Observer design for a class of nonlinear systems with nonscalar-input nonlinear consequents

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Abstract—This paper presents a discrete-time Takagi-Sugeno fuzzy observer design approach for a class of nonlinear systems. Instead of including all the nonlinear terms in the membership functions, some of them are kept as nonlinear consequents, and they need to fulfill a global Lipschitz condition. The form considered permits nonlinear consequents that depend on nonscalar inputs. The design conditions are defined in terms of linear matrix inequalities, and they are less restrictive than previous conditions from the literature. Two numerical examples highlight the advantages obtained.

I. INTRODUCTION

For systems where direct measurements of relevant state variables are not physically possible or the sensors are too expensive, estimation is used. This research field has started with the seminal works [1] and [2], and has been explored in depth for both linear and nonlinear systems.

An influential nonlinear observer design approach is presented in [3], where a slope-bound condition is used to handle the nonlinearities, assuming that each nonlinearity is a function of a given linear combination of the states. A generalization of this approach is given in [4], where less conservative design conditions are developed. Furthermore, in [5], the restriction that the nonlinearities must be a function of the same linear combination of the states is removed. They define a more general form of the nonlinearities that may depend on nonlinear combinations of the states, for example, nonlinearities like cos(x₁x₂). Several extensions of this work can be found, see e.g. [6], [7], [8], [9], [10].

In particular, the discrete-time observer design problem when the dynamics of the system contain such nonlinearities is presented in [10], which is the starting point of our paper. From the structural point of view, we consider a similar model to the one in [10]. There, the models used are Linear Parameter Varying (LPV), which are in direct analogy to the Takagi-Sugeno (TS) fuzzy models that we consider.

Specifically, we present in this paper nonlinear observer design approaches for a class of nonlinear systems represented as TS models with nonscalar-input nonlinear consequents. We provide the following improvements compared to the results in [10].

First, we decouple the direct dependency of the observer gains on the Lyapunov function by adding an extra degree of freedom with a non-symmetric fuzzy matrix, $Q_z$. Second, to further relax the design conditions, we consider a fuzzy Lyapunov function instead of a quadratic one. Finally, in [10] the design conditions in the main theorem are presented as bilinear matrix inequalities (BMIs). There, two options are presented to obtain sufficient LMI conditions. In this paper, next to the two options of [10], we propose an alternative approach to obtain LMIs. The design conditions in this approach are in certain cases less restrictive than in the other two approaches.

On the other hand, there are also related works in the TS fuzzy literature, see e.g. [11], [12], [13], [14], [15]. For example, in [11] the following Lipschitz condition is used for observer design: $||φ_t(x(k)) − φ_t(\hat{x}(k))|| ≤ θ ||x(k) − \hat{x}(k)||$. The above inequality uses the norm of the nonlinearity, and an upper bound is defined for this norm, while the present results are based on the mean-value theorem and are less restrictive. Moreover, our approach handles each state dependency separately for every nonlinearity, and for each such state dependency a different upper bound is defined, which adds flexibility to the design conditions. In [13] the nonlinear consequents can handle only scalar inputs, while the present work can tackle multiple inputs in the nonlinear consequents.

In the sequel, following some notations, the TS fuzzy system with nonlinear consequents and the estimation problem are introduced in Section II. Section III presents the main theoretical results. To highlight the novelty of the paper two numerical examples are provided in Section IV. Finally, conclusions and future directions are presented in Section V.

Notations. Let $F = F^T \in \mathbb{R}^{n \times n}$ be a real symmetric matrix; $F > 0$ and $F < 0$ mean that $F$ is positive definite and negative definite, respectively. I denotes the identity matrix and 0 the zero matrix of appropriate dimensions. The symbol $*$ in a matrix indicates a transposed quantity in the symmetric position, for instance $\begin{pmatrix} P & * \\ A & P \end{pmatrix} = \begin{pmatrix} P & A^T \\ A & P \end{pmatrix}$, $A + * = A + A^T$, and $AP * = APA^T$. The notation $\text{bdiag}(f_1, ..., f_m)$, where $f_i \in \mathbb{R}^{n_i}$ for all $i = 1, ..., m$, stands for the block diagonal matrix, whose diagonal components are $f_1, ..., f_m$ matrices. The set $Co(x, y) = \{λx + (1 − λ)y, 0 ≤ λ ≤ 1\}$ is the convex hull of $\{x, y\}$. The notation $e_n(i) \in \mathbb{R}^n$ refers to a column vector, whose elements are zero, except the $i$-th one:

$$e_n(i) = \begin{bmatrix} 0 & \ldots & 0 & 1 & 0 & \ldots & 0 \end{bmatrix}^T$$

where $n$ is the number of elements.

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II. PRELIMINARIES AND PROBLEM STATEMENT

The classic discrete-time TS fuzzy model is a convex combination of linear models, having the form:

\[
x(k + 1) = \sum_{l=1}^{s} h_l(z(k))(A_l x(k) + B_l u(k))
\]

\[
y(k) = \sum_{l=1}^{s} h_l(z(k))C_l x(k),
\]

where \( x(k) \in \mathbb{R}^{n_x} \) is the state vector, \( u(k) \in \mathbb{R}^{n_u} \) is the control input, \( y(k) \in \mathbb{R}^{n_y} \) is the measured output vector, \( s \) is the number of rules, \( z(k) \in \mathbb{R}^{n_z} \) is the premise vector, and \( h_l, l = 1, ..., s \) are nonlinear functions with the property

\[
h_l \in [0, 1], \ l = 1, ..., s, \ \sum_{l=1}^{s} h_l(z) = 1.
\]

These nonlinear functions are called the membership functions. Matrices \( A_l, B_l, \) and \( C_l \) represent the \( l \)-th local model.

Throughout this paper, the following shorthand notations are used to represent convex sums of matrix expressions:

\[
F_z = \sum_{l=1}^{s} h_l(z(k))F_l, \quad F_{zz+} = \sum_{l=1}^{s} h_l(z(k+1))F_l.
\]

Based on this notation, (1) can be rewritten as

\[
\begin{align*}
x(k + 1) &= A_z x(k) + B_z u(k) \\
y(k) &= C_z x(k).
\end{align*}
\]

A. Lemmas and properties

In order to develop our results we will use the following properties and lemmas.

**Property 1 ([16]):** Let \( T \) and \( R \) be matrices of appropriate dimensions and ranks, with \( R = R^T > 0 \). Then \(-T R^{-1} T \leq -T - T^T + R\).

**Property 2 ([16]):** (Schur complement). Let \( \mathcal{M} = \mathcal{M}^T = \begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix} \), with \( M_{11} \) and \( M_{22} \) square matrices of appropriate dimensions. Then:

\[
\mathcal{M} < 0 \iff \begin{cases} M_{22} < 0 \\
M_{11} - M_{12} M_{22}^{-1} M_{21} < 0 \end{cases}
\]

**Lemma 1 ([16]):** (Congruence) Given matrix \( P = P^T \) and a full column rank matrix \( Q \), it holds that \( P > 0 \Rightarrow QPQ^T > 0 \).

Estimation and control problems are often defined as triple-sum negativity problems having the form

\[
F_{zz+} = \sum_{l_1=1}^{s} \sum_{l_2=1}^{s} \sum_{l_3=1}^{s} h_{l_1}(z)h_{l_2}(z)h_{l_3}(z+)F_{l_1 l_2 l_3} < 0,
\]

with symmetric matrices \( F_{l_1 l_2 l_3} \) and nonlinear functions \( h_l \) satisfying the convex sum property in (2).

**Lemma 2 ([17]):** Equation (6) is satisfied if the following conditions hold

\[
\begin{align*}
2 \frac{1}{s-1} F_{l_1 l_1 l_3} + F_{l_1 l_2 l_3} + F_{l_2 l_1 l_3} < 0,
\end{align*}
\]

for all \( l_1, l_2, l_3 = 1, ..., s, \ l_1 \neq l_2 \).

A useful inequality was presented in [8], which provides a powerful condition for the LMI problem.

**Lemma 3 ([8]):** Let \( X \) and \( Y \) be two given matrices of appropriate dimensions. Then, for any symmetric positive definite matrix \( S \) of appropriate dimension, the following inequality holds:

\[
X^T Y + Y^T X \leq \frac{1}{2} (X + SY)^T S^{-1} (X + SY).
\]

We also use a slightly different form of (7):

\[
X^T Y + Y^T X \leq \frac{1}{2} (S^{-1} X + Y)^T S (S^{-1} X + Y).
\]

For globally Lipschitz functions we use the following lemma.

**Lemma 4 ([10]):** Let \( \phi : \mathbb{R}^n \to \mathbb{R}^q \) be a differentiable function on \( \mathbb{R}^n \). Then the following items are equivalent:

- \( \phi \) is globally Lipschitz
- there exist finite scalar constants \( a_{ij} \) and \( b_{ij} \), so that for all \( v, r \in \mathbb{R}^n \) there exist \( \zeta_i \in Co(v, r) \), \( \zeta_i \neq v \), \( \zeta_i \neq r \) and functions \( \psi_{ij} : \mathbb{R}^n \to \mathbb{R} \) satisfying the following:

\[
\begin{align*}
\phi(v) - \phi(r) &= \sum_{i=1}^{q} \sum_{j=1}^{n} \psi_{ij}(\zeta_i) \delta_i(v - r) \\
a_{ij} &\leq \psi_{ij}(\zeta_i) \leq b_{ij} \\
\psi_{ij} &= \frac{\partial \phi_i}{\partial v_j} (\zeta_i), \ \delta_i = \epsilon_i(v) \epsilon_i(j)^T.
\end{align*}
\]

where \( \epsilon_j \) refers to the \( j \)-th element in the \( v \) vector, and

\[
\epsilon_i(j) = [0...0\ 1\ 0...0]^T, \ \delta_i = [0...0\ 1\ 0...0]^T.
\]

B. Problem statement

The model considered has the following structure:

\[
\begin{align*}
x(k + 1) &= A_z x(k) + G \gamma(x(k)) + g(y(k), u(k)) + E w(k) \\
y(k) &= C_z x(k) + D w(k).
\end{align*}
\]

where \( A_z \) and \( C_z \) have the same meaning as in (1). The disturbance term is denoted with \( w(k) \in \mathbb{R}^{n_w} \), with \( E \) and \( D \) the corresponding matrices. The vector \( g(y(k), u(k)) \in \mathbb{R}^{n_z} \) contains the terms that depend on the input and the output.

It is assumed that the premise vector \( z(k) \) depends only on measured states and inputs. The nonlinear terms that depend on unmeasured states are handled by the nonlinear consequents. The quantity \( \gamma(x(k)) \in \mathbb{R}^m \) contains the nonlinear consequents. It is an \( m \)-dimensional column vector, and the following can be written:

\[
G \gamma(x(k)) = \sum_{i=1}^{m} \gamma_i \left( \sum_{j=1}^{n_l} \nu_i \right),
\]

where \( \gamma_i(\cdot) \) is the \( i \)-th nonlinear function from the \( \gamma(\cdot) \) vector, and \( G_i \) denotes the \( i \)-th column of \( G \). Moreover, \( H_i \in \mathbb{R}^{n_u \times n_z} \), where \( n_l \) denotes the number of inputs of
the $i$-th nonlinearity, and $\nu_i = H_i x(k)$. The observer we propose has the following structure:

$$\dot{x}(k + 1) = A_z \dot{x}(k) + \sum_{i=1}^{m} G_i \gamma_i(\nu_i) + g(y(k), u(k)) + Q_z^{-1} L_z (y(k) - C_z \dot{x}(k)),$$

$$\dot{\nu}_i = H_i \dot{x}(k) + Q_{iz}(y(k) - C_z \dot{x}(k)), \quad L_z = \sum_{i=1}^{s} h_i(z(k)) L_{it},$$

$$Q_z = \sum_{i=1}^{s} h_i(z(k)) Q_{it}, \quad K_{iz} = \sum_{i=1}^{s} h_i(z(k)) K_{it}. \quad (11)$$

An extra degree of freedom is added via the term $Q_z$. It is assumed that $\gamma(\cdot)$ is globally Lipschitz. Based on Lemma 4 the following can be written:

$$G(\gamma(x(k)) - \gamma(\dot{x}(k))) = \sum_{i=1}^{m} \sum_{j=1}^{n_i} \Phi_{ij}(\zeta_i) H_{ij}(\nu_i - \dot{\nu}_i),$$

$$\mathcal{H}_{ij} = G_i e_{ni}(j)^T, \quad \Phi_{ij} = \frac{\partial \gamma_i}{\partial \nu_{ij}}(\zeta_i)$$

$$a_{ij} \leq \Phi_{ij}(\zeta_i) \leq b_{ij}, \quad (12)$$

where $\nu_{ij}$ denotes the $j$-th element from the vector $\nu_i$. Note that in (12) the $G$ matrix is included in $\mathcal{H}_{ij}$, so a simpler form is obtained. The model defined in (9) can be reformulated so that $a_{ij} = 0$, for all $i = 1, \ldots, m, j = 1, \ldots, n_i$. For more details on these modifications we refer the reader to [3], [7].

In what follows we denote: $\Phi_{ij} := \Phi_{ij}(\zeta_i)$ and we consider $a_{ij} = 0$, for all $i = 1, \ldots, m, j = 1, \ldots, n_i$. We denote the error with $e(k) := x(k) - \hat{x}(k)$, and based on (9)-(11) we have the following error dynamics:

$$e(k+1) = A_z x(k) + G \gamma(x(k)) + g(y(k), u(k)) + E w(k)$$

$$- A_z \dot{x}(k) - G \gamma(\dot{x}(k)) - g(y(k), u(k))$$

$$- Q_z^{-1} L_z (y(k) - C_z \dot{x}(k))$$

$$= (A_z - Q_z^{-1} L_z C_z) e(k) + G(\gamma(x(k)) - \gamma(\dot{x}(k)))$$

$$+ (E - Q_z^{-1} L_z D) w(k). \quad (13)$$

Using (12), we can rewrite

$$G(\gamma(x(k)) - \gamma(\dot{x}(k))) = \sum_{i=1}^{m} \sum_{j=1}^{n_i} \Phi_{ij} H_{ij}(\nu_i - \dot{\nu}_i)$$

$$= \sum_{i=1}^{m} \sum_{j=1}^{n_i} \Phi_{ij} H_{ij} \left( (H_i - K_{iz} C_z) e(k) - K_{iz} D w(k) \right).$$

This leads to

$$e(k+1) = \left( \mathbb{A}_L + \sum_{i=1}^{m} \sum_{j=1}^{n_i} \Phi_{ij} H_{ij} \mathbb{H}_K \right) e(k)$$

$$+ \left( \mathbb{E}_L + \sum_{i=1}^{m} \sum_{j=1}^{n_i} \Phi_{ij} H_{ij} \mathbb{D}_K \right) w(k), \quad (14)$$

where

$$\mathbb{A}_L = A_z - Q_z^{-1} L_z C_z, \quad \mathbb{H}_K = H_i - K_{iz} C_z,$$

$$\mathbb{E}_L = E - Q_z^{-1} L_z D, \quad \mathbb{D}_K = K_{iz} D. \quad (15)$$

We consider the following fuzzy Lyapunov function

$$V(e(k)) := e(k)^T P_z e(k), \quad (16)$$

for which the difference across time steps is:

$$\Delta V := e(k+1)^T P_z e(k+1) - e(k)^T P_z e(k). \quad (17)$$

We add an $H_\infty$ performance signal: $c(k) = J e(k), \mu > 0$, and formulate the following criterion:

$$W_k := \Delta V + ||c(k)||^2 - \mu ||w(k)||^2 \leq 0. \quad (18)$$

Now we are ready to present the main results of this paper.

### III. MAIN RESULTS

Theorem 1 presents the improvements we provide on Theorem 2 of [10]. Afterwards, Corollaries 1 and 2 give sufficient LMI conditions to satisfy Theorem 1 following the lines of conditions in [10], while Theorem 2 provides another approach to obtain sufficient LMI conditions.

**Theorem 1:** Consider the error dynamics in (14), and the $H_\infty$ performance index formulated in (18). If there exist matrices $P_{\lambda} = P_1^T \lambda > 0$, $Q_{ij} = S_{ij} > 0$, and $K_{iz}, \Lambda_{iz}$, for $i = 1, \ldots, m, j = 1, \ldots, n_i$ and $l_1, l_2, l_3 = 1, \ldots, s$, such that Lemma 2 holds with

$$F_{l_1 l_2 l_3} = \begin{bmatrix} M_{l_1 l_2 l_3} \quad \lambda \end{bmatrix} \begin{bmatrix} \Omega_{l_1 l_2} \ldots \Omega_{ml_2} \end{bmatrix} \begin{bmatrix} -L \end{bmatrix} \quad (19)$$

where

$$M_{l_1 l_2 l_3} = \begin{bmatrix} -P_{l_1} + J T^2 \quad 0 \quad A^T_{l_1} Q_{l_2} - C^T_{l_1} L_{l_2} T^T \end{bmatrix}$$

$$\Omega_{l_1 l_2} = \begin{bmatrix} \Pi_{l_1 l_2} \ldots \Pi_{l_1 l_2} \end{bmatrix}, \quad \Pi_{l_1 l_2} = \begin{bmatrix} (H^T_{l_2} - C^T_{l_1} K_{l_2}) S_{l_1} \end{bmatrix}$$

$$Q_{l_2} H_{l_2}$$

$$\Lambda = \text{bdia}(\Lambda_1, \ldots, \Lambda_m), \quad \Lambda_i = \text{bdia}\left( \frac{2}{b_{1i}}, \ldots, \frac{2}{b_{mi}} \right) I$$

$$S = \text{bdia}(S_1, \ldots, S_m), \quad S_i = \text{bdia}(S_{i1}, \ldots, S_{im})$$

then the $H_\infty$ performance condition defined in (18) is satisfied.

**Proof:** By calculating $W_k$ along the trajectories of $e(k)$, we obtain:

$$W_k = e(k)^T \left( \left( \mathbb{A}_L + \mathbb{M} \right)^T P_{l_1} e(k) + \mathbb{E}_L \right)$$

$$+ w(k)^T \left( \left( \mathbb{E}_L + \mathbb{N} \right)^T P_{l_2} e(k) \right)$$

$$+ 2e(k)^T \left( \left( \mathbb{A}_L + \mathbb{M} \right)^T P_{l_3} e(k) \right)$$

$$+ \mu w(k)^T \left( \mathbb{D}_K - K_{iz} D \right) w(k) \quad (20)$$

where

$$\mathbb{M} = \sum_{i=1}^{m} \sum_{j=1}^{n_i} \Phi_{ij} H_{ij} \mathbb{H}_K, \quad \mathbb{N} = \sum_{i=1}^{m} \sum_{j=1}^{n_i} \Phi_{ij} H_{ij} \mathbb{D}_K. \quad (21)$$

This can be written as

$$W_k = e(k)^T \begin{bmatrix} e(k) \quad w(k) \end{bmatrix} \Sigma \begin{bmatrix} e(k) \quad w(k) \end{bmatrix},$$
where
\[
\Sigma = \begin{bmatrix} -P_z + J^T J & 0 \\ 0 & -\mu I \end{bmatrix} + \begin{bmatrix} (A_L + M)^T \\ (E_L + N) \end{bmatrix} P_{zz+} \begin{bmatrix} A_L + M \\ E_L + N \end{bmatrix}
\]
(22)
Since \( \Sigma < 0 \) implies \( W_L < 0 \), in what follows we consider only \( \Sigma \). By applying the Schur complement on (22) and congruence with \( \text{bdiag}[I I Q_z] \) the following condition is obtained:
\[
\begin{bmatrix} -P_z + J^T J & 0 & (A_L + M)^T Q_z^T \\ 0 & -\mu I & (E_L + N)^T Q_z^T \\ 0 & * & * & P_{zz+} - Q_z - Q_z^T \end{bmatrix} < 0.
\]
(23)
Using Property 1 on \( Q_z P_{zz+} Q_z^T \), we have:
\[
\begin{bmatrix} -P_z + J^T J & 0 & (A_L + M)^T Q_z^T \\ 0 & -\mu I & (E_L + N)^T Q_z^T \\ 0 & * & * & P_{zz+} - Q_z - Q_z^T \end{bmatrix} < 0.
\]
(24)
Next, by following the steps in the proof of [10] we can separate (24) as:
\[
\begin{bmatrix} -P_z + J^T J & 0 & (A_L + M)^T Q_z^T \\ 0 & -\mu I & (E_L + N)^T Q_z^T \\ 0 & * & * & P_{zz+} - Q_z - Q_z^T \end{bmatrix} + \sum_{i=1}^m \sum_{j=1}^{n_i} \Phi_{ij} \left( \begin{bmatrix} 0 \\ 0 \\ [H_{K_i}, D_{K_i}, 0] \end{bmatrix} + * \right) < 0
\]
(25)
We denote
\[
X_{ij} = \begin{bmatrix} 0 & 0 \\ H_{ij}^T Q_z^T \\ Y_{ij} = \begin{bmatrix} H_{K_i}, D_{K_i}, 0 \end{bmatrix} \end{bmatrix}
\]
(26)
based on Lemma 4 the following inequality holds:
\[
X_{ij}^T Y_{ij} + X_{ij}^T Y_{ij}^T \leq \frac{1}{2} \left( X_{ij} + S_{ij} Y_{ij} \right)^T S_{ij}^{-1} \left( X_{ij} + S_{ij} Y_{ij} \right)
\]
(27)
Since \( 0 \leq \Phi_{ij} \leq b_{ij} \), see (12), (25) holds if:
\[
\begin{bmatrix} -P_z + J^T J & 0 & (A_L + M)^T Q_z^T \\ 0 & -\mu I & (E_L + N)^T Q_z^T \\ 0 & * & * & P_{zz+} - Q_z - Q_z^T \end{bmatrix} + \sum_{i=1}^m \sum_{j=1}^{n_i} \left( X_{ij} + S_{ij} Y_{ij} \right)^T \left( \frac{2}{b_{ij}} S_{ij} \right)^{-1} \left( X_{ij} + S_{ij} Y_{ij} \right) < 0
\]
(28)
Next, by applying the Schur complement on (28) we get:
\[
M_{zzzz} = \begin{bmatrix} \Omega_{1z} \cdots \Omega_{mz} \\ \ast \end{bmatrix} - A_S < 0
\]
\[
M_{zzzz+} = \begin{bmatrix} P_{zz+} - J^T J & 0 \\ 0 & -\mu I \\ * & P_{zz+} - Q_z - Q_z^T \end{bmatrix}
\]
(29)
By applying Lemma 2 we obtain (19).
To highlight the advantages of the presented approach, first we focus on \( X_{ij} \) in (26). In [10] the term \( X_{ij} \) depends on \( H_{ij}^T P_z^T \), where \( P \) must be a positive definite symmetric matrix, and \( H_{ij} \) is a \( n_x \times n_i \) matrix, in which the \( j \)-th column is \( G_i \) and the rest of the columns are 0. Since \( P \) has to be symmetric, the \( X_{ij} \) term makes the design conditions restrictive.
This restrictive form is relaxed in our design. We use a non-symmetric fuzzy matrix \( Q_z = \sum_{i=1}^m h_i(z(k))Q_i \), which introduces unconstrained decision variables in \( X_{ij} \). Matrix \( Q_z \) also helps in \( M_{zzzz} \) in (29), since the observer is completely decoupled from the Lyapunov function, while in Theorem 2 in [10] the observer gains are computed as \( L_z = P^{-1} X_z \), where \( P \) is from the Lyapunov function.
On the other hand, in the Lyapunov synthesis, instead of the quadratic Lyapunov function \( e(k)T Pe(k) \) we use a fuzzy Lyapunov function, having the form: \( e^T(k)P_z e(k) \). This makes the design conditions less restrictive, see [18]. In Theorem 1, if we take a quadratic Lyapunov function, so \( P_l = P \) for all \( l = 1, \ldots, s \), and constant \( Q \), with \( Q = P \), then we obtain Theorem 2 of [10]. We can conclude that the design condition presented in Theorem 2 of [10] is a special case of Theorem 1.
Although the conditions defined in (19) are less restrictive than those in Theorem 2 in [10], they are still bilinear due to the terms \( K_{ij}\Sigma_{ij} \) for all \( i = 1, \ldots, m \) and \( j = 1, \ldots, n_i \). The change of variables, like \( X = K_{ij}\Sigma_{ij} \), is not possible since \( \Sigma_{ij} \) depends on both \( i \) and \( j \). Two solutions are proposed in [10] to obtain sufficient LMI conditions in form of corollaries. The first corollary imposes \( \Sigma_{ij} = \Sigma_i \), so that a variable change can be used: \( Y_i = K_i^T \Sigma_i \), while the second corollary considers \( K_i = 0 \). In what follows we also formulate two corollaries for the options mentioned above.

Corollary 1: Consider the error dynamics in (14), and the \( H_\infty \) performance index formulated in (18). If there exist matrices \( P_{l_i} = P_{T_i}^T > 0 \), \( Q_{l_i}, S_{l_i} = S_{T_i}^T > 0 \), and \( Y_{l_i}, L_{l_i} \), for \( i = 1, \ldots, s \), and \( l_1, l_2, l_3 = 1, \ldots, s \), such that Lemma 2 holds with (19), where
\[
S_{l_i} = \text{bdiag}(S_{1i}, \ldots, S_{ni})
\]
then the \( H_\infty \) performance condition defined in (18) is satisfied, and the observer gains can be recovered from \( K_{il_i} = S_{l_i}^{-1} Y_{l_i}^T \).
\textbf{Proof:} The proof is the same as that of Theorem 1 with \( S_{ij} = \Sigma_i \).

Corollary 2: Consider the error dynamics in (14), and the \( H_\infty \) performance index formulated in (18). If there exist matrices \( P_{l_i} = P_{T_i}^T > 0 \), \( Q_{l_i}, S_{ij} = S_{T_i}^T > 0 \), for \( i = 1, \ldots, m \) and \( j = 1, \ldots, n_i \) and \( l_1, l_2, l_3 = 1, \ldots, s \), such that Lemma 2 holds with (19), then the \( H_\infty \) performance condition defined in (18) is satisfied.
\textbf{Proof:} The proof is as above with \( K_{il_i} = 0 \).

Next, we provide a novel approach as an alternative to obtain sufficient LMI conditions.

Theorem 2: Consider the error dynamics in (14), and the \( H_\infty \) performance index formulated in (18). If there exist matrices \( P_{l_i} = P_{T_i}^T > 0 \), \( Q_{l_i}, S_{ij} = S_{T_i}^T > 0 \), where the \( j \)-th column of \( S_{ij} \) is \( [0 \cdots 0 \alpha_{ij} 0 \cdots 0]^T \), with constants \( \alpha_{ij} \)
\( \alpha_{ij} \), and \( K_{i2}, L_{i1} \), for \( i = 1, \ldots, m, j = 1, \ldots, n \) and \( t_1, t_2, t_3 = 1, \ldots, s \), such that Lemma 2 holds with

\[
F_{t_1 t_2 t_3} = \begin{bmatrix} M_{t_1 t_2 t_3} & [\Omega_{t_1 t_2} \cdots \Omega_{t_1 t_3}] \\ & -\Delta S \end{bmatrix}
\]

where

\[
M_{t_1 t_2 t_3} = \begin{bmatrix} -P_{t_1} + J^T J & \alpha_{i2} C_{t_1}^T Q_{t_1} - C_{t_1}^T L_{t_2} \\ * & -\mu I & E^T Q_{t_2} - D^T L_{t_3} \\ * & * & P_{t_3} - Q_{t_3} - Q_{t_3}^T \end{bmatrix}
\]

\[
\Omega_{t_1 t_2} = [\Pi_{t_1} \cdots \Pi_{t_2}] \quad \Pi_{t_1} = \begin{bmatrix} D^T K_{t_2} \\ \alpha_{ij} Q_{t_2} H_{ij} \end{bmatrix}
\]

and the rest of the elements are as in Theorem 1. Sufficient LMI conditions are obtained applying Lemma 2.

The main advantage of Theorem 2 is that even if it imposes a structural restriction, still every \( \mathcal{H}_{ij} \) term has a corresponding \( S_{ij} \) matrix, and not a single \( S_i \) for all the \( j \)'s like in Corollary 1. If we have a good initial guess for the parameters \( \alpha_{ij} \), the problem becomes a simple LMI. Alternatively, we can search for \( \alpha_{ij} \) in a logarithmically spaced family of values \( \alpha_{ij} \in \{10^{-6}, 10^{-5}, \ldots, 10^0, 10^9\} \). On the other hand, if we have many \( \alpha_{ij} \) parameters the problem can become computationally intractable.

### IV. Comparison with the State of the Art

In order to highlight the advantages obtained by our approach, we compare Corollaries 1 and 2 from [10] with our approaches presented in Corollaries 1 and 2, and Theorem 2 on a numerical example.

**Example 1:** Consider model (9) with two local models and the following matrices:

\[
A_1 = \begin{bmatrix} 1 & 0.008 \\ 0 & 0.29 \end{bmatrix}, \quad A_2 = \begin{bmatrix} 1 & 0.008 \\ 0 & 0.96 \end{bmatrix}, \quad G = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}
\]

\[
C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad H = \begin{bmatrix} 0 & 0.96 \\ 0 & 0.1 \end{bmatrix}, \quad E = \begin{bmatrix} 0 & 1 \\ 0 & 1 \end{bmatrix}, \quad D = 0.02,
\]

Moreover, \( g(y(k), u(k)) = 0 \) and we consider one nonlinearity denoted by \( \gamma \) and it fulfills (12) with \( a_{11} = a_{12} = 0, b_{12} = 0.5 \). This example is simple enough so standard LMI solvers can easily handle, but has a nonlinearity that depends on two states, so approaches in [19], [3], [4] are not suitable for it.

### Table I

<table>
<thead>
<tr>
<th>( b_{11} )</th>
<th>Cor. 1 [10]</th>
<th>Cor. 2 [10]</th>
<th>Cor. 1</th>
<th>Cor. 2</th>
<th>Th. 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>1.0203</td>
<td>0.8754</td>
<td>0.8263</td>
<td>0.6544</td>
<td>0.5642</td>
</tr>
<tr>
<td>2.2</td>
<td>1.0581</td>
<td>0.9022</td>
<td>0.8317</td>
<td>0.6738</td>
<td>0.5644</td>
</tr>
<tr>
<td>2.4</td>
<td>1.0954</td>
<td>0.9287</td>
<td>0.8768</td>
<td>0.6931</td>
<td>0.5646</td>
</tr>
<tr>
<td>2.6</td>
<td>1.1324</td>
<td>0.9551</td>
<td>0.9019</td>
<td>0.7122</td>
<td>0.5648</td>
</tr>
<tr>
<td>2.8</td>
<td>1.1690</td>
<td>0.9814</td>
<td>0.9270</td>
<td>0.7314</td>
<td>0.5650</td>
</tr>
<tr>
<td>3</td>
<td>1.2053</td>
<td>1.0077</td>
<td>0.9520</td>
<td>0.7508</td>
<td>0.5652</td>
</tr>
</tbody>
</table>

We study the minimum \( \mu \) what we can obtain based on \( b_{11} \). To solve the LMI problem, the sedumi solver is used in the Yalmip [20] framework. To fit in the framework of the linear parameter varying models used in [10], we consider the parameter \( \rho \in [0.03, 0.7] \), and matrices

\[
A_0 = \begin{bmatrix} 1 & 0.008 \\ 0 & 0.99 \end{bmatrix}, \quad A_1 = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}
\]

The results obtained are presented in Table I. It can be seen that Corollaries 1-2 outperform the corollaries presented in [10] in terms of the minimum value of \( \mu \). The best results are obtained with Theorem 2, but with the added computational complexity of finding a suitable \( \alpha_{11} \) and \( \alpha_{12} \). Regarding the computational complexity of solving the LMI conditions, according to [16], page 18, a realistic approximation of the numerical complexity using the interior-point method used by sedumi is \( O(N d^{2.5} N l^{1.2}) \), where \( N_d \) is the number of scalar decision variables and \( N_l \) is the row size of the LMI problem. For the conditions in Corollary 1 we have \( N_d = 25, \)
for Corollary 2 this value is $N_d = 24$, and for Theorem 2 we have $N_d = 24$, and for all the cases $N_1 = 56$. To show the advantage of using the fuzzy $Q$ matrix we provide another example dedicated only to this purpose.

**Example 2:** We use (9) with the following matrices:

\[
C_1 = C_3 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}, \quad C_2 = C_4 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & \omega_1 \end{bmatrix},
\]

\[
A_1 = A_2 = \begin{bmatrix} 1 & 0.001 & 0 & 0 \\ 0.1 & 0.2 & 0.1 & 0.001 \\ 0.1 & -0.3 & 0.2 & \omega_2 \\ 1 & 0.001 & 0 & 0 \end{bmatrix}, \quad G = \begin{bmatrix} 1 & -2 \\ -4 & 7 \\ 3 & -1 \\ -12 & 9 \end{bmatrix},
\]

\[
A_3 = A_4 = \begin{bmatrix} 0.1 & 0.2 & 0.1 & 0.3 \\ 0 & 0 & 0 & 0.001 \\ 0 & -0.3 & 0.2 & 1.1 \end{bmatrix},\]

where $\omega_1$ and $\omega_2$ are two parameters. We consider the following two cases:

1.) Corollary 1 with $P_z = P$, $Q_z = P$, equivalent to [10].

2.) Corollary 1 with $P_z = P$.

We vary the values of $\omega_1$ and $\omega_2$ in the range $\omega_1 = [0.8, 2.2]$ and $\omega_2 = [-0.2, 1.2]$, and we look for feasible solutions with respect to the matrices in (39). The results obtained can be seen on Fig. 1. We can see that a much wider range of systems can be handled by adding the extra degree of freedom with $Q_z$.

![Fig. 1. ' -Corollary 1 with $P_z = P$, $Q_z = P$, 'o'-Corollary 1 with $P_z = P$.](image)

**V. CONCLUSIONS AND FUTURE WORK**

This paper presented a novel approach to observer design for discrete-time nonlinear systems with nonlinear consequences. The design exploits the TS fuzzy framework together with globally Lipschitz nonlinearities. An $H_\infty$ performance index was used, and the conditions were formulated so that the effect of the disturbance was minimised. To highlight the novelty of the paper two examples were presented.

There are many future directions, among which we will focus on extending this work to observer-based controller design. On the other hand we plan to consider a wider range of models, for example by considering fuzzy terms also for $G$ matrix.

**REFERENCES**


