Reliable sampled-data fuzzy control for nonlinear systems

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Abstract: This study seeks to provide solutions to the main challenges that arise when dealing with non-linear systems, including uncertainty, external disturbances, and actuator failures. It focuses on solving the reliable sampled-data control problem by proposing a fuzzy output feedback control procedure for nonlinear systems prone to external disturbances and failures of actuators. In this study, the actuator fault model that involves linear and nonlinear terms is adopted, and a reliable sampled-data fuzzy static output feedback (SOF) controller is designed. Based on an appropriate Lyapunov–Krasovskii functional, delay-dependent sufficient conditions are established such that the closed-loop system is stable with a γ level of H_∞ performance against external disturbances. Furthermore, using the decoupling matrix procedure, a set of linear matrix inequalities (LMIs) is formulated to synthesize the controller gains. Finally, The theoretical developments are illustrated through numerical simulations cornering the stability of the vehicle lateral dynamics and the stabilization of Lorenz chaotic system.

Keywords: (TS) fuzzy model, reliable sampled-data control, H_∞ performance, static output feedback, LMI

1. INTRODUCTION

Systems and control theory presents a number of challenges involved in the design and analysis of nonlinear systems. To cope with class of systems, fuzzy logic might come up with an innovative solution for the design analysis and control synthesis of various industrial plants. Alternatively, Takagi–Sugeno (TS) fuzzy models exhibit excellent ability to express nonlinear systems through the combination of fuzzy logic and linear control theories Takagi and Sugeno (1985). Therefore, the application of the (TS) fuzzy model greatly expands the research field of nonlinear control theory. As a result, a rich literature related to controller design, filtering design, and stability analysis on (TS) have been published Shi et al. (2020); Makni et al. (2019); Tao et al. (2018); Kchaou et al. (2018).

Sampled-data control is particularly important for embedded digital systems, where multiple tasks need to be performed with a minimum level of operation load. To reduce the number of shared signals, a sampling interval threshold is determined by the sampling data control scheme. Hence, sampled data control has become an interesting control topic, since it exhibits many advantages, such as high reliability, lower computational burden, low implementation cost, and easy implementation Gao and Chen (2007); Zhang et al. (2021); Tang and Ma (2021). In terms of feedback control, a sampling procedure leads to a time-delay closed-loop system, and a variety of sampled-data control issues have been addressed by employing the time-dependent Lyapunov functional approach. In the quoted papers, the sampled-data control problem for (TS) fuzzy models have been tackled Kang and Lee (2018); Wang et al. (2018a); Jin et al. (2021); Wang and Wu (2015)

Another issue with feedback control is that, as industrial engineering has progressed, many practical plants have become highly complicated, and, in addition, various environmental factors have become more relevant, such as sudden changes in working conditions, corroded internal components, and aged sensors and actuators. Because actuator/sensor failures can have a negative impact on system performance, control communities are interested about this control problem. The goal of this issue is to introduce the concept of fault-tolerant control (FTC) and fault diagnosis as critical approaches for designing reliable controllers that are capable of maintaining the critical functionality of systems subject to problems and failures. Reviewing the literature, many elegant reported results related to this area have been proposed for different classes of systems Wang et al. (2018b); Kchaou et al. (2021); Yan et al. (2019). To mention a few, Kavarian et al develop a method for designing fault-tolerant controllers for power systems subject to random changes and actuator failures in Kaviarasan et al. (2016). The FTC method for wind-diesel hybrid systems with time-varying bounded sensor faults has been proposed in Kamal et al. (2013). In Wang et al. (2015b), the reliable observer-based control problem for discrete-time Takagi-Sugeno fuzzy systems with time-varying delay and stochastic actuator faults is formulated from the input-output approach.

In modern applications, it is often not possible to have knowledge to all state variables, and only partial data is available via measured outputs. The static output-feedback controller is often investigated as an alternative to control engineering processes Latrech et al. (2018); Kang and Lee (2018).

Having been inspired by the statements above, this article contributes reliable control schemes for non-linear systems. In real-world applications, external disturbances and actuator malfunctions can disrupt systems, and the control scheme is designed to handle these problems. Using (TS) fuzzy models in combination with sampled data, we aim to develop a fuzzy SOF control law for partially measured systems. The main contributions of this paper are highlighted as follows:

(1) Instead of existing fuzzy static output control schemes Latrech et al. (2018); Kang and Lee (2018), this study introduces a new model of the fault including a nonlinear part to deal with reliable sampled-data control problem for (TS) fuzzy systems subject to exogenous disturbance, and nonlinear actuator faults.
(2) Based on non-quadratic Lyapunov functional, sufficient conditions for stability with H_∞ performance of the resulting closed-loop system are derived.
(3) Different to the results suggested in Latrech et al. (2018); Kang and Lee (2018), where the descriptor-redundancy scheme is adopted to design the SOF controller, this study investigates the decoupling matrix procedure to cope with bi-linear matrix conditions. Moreover, the design conditions are derived as a one-step LMI problem without ensuing equality constraints.

Having been inspired by the statements above, in this article, the reliable sampled-data control H_∞ static output feedback control problem for nonlinear systems with exogenous disturbance and actuator faults will be investigated. The main contributions of this paper are highlighted as follows:

(1) Instead of existing fuzzy static output control schemes Latrech et al. (2018); Kang and Lee (2018), this study introduces a new model of the fault including a nonlinear part to deal with reliable sampled-data control problem for (TS) fuzzy systems subject to exogenous disturbance, and nonlinear actuator faults.
(2) Based on non-quadratic Lyapunov functional, sufficient conditions for stability with H_∞ performance of the resulting closed-loop system are derived.
(3) Different to the results suggested in Latrech et al. (2018); Kang and Lee (2018), where the descriptor-redundancy scheme is adopted to design the SOF controller, this study investigates the decoupling matrix procedure to cope with bi-linear matrix conditions. Moreover, the design conditions are derived as a one-step LMI problem without ensuing equality constraints.

Notations: The notations used in this paper are standard, where $X \in \mathbb{R}^n$ is the set of $n-$dimensional Euclidean space; $X \in \mathbb{R}^{n\times m}$ is the set of $n \times m$ real matrices; $X > 0$ is the real symmetric positive definite matrix; $sym(X)$ stands for $X + X^T$. It is noted also $X_\rho = \sum_{i=1}^{r} \rho_i$, $X_{\rho\rho} = \sum_{i=1}^{r}\sum_{j=1}^{r} \rho_i\rho_j X_{ij}$, and $\dot{X}_\rho = \sum_{i=1}^{r} \dot{\rho}_l X_l$, $*$ denotes the term that is induced by symmetry.

2. SYSTEM DESCRIPTION AND PRELIMINARIES

In this paper, the classs of non-linear systems described by the following (TS) fuzzy model is considered:

Plant rule i :

IF $\theta_1(t)$ is M_{i1} and $\cdots$ $\theta_s(t)$ is M_{is} THEN

$$\begin{cases} \dot{x}(t) = A_i x(t) + B_{2i} u^f(t) + B_{1i} w(t) \\ z(t) = C_{1i} x(t) + D_{1i} w(t) \\ y(t) = C_{2i} x(t) \end{cases} \tag{1}$$

where $\theta(t) = [\theta_1(t),\ \theta_2(t),\ \cdots \theta_s(t)]$ is the premise variable, and $Mij(i = 1, \cdots, r, j = 1, \cdots, s)$ are the fuzzy sets. r denotes the index number of the fuzzy rules. $x(t) \in \mathbb{R}^n$ is the state vector, $u^f(t) \in \mathbb{R}^m$ is the control input vector, $y(t) \in \mathbb{R}^q$ is the measured output, $w(t) \in \mathbb{R}^w$ is exogenous disturbance input taking value in L_2, and $z(t)$ is control output. A_i, B_{2i}, B_{1i}, C_{1i}, D_{1i} and C_{2i} are constant matrices with appropriate dimensions. Assume that matrix C_{2i} is row full rank.

By using the inference method, the (T-S) fuzzy system can be inferred as follows:

$$\begin{cases} \dot{x}(t) = \displaystyle\sum_{i=1}^{r} \rho_i(\theta(t)) \Big\{ A_i x(t) + B_{2i} u^f(t) + B_{1i} w(t) \Big\} \\ z(t) = \displaystyle\sum_{i=1}^{r} \rho_i(\theta(t)) \Big\{ C_{1i} x(t) + D_{1i} w(t) \Big\} \\ y(t) = \displaystyle\sum_{i=1}^{r} \rho_i(\theta(t)) C_{2i} x(t) \end{cases} \tag{2}$$

where $\rho_i(\theta(t)) = \frac{\varrho_i(\theta(t))}{\sum_{i=1}^{r} \varrho_i(\theta(t))}$, and $\varrho_i(\theta(t)) = \prod_{j=1}^{s} M_{ij}(\theta_j)$.

Thus, the normalized membership functions satisfy that

$$\rho_i(\theta(t)) \in [0\ 1],\ \sum_{i=1}^{r} \rho_i(\theta(t)) = 1$$

In this paper, it is assumed that the control signal is generated from the digital controller and transmitted to the physical plant. The control message is assumed to be generated by the ZOH where the sampling instant t_k satisfies $0 = t_0 < t_1 < \cdots < t_k < \cdots < \lim_{k\longrightarrow\infty} t_k = \infty$. Defining the variable sampling interval within upper bounds as follows:

$$0 \le h_k = t_{k+1} - t_k \le \hbar \tag{3}$$

The following state feedback controller is introduced

$$u(t_k) = \sum_{i=1}^{r} \rho_i(\theta(t_k)) K_i y(t_k),\ t_k \le t < t_{k+1} \tag{4}$$

where K_i is the controller gain to be designed.

Assume that the actuator failure happens. The following new actuator fault input model, that involves linear and nonlinear terms, is used :

$$u^f(t) = \Omega u(t) + \Phi\phi(u(t)) \quad (5)$$

where $0 < \Omega \leq 1$ stand for the actuator fault matrix, and $\phi(u(t))$ is a nonlinear vector function satisfying:

$$\phi^T(u(t))\phi(u(t)) \leq \sigma^2 u^T(t)H^T H u(t) \quad (6)$$

where H is a matrix with appropriate dimension.

By denoting

$$0 \leq h(t) = t - t_k \leq \hbar \quad (7)$$

the closed-loop system can be written as

$$\begin{aligned}\dot{x}(t) = &\sum_{i=1}^{r}\sum_{j=1}^{r}\rho_i(\theta(t))\rho_j(\theta(t_k))\Big(A_i x(t) \\ &+ B_{2i}\Omega K_j C_{2j} x(t-h(t)) + B_{2i}\Phi\phi(u(t_k)) + B_{1i}w(t)\Big), \\ &t_k \leq t < t_{k+1}\end{aligned} \quad (8)$$

equivalently, one gets

$$\begin{aligned}\dot{x}(t) = &A_\rho x(t) + A^{\hbar}_{\rho\rho_k} x(t-h(t)) + B_{2\rho}\Phi\phi(u(t_k)) + B_{1\rho}w(t) \\ &t_k \leq t < t_{k+1}\end{aligned} \quad (9)$$

where $A^{\hbar}_{\rho\rho_k} = \sum_{i=1}^{r}\sum_{j=1}^{r}\rho_i(\theta(t))\rho_j(\theta(t_k))B_{2i}\Omega K_j C_{2j}$ Two cases can be obtained according to model (5)

(1) If $\Omega = 1$, and $\Phi = 1$, the actuator is working in normal mode.
(2) If $\Omega \neq 1$, and $\Phi \neq 1$ the actuator is working in failure mode.

It is important that the sampling period of the network be chosen carefully, because it plays an essential role in cutting down the transmission of useless and inefficient messages and speeding up network transmission. Thus, a larger sampling period results in fewer unnecessary messages becoming transmitted. This is accomplished by using the memory sampled-data control, which has a longer sampling period. Moreover, a time-varying sampling period with an upper bound is generally investigated in the sampling process to reduce the transmission of useless messages.

Before giving our main results, the following useful lemmas are introduced.

Lemma 1. Latrech et al. (2018) For given symmetrical matrices $X_{ij} > 0$, the following condition holds

$$\sum_{i=1}^{r}\sum_{j=1}^{r}\rho_i\rho_j^k X_{ij} = \sum_{i=1}^{r}\sum_{j=1}^{r}\rho_i^2\bar{X}_{ii} + \sum_{i=1}^{r}\sum_{j>i}^{r}\rho_i\rho_j(\bar{X}_{ij} + \bar{X}_{ji}) \quad (10)$$

where $\bar{X}_{ij} = X_{ij} + \sum_{k=1}^{r}\tau_k X_{ik}$ and τ_k is known Lipschitz constants, satisfing the following condition $|\rho_i^k - \rho_i| \leq \tau_i$.

Lemma 2. For any positive matrix M, vector $\dot{x}() : [\hbar, 0] \to \mathbb{R}^n$, and $\begin{bmatrix} M & N \\ * & M\end{bmatrix} \geq 0$, the following inequality holds:

$$\begin{aligned}&-\hbar\int_{t-\hbar}^{t}\dot{x}^T(s)M\dot{x}(s)\mathrm{d}s \\ &\leq \aleph^T(t)\begin{bmatrix} -M & M-N & N \\ * & -2M+sym(N) & M-N \\ * & * & -M\end{bmatrix}\aleph(t)\end{aligned}$$

where $\aleph(t) = [x^T(t)\ x^T(t-h(t))\ x^T(t-\hbar)]^T$.

3. MAIN RESULTS

3.1 stability analysis

This subsection of the paper focuses on the development of a reliable H_∞ control law such that the resulting closed-loop system is stable with H_∞ performance.

Theorem 3. For given scalars $\eta_i < 0$, and λ, closed-loop system (8) is stable with H_∞ performance γ, if there exist matrices $P_i > 0$, $Q_i > 0$, $R_i > 0$, N_i, Z and scalars $\varepsilon_{1i} > 0$ and $\gamma > 0$ such that the following inequalities hold for $i, j, l = 1, 2, \cdots, r$:

$$\begin{bmatrix} R_i & N_i \\ * & R_i\end{bmatrix} > 0 \quad (11)$$

$$P_i + Z \geq 0 \quad (12)$$

$$\Psi^l_{ij} = \begin{bmatrix} \Psi^l_{11ij} & \Psi_{12ij} & N_i & \varepsilon_{1i}B_{2i}\Phi & B_{1i} & P_iC_i^T & \Psi_{17ij} & 0 \\ * & \Psi_{22i} & \Psi_{23i} & 0 & 0 & 0 & \Psi_{27ij} & \Psi_{28ij} \\ * & * & \Psi_{33i} & 0 & 0 & 0 & 0 & 0 \\ * & * & * & \varepsilon_{1i}I & 0 & & \Psi_{47ij} & 0 \\ * & * & * & * & -\gamma I & D_i^T & \hbar B_{1i}^T & 0 \\ * & * & * & * & * & -\gamma I & 0 & 0 \\ * & * & * & * & * & * & \Psi_{77i} & 0 \\ * & * & * & * & * & * & * & -\varepsilon_{1i}I\end{bmatrix} < 0, \quad (13)$$

where $\Psi^l_{11ij} = -\sum_{l=1}^{2}\eta_l(P_l + Z) + sym(A_iP_i)$, $\Psi_{12ij} = B_{2i}\Omega K_j C_{2j}P_i + R_i - N_i$, $\Psi_{22i} = -2R_i + sym(N_i)$, $\Psi_{23i} = R_i - N_i$, $\Psi_{33i} = -R_i - Q_i$, $\Psi_{17i} = \hbar(A_iP_i)^T$, $\Psi_{27ij} = \hbar(B_{2i}\Omega K_j C_{2j}P_i)^T$, $\Psi_{47ij} = (\hbar B_{2i}\Phi)^T$ $\Psi_{77i} = 2\lambda P_i - \lambda^2 R_i$, $\Psi_{28ij} = (\sigma H K_i C_{2j}P_i)^T$.

Proof. To address the stability analysis the following non-quadratic fuzzy Lyapunov function is introduced:

$$\begin{aligned}V(t) &= V_1(t) + V_2(t) \\ V_1(t) &= x^T(t)P_\rho^{-1}x(t) \\ V_2(t) &= \hbar\int_{t-\hbar}^{t}x^T(s)Qx(s)\,\mathrm{d}s \\ &+ \hbar\int_{-\hbar}^{0}\int_{t+s}^{t}\dot{x}^T(\upsilon)R\dot{x}(\upsilon)\,\mathrm{d}\upsilon\mathrm{d}s\end{aligned} \quad (14)$$

The evaluation of $\dot{V}_1(t)$ onward the solutions of system (8), provides

$$\begin{aligned}\dot{V}_1(t) &= 2x^T(t)P_\rho^{-1}\dot{x}(t) + x^T(t)\dot{P}_\rho^{-1}x(t) \\ &= 2x^T(t)P_\rho^{-1}\big(A_\rho x(t) + A^{\hbar}_{\rho\rho_k}x(t-h(t)) + B_{2\rho}\Phi\phi(u(t_k)) \\ &+ B_{1\rho}w(t)\big)x(t) - x^T(t)P_\rho^{-1}\dot{P}_\rho P_\rho{}^{-1}x(t) \\ \dot{V}_2(t) &= x^T(t)Qx(t) - x^T(t-\hbar)Qx(t-\hbar) \\ &+ \hbar^2\dot{x}^T(t)R\dot{x}(t) - \hbar\int_{t-\hbar}^{t}\dot{x}^T(\upsilon)R\dot{x}(\upsilon)\,\mathrm{d}\upsilon\end{aligned} \quad (15)$$

According to Lemma 2, one knows that

$$
\begin{aligned}
&-\hbar\int_{t-\hbar}^{t}\dot{x}^T(s)R\dot{x}(s)\mathrm{d}s\\
&\leq \aleph^T(t)\begin{bmatrix}-R & R-N & N\\ * & -2R+sym(N) & R-N\\ * & * & -R\end{bmatrix}\aleph(t)
\end{aligned}
$$

where $\aleph(t) = [x^T(t)\ x^T(t-h(t))\ x^T(t-\hbar)]^T$.

On the other hand, it is easy to deduce from $\sum_{i=1}^{r}\rho_i = 1$ that $\sum_{i=1}^{r}\dot{\rho}_i = 0$. Thus, for any matrix Z, the following equation holds

$$
\sum_{i=1}^{r}\dot{\rho}_i {P_\rho}^{-T} Z {P_\rho}^{-1} = P_\rho^{-1}\dot{Z}{P_\rho}^{-1} = 0 \tag{16}
$$

Based on the condition in (6), inequality (17) holds for any scalar $\varepsilon_{1h} > 0$:

$$
\begin{aligned}
&-\varepsilon_{1h}^{-1}\phi^T(u(t))\phi(u(t))\\
&+\varepsilon_{1h}^{-1}\sigma^2 x^T(t-h(t))(K_\rho C_{2\rho})^T H^T H(K_\rho C_{2\rho})x(t-h(t)) \geq 0
\end{aligned} \tag{17}
$$

Here, our main intention is to examine the H_∞ performasnce for the system in (8). For this purpose, the following index is investigated

$$
J = \int_0^\infty (\gamma^{-1}z^T(s)z(s) - \gamma w^T(s)w(s))ds \tag{18}
$$

Defining $J_{zw}(t) = \gamma^{-1}z^T(t)z(t) - \gamma w^T(t)w(t)$. Accordingly, by combining (15)-(17), it can be concluded that

$$
\dot{V}(x(t)) + J_{zw}(t) = \xi(t)\Psi^\rho_{\rho\rho_k}\xi(t) \tag{19}
$$

where $\xi(t) = [x^T(t)\ x^T(t-h(t))\ x^T(t-\hbar)\ \phi^T(u(t_k))\ w^T(t)]^T$,

$$
\Psi^\rho_{\rho\rho_k} = \begin{bmatrix}
\Psi^\rho_{11_{\rho\rho}} & \Psi_{12\rho\rho_k} & N & P_\rho^{-1}B_{2\rho}\Phi & P_\rho^{-1}B_{1\rho}\\
* & \Psi_{22\rho\rho_k} & R-N & 0 & 0\\
* & * & -R-Q & 0 & 0\\
* & * & * & -\varepsilon_{1\rho}^{-1}I & 0\\
* & * & * & * & -\gamma I
\end{bmatrix} \tag{20}
$$

$$
+\gamma^{-1}\begin{bmatrix}C_\rho^T\\0\\0\\0\\D_\rho^T\end{bmatrix}\begin{bmatrix}C_\rho^T\\0\\0\\0\\D_\rho^T\end{bmatrix}^T + \begin{bmatrix}A_\rho^T\\(A^\hbar_{\rho\rho_k})^T\\0\\B_{2\rho}^T\Phi\\B_{1\rho}^T\end{bmatrix} R \begin{bmatrix}A_\rho^T\\(A^\hbar_{\rho\rho_k})^T\\0\\B_{2\rho}^T\Phi\\B_{1\rho}^T\end{bmatrix}^T
$$

$\Psi^\rho_{11\rho\rho} = sym(P_\rho^{-1}A_\rho) - P_\rho^{-1}(\dot{P}_\rho + \dot{Z}){P_\rho}^{-1} - R + Q$, $\Psi_{12\rho\rho_k} = R - N + P_\rho^{-1}A^\hbar_{\rho\rho_k}$, and $\Psi_{22\rho\rho_k} = -2R + sym(N) + \varepsilon_{1\rho}^{-1}\sigma^2(K_\rho C_{2\rho})^T H^T H(K_\rho C_{2\rho})$

Assuming that $\dot{\rho}_l \geq \eta_l$. By performing the congruence transformation to (13) by $diag\{P_i^{-1},\ P_i^{-1},\ P_i^{-1}\ \varepsilon_{1h}^{-1}I, I,\ I\}$, and using the fact $(\lambda P_i - R^{-1})^T R(\lambda P_i - R^{-1}) \geq 0$, one gets $-R^{-1} \leq 2\lambda P_i - \lambda^2 R_i$ and

$$
\begin{bmatrix}
\Psi^\rho_{11\rho\rho} & \Psi_{12\rho\rho_k} & N & P_\rho^{-1}B_{2\rho}\Phi & P_\rho^{-1}B_{1\rho} & C_\rho^T & (A_\rho)^T & 0\\
* & \Psi_{22\rho\rho_k} & R-N & 0 & 0 & 0 & (A^\hbar_{\rho\rho_k})^T & (\sigma H K_\rho C_{2\rho})^T\\
* & * & -R & -Q & 0 & 0 & 0 & 0\\
* & * & * & -\varepsilon_{1\rho}^{-1}I & 0 & 0 & B_{2\rho}^T\Phi & 0\\
* & * & * & * & -\gamma I & D_\rho^T & B_{1\rho}^T & 0\\
* & * & * & * & * & -\gamma I & 0 & 0\\
* & * & * & * & * & * & -R^{-1} & 0\\
* & * & * & * & * & * & * & -\varepsilon_{1\rho}I
\end{bmatrix} \tag{21}
$$

Then, the Schur Complement Lemma produces $\Psi^\rho_{\rho\rho_k} < 0$, and

$$
J \leq \int_0^\infty \left(\dot{V}(t) +\ J_{zw}(s)\right)ds < 0 \tag{22}
$$

Moreover, for $w(t) = 0$, it can be deduced that $\dot{V}(t) < 0$. Hence, it can be concluded that the closed-loop system is stable and acheive a γ level of the H_∞ performance.

Remark 4. Theorem 3 establishes the existence of the controller such that the closed-loop system is robustly stable with a γ level of H_∞ performance against external disturbances. Due to the nonlinear nature of condition (13) in the theorem, it cannot be solved with existing LMI solvers. The next section demonstrates the decoupling matrix procedure to design the controller and overcoming the BMI terms in (13).

3.2 Controller design

Theorem 5. For given scalars $\eta_i < 0$, λ, and α, closed-loop system (8) is stable with H_∞ performance γ, if there exist matrices $P_i > 0$, $Q_i > 0$, $R_i > 0$, N_i, W_i, Z and scalars $\varepsilon_{1i} > 0$ and $\gamma > 0$ such that the following inequalities hold for $i, j, l = 1, 2, \cdots, r$:

$$
\begin{bmatrix}R_i & N_i\\ * & R_i\end{bmatrix} > 0 \tag{23}
$$

$$
P_i + Z \geq 0 \tag{24}
$$

$$
\tilde{\Psi}^l_{ii} < 0 \tag{25}
$$

$$
\tilde{\Psi}^l_{ij} + \tilde{\Psi}^l_{ji} < 0 \tag{26}
$$

where $\tilde{\Psi}_{ji} = \sum_{k=1}^{r}\tau_k\bar{\Psi}^l_{ik} + \bar{\Psi}^l_{ij}$.

$$
\bar{\Psi}^l_{ij} =
$$

$$
\begin{bmatrix}
\Psi^l_{11ij} & \bar{\Psi}_{12ij} & N_i & \varepsilon_{1i}B_{2i}\Phi & B_{1i} & P_iC_i^T & \Psi_{17ij} & 0 & \bar{\Psi}_{19ij}\\
* & \Psi_{22i} & \Psi_{23i} & 0 & 0 & 0 & \bar{\Psi}_{27ij} & \bar{\Psi}_{28ij} & \bar{\Psi}_{29ij}\\
* & * & \Psi_{33i} & 0 & 0 & 0 & 0 & 0 & 0\\
* & * & * & \varepsilon_{1i}I & 0 & & \Psi_{47ij} & 0 & 0\\
* & * & * & * & -\gamma I & D_i^T & B_{1i}^T & 0 & 0\\
* & * & * & * & * & -\gamma I & 0 & 0 & 0\\
* & * & * & * & * & * & \Psi_{77i} & 0 & B_{2i}\Omega Y_j\\
* & * & * & * & * & * & * & -\varepsilon_{1i}I & \sigma H Y_j\\
* & * & * & * & * & * & * & * & \bar{\Psi}_{99j}
\end{bmatrix}
$$

where $\bar{\Psi}_{12ij} = B_{2i}\Omega Y_j C_{2j} + R_i - N_i$, $\bar{\Psi}_{27ij} = (B_{2i}\Omega Y_j C_{2j})^T$, $\bar{\Psi}_{28ij} = (\sigma H Y_j C_{2j})^T$. $\bar{\Psi}_{19ij} = B_{2i}\Omega Y_j$, $\bar{\Psi}_{29ij} = \alpha(C_{2j}P_i -$

$W_jC_{2j})^T$ and $\bar{\Psi}_{99j} = -\alpha(W_j + W_j^T)$. Furthermore, the controller gain is calculated by $K_i = Y_iW_i^{-1}$.

Proof. According to Lemma 1, one has

$$\sum_{l=1}^{r}\rho_l\sum_{i=1}^{r}\sum_{j=1}^{r}\rho_i\rho_j^k\bar{\Psi}_{ij}^l < 0 \tag{27}$$

Let $\mathbb{T} = \begin{bmatrix} I_{8\times 8} \\ W_j^{-1}(C_{2j}P_i - W_jC_{2j}) \;\; 0_{1\times 7}\end{bmatrix}$. By performing the congruence transformation, one easily gets

$$\Psi_{ij}^l = \mathbb{T}^T\bar{\Psi}_{ij}^l\mathbb{T} < 0 \tag{28}$$

using the following terms $B_{2i}\Omega Y_jC_{2j} + B_{2i}\Omega Y_jW_j^{-1}(C_{2j}P_i - W_jC_{2j}) = B_{2i}\Omega K_jC_{2j}P_i$,
$\sigma HY_jC_{2j} + \sigma HY_jW_j^{-1}(C_{2j}P_i - W_jC_{2j}) = \sigma HK_jC_{2j}P_i$, and $Y_i = K_iW_i$.

Thus, in view of Theorem 3, closed-loop system (8) is stable with a γ level of H_∞ performance for all $0 \neq w(k) \in L_2[0,\infty)$.

Note that the optimal performance index γ^* for H_∞ performance can be obtained by solving the following optimization problem :

$$\begin{array}{l}\min\gamma \\ \text{s.t, LMIs } (23) - (25)\end{array} \tag{29}$$

4. SIMULATION RESULTS

Our discussion in this section provides a concise description of the computational framework and illustrates the efficacy and advantages of the proposed control scheme with two examples.

4.1 Computational Framework and Algorithm

The computation experiments are performed on a computer with the following characteristics:(i) [OS] Windows 10 Enterprise for 64 bits; (ii) [RAM] 8 Gigabytes; and (iii) [Processor] Intel(R) Core(TM) i7-4790T CPU @ 2.70 GigaHertz.

A detailed explanation of the detailed procedure is given in Algorithm 1. Using `Yalmip` software and the optimization toolbox `mosek`, the algorithm 1 was executed. Figure 1 displays a flowchart that gives a clear description of the proposed control scheme

Algorithm 1 Procedure design

1: Describe the nonlinear system by the TS fuzzy model .
2: Choose the parameters of the actuator fault model described in (5)-(6).
3: Determine the gains K_j by solving the problem in 29.
4: Apply the designed control law expressed in (4) to the model.

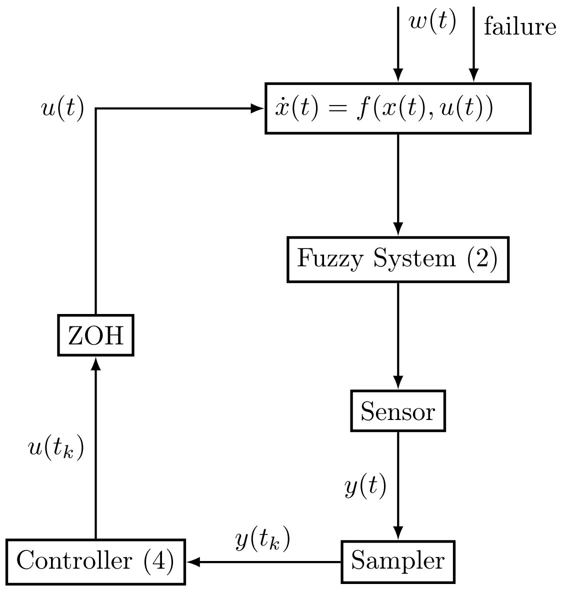


Fig. 1. Flowchart of the control scheme.

4.2 Example 1

With nonlinear tire characteristics of the four wheels vehicle behavior, the model of the vehicle can defined by the following differential equations Wang et al. (2020, 2015a); Jin et al. (2018); Wang et al. (2016); Latrech et al. (2018)

$$\begin{cases}\dot{\beta} = \dfrac{2F_f + 2F_r}{mV} - \Omega_z \\ \dot{\Omega}_z = \dfrac{2l_fF_f - 2l_rF_r + M_z}{J_z}\end{cases} \tag{30}$$

Where β denotes the slide slip angle, Ω_z is the yaw velocity, F_f is the nonlinear cornering force of the two front tires, F_r is the nonlinear cornering force of the two rear tires and M_z is yaw moment. V is the vehicle velocity, J_z is the yaw moment of inertia, m is the vehicle mass.

Using the (TS) fuzzy approach, the forces F_f and F_r can be described as follows Latrech et al. (2018) :

$$\begin{cases}F_f = \rho_1(|\alpha_f|)C_{f1}\alpha_f + \rho_2(|\alpha_f|)C_{f2}\alpha_f \\ F_r = \rho_1(|\alpha_f|)C_{r1}\alpha_r + \rho_2(|\alpha_f|)C_{r2}\alpha_r\end{cases} \tag{31}$$

where $\rho_i(i = 1, 2)$ identify the bell membership functions as below:

$$\rho_1(\alpha_f) = \frac{\omega_1(\alpha_f)}{\omega_1(\alpha_f) + \omega_2(\alpha_f)}, \quad \rho_2(\alpha_f) = \frac{\omega_2(\alpha_f)}{\omega_1(\alpha_f) + \omega_2(\alpha_f)}, \tag{32}$$

$$\omega_1(\alpha_f) = \frac{1}{(1 + |\frac{|\alpha_f| - C_1}{a_1}|)^{2b_1}}, \quad \omega_2(\alpha_f) = \frac{1}{(1 + |\frac{|\alpha_f| - C_2}{a_2}|)^{2b_2}}. \tag{33}$$

α_f, α_r are the front and rear tire side slip which can be determined using thre following expression:

$$\begin{cases}\alpha_f \cong -\beta - \dfrac{l_f\Omega_z}{V} + \delta_f \\ \alpha_r \cong -\beta - \dfrac{l_r\Omega_z}{V}\end{cases} \tag{34}$$

Thus, the following (TS) fuzzy model for the vehicle lateral dynamic is obtained:

$$
\begin{cases}
\dot{x}(t) = \sum_{i=1}^{2} \rho_i(\alpha_f)\{A_i x + B_{2i}u(t) + B_{1i}w(t)\} \\
z(t) = \sum_{i=1}^{2} \rho_i(\alpha_f) C_{1i}x(t) \\
y(t) = \sum_{i=1}^{2} \rho_i(\alpha_f)\{C_{2i}x(t)\}
\end{cases} \tag{35}
$$

where $x(t) = \left[\beta^T \;\; \Omega_z^T\right]^T$, $u(t) = M_z$, $w(t) = \delta_f$

$$
\begin{aligned}
&A_i = \begin{bmatrix} -2\frac{C_{fi}+C_{ri}}{mV} & -2\frac{C_{fi}l_f - C_{ri}l_r}{mV^2} - 1 \\ -2\frac{C_{fi}l_f - C_{ri}l_r}{J_z} & -2\frac{C_{fi}l_f^2 + C_{ri}l_r^2}{J_z V} \end{bmatrix}, \\
&B_{1i} = \begin{bmatrix} 2\frac{C_{fi}}{mV} \\ 2\frac{a_f C_{fi}}{J_z} \end{bmatrix}, \; B_{2i} = \begin{bmatrix} 0 \\ \frac{1}{J_z} \end{bmatrix}, \; C_{2i} = [0 \;\; 1]\,, i = 1, 2 \\
&C_{11} = C_{12} = [0.1 \;\; 0]\,, \; D_{11} = D_{12} = 0.1
\end{aligned} \tag{36}
$$

Assume that the parameters of the model are selected from Latrech et al. (2018) as $m = 1740kg$, $I_z = 3000kg.m^2$, $l_r = 1.3$ $l_f = 1.2$ and $V = 20m/s$. For $\mu = 0.7$ the parameters of membership functions are $a_1 = 0.0908$, $a_2 = 23.3421$, $b_1 = 0.7237$, $b_2 = 204.0533$, $c_1 = 0.0415$, $c_2 = 23.4094$, $C_{f1} = 1.6354 \times 10^5$, $C_{f2} = 0.0317 \times 10^5$, $C_{r1} = 1.4226 \times 10^5$, $C_{r2} = 0.0198 \times 10^5$.

By selecting $\lambda = 0.1$, $\alpha = 1270$, $\eta_1 = \eta_2 = -0.1$, the optimization problem in (29) produces a feasible solution with $\gamma^* = 3.1392$ and the the following parameters:

$$K_1 = -8716.6, \quad K_2 = -81445 \tag{37}$$

For simulation, the range of actuator fault matrix is $\Omega = 0.6$, the nonlinear fault function is selected as $\phi(u(t_k)) = 0.1sin(4u(t_k))$, and the initial condition is $x_0(t) = [0.01 \;\; 0.1]^T$.

According to Figure2, the proposed control strategy ensures that states do not diverge and the dynamic stability of the vehicle is maintained by reducing the effect of the-sideslip angle and yaw rate. However, using the following gains proposed in Latrech et al. (2018)

$$K_1 = -8716.6, \quad K_2 = -81445 \tag{38}$$

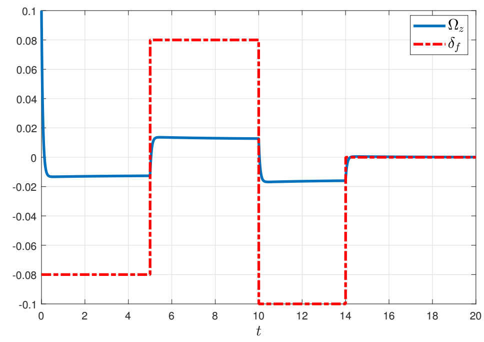
the behavior of the vehicle becomes unstable as shown in 3.

Simulation results suggest that the designed controller stabilises the vehicle system, while the fuzzy static output controller has the benefit of dealing with sampling data constraints as well as exogenous disturbances.

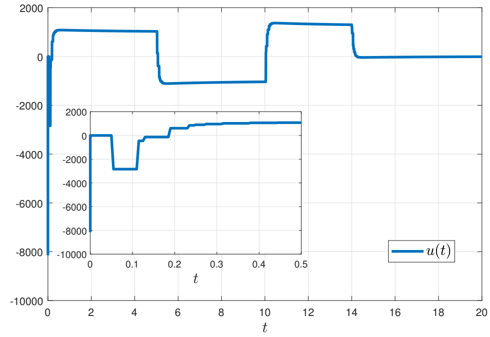
4.3 Example 2

In this example, a simulation for Lorenz system is given by using the proposed method. The dynamic of such a nonlinear system is as follows :

$$
\begin{cases}
\dot{x}_1(t) &= a(x_2(t) - x_1(t)) + u(t) \\
\dot{x}_2(t) &= -cx_1(t) - x_2(t) - x_1(t)x_3(t) \\
\dot{x}_3(t) &= x_1(t)x_2(t) - bx_3(t) + 0.1w(t)
\end{cases} \tag{39}
$$



(a) Ω_z trajectory



(b) M_z trajectory

Fig. 2. Output and input trajectories using controller (37) trajectory

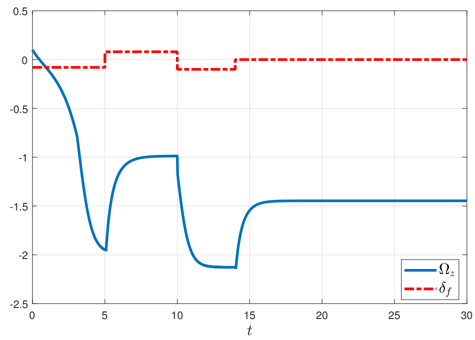


Fig. 3. Output trajectory Ω_z using controller (38)

The system can be expressed by (TS) fuzzy model with the format of 2 by assuming that the state satisfies $x_1(t) \in [-d, d]$, whose parameters are as follows:

$$
\begin{aligned}
&A_1 = \begin{bmatrix} -a & a & 0 \\ c & -1 & -d \\ 0 & d & -b \end{bmatrix}, \; A_2 = \begin{bmatrix} -a & a & 0 \\ c & -1 & d \\ 0 & -d & -b \end{bmatrix}, \\
&B_{21} = B_{22} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \; B_{11} = B_{12} = \begin{bmatrix} 0 \\ 0 \\ 0.1 \end{bmatrix} \\
&C_{21} = C_{22} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, C_{11} = C_{12} = [0.001 \;\; 0 \;\; 0]\,, \\
&D_{11} = D_{12} = 0.1
\end{aligned} \tag{40}
$$

and the membership functions $\rho_1(x_1) = \dfrac{x_1 + d}{2d}$ and $\rho_2(x_1) = 1 - \rho_1(x_1)$. The parameters are given as $a = 10$, $b = 8/3$, $c = 28$ and $d = 25$.

By choosing $\eta_1 = \eta_2 = -0.0001$, $\lambda = 0.1$ and $\alpha = 2000$, using Yalmip's toolbox in conjunction with Mosek's solver the optimization problem in (29) gives feasible solutions for the following to cases:

(1) $\Phi = 1$, and $\sigma = 0$, (Normal case)
(2) $\Phi = 0.6$, and $\sigma = \sqrt{0.1}$, (Failure case)

Methods	controller gains
proposed method for case 1	$K_1 = [-32.438 - 9.3307 \quad 24.279]$ $K_2 = [-42.694 - 7.3989 \quad -31.526]$
proposed method for case 2	$K_1 = [-139.18 - 25.85 \quad 106.18]$ $K_2 = [-236.96 - 26.039 \quad -175.13]$
Jin et al. (2021)	$K_1 = [-17.2296 - 10.0263 \quad 15.0687]$ $K_2 = [-17.2296 - 10.0263 \quad 15.0687]$
Wang and Wu (2015)	$K_1 = [-25.5765 - 15.3958 \quad 10.6585]$ $K_2 = [-25.5765 - 15.3958 \quad 10.6585]$

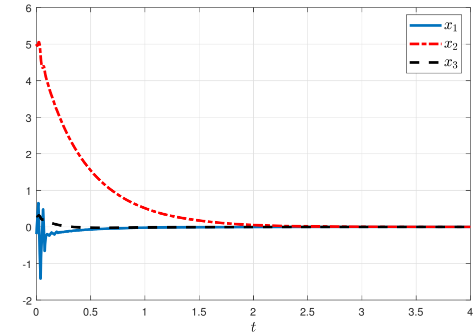
Table 1. Controller gains for diffrent methods

Table 2 provides the controller gains using the proposed method for the both cases and the methods proposed in Jin et al. (2021) and Wang and Wu (2015). From, this table one remarks that the methods in Jin et al. (2021) and Wang and Wu (2015) provides non-fuzzy controllers since the gains are equal. For all methods, the simulations are undergone with the initial condition $x(t) = [-0.2,\ 5,\ -0.3]^T$, and $g(u(t)) = 0.1sin(u(t))$. The results of the numerical simulation analysis are depicted in Figures 6-7, from where it is represented for each method the system states variables. It is observed that, when the reliable control law (case 1) is applied the system dynamics are stabilized despite actuator failures, however, when the control laws are designed without taking into account of the actuator failures as in case 2, Wang and Wu (2015), and Jin et al. (2021), and applied to the system with failures, it can be seen that the performances of the system are degraded. Thus, The simulations validate that the proposed control scheme is effective in accommodating actuator faults in the system.

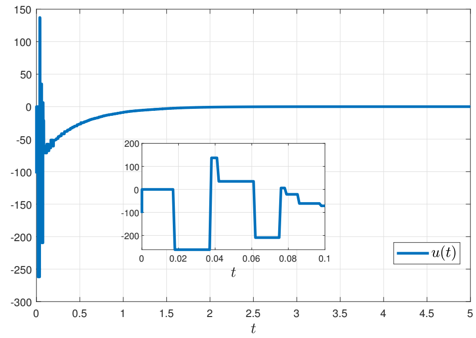
4.4 Comparative Discussion

Multiple studies have been conducted on the control of networked control systems, so several methods can be considered comparable to the approach suggested in this article. Nevertheless, our approach differs in different ways as follows:

- In Hanchevici et al. (2012), a networked control strategy for linear SISO systems affected by variant communication delays was presented. In our approach, the problem is tackled in a more general manner, since it allows us to design fuzzy controllers for MIMO nonlinear systems with uncertain parameters and external disturbances. Despite the constraints outlined above, we believe that the approach in Hanchevici et al. (2012) will not achieve satisfactory performance.
- By incorporating membership function information into fuzzy sampled-data controller design, we obtain less conservative stabilization conditions than previous methods developed in Ge et al. (2014, 2017).



(a) state response $x(t)$



(b) input response $u(t_k)$

Fig. 4. Simulation plots for reliable controller (case 2)

4.5 Limitations

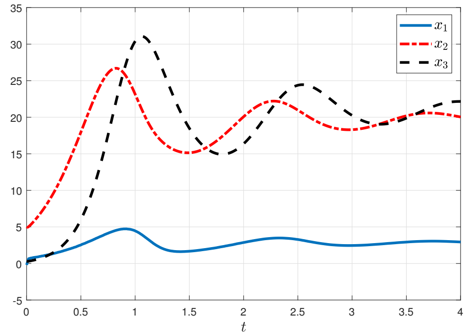
In remark 4, one key aspect in controller scheme design is to overcome bilinear terms with the decoupling matrix technique. It is possible, however, that this approach will result in conservative results. For computing controller gains, a meta-heuristic method can be used to obtain an adequate solution. An approach that implements meta-heuristic optimization is a promising direction for this work Chen et al. (2020).

4.6 Example 2

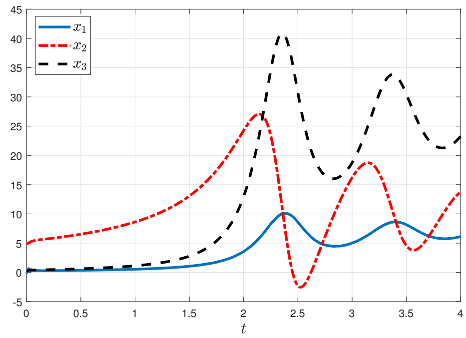
In this example, a simulation for Lorenz system is given by using the proposed method. The dynamic of such a nonlinear system is as follows :

$$\begin{cases} \dot{x}_1(t) &= a(x_2(t) - x_1(t)) + u(t) \\ \dot{x}_2(t) &= -cx_1(t) - x_2(t) - x_1(t)x_3(t) \\ \dot{x}_3(t) &= x_1(t)x_2(t) - bx_3(t) + 0.1w(t) \end{cases} \quad (41)$$

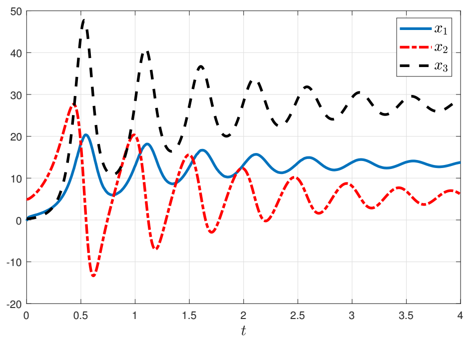
The system can be expressed by (TS) fuzzy model with the format of 2 by assuming that the state satisfies $x_1(t) \in [-d, d]$, whose parameters are as follows:



(a) state response $x(t)$ for case 2



(b) input response $x(t)$ for method Wang and Wu (2015)



(c) state response $x(t)$ for method Jin et al. (2021)

Fig. 5. Simulation plots for non-reliable controllers.

$$
\begin{aligned}
&A_1 = \begin{bmatrix} -a & a & 0 \\ c & -1 & -d \\ 0 & d & -b \end{bmatrix},\ A_2 = \begin{bmatrix} -a & a & 0 \\ c & -1 & d \\ 0 & -d & -b \end{bmatrix}, \\
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&D_{11} = D_{12} = 0.1
\end{aligned} \tag{42}
$$

and the membership functions $\rho_1(x_1) = \dfrac{x_1 + d}{2d}$ and $\rho_2(x_1) = 1 - \rho_1(x_1)$. The parameters are given as $a = 10$, $b = 8/3$, $c = 28$ and $d = 25$.

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4.7 *Comparative Discussion*

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- By incorporating membership function information into fuzzy sampled-data controller design, we obtain less conservative stabilization conditions than previous methods developed in Ge et al. (2014, 2017).

4.8 *Limitations*

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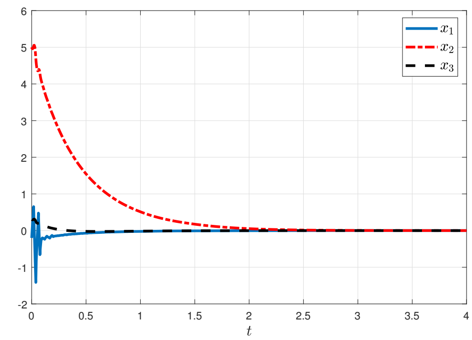
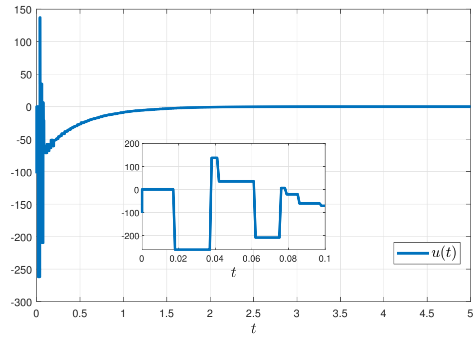


(a) state response $x(t)$



(b) input response $u(t_k)$

Fig. 6. Simulation plots for reliable controller (case 2)

technique. It is possible, however, that this approach will result in conservative results. For computing controller gains, a meta-heuristic method can be used to obtain an adequate solution. An approach that implements meta-heuristic optimization is a promising direction for this work Chen et al. (2020).

5. CONCLUSIONS AND FUTURE WORK

The reliable sampled-data control problem presented in this paper is for nonlinear systems with actuator faults and exgenous disturbance. Among the main results, the main findings are as follows: (i) The model of the fault includes a nonlinear part which is more general than the conventional actuator fault models (ii) The input delay combined with Lyapunov-Krasovskii functional are adopted to deal with the sampled-data control problem where a H_∞ stability criterion has been developed (iii) The decoupling matrix method is investigated to synthesize in one step the reliable static output feedback controller. To conclude, simulation studies have confirmed that the proposed strategy is more effective and less conservative. As part of future research topics, the suggested developments will be extend to non-linear systems with event-triggered control issue.

ACKNOWLEDGMENT

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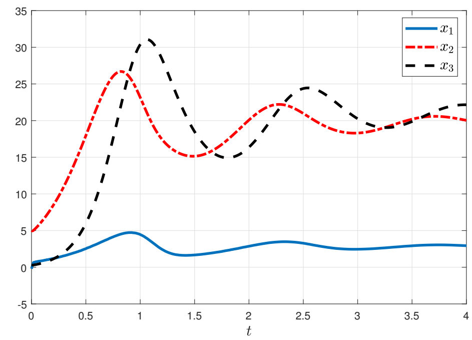
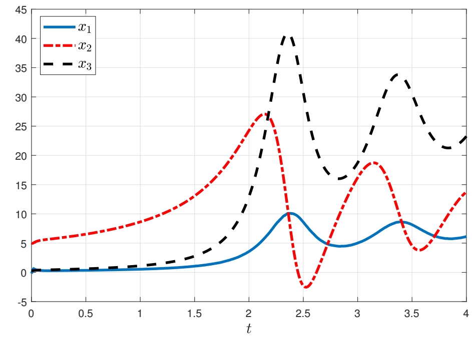
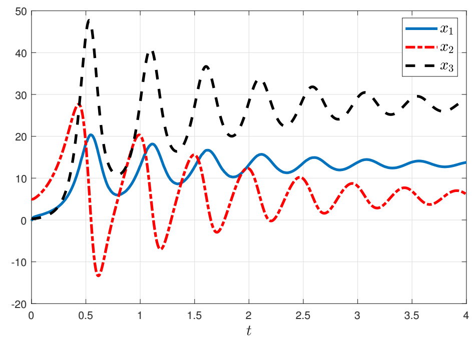


(a) state response $x(t)$ for case 2



(b) input response $x(t)$ for method Wang and Wu (2015)



(c) state response $x(t)$ for method Jin et al. (2021)

Fig. 7. Simulation plots for non-reliable controllers.

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