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DESIGN AN ESTIMATOR WITH ROBUST UNKNOWN INPUT FOR UNDEFINED INTERVAL TYPE-2 FUZZY SYSTEMS WITH IMMEASURABLE DECISION VARIABLES

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Abstract: In this paper, an innovative approach is proposed for designing an estimator with robust unknown input for undefined interval type-2 T-S fuzzy systems with immeasurable decision variables. In system modeling by the T-S fuzzy model, decision variables may be a function of system modes, which in many cases are immeasurable due to the structure of the system. Therefore, in this paper, the decision variables of the system are considered immeasurable. This assumption has led to a new trend in robot design. Also, in order to create a residual signal that has the highest sensitivity to a fault and the lowest sensitivity to unknown input, the H_∞ / H optimization criterion is considered. The existence of this criterion in design has led to two theorems in estimator design with new conditions based on linear matrix inequalities.

Keywords: fuzzy system, new trend in robot design, H_∞ / H optimization criterion

1. INTRODUCTION

In the system identification methods, describing a system is highly dependent on prior knowledge about the system. In addition to the physical description, using signal bases methods are common as described in [1-2] for the space application and in tracking systems [3]. Meanwhile, in the identification process, the measured parameters by sensors must be transmitted in real-time mode. The compressed sensing methods are usually used to decrease the required bandwidth in the communication link. The time for generating compressed data for transmission is an essential key when we consider mobile devices, with the fact that data should be sent to the central processor as soon as possible. In addition, there are some wearable sensors that have a limited amount of power, and may only be capable of doing simple computations. With the aim of increasing the speed and simplicity of the compressors, [4] proposes an approach that can generate compressed ECG samples in a linear method and with CR 75%. In structural health monitoring/identification (SHMI), sensors intermittently monitor the operational condition of the system and send the recorded data to a remote server for processing. Data compression can be used to decrease the required storage size of the received data, and for efficient use of transmission link bandwidth, because of the enormous volumes of sensor data produced from the sensors. In [5-6-7], the fundamentals for acquiring the data for the control purposes are presented. An effective way to model complex nonlinear systems is to use Takagi-Sugeno (T-S) fuzzy systems [8,9]. In modeling nonlinear systems using T-S fuzzy systems, activation functions are very important. Typically, in previous works, activation functions were considered as a function of the measurable variables (system output or system input). But it turns out that in some cases, such a choice does not create the right model of a nonlinear system [10]. In this regard, the use of system states in the activation functions of fuzzy systems, makes it possible to model a wider range of nonlinear systems [11]. Considering state variables with the assumption that they are non-measurable, the discussion of observer design for T-S fuzzy systems with the non-measurable decision variable is one of the most challenging and complex topics in recent years. The assumption that these variables are immeasurable causes a great deal of complexity in the design process, and so far, few methods have been implemented for this purpose [12,13]. Also, according to recent research on the inability of type-1 fuzzy sets to model uncertainties [14], in the present work, type-2 fuzzy sets are considered as a solution to this issue [15].

According to the contents on the importance of the subject, in this paper, the design of the observer with an unknown input for interval type 2 T-S fuzzy systems is discussed. In designing this observer, it is assumed that the decision variables are immeasurable. This assumption creates a new trend in the design of this group of observers. Also, in order to create an optimal residual signal in the presence of disturbance and unknown input, which has the highest sensitivity to fault and the lowest sensitivity to an unknown input, H_∞ / H optimization criteria have been used. To achieve such a criterion, two theorems are proved to provide the necessary conditions for design in terms of linear matrix inequalities.

2. MAIN RESULTS

The system considered in this paper is interval type 2 fuzzy T-S. The system under study involves a variable delay with time in the system input and output. Also, this system is affected by disturbance and unknown input as noise. As you know, T-S systems are generally weighted by linear subsystems. The system considered in this article is as follows:

$$\dot{x}(t)=\sum_{i=1}^{p}\mu_i\left(x(t)\right)\times\left[A_i x(t)+A_{d_i}x\left(t-\tau_1(t)\right)+B_i u(t)+B_{d_i}u\left(t-\tau_2(t)\right)+E_i d(t)+H_i w(t)+F_{x_i}f(t)\right]$$
$$y(t)=Cx(t)+Dd(t)+F_w w(t)+F_y f(t) \qquad (1)$$

where $x(t)\in R^n$ represents the system state vector, $u(t)\in R^q$ shows the system input vector, $y(t)\in R^p$ is the output vector, $d(t)\in R^m$ is the disturbance signal, $w(t)\in R^r$ shows the unknown input and $f(t)\in R^f$ represents the fault in the system. Also, τ_1 and τ_2 are delays vary with time that are variable when the conditions $0<\tau_i(t)<\hat{h}_d<\infty$ and $0<\dot{\tau}_i(t)<\bar{h}_{d_i}<1$ are satisfied. Also, the activation function $\mu_i\left(x(t)\right)$ can be calculated by the following equation:

$$\mu_i\left(x(t)\right)=\mu_i^L\left(x(t)\right)\underline{v}_i\left(x(t)\right)+\mu_i^U\left(x(t)\right)\bar{v}_i\left(x(t)\right) \qquad (2)$$

where in this equation, $\mu_i^L(x(t)$ and $\mu_i^U\left(x(t)\right)$ are the lower and upper bonds of the fire range can be calculated based on the basics governing type-2 interval fuzzy systems. Furthermore, $\bar{v}_i\left(x(t)\right)\in[0,1]$ and $\underline{v}_i\left(x(t)\right)\in[0,1]$ are considered as nonlinear functions in general if $\underline{v}_i\left(x(t)\right)+\bar{v}_i\left(x(t)\right)=1$ is satisfied.

Accordingly, the structure of the observer with the unknown input in this article is as follows:

$$\dot{z}(t)=\sum_{i=1}^{p}\mu_i\left(\hat{x}(t)\right)\times\left[N_i z(t)+G_i z\left(t-\tau_1(t)\right)+Q_i u(t)+J_i u\left(t-\tau_2(t)\right)+K_{1z_i}y(t)+K_{2z_i}y\left(t-\tau_1(t)\right)\right]$$
$$\hat{x}(t)=z(t)+L_1 y(t) \qquad \hat{y}(t)=C\hat{x}(t) \qquad r(t)=V\left(y(t)-\hat{y}(t)\right) \qquad (3)$$

where $y(t)$ and $u(t)$ are measurable variables and $\hat{x}$ is estimated variable. By defining the estimation error as $e(t)=x(t)-\hat{x}(t)$, the dynamics of the error can be obtained as follows:

$$\dot{e}(t)=\sum_{i=1}^{p}\mu_i\left(\hat{x}(t)\right)\left[N_i e(t)+G_i e\left(t-\tau_1(t)\right)+\bar{F}_{w_i}\bar{w}(t)+\bar{F}_{f_i}\bar{f}(t)\right]+T\Delta\left(\mu(x),\mu(\hat{x}),x,u,d,w\right)$$
$$r(t)=VCe(t)+VK_1\bar{w}(t)+VK_2\bar{f}(t) \qquad (4)$$

where $\bar{F}_{w_i}=\left[TH_i+L_{2i}F_w-L_1F_w\right],\bar{w}(t)=\left[w(t)\ \ \dot{w}(t)\right]$ $\bar{F}_{f_i}=\left[TF_{x_i}+L_{2i}F_y-L_1F_y\right],\bar{f}(t)=\left[f(t)\ \ \dot{f}(t)\right]$

$$\Delta(0)=\left(\sum_{i=1}^{p}\mu_i\left(x(t)\right)-\sum_{i=1}^{p}\mu_i\left(\hat{x}(t)\right)\right)\times\left[A_i x(t)+A_{d_i}x\left(t-\tau_1(t)\right)+B_i u(t)+B_{d_i}u\left(t-\tau_2(t)\right)E_i d(t)+H_i w(t)+F_{x_i}f(t)\right]$$

In obtaining such a dynamic for error, the following definitions:

$$D1.T=I-L_1C \qquad D2.L_{2i}=N_iL_1-K_{1z_i} \qquad D3.L_{3i}=G_iL_1-K_{2z_i}$$

and also the following assumptions:

$$C1.L_{3i}=0 \quad C2.TA_i+L_{2i}C-N_i=0 \quad C3.TA_{d_i}+L_{3i}C-G_i=0$$
$$C4.TB_i-Q_i=0 \qquad C5.TB_{d_i}-J_i=0 \qquad C6.TR_i+L_{2i}D=0$$

are considered.

It should be noted that the residual signal is based on the assumption $VD=0$. To get observer gain matrices, you first need to calculate the L_1,L_{2i},L_{3i} and V matrices. Then, using $D1-D3$ and $C1-C5$ conditions, the observer gains are calculated.

The remarkable point in the design of this observer is the presence of the $T\Delta(0)$ term in dynamic of the error obtained. This complicates the process of designing and creating new cases in the field of observers with unknown inputs, which, according to the authors, has not yet provided such conditions in the design of this group of observers in previous works.

In the following, two theorems are presented to create a residual signal with the highest fault sensitivity and the lowest sensitivity to unknown input. The two cases mentioned above and the algorithm that is finally introduced show the process of designing the benefits of this observer.

Lemma 1 [12]. For each X and Y matrix with appropriate dimensions, the following inequality is established for each positive constant $\grave{o}$:

$$X^TY+Y^TX \le \epsilon X^TX+\epsilon^{-1}Y^TY$$

Assumption 1. In this paper, it is assumed that $\Delta(0)\le \gamma e(t)$ where γ is a positive constant.

Theory 1. For the scalar variables γ,β,δ and $\epsilon>0$, if there are symmetric positive definite matrices P,S,Q and symmetric positive semi definite matrix Z and X,Y,Φ_1,Φ_2 and F matrices, in such a way that the following conditions are established for $i=1,2,\dots,p$:

$$\begin{bmatrix} \Theta_{11}^i & PG_i+Y^T-X & \Theta_{13}^i & -\sqrt{\hat{h}_{d_i}}X \\ * & \Theta_{22}^i & -F^T & -\sqrt{\hat{h}_{d_i}}Y \\ * & * & -\beta^2 I+K_2^TZK_2 & -\sqrt{\hat{h}_{d_i}}F \\ * & * & * & -Q \end{bmatrix}<0 \qquad \begin{bmatrix} -P+\epsilon\gamma^2 I & PN_i+P & P \\ * & -P & 0 \\ * & * & -\epsilon I \end{bmatrix}<0$$

$$\Phi_1 D=0 \qquad PR_i-\Phi_1 CR_i+\Phi_{2i}D=0 \qquad ZD=0 \tag{5}$$

where $\Theta_{11}^i=S+sym(X)-C^TZC \quad \Theta_{13}^i=P\bar{F}_{f_i}+F^T-C^TZK_2 \quad \Theta_{22}^i=-\left(1-\bar{h}_{d_i}\right)S-sym(Y)$

$$PN_i=PA_i-\Phi_1CA_i+\Phi_{2i}C \quad PG_i=PA_{d_i}-\Phi_1CA_{d_i} \quad P\bar{F}_{f_i}=\left[PF_{xi}-\Phi_1CF_{xi}+\Phi_{2i}F_y-\Phi_1F_y\right]$$

$$Z=V^TV$$

Then, the following system is permanently stable and $G_{r,\bar{f}\infty}\ge\beta$:

$$\dot{e}(t)=\sum_{i=1}^{p}\mu_i\left(\hat{x}(t)\right)\left[N_ie(t)+G_ie\left(t-\tau_1(t)\right)+\bar{F}_{f_i}\bar{f}(t)\right]+T\Delta(0)$$
$$r(t)=VCe(t)+VK_2\bar{f}(t) \tag{6}$$

Also, the observer gains can be calculated by $V=Z^{\frac{1}{2}}$ and $L_1=P^{-1}\Phi_1$ and $L_{2i}=P^{-1}\Phi_{2i}$.

Proof of Theorem 1. The method used to prove this theorem is Lyapunov's indirect method. Accordingly, the LKF function considered to prove this as follows:

$$V(t)=e^T(t)Pe(t)+\int_{t-\tau_1(t)}^{t}e^T(\tau)Se(\tau)d\tau \tag{7}$$

The optimality criteria $G_{r,\bar{f}}>\beta$ is equivalent to:

$$J_{r,\bar{f}}=\int_0^\infty\left[r^T(t)r(t)-\beta^2\bar{f}^T(t)\bar{f}(t)\right]dt\ge 0 \tag{8}$$

According to the $V(\infty)>0$, it can be written:

$$J_{r,\bar{f}}=\int_0^\infty\left[r^T(t)r(t)-\beta^2\bar{f}^T(t)\bar{f}(t)-\dot{V}(t)\right]dt\ge 0$$

Given the above relationship, we need to calculate the derivative of the first order of the LKF function presented before. To calculate this derivative, the Leibnitz integral formula is required as follows:

$$\frac{d}{dt}\left(\int_{a(x)}^{b(x)}f(x,t)dt\right)=f\left(x,b(x)\right).b'(x)-f\left(x,a(x)\right).a'(x)+\int_{a(x)}^{b(x)}f_x(x,t)dt \tag{9}$$

Considering this relationship and also the properties that were expressed for the system under review, it can be concluded that:

$$\dot{V}(t)\le 2e^T(t)P\dot{e}(t)+e^T(t)Se(t)-\left(1-\bar{h}_{d_1}\right)e^T\left(t-\tau_1(t)\right)Se\left(t-\tau_1(t)\right)+$$
$$2\left[e^T(t)X+e^T\left(t-\tau_1(t)\right)Y+\bar{f}(t)F\right]\times[e(t)-e\left(t-\tau_1(t)\right)-\int_{t-\tau_1(t)}^{t}\dot{e}(\tau)d\tau]$$

Considering the derivative of the first order of the LKF function, the optimal criterion can be rewritten as follows:

$$J_{r,\bar{f}}\ge\int_0^\infty\left[\mu_i\left(\hat{x}(t)\right)\Theta_i+\int_{t-\tau_1(t)}^{t}\Gamma^T(t,\tau)Q^{-1}\Gamma(t,\tau)d\tau-2e^T(t)P\Delta(0)-e^T(t)PN_ie(t)-e^T(t)N_i^TPe(t)\right]$$

where in this inequality we have:

$$\eta(t)=\begin{bmatrix} e(t) \\ e\left(t-\tau_1(t)\right) \\ \bar{f}(t) \end{bmatrix} \qquad \Theta_i=\eta^T(t)\tilde{\Theta}_i\eta(t)+\hat{h}_{d_i}\eta^T(t)\begin{bmatrix} X \\ Y \\ F \end{bmatrix}^T Q^{-1}\begin{bmatrix} X \\ Y \\ F \end{bmatrix}\eta(t)$$

$$\tilde{\Theta}_i = \begin{bmatrix} \Upsilon_{11} & -PG_i + X - Y^T & C^T V^T V K_2 - F^T \\ * & \left(1-\bar{h}_{d_i}\right) S + sym(Y) & F^T \\ * & * & -\beta^2 I + K_2^T V^T V K_2 \end{bmatrix} \qquad \Upsilon_{11} = C^T V^T V C - sym(X) - S \qquad \Gamma(t,\tau) = \eta^T(t) \begin{bmatrix} X \\ Y \\ F \end{bmatrix}$$

Based on Lemma 1 and Assumption 1, this relationship can turn into the following:

$$J_{r,\bar{f}} \geq \int_0^{\infty} \left[\sum_{i=1}^{p} \mu_i\left(\hat{x}(t)\right)\left\{\Theta_i - e^T(t)\bar{\Theta}_i e(t)\right\} \right] dt$$

$$\bar{\Theta}_i = PN_i + N_i^T P + \epsilon^{-1} PTT^T P + \epsilon \beta^2 I$$

Now, in order to obtain the condition $J_{r,\bar{f}} \geq 0$, it is sufficient that the two conditions $\Theta_i > 0$ and $\bar{\Theta}_i < 0$ are established simultaneously.

Theorem 2. For the scalar variables γ, β, δ and $\epsilon > 0$, if there are symmetric positive definite matrices P, S, Q and symmetric positive semi definite matrix Z and X, Y, Φ_1, Φ_2 and W matrices, in such a way that the following conditions are established for $i = 1, 2, \ldots, p$:

$$\begin{bmatrix} \Theta_{11}^i & PG_i + Y^T - X & \Theta_{13}^i & -\sqrt{\hat{h}_{d_i}} X \\ * & \Theta_{22}^i & -F^T & -\sqrt{\hat{h}_{d_i}} Y \\ * & * & -\alpha^2 I + K_1^T Z K_1 & -\sqrt{\hat{h}_{d_i}} W \\ * & * & * & -Q \end{bmatrix} < 0 \qquad \begin{bmatrix} -P + \epsilon\gamma^2 I & PN_i + P & P \\ * & -P & 0 \\ * & * & -\epsilon I \end{bmatrix} < 0$$

$$\Phi_1 D = 0 \qquad PR_i - \Phi_1 C R_i + \Phi_{2i} D = 0 \qquad ZD = 0 \tag{10}$$

$$\Theta_{11}^i = S + sym(X) - C^T Z C \qquad \Theta_{13}^i = P\bar{F}_{w_i} + W^T - C^T Z K_1 \qquad \Theta_{22}^i = -\left(1-\bar{h}_{d_i}\right) S - sym(Y)$$

$$PN_i = PA_i - \Phi_1 C A_i + \Phi_{2i} C \qquad PG_i = PA_{d_i} - \Phi_1 C A_{d_i} \qquad P\bar{F}_{w_i} = \left[PH_i - \Phi_1 C H_i + \Phi_{2i} F_w - \Phi_1 F_w\right]$$

$$Z = V^T V$$

Then, the following system is permanently stable and $G_{r,\bar{f}\infty} \leq \alpha$

$$\dot{e}(t) = \sum_{i=1}^{p} \mu_i\left(\hat{x}(t)\right)\left[N_i e(t) + G_i e\left(t - \tau_1(t)\right) + \bar{F}_{w_i} \bar{w}(t)\right] + T\Delta(0)$$

$$r(t) = VCe(t) + VK_1 \bar{w}(t)$$

Also, the desired observer gain can be calculated by the following relationships, $L_1 = P^{-1}\Phi_1$, $L_{2i} = P^{-1}\Phi_{2i}$ and $V = Z^{\frac{1}{2}}$.

Proof of Theorem 2. The optimization criterion in this case can be equated as follows:

$$J_{r,\bar{w}} := \int_0^{\infty} \left[r^T(t) r(t) - \alpha^2 \bar{w}^T(t) \bar{w}(t)\right]$$

Given the condition $V(\infty) > 0$ and the procedure used to prove Theorem 1, the LMI conditions and the equality in Theorem 2 can be easily obtained.

So far, two separate theorems have been proposed to create a residual signal with the highest sensitivity to fault event and the lowest sensitivity to unknown input. In order to use these two theorems simultaneously, a repetitive algorithm is presented in [16] which has been used in the simultaneous application of these two theorems.

3. SIMULATION RESULTS

In order to evaluate the validity of the method presented in the design of the observer, the system parameters (1) are considered as follows:

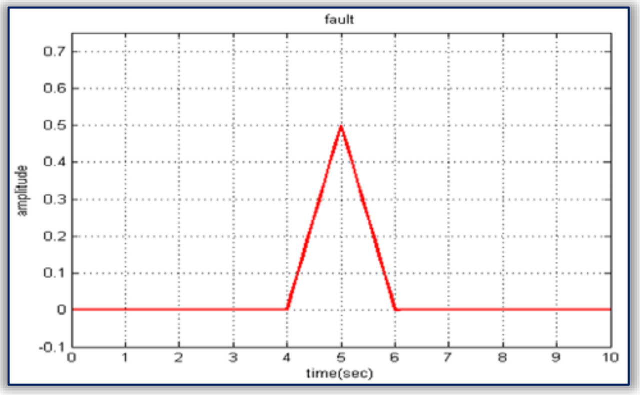

Figure 1. The fault event considered in the system

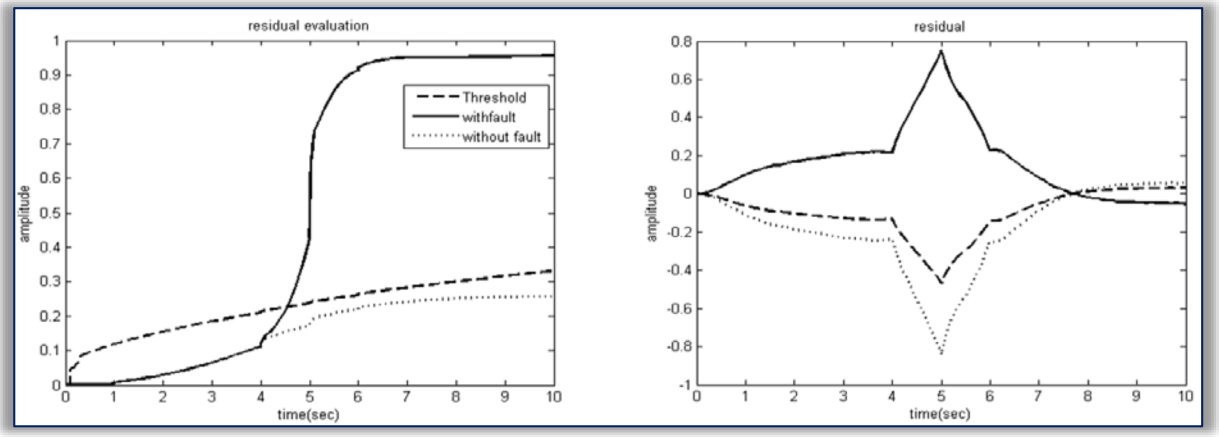

Figure 2. Residual signals and its evaluation criteria; Measurable decision variables

$$A_1=\begin{bmatrix}-2.7 & 0.75 & -0.65\\ 0.5 & -2.4 & 1\\ -0.53 & 1.7 & -2.2\end{bmatrix},\quad A_2=\begin{bmatrix}-1 & 0.75 & -0.75\\ 0.15 & -1 & 0.9\\ -1.3 & 0.3 & -1.1\end{bmatrix}\quad A_{d_1}=\begin{bmatrix}1.1 & 0.15 & -0.52\\ 0.1 & -1.2 & 0.62\\ 0.2 & -1.1 & 0.75\end{bmatrix},\quad A_{d_2}=\begin{bmatrix}0.8 & -0.3 & -1.1\\ 0.3 & -0.2 & 0.1\\ -0.5 & -0.3 & -0.3\end{bmatrix}$$

$$B_1=\begin{bmatrix}0.4 & 0.5 & -0.3\end{bmatrix}^T,\quad B_2=\begin{bmatrix}0.1 & 0.7 & -1.1\end{bmatrix}^T\quad B_{d_1}=\begin{bmatrix}-0.45 & 0.2 & -0.65\end{bmatrix}^T,\quad B_{d_2}=\begin{bmatrix}1.1 & -0.6 & 0\end{bmatrix}^T$$

$$E_1=\begin{bmatrix}-0.7 & 0.68 & -0.43\end{bmatrix}^T,\quad E_2=\begin{bmatrix}0.9 & 0.4 & -0.9\end{bmatrix}^T\quad H_1=\begin{bmatrix}0.8 & 0.8 & -0.8\end{bmatrix}^T,\quad H_2=\begin{bmatrix}0.4 & -0.2 & -0.5\end{bmatrix}^T$$

$$F_{x_1}=\begin{bmatrix}0.9 & -0.45 & 1.04\end{bmatrix}^T,\quad F_{x_2}=\begin{bmatrix}0.45 & 0.5 & -0.6\end{bmatrix}^T$$

$$C=\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 0\\ 0 & 1 & 1\end{bmatrix},\quad F_y=\begin{bmatrix}0.6 & 0.4 & -0.9\end{bmatrix}^T\quad F_w=\begin{bmatrix}-0.9 & 0.5 & -0.7\end{bmatrix}^T,\quad D=\begin{bmatrix}0.4 & 0.2 & -0.5\end{bmatrix}^T$$

Considering such parameters for the system, solving Theorems 1 and 2 simultaneously with the introduced duplicate algorithm results in observer gains. The following parameters are obtained:

$$N_1=\begin{bmatrix}-1.38 & -0.12 & 0.08\\ 0.22 & -2.77 & 1.44\\ -0.06 & 0.95 & -2.23\end{bmatrix},\quad N_2=\begin{bmatrix}-2.62 & -0.08 & -0.13\\ -0.09 & -2.93 & 1.93\\ -0.41 & 1.24 & -3\end{bmatrix}\quad G_1=\begin{bmatrix}0.33 & -0.33 & 0.2\\ 0.1 & -0.74 & 0.15\\ 0.67 & -0.14 & 0.53\end{bmatrix},\quad G_2=\begin{bmatrix}0.14 & -0.17 & 0.22\\ 0.12 & -0.28 & 0.16\\ 0.07 & -0.1 & 0.52\end{bmatrix}$$

$$Q_1=\begin{bmatrix}-0.03 & 0.2 & -0.4\end{bmatrix}^T,\quad Q_2=\begin{bmatrix}0.12 & 0.37 & -0.08\end{bmatrix}^T\quad J_1=\begin{bmatrix}-0.01 & -0.02 & 0.12\end{bmatrix}^T,\quad J_2=\begin{bmatrix}0 & -0.14 & -0.05\end{bmatrix}^T$$

$$K_{1z_1}=\begin{bmatrix}-0.29 & -0.05 & -0.09\\ 0.48 & -0.26 & -0.64\\ -0.2 & -0.32 & -0.03\end{bmatrix},\quad K_{1z_2}=\begin{bmatrix}-0.1 & 0.41 & 0.52\\ 0.59 & -0.01 & -1.03\\ -0.23 & -0.42 & 0.86\end{bmatrix}\quad K_{2z_1}=\begin{bmatrix}0.32 & -0.16 & -0.11\\ 0.16 & -0.09 & -0.05\\ 0.61 & -0.3 & -0.22\end{bmatrix},\quad K_{2z_2}=\begin{bmatrix}0.15 & -0.07 & -0.05\\ 0.14 & -0.07 & -0.04\\ 0.11 & -0.05 & -0.03\end{bmatrix}$$

At this stage, the gain of the observer is attempted to create and evaluate the residual signal in the presence of the fault. For this purpose, the input of the system is considered a unit step. The $0.5(1+\sin t)$ and $0.2(1-\sin t)$ signals are considered system states time variable delay and its input, respectively. Unknown entries are used in the form of white Gaussian noise with a power of 0.005 and disturbance as $t/(1+t^2)$ in the simulation.

The fault event considered in this paper is a triangular pulse which is shown in Figure (1). As can be seen, the fault was applied to the system within 4 to 6 seconds of simulation, with the amplitude of 0.5.

Applying such a fault event to the system, assuming that the decision variables are measurable, creates a residual signal as shown in Figure (2). Also, in order to evaluate the designed residual signal, a criterion is presented in [17]. This comparable criterion can be calculated by solving an LMI in order to obtain it. The selection of this criterion is logically related to the structure of the residual signal, and therefore, the correct and reliable criterion in the evaluation of the residual and fault detection. According to Figure (2), shortly after the fault occurs, the evaluation criterion exceeds the threshold and the fault occurs. In the continuation of simulating this article, it is assumed that the decision variables are immeasurable, and finally, the signal remains and the evaluation criterion in diagnosing the occurrence of the fault event is shown in Figure (3). The results indicate the detection of a fault shortly after occurrence in the system. The reason for the short delay created in the evaluation criterion goes back to the first derivative of the fault. As can be seen, there was both a fault and a derivative in the formation of the residual signal, since the derivative of the triangular signal is a small, there is a little delay in detecting the fault. If the fault is selected as a square pulse with a large derivative in the 4th second of the simulation, the occurrence of the fault is immediately recognized, which is not provided here due to the limitations of the pages of this article.

4. CONCLUSION

Due to the importance of T-S fuzzy systems in modeling nonlinear systems, the topic of observer design for this category of systems was presented in this article. In using T-S fuzzy systems, decision-making variables and how to select them are important; So that if they are not well selected, a good model for nonlinear systems will not be created. In this regard, in this article, in order to better model systems, system states are considered as decision variables of activation functions. If these variables are immeasurable, this choice will create a complex design process. Also, in order to create an optimal residual signal that has the highest sensitivity to the fault event and the least sensitivity to the unknown input, the H_∞ / H optimization criterion was used. The result was the creation of two theorems in the design of the observer, which provided the necessary conditions for the creation of the observer based on the LMI. Generalize the results in the event that parametric uncertainties are considered. Using this method in designing other observers such as the slider model observer, using the model adaptation method, as well as selecting other optimization criteria can be used as an extension. Consider the method presented in this article.

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