 & 0.3110 \\ -101.6108 & 336.9255 \\ -608.0136 & 908.4754 \end{bmatrix} \quad \text{and} \quad L_2 = \begin{bmatrix} -421.6323 & 106.0784 \\ 93.6932 & 266.3481 \\ -273.6247 & 165.1607 \end{bmatrix}
\]

The scalars are of values: \( \lambda_1 = 0.5863 \), \( \lambda_2 = 0.0094 \) and \( \gamma = 0.1575 \).
The results of simulation corresponding to the evolution of the state estimation error are presented in Figure 3, Figure 4 and Figure 5.

5. CONCLUSIONS

The design descriptor observer was studied in this paper. The considered systems are modeled in the Takagi-Sugeno descriptor structure with measurable and unmeasurable premise variables. The strategy is based on the use of the Lipschitz condition. The stability is studied with the Lyapunov theory and a quadratic function that allows to derive conditions ensuring the convergence of the state estimation error. The existence conditions are expressed in terms of LMIs that can be solved with LMIS Toolbox in Matlab.

REFERENCES

[1] K. Tanaka, T. Ikeda and H.O Wang, “Fuzzy Regulators and Fuzzy Observers: Relaxed Stability Conditions and LMI-Based Designs”, IEEE Trans. Fuzzy Syst., Vol. 6, pp. 250-265, 1998.
[2] L. Dai, “Singular Control Systems, Springer, Germany”, 1989.
[3] T. Taniguchi, K. Tanaka, K. Yamafuji and H.O Wang, “Fuzzy Descriptor Systems: Stability Analysis and Design via LMIs”, Proc. of the Amer. Contr. Conf, Vol. 3, pp. 827-1831, 1999.
[4] C.S. Tseng, B.S. Chen and H.J. Uang, “Fuzzy Tracking Control Design for Nonlinear Dynamic Systems via T–S Fuzzy Model, IEEE Transactions On Fuzzy Systems, Vol. 9, pp. 381-392, 2001.
[5] K. Tanaka and H. Wang, “Fuzzy Regulators and Fuzzy Observers: A Linear Matrix Inequality Approach”, Proc. 36th IEEE Conf. on Decision and Control, Vol. 2, pp. 1315-1320, 1997.
[6] P. Bergsten, R. Palm and D. Driankov, “Fuzzy Observers”, Proc. 10th IEEE Internat. Conf. on Fuzzy Systems, Vol. 2, pp.700-703, 2001.
[7] P. Bergsten, R. Palm and D. Driankov, “Observers for Takagi–Sugeno Fuzzy Systems”, IEEE Transactions on Systems Man and Cybernetics, pp.114-121, 2002.
[8] R. Palm and P. Bergsten, “Sliding Mode Observer for a Takagi-Sugeno Fuzzy System”, Proc. 9th IEEE Internat. Conf. on Fuzzy Systems, Vol. 2, pp. 665-670, 2000.
[9] G. Lu, D. Wang and Y. Sun, “Observer Design for a Class of Nonlinear Descriptor Systems”, International Conference on Control and Automation , Budapest, Hungary, 2005.
[10] K. Guelton, S. Delprat and T.M. Guerra, “An Alternative to Inverse Dynamics Joint Torques Estimation Human Stance Based on a Takagi–Sugeno Unknown-Inputs Observer in The Descriptor Form”, Control Engineering Practice, pp.1414-1426, 2008.
[11] A. M. Nagy-Kiss, B. Marx, G. Mourot, G. Schutz and J. Ragot, “State Estimation of Two-Time Scale Multiple Models with Unmeasurable Premise Variables. Application to biological reactors”, 49th IEEE Conference on Decision and Control, pp. 5689-5694, 2011.
[12] G. Lu, D. Wang and Y. Sun, “Observer Design for Descriptor Systems with Lipschitz Constraint”, International Conference on Control and Automation, pp. 220-223, 2005.
[13] R. Palm and P. Bergsten, “Sliding Mode Observer for a Takagi-Sugeno Fuzzy System”, Proc. 9th IEEE Internat. Conf. on Fuzzy Systems, Vol. 2, pp. 665-670, 2000.
[14] T. Bouarar, “Contribution à la Synthèse de Lois de Commande pour les Descripteurs de Type Takagi-Sugeno Incertains et Perturbés”, Thèse de doctorat, 2009.
[15] T.M Guerra and L. Vermeiren, (2003) “Stabilité et Stabilisation à Partir de Modèles Flous, Commande Flous 1: De la Stabilisation à La Supervision”, Hermes, pp. 59-98.