Observer-Based Event-Triggered Control for Interval Type-2 Fuzzy Networked System With Network Attacks

Yushun Tan, Ye Yuan, Xiangpeng Xie, Engang Tian, and Jinliang Liu

***Abstract*—This article is focused on the adaptive event-based interval type-2 (IT-2) fuzzy security control problem for networked control systems with multiple network attacks. In order to save the network resources, this article proposes an improved adaptive event-triggered model, which can adjust the threshold dynamically according to the change of current signal and previous triggering signal. In addition, due to the change of external environment, the impact of randomly occurring output bias is considered in the systems. Taking the effects of multiple network attacks and adaptive event-triggered scheme into consideration, a class of augmented error fuzzy system model is established. Next, some sufficient conditions are obtained for the stochastic stability with an H_∞ performance index via the Lyapunov stability analysis method. The corresponding parameters of the IT-2 fuzzy controllers and observers are also derived by some linear matrix inequalities. Finally, two simulation examples are given to support the advantages of the proposed method.**

***Index Terms*—Adaptive event-triggered scheme, interval type-2 (IT-2) fuzzy model, network attacks, randomly occurring output bias.**

I. Introduction

Due to the advantages on the network communication, such as low cost, easy maintenance, and resource sharing, networked control systems (NCSs) have attracted much attention and made a lot of achievements [1], [2], [3], [4], [5]. In addition, nonlinearity issues are widespread in practical network communication and it is difficult to analyze and synthesize these nonlinear systems. Many various methods have been proposed to deal with nonlinearities, such as the Takagi–Sugeno (T–S) fuzzy method, which has been an effective tool for the nonlinear plants [6], [7], [8], [9], [10]. According to the T–S fuzzy model, the nonlinearity for the original plant can be rewritten as a series of linear systems. Therefore, through T–S fuzzy modeling method, the analysis and synthesis for the linear system can be extended to the nonlinear case. Nevertheless, in some actual T–S fuzzy control systems, the membership functions (MFs) information is partially unknown, which increases the complexity of the stability analysis of the control system. In order to solve these problems, an interval type-2 (IT-2) fuzzy method is proposed according to the T–S fuzzy model. By introducing the upper and lower MFs, the IT-2 fuzzy model can deal with more complex nonlinear systems. So far, a great number of works have been published about the IT-2 fuzzy model. For instance, Lin et al. [11] achieved fewer test errors and less computational complexity than others by introducing a simplified IT-2 fuzzy neural network model. Rong and Wang [12] investigated a class of impulsive control issue for the IT-2 fuzzy interconnected system. Pan et al. [13] proposed a resilient event-triggered-based security controller for the IT-2 fuzzy networked systems with nonperiodic denial-of-service (DoS) attacks. Therefore, it is worth utilizing the IT-2 fuzzy model instead of T–S fuzzy model to investigate the nonlinear NCSs with MFs partially unknown.

Although the design for the state output feedback control has achieved great progress on chemical systems [14], vehicle dynamic systems [15], neural networks [16], and so on, it cannot apply directly to some networked systems. In fact, system state variables cannot be accurately measured in some practical systems. Therefore, an observer is designed to estimate the system state and analyze the stability. Recently, great attentions have been paid to the observer-based control problems for NCSs.

For example, Wang et al. [17] designed a novel fuzzy observer-based repetitive controller to evaluate the partly unmeasurable states and studied the periodic tracking control problem for nonlinear systems. Xie et al. [18] proposed a new robust synthesis approach for the observer-based system and investigated the control problem of the T–S fuzzy system with unknown external disturbances. Gu et al. [19] studied

Manuscript received 6 December 2022; accepted 15 January 2023. Date of publication 18 January 2023; date of current version 4 August 2023. This work was supported in part by the National Natural Science Foundation of China under Grant 61873107, Grant 61973152, Grant 62273174, and Grant 62022044, and in part by the Jiangsu Natural Science Foundation for Distinguished Young Scholars under Grant BK20190039. *(Corresponding authors: Jinliang Liu; Xiangpeng Xie.)*

Yushun Tan and Ye Yuan are with the School of Applied Mathematics, Nanjing University of Finance and Economics, Nanjing 210023, China (e-mail: tyshun994@163.com; 949293298@qq.com).

Xiangpeng Xie is with the Institute of Advanced Technology, Nanjing University of Posts and Telecommunications, Nanjing 210023, China (e-mail: xiexp@njupt.edu.cn).

Engang Tian is with the School of Optical-Electrical and Computer Engineering, University of Shanghai for Science and Technology, Shanghai 200093, China (e-mail: tianengang@163.com).

Jinliang Liu is with the School of Information Engineering, Nanjing University of Finance and Economics, Nanjing 210023, China (e-mail: liujinliang@vip.163.com).

Color versions of one or more figures in this article are available at https://doi.org/10.1109/TFUZZ.2023.3237846.

Digital Object Identifier 10.1109/TFUZZ.2023.3237846

the associated multiple disturbances for the Markov jump systems and designed a class of event-triggered antidisturbance observer. In addition, the system output exists some nonlinear deviations according to its own dynamic rules to a certain extent. These factors will affect the measurement output and reduce the estimation results. Therefore, it is of great practical significance to investigate the problem of observer-based fuzzy syste with the sensor output bias.

For the sampled NCSs, the signals are transmitted at a fixed time interval, which may result in redundant transmission. To save the communication resources, an event-triggered mechanism (ETM) is proposed in [20], [21], and [22]. The ETM aims to advocate the data transmitted only when the change rate of the signals surpass a fixed threshold. In this way, the signals are transmitted with a lower releasing rate. Recently, the ETM has achieved a lot of attention in the NCSs. For instance, Pan and Yang [20] introduced an ETM for the nonlinear NCSs and studied event-triggered fuzzy control problem. Liu et al. [22] designed two ETMs for T–S fuzzy systems, where two different trigger algorithms determine whether the output measurement and control input signal are transmitted or not. However, the ETMs mentioned above were all static by selecting a fixed threshold parameter. In recent years, the adaptive/dynamic ETM is more popular for researchers because it has been verified to have a longer release interval than static one. Li et al. [23] introduced a novel adaptive event-triggered mechanism (AETM) to investigate the control issue for the active vehicle suspension systems. In addition, Gu et al. [24] introduced a novel AETM to design the controllers to save limited network resource and improve the reliability of control systems. In regard to the AETM mentioned above, the sampled signals t_k^i are transmitted when the following constraints hold:

$$t_{k+1} = \min_{i\geq 1}\left\{t_k^i | e_k^T(t)\Omega_1 e_k(t) \geq \lambda(t) y^T(t_k)\Omega_2 y(t_k)\right\}$$

where t_{k+1} is the triggered instant, $e_k(t)$ is defined as (10), and the triggering threshold $\lambda(t)$ is a dynamic variable. When the threshold is a predetermined fixed constant, i.e. $\lambda(t) = \bar{\lambda}$, the AETM will tend to be the ETM. Owing to the existence of complex nonlinear interference, it brings great errors to the event-triggered conditions and degrade the control performance. In order to alleviate these problems, this article will introduce two adaptive threshold functions by combining the current sampled signals and the last triggered signals. Such an improved adaptive event-triggered condition is designed as follows:

$$\begin{aligned} t_{k+1} = \min_{i\geq 1}\Big\{ & t_k^i | e_k^T(t)\Omega_1 e_k(t) \\ & \geq \lambda_1(t) y^T(t_k)\Omega_2 y(t_k) + \lambda_2(t) y^T(t_k^i)\Omega_2 y(t_k^i)\Big\}. \end{aligned}$$

By introducing two thresholds, it will reduce the number of error triggering signals and improve the performance of the systems. Based on the analysis above, the event-triggered control with multiple thresholds for the fuzzy system is very worthy of study at present.

Although the introduction of communication networks provides higher efficiency for control systems, it also brings some network problems, including deception attacks [25], [26] and DoS attacks [27], [28]. On the one hand, the deception attacks degrade system performance by injecting the deception information into the data-communication channel of NCSs. To deal with these problems, Gu et al. [25] presented adaptive control laws to estimate the unknown bounds of the nonlinear deception attacks. To cope with stochastic deception attacks for the NCSs, Wu et al. [26] designed an event-based H_∞ filter and derived some stability criteria to ensure the finite-time boundness of the closed-loop filtering error systems. On the other hand, the DoS attacks also degrade the system performance through blocking the signal from reaching the controller. To address the system stability under DoS attacks, Xu et al. [27] designed an observer-based sliding-mode controllers for the connected vehicle systems. Moreover, Li and Ye [28] studied a class of nonperiodic DoS attacks and discussed security control issues for the IT-2 fuzzy networked systems. However, most of the existing pieces of literature only consider single network attack, and it does not adapt to the complex network environment in practical industry. As a consequence, it is necessary to study the influence of the multiple network attacks for IT-2 fuzzy NCSs.

Motivated by the above analysis, this article will focus on the observer-based control problems for IT-2 fuzzy NCSs with multiple network attacks. Meanwhile, an improved AETM is proposed to reduce the network burden. Due to the complex disturbance in the actual systems, the randomly occurring output bias is considered during the process of the output. Compared with the existing results, the main contributions can be summarized as follows: First, this article proposes an improved AETM, which can adjust the information transmission rate with two dynamic thresholds functions. Compared with the literature [7], the proposed method introduces two threshold functions, which can adjust the release rate of the signal more flexibly and reduce the the burden of network bandwidth. Second, considering the impact of interference in the practical industry, the observer-based fuzzy system model with random sensor output bias and multiple network attacks is established. Third, by effectively handling the asynchronous problem of fuzzy premise variables caused by event-triggered scheme, some sufficient conditions are derived for the existence of event-based controller, which can ensure augmented error system has stochastic stability with a prescribed H_∞ performance. A set of linear matrix inequalities (LMIs) are introduced and the gains of the fuzzy observers and controllers can be developed simultaneously.

The rest of this article is organized as follows. In Section II, an adaptive event-based IT-2 fuzzy system model with randomly occurring output bias and multiple network attacks is established. In Section III, some sufficient conditions for ensuring the stochastic stability for the augmented error system are derived, and the corresponding gains of the observers and controllers are also obtained. In Section IV, two simulation examples are shown to verify the obtained method. Finally, Section V concludes this article.

Notation: $\mathbb{R}^n$ denotes the n-dimensional Euclidean space; $L_2[0,\infty)$ represents the space of square integrable vector function over $[0,\infty)$; the X^T and X^{-1} stand for the transposition and inverse of the matrix X, respectively; $\mathcal{E}\{X\}$ denotes the expectation of X; The nation $*$ represents the symmetric term in symmetric block matrices; $\text{sym}\{X\}$ denotes the sum of X^T

and X; diag$\{\cdots\}$ denotes the block-diagonal matrix and X_n stands for diag$\{\underbrace{X, X, \ldots, X}_{n}\}$.

II. Problem Formulations

A. IT-2 Fuzzy Model

Consider a class of continuous-time nonlinear networked system, which can be represented as an IT-2 fuzzy model with r fuzzy rules.

RULE i: *If* $\varsigma_1(x(t))$ *is* F_{1i} *and* $\cdots$ *and* $\varsigma_\rho(x(t))$ *is* $F_{\rho i}$, *then*

$$\begin{cases}\dot{x}(t) = A_i x(t) + B_i u(t) + B_{wi} w(t), x(0) = x_0 \\ y(t) = C[x(t) + \alpha(t) b(t)] \\ z(t) = E_i x(t)\end{cases} \tag{1}$$

where $x(t) \in \mathbb{R}^n$ is the system state; $u(t) \in \mathbb{R}^u$ is the controlled input; $y(t) \in \mathbb{R}^y$ is the measured output; $z(t) \in \mathbb{R}^z$ is the control output; $w(t)$ is the unknown disturbance input, which belongs to $L_2[0, \infty)$; $b(t)$ is the sensor output bias generated by $\dot{b}(t) = -\Delta m(t) b(t) + w(t), \|\Delta m(t)\| < 1$. $\alpha(t) \in \{1, 0\}$ is an independent Bernoulli stochastic variable, which satisfies $\mathcal{E}\{\alpha(t) - \bar{\alpha}\} = 0$ and $\mathcal{E}\{(\alpha(t) - \bar{\alpha})^2\} = v_\alpha^2$. A_i, B_i, B_{wi}, E_i, and C are given system matrices with suitable dimensions. F_{si} is the fuzzy set of rule i corresponding to function $\varsigma_s(x(t))$ with $s = 1, 2, \ldots, \rho$ and $i = 1, 2, \ldots, r$. The firing strength of the ith rule is in the following format:

$$\widetilde{\omega}_i(x(t)) = [\underline{\omega}_i(x(t)), \overline{\omega}_i(x(t))] \tag{2}$$

where

$$\underline{\omega}_i(x(t)) = \prod_{s=1}^{\rho} \underline{\nu}_{F_{si}}(\varsigma_s x(t)), \quad \overline{\omega}_i(x(t)) = \prod_{s=1}^{\rho} \overline{\nu}_{F_{si}}(\varsigma_s x(t)).$$

$\underline{\omega}_i(x(t))$ and $\overline{\omega}_i(x(t))$ are the lower and upper grades. $\underline{\nu}_{F_{si}}(\varsigma_s x(t))$ and $\overline{\nu}_{F_{si}}(\varsigma_s x(t))$ are the lower and upper MFs with $\underline{\nu}_{F_{si}}(\varsigma_s x(t)) \leq \overline{\nu}_{F_{si}}(\varsigma_s x(t))$. Obviously, $\underline{\omega}_i(x(t)) \leq \overline{\omega}_i(x(t))$. Then, the global IT-2 fuzzy system can be rewritten as follows:

$$\begin{cases}\dot{x}(t) = \sum_{i=1}^{r} \omega_i(x(t))[A_i x(t) + B_i u(t) + B_{wi} w(t)] \\ y(t) = C[x(t) + \alpha(t) b(t)] \\ z(t) = \sum_{i=1}^{r} \omega_i(x(t)) E_i x(t)\end{cases} \tag{3}$$

where $\omega_i(x(t)) = \hat{\omega}_i(x(t)) / \sum_{s=1}^{r} \hat{\omega}_s(x(t)), \hat{\omega}_i(x(t)) = \underline{\alpha}_i(x(t))\underline{\omega}_i(x(t)) + \overline{\alpha}_i(x(t))\overline{\omega}_i(x(t))$, and $\sum_{i=1}^{r} \omega_i(x(t)) = 1$; $\underline{\alpha}_i(x(t)) \in [0, 1]$ and $\overline{\alpha}_i(x(t)) \in [0, 1]$ are the nonlinear weighting functions with $\underline{\alpha}_i(x(t)) + \overline{\alpha}_i(x(t)) = 1$.

Remark 1: The structure of the overall block diagram for the control system is depicted in Fig. 1. Some nonlinear systems are approximated by T–S fuzzy models, where there are certain parameters in the MFs. However, some problems of MFs with uncertainties cannot be solved by the T–S fuzzy approach. According to the IT-2 fuzzy model, the lower and upper MFs, and the MFs $\omega_i(x(t))$ can be calculated by defining nonlinear weighting functions. The corresponding IT-2 fuzzy observers and controllers' models are both designed as the same method.

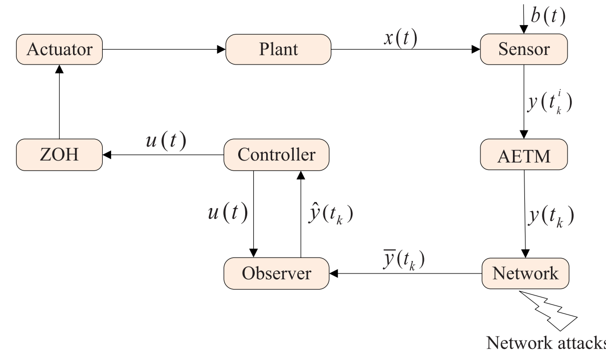

Fig. 1. Diagram of the NCS design.

B. Observer-Based Controller Design

In order to handle unknown state variables, an IT-2 fuzzy observer with r rules is designed as follows:

RULE j: *If* $\theta_1(\hat{x}(t))$ *is* M_{1j} *and* $\cdots$ *and* $\theta_q(\hat{x}(t))$ *is* M_{qj}, *then*

$$\begin{cases}\dot{\hat{x}}(t) = A_j \hat{x}(t) + B_j u(t) + L_j(\overline{y}(t) - \hat{y}(t)) \\ \hat{y}(t) = C\hat{x}(t) \\ \hat{x}(0) = \hat{x}_0\end{cases} \tag{4}$$

where $\hat{x}(t) \in \mathbb{R}^n$ is the estimated state, $\hat{x}_0$ is the initial value of observer state; $\hat{y}(t) \in \mathbb{R}^y$ is the signal of the observer, and $\overline{y}(t) \in \mathbb{R}^y$ is the final measured output to the observer; L_j is the fuzzy observer parameter to be determined. M_{sj} is the fuzzy set of rule j corresponding to function $\theta_s(\hat{x}(t))$ with $s = 1, 2, \ldots, q$ and $j = 1, 2, \ldots, r$. The firing strength of the jth rule is given as follows:

$$\widetilde{\mu}_j(\hat{x}(t)) = \left[\underline{\mu}_j(\hat{x}(t)), \overline{\mu}_j(\hat{x}(t))\right] \tag{5}$$

where

$$\underline{\mu}_j(\hat{x}(t)) = \prod_{s=1}^{q} \underline{\mu}_{M_{sj}}(\theta_s \hat{x}(t)), \quad \overline{\mu}_j(\hat{x}(t)) = \prod_{s=1}^{q} \overline{\mu}_{M_{sj}}(\theta_s \hat{x}(t)).$$

$\underline{\mu}_j(\hat{x}(t)) \in [0, 1]$ and $\overline{\mu}_j(\hat{x}(t)) \in [0, 1]$ are the lower and upper grades of membership. It is noticed that $\underline{\mu}_j(\hat{x}(t)) \leq \overline{\mu}_j(\hat{x}(t))$, and the global IT-2 fuzzy observer is defined as follows:

$$\begin{cases}\dot{\hat{x}}(t) = \sum_{j=1}^{r} \mu_j[A_j \hat{x}(t) + B_j u(t) + L_j(\overline{y}(t) - \hat{y}(t))] \\ \hat{y}(t) = C\hat{x}(t)\end{cases} \tag{6}$$

where $\mu_j = \hat{\mu}_j(\hat{x}(t)) / \sum_{s=1}^{r} \hat{\mu}_s(\hat{x}(t)), \hat{\mu}_j(\hat{x}(t)) = \underline{\chi}_j(\hat{x}(t)) \underline{\mu}_j(\hat{x}(t)) + \overline{\chi}_j(\hat{x}(t))\overline{\mu}_j(\hat{x}(t))$, and $\sum_{i=1}^{r} \mu_j(\hat{x}(t)) = 1$; $\underline{\chi}_j(\hat{x}(t)) \in [0, 1]$ and $\overline{\chi}_j(\hat{x}(t)) \in [0, 1]$ are the nonlinear weighting functions with $\underline{\chi}_j(\hat{x}(t)) + \overline{\chi}_j(\hat{x}(t)) = 1$.

Similarly, the lth fuzzy rule of the controller is obtained as follows:

RULE 1: If $\theta_1(\hat{x}(t))$ *is* M_{1l} *and* $\cdots$ *and* $\theta_q(\hat{x}(t))$ *is* M_{ql}, *then*

$$u(t) = K_l \hat{x}(t) \tag{7}$$

where K_l is the lth controller parameter to be determined. Then, the global IT-2 fuzzy controller is rewritten as follows:

$$u(t) = \sum_{l=1}^{r} \mu_l(\hat{x}(t)) K_l \hat{x}(t). \tag{8}$$

For brevity, ω_i, μ_j, and μ_l represent the abbreviations of $\omega_i(x(t))$, $\mu_j(\hat{x}(t))$, and $\mu_l(\hat{x}(t))$ in the next description.

C. Improved AETM

Considering the limited network bandwidth, an event generator is set between the sensor and network, which can reduce the redundant transmission. According to the conventional event-triggered scheme, an AETM with time-varying threshold is designed in [7]

$$t_{k+1} = \min_{i\geq 1}\{t_k^i | e_k^T(t)\Omega_1 e_k(t) \geq \lambda(t) y^T(t_k)\Omega_2 y(t_k)\} \tag{9}$$

where $t_k (k = 0, 1, 2, \ldots)$ represent the release times and $t_0 = 0$ is the initial time. t_k^i represents the current sampled time. $e_k(t) = y(t_k) - y(t_k^i)$, where $y(t_k)$ is the triggered signal and $y(t_k^i)$ is the current sampled signal. The triggering threshold $\lambda(t) \in [0, 1]$ is a time-varying function. Ω_1 and Ω_2 are the weight matrices to be determined.

When the sampled signal meets the given event-triggered condition (9), the signal will be updated and sent to the network. Inspired by this method, considering the sampling data at the current time and the one at the previous triggering time, an improved ETM is constructed as follows:

$$\begin{cases} t_{k+1} = \min_{i\geq 1}\{t_k^i | e_k^T(t)\Omega_1 e_k(t) \\ \qquad \geq \lambda_1(t) y^T(t_k)\Omega_2 y(t_k) + \lambda_2(t) y^T(t_k^i)\Omega_2 y(t_k^i)\} \\ \dot{\lambda}_1(t) = \frac{1}{\lambda_1(t)}\left(\frac{1}{\lambda_1(t)} - \lambda_1^0\right)(e_k^T(t)\Omega_1 e_k(t) \\ \qquad -\theta_1 y^T(t_k^i)\Omega_2 y(t_k^i) + \theta_1 y^T(t_k)\Omega_2 y(t_k)) \\ \dot{\lambda}_2(t) = \frac{1}{\lambda_2(t)}\left(\frac{1}{\lambda_2(t)} - \lambda_2^0\right)(e_k^T(t)\Omega_1 e_k(t) \\ \qquad -\theta_2 y^T(t_k)\Omega_2 y(t_k) + \theta_2 y^T(t_k^i)\Omega_2 y(t_k^i)) \end{cases} \tag{10}$$

where $e_k(t) := y(t_k) - y(t_k^i)$, $\frac{1}{\lambda_1^0} \leq \lambda_1(t) \leq \theta_1$, and $\frac{1}{\lambda_2^0} \leq \lambda_2(t) \leq \theta_2$; λ_1^0, λ_2^0, θ_1, and θ_2 are the given positive constants.

Remark 2: Compared with the existing ETM in [7], the proposed adaptive event-triggered algorithm introduces two different time-varying threshold functions $\lambda_1(t)$ and $\lambda_2(t)$. Combining both the current sampled data and the previous triggered data, the AETM can reduce the transmission of redundant signals with the changes of system environment, which will be verified in the simulation examples.

Similar with the literature [29], divide $[t_k, t_{k+1})$ into T intervals as follows:

$$[t_k, t_{k+1}) = \bigcup_{s=1}^{T} \Im_k^s \tag{11}$$

where $\Im_k^1 = [t_k, t_k^1)$ and $\Im_j^s = [t_k^{s-1}, t_k^s), 2 \leq s \leq T$.

For simplicity, the delayed functions $h(t)$ and the error function $e_k(t)$ are defined as follows:

$$h(t) = \begin{cases} t - t_k, & t \in \Im_k^1 \\ t - t_k^1, & t \in \Im_k^2 \\ \vdots \\ t - t_k^{T-1}, & t \in \Im_k^T \end{cases} \tag{12}$$

$$e_k(t) = \begin{cases} 0, & t \in \Im_k^1 \\ x(t_k) - x(t_k^1), & t \in \Im_k^2 \\ \vdots \\ x(t_k) - x(t_k^{T-1}), & t \in \Im_k^T. \end{cases} \tag{13}$$

Suppose the delayed function sequence $h(t)$ belongs to $(0, \bar{h}]$. Therefore, the last triggered instant signal and the current sampled instant signal can be converted into

$$y(t_k) = Ce_k(t) + y(t - h(t)), \quad t \in [t_k, t_{k+1}). \tag{14}$$

D. Multiple Network Attacks

Owing to the openness of the transmission network, network attacks have become a kind of the most significant factors to threaten the system security. In this article, it is assumed that the attackers can launch deception attacks and DoS attacks with a certain probability, and the received output to the controller is expressed by

$$\bar{y}(t) = \beta(t) y(t_k) + (1 - \beta(t))\gamma(t) C f(y(t)), t \in [t_k, t_{k+1}) \tag{15}$$

where $\beta(t) \in \{0, 1\}$ and $\gamma(t) \in \{0, 1\}$ represent the independent Bernoulli stochastic variables with $\mathcal{E}\{\beta(t) - \bar{\beta}\} = 0$, $\mathcal{E}\{\gamma(t) - \bar{\gamma}\} = 0$, $\mathcal{E}\{(\beta(t) - \bar{\beta})^2\} = v_\beta^2$, and $\mathcal{E}\{(\gamma(t) - \bar{\gamma})^2\} = v_\gamma^2$. $f(y(t))$ denotes the attack signal from network space.

Remark 3: As mentioned in (15), the objective of the proposed multiple attacks model contains three scenarios. When $\beta(t) = 1$, the output signal can be rewritten as $\bar{y}(t) = y(t_k)$, this indicates that there are no attacks in the real network environment. When $\beta(t) = 0$ and $\gamma(t) = 0$, it implies that there exists DoS attacks during the transmission. When $\beta(t) = 0$ and $\gamma(t) = 1$, it transforms into a class of deception attacks model. Based on the above discussion, the multiple network attacks model, including deception attacks and DoS attacks, is studied in a unified framework, which is more general than the conventional attacks in [30] and [31].

Let vectors $\tilde{z}(t) = x(t) - \hat{x}(t)$, $\varphi(t) := \text{col}\{\hat{x}(t), \tilde{z}(t)\}$, $e_b(t) := \text{col}\{e_k(t), b(t)\}$, and $v(t) := \text{col}\{f(y(t)), w(t)\}$. Combining (3), (6), (8), (14), and (15), the augmented error system is described as follows:

$$\begin{aligned} \dot{\varphi}(t) = \sum_{i=1}^{r}\sum_{j=1}^{r}\sum_{l=1}^{r} \omega_i \mu_j \mu_l [&\eta_1(t) + (\beta(t) - \bar{\beta})\eta_2(t) \\ &+ (\gamma(t) - \bar{\gamma})\eta_3(t) + (\beta(t) - \bar{\beta})(\alpha(t) - \bar{\alpha})\eta_5(t) \\ &+ (\alpha(t) - \bar{\alpha})\eta_4(t) + (\beta(t) - \bar{\beta})(\gamma(t) - \bar{\gamma})\eta_6(t)] \end{aligned} \tag{16}$$

where

$$\eta_1(t) = \mathcal{A}^1_{ijl}\varphi(t) + \mathcal{A}^2_{ijl}\varphi(t-h(t)) + \mathcal{A}^3_{ijl}e_b(t) + \mathcal{A}^4_{ijl}v(t)$$

$$\eta_2(t)=\mathcal{B}^2_{ijl}\varphi(t-h(t))+\mathcal{B}^3_{ijl}e_b(t)+\mathcal{B}^4_{ijl}v(t), \quad \eta_3(t)=\mathcal{C}^4_{ijl}v(t)$$

$$\eta_4(t) = \mathcal{D}^3_{ijl}e_b(t), \quad \eta_5(t) = \mathcal{F}^3_{ijl}e_b(t), \quad \eta_6(t) = \mathcal{G}^4_{ijl}v(t)$$

$$\mathcal{A}^1_{ijl} = \begin{bmatrix} A_j + B_jK_l - L_jC & 0 \\ A_i - A_j + (B_i - B_j)K_l + L_jC & A_i \end{bmatrix}$$

$$\mathcal{A}^2_{ijl} = \begin{bmatrix} \bar\beta L_jC & \bar\beta L_jC \\ -\bar\beta L_jC & -\bar\beta L_jC \end{bmatrix}, \quad \mathcal{A}^3_{ijl} = \begin{bmatrix} \bar\beta L_jC & -\bar\alpha L_jC \\ -\bar\beta L_jC & \bar\alpha L_jC \end{bmatrix}$$

$$\mathcal{A}^4_{ijl} = \begin{bmatrix} (1-\bar\beta)\bar\gamma L_jC & 0 \\ -(1-\bar\beta)\bar\gamma L_jC & B_{wi} \end{bmatrix}, \quad \mathcal{B}^2_{ijl} = \begin{bmatrix} L_jC & L_jC \\ -L_jC & -L_jC \end{bmatrix}$$

$$\mathcal{B}^3_{ijl} = \begin{bmatrix} -L_jC & -\alpha L_jC \\ L_jC & \alpha L_jC \end{bmatrix}, \quad \mathcal{B}^4_{ijl} = \begin{bmatrix} -\bar\gamma L_jC & 0 \\ \bar\gamma L_jC & 0 \end{bmatrix}$$

$$\mathcal{C}^4_{ijl} = \begin{bmatrix} (1-\bar\beta)L_jC & 0 \\ -(1-\bar\beta)L_jC & 0 \end{bmatrix}, \quad \mathcal{D}^3_{ijl} = \begin{bmatrix} 0 & L_jC \\ 0 & -L_jC \end{bmatrix}$$

$$\mathcal{F}^3_{ijl} = \begin{bmatrix} 0 & L_jC \\ 0 & -L_jC \end{bmatrix}, \quad \mathcal{G}^4_{ijl} = \begin{bmatrix} -L_jC & 0 \\ L_jC & 0 \end{bmatrix}.$$

Next, the following lemmas and assumptions are introduced to facilitate the main results of the article.

Assumption 1 (See [32]): The nonlinear functions $f(y(t))$ in (15) are continuous. There exits a real constant matrix F such that the following formula holds:

$$\|f(y(t))\|_2 \le \|F \cdot y(t)\|_2. \tag{17}$$

Lemma 1 (See [33]): For positive matrix R, variable $h(t) \in (0, \bar h)$, and the vector function $\varphi(t) : [-\bar h, 0] \to \mathbb{R}^n$. If there exist matrices M satisfying

$$\begin{bmatrix} R & * \\ M & R \end{bmatrix} \ge 0$$

the following inequality maintains:

$$-\bar h \int_{t-\bar h}^{t} \dot\varphi^T(s)G^TRG\dot\varphi(s)ds \le \psi_h^T(t)\mathbf{M}\psi_h(t) \tag{18}$$

where

$$\psi_h(t) = \begin{bmatrix} \varphi(t) & \varphi(t-h(t)) & \varphi(t-\bar h) \end{bmatrix}^T$$

$$\mathbf{M} = \begin{bmatrix} -R & * & * \\ R+M & -2R - \text{sym}\{M\} & * \\ -M & R+M & -R \end{bmatrix}.$$

Lemma 2 (See [28] and [34]): For a column full rank matrix $C \in \mathbb{R}^{n_1\times n_2}$, its singular value decomposition is represented as $C = S[V\ 0]D^T$ in which $V = \text{diag}\{v_1, v_2, \dots, v_n\}, SS^T = I$, and $DD^T = I$. Here, denote matrices $X > 0, X_{11} \in \mathbb{R}^{n_1\times n_1}$, and $X_{22} \in \mathbb{R}^{(n_2-n_1)\times(n_2-n_1)}$, there exits a matrix $\bar X = SV^{-1}X_{11}VS^T$ such that $CX = \bar XC$, if the matrix condition $X = D\begin{bmatrix} X_{11} & 0 \\ 0 & X_{22} \end{bmatrix} D^T$ holds.

III. Main Results

In the section, we will investigate the analysis of the stability with an H_∞ performance for the augment error system (16) and present some stability criteria under the proposed event-triggered scheme (10). Then, on the basis of the derived stability criteria and LMI techniques, we will derive the design of the fuzzy observers and controllers for the system.

Theorem 1: Given the scalars $\bar h > 0, \bar\alpha > 0, \bar\beta > 0, \bar\gamma > 0, v_\alpha > 0, v_\beta > 0, v_\gamma > 0$, event trigger parameters $\lambda_1^0 > 0, \lambda_2^0 > 0, \theta_1 > 0, \theta_2 > 0$, disturbance parameter $\gamma > 0$, the membership parameter $0 < \iota_i < 1$, and matrices F, K_l, L_j. If there exist symmetric positive-definite matrices $P \in \mathbb{R}^{2n\times 2n}, Q \in \mathbb{R}^{n\times n}, R \in \mathbb{R}^{n\times n}, \Omega_1, \Omega_2$, and slack matrices M, Δ_i such that the following constraints hold with $\mu_j - \iota_j\omega_j \ge 0, i < j$:

$$\Psi_{ijl} - \Delta_i < 0 \tag{19}$$

$$\iota_i\Psi_{iil} - \iota_i\Delta_i + \Delta_i < 0 \tag{20}$$

$$\iota_j\Psi_{ijl} + \iota_i\Psi_{jil} - \iota_j\Delta_i - \iota_i\Delta_j + \Delta_i + \Delta_j < 0 \tag{21}$$

$$\begin{bmatrix} R & * \\ M & R \end{bmatrix} \ge 0 \tag{22}$$

where

$$\Psi_{ijl} = \begin{bmatrix} \Upsilon_{11}^{ijl} & * \\ \Upsilon_{21}^{ijl} & \Upsilon_{22}^{ijl} \end{bmatrix}$$

$$\Upsilon_{11}^{ijl} = \begin{bmatrix} \Lambda_{11} & * & * & * & * \\ \Lambda_{21} & \Lambda_{22} & * & * & * \\ MG & \Lambda_{32} & \Lambda_{33} & * & * \\ \mathcal{A}^{3\,T}_{ijl}P & \Lambda_{42} & 0 & \Lambda_{44} & * \\ \mathcal{A}^{4\,T}_{ijl}P & 0 & 0 & G_2^TG_2 & \Lambda_{55} \end{bmatrix}$$

$$\Upsilon_{21}^{ijl} = \text{col}\{\bar hP\Upsilon_{211}, \bar hv_\beta P\Upsilon_{212}, \bar hv_\gamma P\Upsilon_{213}, \bar hv_\alpha P\Upsilon_{214}, \bar hv_\beta v_\alpha P\Upsilon_{215}, \bar hv_\beta v_\gamma P\Upsilon_{216}, \Upsilon_{217}, \Upsilon_{218}\}$$

$$\Upsilon_{22}^{ijl} = \text{diag}\{-R, -R, -R, -R, -R, -R, -I, -I\}$$

$$\Upsilon_{211} = \begin{bmatrix} RG\mathcal{A}^1_{ijl} & RG\mathcal{A}^2_{ijl} & 0 & RG\mathcal{A}^3_{ijl} & RG\mathcal{A}^4_{ijl} \end{bmatrix}$$

$$\Upsilon_{212} = \begin{bmatrix} 0 & RG\mathcal{B}^2_{ijl} & 0 & RG\mathcal{B}^3_{ijl} & RG\mathcal{B}^4_{ijl} \end{bmatrix}$$

$$\Upsilon_{213} = \begin{bmatrix} 0 & 0 & 0 & 0 & RG\mathcal{C}^4_{ijl} \end{bmatrix}$$

$$\Upsilon_{214} = \begin{bmatrix} 0 & 0 & 0 & RG\mathcal{D}^3_{ijl} & 0 \end{bmatrix}$$

$$\Upsilon_{215} = \begin{bmatrix} 0 & 0 & 0 & RG\mathcal{F}^3_{ijl} & 0 \end{bmatrix}$$

$$\Upsilon_{216} = \begin{bmatrix} 0 & 0 & 0 & 0 & RG\mathcal{G}^4_{ijl} \end{bmatrix}$$

$$\Upsilon_{217} = \begin{bmatrix}\sqrt{\bar{\beta}}FCG & 0 & 0 & \sqrt{\bar{\alpha}\bar{\beta}}FCG_2 & 0\end{bmatrix}$$
$$\Upsilon_{218} = \begin{bmatrix}E_iG & 0 & 0 & 0 & 0\end{bmatrix}$$
$$\Lambda_{11} = \mathrm{sym}\{P\mathcal{A}^1_{ijl}\} + G^TQG - G^TRG$$
$$\Lambda_{21} = \mathcal{A}^{2T}_{ijl}PG + RG - MG$$
$$\Lambda_{22} = -2G^TRG + \mathrm{sym}\{M\} + (\kappa_2+\kappa_3)G^T\Omega_2G$$
$$\Lambda_{32} = G^TRG - M, \quad \Lambda_{33} = -G^TQG - G^TRG$$
$$\Lambda_{42} = G_1^T\Omega_2G_1, \quad \Lambda_{44} = -2G_2^TG_2 + (\kappa_3-\kappa_1)G_1^T\Omega_1G_1$$
$$\Lambda_{55} = -\gamma^2I - \bar{\beta}G_1^TG_1, \quad G = \begin{bmatrix}I & I\end{bmatrix}^T, \quad G_1 = \begin{bmatrix}I & 0\end{bmatrix}^T$$
$$G_2 = \begin{bmatrix}0 & I\end{bmatrix}^T, \quad \kappa_1 = \lambda_1^0+\lambda_2^0, \quad \kappa_2 = I+\theta_1\lambda_1^0,$$
$$\kappa_3 = I+\theta_2\lambda_2^0.$$

Then, the error system (16) under multiple network attacks is asymptotically stable.

Proof: Construct the Lyapunov–Krasovskii functional candidate as follows:

$$V(\varphi(t),t) = V_1(\varphi(t),t) + V_2(\varphi(t),t) + V_3(\varphi(t),t) \tag{23}$$

where

$$V_1(\varphi(t),t) = \varphi^T(t)P\varphi(t) + b^T(t)b(t)$$
$$V_2(\varphi(t),t) = \int_{t-\bar{h}}^{t}\varphi^T(s)G^TQG\varphi(s)ds + \bar{h}\int_{-\bar{h}}^{0}\int_{t+\theta}^{t}\dot{\varphi}^T(s)G^TRG\dot{\varphi}(s)dsd\theta$$
$$V_3(\varphi(t),t) = \frac{1}{2}\lambda_1^T(t)\lambda_1(t) + \frac{1}{2}\lambda_2^T(t)\lambda_2(t).$$

Along the trajectory of the error system (6), computing the derivation and mathematical expectation of $V(\varphi(t),t)$ with respect to time t, we obtain

$$\mathcal{E}\{\dot{V}_1(\varphi(t),t)\} = \sum_{i=1}^{r}\sum_{j=1}^{r}\sum_{l=1}^{r}\omega_i\mu_j\mu_l 2\{\varphi^T(t)P\dot{\varphi}(t) + b^T(t)\dot{b}(t)\} \tag{24}$$

$$\begin{aligned}\mathcal{E}\{\dot{V}_2(\varphi(t),t)\} = \sum_{i=1}^{r}\sum_{j=1}^{r}\sum_{l=1}^{r}\omega_i\mu_j\mu_l\{&\varphi^T(t)G^TQG\varphi(t)\\ &-\varphi^T(t-\bar{h})G^TQG\varphi(t-\bar{h}) + \bar{h}^2\dot{\varphi}^T(t)G^TRG\dot{\varphi}(t)\\ &-\bar{h}\int_{t-\bar{h}}^{t}\dot{\varphi}^T(t)G^TRG\dot{\varphi}(t)dt\}\end{aligned} \tag{25}$$

$$\mathcal{E}\{\dot{V}_3(\varphi(t),t)\} = \sum_{i=1}^{r}\sum_{j=1}^{r}\sum_{l=1}^{r}\omega_i\mu_j\mu_l\{\lambda_1^T(t)\dot{\lambda}_1(t) + \lambda_2^T(t)\dot{\lambda}_2(t)\}. \tag{26}$$

Due to $\|\Delta m(t)\| < 1$, one can see that

$$\begin{aligned}\mathcal{E}\{\dot{V}_1(\varphi(t),t)\} \le \sum_{i=1}^{r}\sum_{j=1}^{r}\sum_{l=1}^{r}\omega_i\mu_j\mu_l\{&2\varphi^T(t)P\eta_1(t)\\ &-2b^T(t)b(t) + b^T(t)w(t) + w(t)b(t)\}.\end{aligned} \tag{27}$$

Applying Lemma 2 to (25), it gives

$$-\bar{h}\int_{t-\bar{h}}^{t}\dot{\varphi}^T(s)G^TRG\dot{\varphi}(s)ds \le \psi_h^T(t)\mathbf{M}\psi_h(t) \tag{28}$$

where $\psi_h(t) = \begin{bmatrix}\varphi(t) & G\varphi(t-h(t)) & G\varphi(t-\bar{h})\end{bmatrix}^T$ and

$$\mathbf{M} = \begin{bmatrix}-G^TRG & * & *\\ RG+MG & -2R-\mathrm{sym}\{M\} & *\\ -MG & RG+MG & -R\end{bmatrix}.$$

Define the augmented state vector as $\xi(t) = [\varphi^T(t), \varphi^T(t-h(t))G^T, \varphi^T(t-\bar{h})G^T, e_k^T(t), v^T(t)]^T$. Then, combining (24)–(28) with (10) and (17), one can obtain

$$\begin{aligned}&\mathcal{E}\{\dot{V}(\varphi(t),t) + z^T(t)z(t) - \gamma^2v^T(t)v(t)\}\\ &\le \sum_{i=1}^{r}\sum_{j=1}^{r}\sum_{l=1}^{r}\omega_i\mu_j\mu_l\{2\varphi^T(t)P\eta_1(t) - 2b^T(t)b(t) + b^T(t)w(t)\\ &+ w(t)b(t) + \varphi^T(t)G^TQG\varphi(t) - \varphi^T(t-\bar{h})G^TQG\varphi(t-\bar{h})\\ &+ \bar{h}^2\dot{\varphi}^T(t)G^TRG\dot{\varphi}(t) - \bar{h}\int_{t-\bar{h}}^{t}\dot{\varphi}^T(t)G^TRG\dot{\varphi}(t)dt\\ &+ \lambda_1^T(t)\dot{\lambda}_1(t) + \lambda_2^T(t)\dot{\lambda}_2(t) + e_k^T(t)\Omega_1e_k(t)\\ &- \lambda_1(t)(Ce_k(t) + y(t-h(t)))^T\Omega_2(Ce_k(t) + y(t-h(t)))\\ &- \lambda_2(t)y^T(t-h(t))\Omega_2y(t-h(t)) + \bar{\beta}y^T(t)F^TFy(t)\\ &- \bar{\beta}f^T(t)f(t) + z^T(t)z(t) - \gamma^2v^T(t)v(t)\}\\ &\le \sum_{i=1}^{r}\sum_{j=1}^{r}\sum_{l=1}^{r}\omega_i\mu_j\mu_l\xi^T(t)\left\{\Upsilon_{11}^{ijl} + \Upsilon_{21}^{ijl}\left(\Upsilon_{22}^{ijl}\right)^{-1}\left(\Upsilon_{21}^{ijl}\right)^T\right\}\xi(t).\end{aligned}$$

For the convenience of analysis, some slack matrices $\Delta_i = \Delta_i^T$ are introduced. Denote $\Psi_{ijl} = \Upsilon_{11}^{ijl} + \Upsilon_{21}^{ijl}(\Upsilon_{22}^{ijl})^{-1}(\Upsilon_{21}^{ijl})^T$, according to the characters $\sum_{i=1}^{r}\sum_{j=1}^{r}\sum_{l=1}^{r}\omega_i\mu_j(\omega_i - \mu_l)\Delta_i = 0$, it yields that

$$\begin{aligned}&\sum_{i=1}^{r}\sum_{j=1}^{r}\sum_{l=1}^{r}\omega_i\mu_j\mu_l\Psi_{ijl}\\ &= \sum_{i=1}^{r}\sum_{j=1}^{r}\omega_i(\omega_i - \mu_j - \iota_j\omega_j + \iota_j\omega_j)\Delta_i + \sum_{i=1}^{r}\sum_{j=1}^{r}\omega_i\mu_j\Phi_{ijl}\\ &= \sum_{i=1}^{r}\sum_{j=1}^{r}\sum_{l=i}^{r}\omega_i\mu_l(\mu_j - \iota_j\omega_j)[\Psi_{ijl} - \Delta_i] + \sum_{i=1}^{r}\sum_{l=1}^{r}\omega_i\mu_l\\ &\quad[\iota_i\Psi_{iil} - \iota_i\Delta_i + \Delta_i] + \sum_{i=1}^{r}\sum_{l=1}^{r}\sum_{j=i+1}^{r}\omega_i\mu_j\mu_l[\iota_j\Psi_{ijl}\\ &\quad + \iota_i\Psi_{jil} - \iota_j\Delta_i - \iota_i\Delta_j + \Delta_i + \Delta_j].\end{aligned}$$

Then, by applying the conditions (19)–(21) in Theorem I, one can derive that

$$\mathcal{E}\{\dot{V}(\xi(t)) + +z^T(t)z(t) - \gamma^2 v^T(t)v(t)\} < 0. \quad (29)$$

Thus, when $v(t) = 0$, by applying the Schur complement, we can derive that $\mathcal{E}\{\dot{V}(\xi(t))\} < 0$, which implies that the system is asymptotically stable. On the other hand, when $v(t) \neq 0$, integrating both sides of the inequality (29) from 0 to ∞ and taking the expectation, one has

$$\mathcal{E}\left\{\int_0^\infty z^T(t)z(t)dt\right\} \leq \gamma^2\mathcal{E}\left\{\int_0^\infty w^T(t)w(t)dt\right\} \quad (30)$$

and the H_∞ performance condition is satisfied.

Remark 4: This article discusses the asynchronous control problems for the IT-2 fuzzy networked systems. The premise variables are assumed to be unequal, i.e, $\omega_i(x(t)) \neq \mu_l(\hat{x}(t))$. Inspired by the literature [13], [28], some symmetric slack matrices Δ_i are introduced to establish the relationship between variables $\omega_i(x(t))$ and $\mu_l(\hat{x}(t))$, which can reduce some conservatism.

Remark 5: In Theorem 1, the sufficient criteria are presented to guarantee the stability with an H_∞ performance for the augmented error system (16). However, due to the existence of nonlinear term, it is difficult to obtain the observer and controller paraments directly by LMIs toolbox. Thus, the next theorem will tackle these issues and give a solvable sufficient criterion.

Theorem 2: Given the scalars $\bar{h} > 0, \epsilon > 0, \bar{\alpha} > 0, \bar{\beta} > 0, \bar{\gamma} > 0, v_\alpha > 0, v_\beta > 0, v_\gamma > 0$, event trigger parameters $\lambda_1^0 > 0, \lambda_2^0 > 0, \theta_1 > 0, \theta_2 > 0$, disturbance parameter $\gamma > 0$, the membership parameter $0 < \iota_i < 1$, and matrix F. If there exist symmetric positive-definite matrices $X, \tilde{Q}, \tilde{R}, \tilde{\Omega}_1, \tilde{\Omega}_2, Y_{1l}, Y_{2j}$ and slack matrices $\tilde{M}, \tilde{\Delta}_i$ of appropriate dimensions such that the following LMIs hold with $\mu_j - \iota_j\omega_j \geq 0, i < j$:

$$\tilde{\Psi}_{ijl} - \tilde{\Delta}_i < 0 \quad (31)$$

$$\iota_i\tilde{\Psi}_{iil} - \iota_i\tilde{\Delta}_i + \tilde{\Delta}_i < 0 \quad (32)$$

$$\iota_j\tilde{\Psi}_{ijl} + \iota_i\tilde{\Psi}_{jil} - \iota_j\tilde{\Delta}_i - \iota_i\tilde{\Delta}_j + \tilde{\Delta}_i + \tilde{\Delta}_j < 0 \quad (33)$$

$$\begin{bmatrix} \tilde{R} & * \\ \tilde{M} & \tilde{R} \end{bmatrix} \geq 0 \quad (34)$$

where

$$\tilde{\Psi}_{ijl} = \begin{bmatrix} \Theta_{11}^{ijl} & * & * & * \\ \Theta_{21}^{ijl} & \Theta_{22}^{ijl} & * & * \\ \Theta_{31}^{ijl} & \Theta_{32}^{ijl} & \Theta_{33}^{ijl} & * \\ \Theta_{41}^{ijl} & \Theta_{42}^{ijl} & 0 & \Theta_{44}^{ijl} \end{bmatrix}$$

$$\Theta_{11}^{ijl} = \begin{bmatrix} \tilde{\Lambda}_{11} & * & * & * \\ \tilde{\Lambda}_{21} & \tilde{\Lambda}_{22} & * & * \\ \tilde{\Lambda}_{31} & \tilde{\Lambda}_{32} & \tilde{\Lambda}_{33} & * \\ \tilde{M} & \tilde{M} & \tilde{\Lambda}_{43} & \tilde{\Lambda}_{44} \end{bmatrix}$$

$$\Theta_{21}^{ijl} = \mathrm{col}\{\Gamma_{211}, \Gamma_{212}, \Gamma_{213}, \Gamma_{214}\}$$

$$\Theta_{22}^{ijl} = \mathrm{diag}\{(\kappa_3 - \kappa_1)\tilde{\Omega}_1, -4\epsilon X + 2\epsilon^2 I, -\sigma(2\epsilon X - \epsilon^2 I), - \gamma^2 I\}$$

$$\Theta_{31}^{ijl} = \mathrm{col}\{\bar{h}\Gamma_{311}, 0, 0, 0, 0, 0\}, \ \Theta_{32}^{ijl} = \mathrm{col}\{\Gamma_{321}, 0, 0, 0, 0, 0\}$$

$$\Theta_{41}^{ijl} = \mathrm{col}\{\Gamma_{411}, \Gamma_{412}\},$$

$$\Theta_{33}^{ijl} = \mathrm{diag}\{-2\epsilon X + \epsilon^2\tilde{R}, -2\epsilon X + \epsilon^2\tilde{R}, -2\epsilon X + \epsilon^2\tilde{R}, - 2\epsilon X + \epsilon^2\tilde{R}, -2\epsilon X + \epsilon^2\tilde{R}, -2\epsilon X + \epsilon^2\tilde{R}\}$$

$$\Theta_{42}^{ijl} = \mathrm{col}\{\Gamma_{421}, 0\}, \quad \Theta_{44}^{ijl} = \mathrm{diag}\{-I, -I\}$$

$$\Gamma_{211} = \begin{bmatrix} \bar{\beta}Y_{2j}^T & -\bar{\beta}Y_{2j}^T & \tilde{\Omega}_2 & 0 \end{bmatrix}$$

$$\Gamma_{212} = \begin{bmatrix} \bar{\alpha}Y_{2j}^T & -\bar{\alpha}Y_{2j}^T & 0 & 0 \end{bmatrix}, \quad \Gamma_{214} = \begin{bmatrix} 0 & B_{wi}^T & 0 & 0 \end{bmatrix}$$

$$\Gamma_{213} = \begin{bmatrix} \bar{\gamma}(1-\bar{\beta})Y_{2j}^T & -\bar{\gamma}(1-\bar{\beta})Y_{2j}^T & 0 & 0 \end{bmatrix}$$

$$\Gamma_{311} = \begin{bmatrix} A_iX + B_iY_{1l} & A_iX + B_iY_{1l} & 0 & 0 \end{bmatrix}$$

$$\Gamma_{411} = \begin{bmatrix} \sqrt{\bar{\beta}}FCX & \sqrt{\bar{\beta}}FCX & 0 & 0 \end{bmatrix}$$

$$\Gamma_{321} = \begin{bmatrix} 0 & 0 & 0 & B_{wi} \end{bmatrix}, \quad \Gamma_{421} = \begin{bmatrix} 0 & \bar{\alpha}FCX & 0 & B_{wi} \end{bmatrix}$$

$$\tilde{\Lambda}_{11} = \mathrm{sym}\{A_jX + B_jY_{1l} - \bar{\alpha}Y_{2j}\} + \tilde{Q} - \tilde{R}$$

$$\tilde{\Lambda}_{21} = (A_i - A_j)X + (B_i - B_j)Y_{1l} + \bar{\alpha}Y_{2j} + \tilde{Q} - \tilde{R}$$

$$\tilde{\Lambda}_{22} = \mathrm{sym}\{A_iX + B_iY_{1l}\} + \tilde{Q} - \tilde{R}, \quad \tilde{\Lambda}_{31} = \tilde{R} - \tilde{M}$$

$$\tilde{\Lambda}_{32} = \tilde{R} - \tilde{M}, \quad \tilde{\Lambda}_{33} = \mathrm{sym}\{\tilde{M}\} - 2\tilde{R} + (\kappa_2 + \kappa_3)\Omega_2$$

$$\tilde{\Lambda}_{43} = \tilde{R} - \tilde{M}, \quad \tilde{\Lambda}_{44} = -\tilde{R} - \tilde{Q}, \quad \sigma = \gamma^2 + \bar{\beta}$$

$$\kappa_1 = \lambda_1^0 + \lambda_2^0, \quad \kappa_2 = I + \theta_1\lambda_1^0, \quad \kappa_3 = I + \theta_2\lambda_2^0.$$

Then, the event-based error system with

$$K_l = Y_{1l}X^{-1}, \quad L_j = Y_{2j}SV^{-1}X_{11}^{-1}VS^T \quad (35)$$

is asymptotically stable in the presence of the multiple network attacks.

Proof: By using Schur complement, the conditions (19)–(21) are equivalent to the following inequalities:

$$\bar{\Psi}_{ijl} - \Delta_i < 0 \quad (36)$$

$$\iota_i\bar{\Psi}_{iil} - \iota_i\Delta_i + \Delta_i < 0 \quad (37)$$

$$\iota_j\bar{\Psi}_{ijl} + \iota_i\bar{\Psi}_{jil} - \iota_j\Delta_i - \iota_i\Delta_j + \Delta_i + \Delta_j < 0 \quad (38)$$

where $\bar{\Psi}_{ijl} = \begin{bmatrix} \Upsilon_{11}^{ijl} & * \\ \bar{\Upsilon}_{21}^{ijl} & \bar{\Upsilon}_{22}^{ijl} \end{bmatrix}$ $\bar{\Upsilon}_{21}^{ijl} = \mathrm{col}\{\bar{h}P\Upsilon_{211}, \bar{h}v_\beta P\Upsilon_{212}, \bar{h}v_\gamma P\Upsilon_{213}, \bar{h}v_\alpha P\Upsilon_{214}, \bar{h}v_\beta v_\alpha P\Upsilon_{215}, \bar{h}v_\beta v_\gamma P\Upsilon_{216}, \Upsilon_{217}, \Upsilon_{218}\}$, $\bar{\Upsilon}_{22}^{ijl} = \mathrm{diag}\{-PR^{-1}P, -PR^{-1}P, -PR^{-1}P, -PR^{-1}P, -PR^{-1}P, -PR^{-1}P, -I, -I\}$.

Define $P = \mathrm{diag}\{P_1, P_1\}, X = P_1^{-1}, \tilde{Q} = XQX, \tilde{R} = XRX, \tilde{\Omega}_1 = X\Omega_1X, \tilde{\Omega}_2 = X\Omega_2X, \tilde{M}_1 = XM_1X, \tilde{M}_2 = XM_2X, \tilde{M}_3 = XM_3X, \tilde{M}_4 = XM_4X, Y_{1l} = K_lX,$ and Y_{2j}

$= L_j\bar{X}$. Based on Lemma 2, for $X = U\begin{bmatrix} X_{11} & 0 \\ 0 & X_{22}\end{bmatrix} U^T$, there exists $\bar{X} = SV^{-1}X_{11}VS^T$, make $CX = \bar{X}C$ maintain. Multiply the left and right sides of the inequalities (36)–(38) and (34) by the matrix J_1, J_1, J_1, J_2, where $J_1 = \mathrm{diag}\{X_7, I, X_6, I, I\}$ and $J_2 = \{X, X, X, X\}$. One can get the following inequalities:

$$\check{\Psi}_{ijl} - \tilde{\Delta}_i < 0 \tag{39}$$

$$\iota_i\check{\Psi}_{iil} - \iota_i\tilde{\Delta}_i + \tilde{\Delta}_i < 0 \tag{40}$$

$$\iota_j\check{\Psi}_{ijl} + \iota_i\check{\Psi}_{jil} - \iota_j\tilde{\Delta}_i - \iota_i\tilde{\Delta}_j + \tilde{\Delta}_i + \tilde{\Delta}_j < 0 \tag{41}$$

$$\begin{bmatrix} \tilde{R} & * \\ \tilde{M} & \tilde{R}\end{bmatrix} \geq 0 \tag{42}$$

where

$$\tilde{\Psi}_{ijl} = \begin{bmatrix} \Theta_{11}^{ijl} & * & * & * \\ \Theta_{21}^{ijl} & \Theta_{22}^{ijl} & * & * \\ \Theta_{31}^{ijl} & \Theta_{32}^{ijl} & \check{\Theta}_{33}^{ijl} & * \\ \Theta_{41}^{ijl} & \Theta_{42}^{ijl} & 0 & \Theta_{44}^{ijl}\end{bmatrix}$$

$$\Theta_{33}^{ijl} = \mathrm{diag}\{-X\tilde{R}^{-1}X, -X\tilde{R}^{-1}X, -X\tilde{R}^{-1}X, -X\tilde{R}^{-1}X, -X\tilde{R}^{-1}X, -X\tilde{R}^{-1}X\}.$$

Due to $(\tilde{R} - \epsilon^{-1}P)\tilde{R}^{-1}(\tilde{R} - \epsilon^{-1}P) \geq 0$, one can obtain that

$$-P\tilde{R}^{-1}P \leq -2\epsilon P + \epsilon^2\tilde{R}. \tag{43}$$

By substituting (43) into (39)–(42), the LMIs' conditions (31)–(33) in Theorem 2 are derived, and meanwhile, the gains of the observers and controllers are given as $K_l = Y_{1l}X^{-1}$ and $L_j = Y_{2j}SV^{-1}X_{11}^{-1}VS^T$. This completes the proof.

IV. Numerical Example and Simulation

Example 1: To illustrate the effectiveness of the proposed control scheme, a mass–spring–damper system in [28] is presented as follows:

$$\ddot{x} + 2\dot{x} + kx + 0.09kx^3 = u(t). \tag{44}$$

Let $x(t) = [x, \dot{x}]^T = [x_1(t), x_2(t)]^T$ and $k \in [5, 8]$, one has

$$\dot{x}(t) = \begin{bmatrix} 0 & 1 \\ -k(x(t), t) & -2\end{bmatrix} x(t) + \begin{bmatrix} 0 \\ 1\end{bmatrix} u(t) \tag{45}$$

where $k(x(t), t) = k + 0.09kx^2$ and it is easy to get $k(x(t), t) \in [5, 10.88]$. It is assumed that there exists a bounded external disturbance. Then, the system (45) is rewritten as follows with the IT-2 fuzzy model.

Rule 1: If $x_1(t)$ is F_{11}, then

$$\begin{cases} \dot{x}(t) = A_1x(t) + B_1u(t) + B_{w1}w(t) \\ y(t) = C[x(t) + \alpha(t)b(t)] \\ z(t) = E_1(t). \end{cases}$$

Rule 2: If $x_2(t)$ is F_{12}, then

$$\begin{cases} \dot{x}(t) = A_2x(t) + B_2u(t) + B_{w2}w(t) \\ y(t) = C[x(t) + \alpha(t)b(t)] \\ z(t) = E_2(t) \end{cases}$$

where

$$A_1 = \begin{bmatrix} 0 & 1 \\ -10.88 & -2\end{bmatrix}, \quad A_2 = \begin{bmatrix} 0 & 1 \\ -5 & -2\end{bmatrix}$$

$$B_{w1} = B_{w2} = \mathrm{diag}\{0.1, 0.1\}, \quad C = \begin{bmatrix} 0.1 & 0\end{bmatrix}$$

$$B_1 = B_2 = \begin{bmatrix} 0.1 & 0\end{bmatrix}^T, \quad E_1 = E_2 = \begin{bmatrix} 0.1 & 0\end{bmatrix}.$$

According to the uncertainty parameter k, the upper and lower MFs and some paraments are chosen as follows:

$$\underline{\omega}_1(x(t)) = \frac{q_1 - 0.45x_1^2(t) + z_{\max}}{z_{\max} - z_{\min}}$$

$$\overline{\omega}_1(x(t)) = \frac{q_2 - 0.72x_1^2(t) + z_{\max}}{z_{\max} - z_{\min}}$$

$$\underline{\omega}_2(x(t)) = \frac{-q_1 + 0.45x_1^2(t) - z_{\min}}{z_{\max} - z_{\min}}$$

$$\overline{\omega}_2(x(t)) = \frac{-q_2 + 0.72x_1^2(t) - z_{\min}}{z_{\max} - z_{\min}}$$

$$\underline{\mu}_j(\hat{x}(t)) = \sin^2(x_1(t)), \quad \overline{\mu}_j(\hat{x}(t)) = \cos^2(x_1(t))$$

$$q_1 = -5, q_2 = -8, z_{\max} = -5, z_{\min} = -10.88, \underline{\alpha}_i = 0.4$$

$$\overline{\alpha}_i = 0.6, \underline{\chi}_j = 0.5, \overline{\chi}_j = 0.5, i, j = 1, 2.$$

Then, the MFs of the nonlinear systems (44) and observer-based controller are rewritten as follows:

$$\omega_1(x(t)) = 0.4\underline{\omega}_1(x(t)) + 0.6\overline{\omega}_1(x(t))$$

$$\mu_1(x(t)) = 0.4\underline{\mu}_1(x(t)) + 0.6\overline{\mu}_1(x(t))$$

$$\omega_2(x(t)) = 1 - \omega_1(x(t)), \mu_2(x(t)) = 1 - \mu_1(x(t)).$$

Let $\iota_1 = 0.5, \iota_2 = 0.8, \lambda_1^0 = 8, \lambda_2^0 = 5, \theta_1 = 1.5, \theta_2 = 1, \bar{\alpha} = 0.8, \bar{\beta} = 0.3, \bar{\gamma} = 0.1$, and $\Delta m(t) = 0.5|\sin(t)|$. Besides, the disturbance input $w(t)$ and the deception attacks $f(y(t))$ are assumed to satisfy

$$w(t) = \begin{bmatrix} 10e^{-t+1}\sin(5t) & 10e^{-t+1}\sin(5t)\end{bmatrix}^T, t \in [0, 10]$$

$$f(y(t)) = \begin{bmatrix} 0.15\tanh(y(t)) & 0.15\tanh(y(t))\end{bmatrix}^T.$$

By using Theorem 2 and MATLAB LMIs toolbox, for the performance attenuation level $\gamma = 0.4$, the parameters of the controllers, observers, and the event-triggered matrices are calculated as follows:

$$K_1 = \begin{bmatrix} -187.8091 & 189.6873\end{bmatrix},$$

$$K_2 = \begin{bmatrix} -58.7836 & -3.0744\end{bmatrix},$$

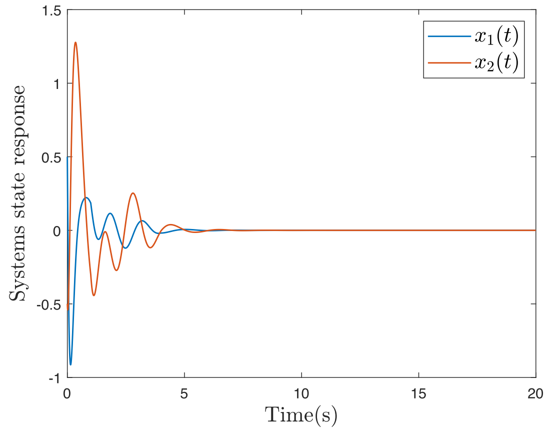

Fig. 2. State response of the control system.

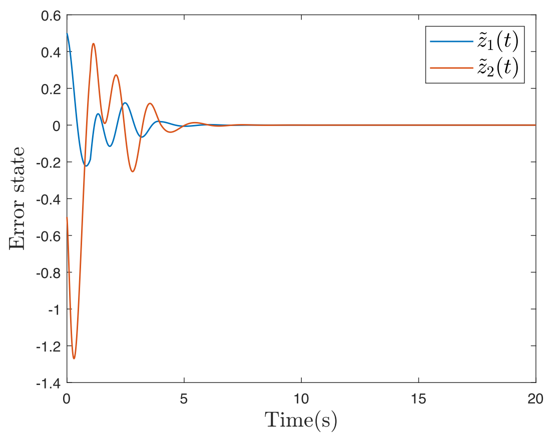

Fig. 3. Trajectories of the error system.

TABLE I
COMPARISON OF TWO ETMS

Trigger cases	Improved event trigger	Event trigger in [7]
Transmitted package	150	193
Transmission rate	7.50 %	9.65 %

$$L_1 = \begin{bmatrix} 0.0923 \\ 0.0272 \end{bmatrix}, \quad L_2 = \begin{bmatrix} -0.1500 \\ -0.0209 \end{bmatrix}, \quad \Omega_1 = 48.0518,$$

$$\Omega_2 = 2.7112.$$

Set the sampling period $h = 0.01$, the initial value of $x(t)$, $\hat{x}(t)$, $b(t)$, $\lambda_1(t)$, and $\lambda_2(t)$ as $x(0) = \begin{bmatrix} 0.5 & -0.5 \end{bmatrix}^T$, $\hat{x}(0) = \begin{bmatrix} 1 & -1 \end{bmatrix}^T$, $b(0) = \begin{bmatrix} 0.2 & 0.3 \end{bmatrix}^T$, $\lambda_1(0) = 0.5$, and $\lambda_2(0) = 0.7$, respectively. Fig. 2 displays the state response of the system with control input. Fig. 3 depicts the trajectories of the augmented error system. Fig. 4 shows the comparison of the release instants between the improved AETM proposed in this article and the AETM in the literature [7]. Besides, the number of transmitted package and transmission rate is shown in Table I. Fig. 5 depicts the instants of the multiple network attacks.

Remark 6: Example 1 makes the comparison of the release instants between two different AETMs. By calculating the rate

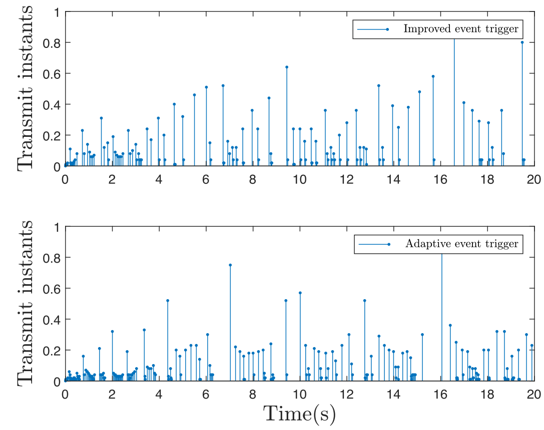

Fig. 4. Transmit instants of two different ETMs.

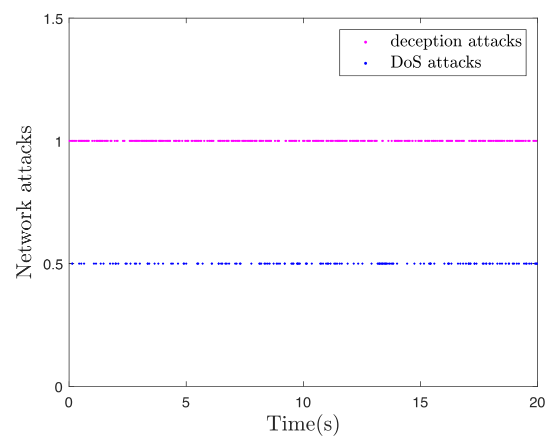

Fig. 5. Instants of network attacks.

of transmission signals, we can find that only 7.5% of sampling data can be transmitted in this article, while 9.65% of sampling data to be transmitted in [7]. Thus, the proposed AETM can relieve more network burden.

Example 2: A numerical example of the IT-2 fuzzy system is proposed and the corresponding parameters are chosen as follows:

$$A_1 = \begin{bmatrix} -1.1 & 0.2 & 1.3 \\ 0.2 & -1.5 & 0.1 \\ 0.8 & 0.1 & -0.4 \end{bmatrix}, \quad A_1 = \begin{bmatrix} -1.8 & 0.4 & 0.1 \\ 0.3 & -2 & 0.1 \\ 0.5 & 0.2 & -0.3 \end{bmatrix}$$

$$B_{w1} = B_{w2} = \begin{bmatrix} 0.1 & 0 & 0 \\ 0 & 0 & 0.1 \\ 0 & 0.1 & 0.2 \end{bmatrix}, \quad C = \begin{bmatrix} 0.01 & 0 & 0 \end{bmatrix}$$

$$B_1 = B_2 = \begin{bmatrix} 0.2 & 0.1 & 0.1 \end{bmatrix}^T, \quad E_1 = E_2 = \begin{bmatrix} 0.1 & 0 \end{bmatrix}$$

and the upper and lower MFs and some paraments are chosen as follows:

$$\underline{\omega}_1(x(t)) = 1 - e^{\frac{-x_1^2(t)}{5}}, \quad \underline{\omega}_2(x(t)) = 1 - \overline{\omega}_1(x(t))$$

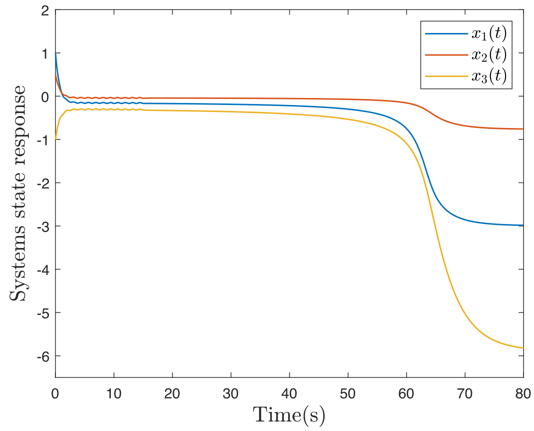

Fig. 6. State response of the system without control.

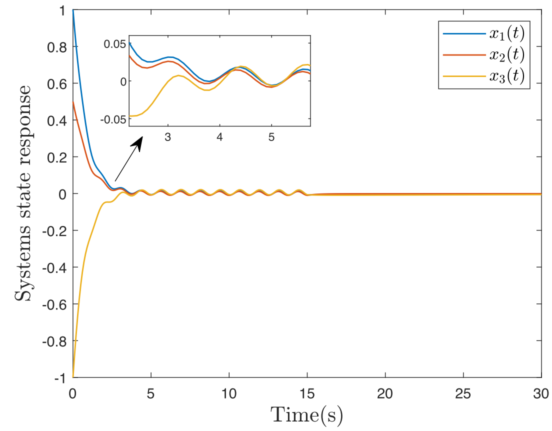

Fig. 7. State response of the control system.

$$\overline{\omega}_1(x(t)) = 1 - e^{\frac{-x_1^2(t)}{2}}, \quad \overline{\omega}_2(x(t)) = 1 - \underline{\omega}_1(x(t))$$

$$\underline{\mu}_1(\hat{x}(t)) = \overline{\mu}_1(\hat{x}(t)) = 1 - e^{\frac{-x_1^2(t)}{5}}$$

$$\underline{\mu}_2(\hat{x}(t)) = \overline{\mu}_2(\hat{x}(t)) = e^{\frac{-x_1^2(t)}{5}}$$

$$\underline{\alpha}_i = 0.6, \quad \overline{\alpha}_i = 0.4, \quad \underline{\chi}_j = 0.6 \sin^2(x_1(t))$$

$$\overline{\chi}_j = 1 - 0.6 \sin^2(x_1(t)), i, j = 1, 2.$$

Let $\iota_1 = 0.5, \iota_2 = 0.9, \lambda_1^0 = 2.5, \lambda_2^0 = 2.5, \theta_1 = 1, \theta_2 = 1, \bar{\alpha} = 0.7, \bar{\beta} = 0.7, \bar{\gamma} = 0.1$, and $\Delta m(t) = 0.5|\sin(t)|$. Besides, the disturbance input $w(t)$ and the deception attacks $f(y(t))$ are supposed to satisfy

$$w(t) = [0.1\sin(5t), 0.1\ \sin(5t), 0.1\ \sin(5t)]^T, t \in [0, 15]$$

$$f(y(t)) = [0.15\tanh(y(t)), 0.12\tanh(y(t)), 0.10\tanh(y(t))]^T.$$

By using Theorem 2 and MATLAB LMIs toolbox, for the performance attenuation level $\gamma = 0.5$, the parameters of the controllers, observers, and the event-triggered matrices are calculated as follows:

$$K_1 = \begin{bmatrix} -13.2937 & -4.0707 & -18.6273 \end{bmatrix}$$

$$K_2 = \begin{bmatrix} -1.3793 & -0.5220 & -3.6763 \end{bmatrix}$$

$$L_1 = \begin{bmatrix} -0.0924 \\ 0.0389 \\ 0.0236 \end{bmatrix}, \quad L_2 = \begin{bmatrix} -0.0518 \\ 0.0243 \\ -0.0274 \end{bmatrix}$$

$$\Omega_1 = 91.1248, \quad \Omega_2 = 2.7073.$$

In this example, the state response of system with the initial condition $x(t) = [1; 0.5; -1]^T$ is derived in Fig. 6; it is obvious that the system without control is not stable. Then, set the sampling period $h = 0.1$, the initial value of $\hat{x}(t) = [0.5; 0.3; -0.5]^T, b(t) = [0.5; 0.3; 0.1], \lambda_1(t) = 0.5$, and $\lambda_2(t) = 0.5$. The results are shown in Figs. 7–9. Fig. 7 displays the state of system with control input. The trajectories of estimation error are plotted in Fig. 8. Fig. 9 describes the release instants and intervals of the proposed AETM.

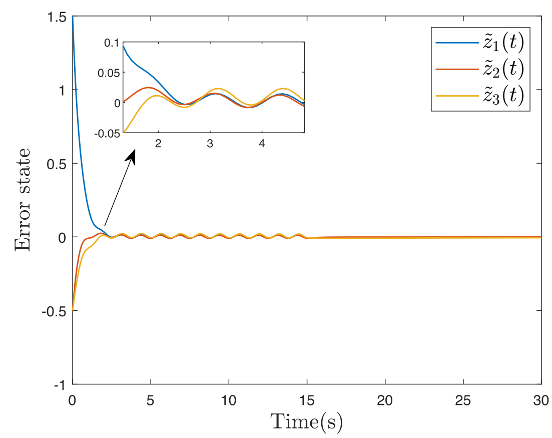

Fig. 8. Trajectories of the error state.

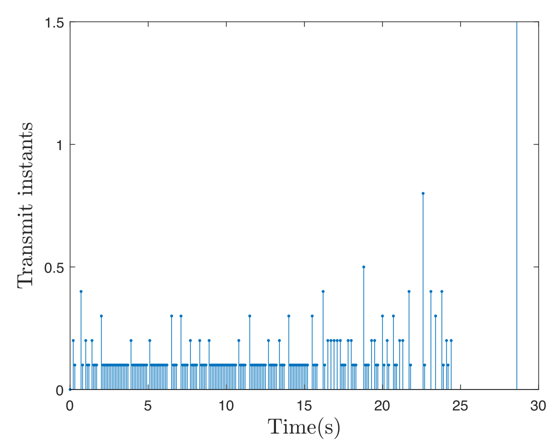

Fig. 9. Transmit instants.

V. Conclusion

In this article, the IT-2 fuzzy control problem for NCSs with sensor output bias and multiple network attacks is investigated.

To save the network resources, a novel adaptive event-triggered method is proposed, which can adjust the thresholds dynamically according to the change of current signal and previous trigger signal. Furthermore, the randomly occurring output bias from the measurement is considered in the system's model. Taking account of these influence, an observer-based event-triggered IT-2 fuzzy control model is constructed. By utilizing the theory of Lyapunov function and LMI techniques, some sufficient conditions that ensure the asymptotic stability of the augmented error system are obtained. Moreover, the parameters of the IT-2 fuzzy controllers and observers are both derived simultaneously by solving some LMIs. Finally, two simulation examples are given to support advantages of the proposed method.

REFERENCES

[1] H. Chu, S. Fei, D. Yue, C. Peng, and J. Sun, "H_∞ quantized control for nonlinear networked control systems," *Fuzzy Sets Syst.*, vol. 174, no. 1, pp. 99–113, 2011.

[2] Y. Shi, J. Huang, and B. Yu, "Robust tracking control of networked control systems: Application to a networked DC motor," *IEEE Trans. Ind. Electron.*, vol. 60, no. 12, pp. 5864–5874, Dec. 2013.

[3] Z. Du, D. Yue, and S. Hu, "H_∞ stabilization for singular networked cascade control systems with state delay and disturbance," *IEEE Trans. Ind. Inform.*, vol. 10, no. 2, pp. 882–894, May 2014.

[4] F. Wang, B. Chen, Y. Sun, Y. Gao, and C. Lin, "Finite-time fuzzy control of stochastic nonlinear systems," *IEEE Trans. Cybern.*, vol. 50, no. 6, pp. 2617–2626, Jun. 2020.

[5] L. Cao, D. Yao, H. Li, W. Meng, and R. Lu, "Fuzzy-based dynamic event triggering formation control for nonstrict-feedback nonlinear MASs," *Fuzzy Sets Syst.*, vol. 452, pp. 1–22, 2023, doi: 10.1016/j.fss.2022.03.005.

[6] S. Hu, D. Yue, X. Xie, Y. Ma, and X. Yin, "Stabilization of neural-network-based control systems via event-triggered control with nonperiodic sampled data," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 29, no. 3, pp. 573–585, Mar. 2018.

[7] J. Liu, T. Yin, J. Cao, D. Yue, and H. R. Karimi, "Security control for T–S fuzzy systems with adaptive event-triggered mechanism and multiple cyber-attacks," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 51, no. 10, pp. 6544–6554, Oct. 2021.

[8] G. Wang, L. Jia, and H. Zhang, "Stability and stabilization of T–S fuzzy time-delay system via relaxed integral inequality and dynamic delay partition," *IEEE Trans. Fuzzy Syst.*, vol. 29, no. 10, pp. 2829–2843, Oct. 2021.

[9] J. Zhao, S. Xu, and J. H. Park, "Improved criteria for the stabilization of T-S fuzzy systems with actuator failures via a sampled-data fuzzy controller," *Fuzzy Sets Syst.*, vol. 392, pp. 154–169, 2020.

[10] B. Zhu, Y. Wang, H. Zhang, and X. Xie, "Fuzzy functional observer-based finite-time adaptive sliding-mode control for nonlinear systems with matched uncertainties," *IEEE Trans. Fuzzy Syst.*, vol. 30, no. 4, pp. 918–932, Apr. 2022.

[11] Y.-Y. Lin, S.-H. Liao, J.-Y. Chang, and C.-T. Lin, "Simplified interval type-2 fuzzy neural networks," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 25, no. 5, pp. 959–969, May 2014.

[12] N. Rong and Z. Wang, "Event-based impulsive control of IT2 T–S fuzzy interconnected system under deception attacks," *IEEE Trans. Fuzzy Syst.*, vol. 29, no. 6, pp. 1615–1628, Jun. 2020.

[13] Y. Pan, Y. Wu, and H.-K. Lam, "Security-based fuzzy control for nonlinear networked control systems with DoS attacks via a resilient event-triggered scheme," *IEEE Trans. Fuzzy Syst.*, vol. 30, no. 10, pp. 4359–4368, Oct. 2022, doi: 10.1109/TFUZZ.2022.3148875.

[14] J. Zhai, "Dynamic output-feedback control for nonlinear time-delay systems and applications to chemical reactor systems," *IEEE Trans. Circuits Syst. II, Express Briefs*, vol. 66, no. 11, pp. 1845–1849, Nov. 2019.

[15] C. Latrach, M. Kchaou, and H. Gueguen, "H_∞ observer-based decentralised fuzzy control design for nonlinear interconnected systems: An application to vehicle dynamics," *Int. J. Syst. Sci.*, vol. 48, no. 7, pp. 1485–1495, 2017.

[16] H. Yan, H. Zhang, X. Zhan, Y. Wang, S. Chen, and F. Yang, "Event-triggered sliding mode control of switched neural networks with mode-dependent average dwell time," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 51, no. 2, pp. 1233–1243, Feb. 2021.

[17] Y. Wang, L. Zheng, H. Zhang, and W. X. Zheng, "Fuzzy observer-based repetitive tracking control for nonlinear systems," *IEEE Trans. Fuzzy Syst.*, vol. 28, no. 10, pp. 2401–2415, Oct. 2020.

[18] W.-B. Xie, B. Liu, L.-W. Bu, Y.-L. Wang, and J. Zhang, "A decoupling approach for observer-based controller design of T–S fuzzy system with unknown premise variables," *IEEE Trans. Fuzzy Syst.*, vol. 29, no. 9, pp. 2714–2725, Sep. 2021.

[19] Y. Gu, J. H. Park, M. Shen, and D. Liu, "Event-triggered control of Markov jump systems against general transition probabilities and multiple disturbances via adaptive-disturbance-observer approach," *Inf. Sci., Int. J.*, vol. 608, pp. 1113–1130, 2022.

[20] Y. Pan and G.-H. Yang, "Event-triggered fuzzy control for nonlinear networked control systems," *Fuzzy Sets Syst.*, vol. 329, pp. 91–107, 2017.

[21] Z. Du, W. Yuan, and S. Hu, "Discrete-time event-triggered H_∞ stabilization for networked cascade control systems with uncertain delay," *J. Franklin Inst.*, vol. 356, no. 16, pp. 9524–9544, 2019.

[22] D. Liu, G.-H. Yang, and M. J. Er, "Event-triggered control for T–S fuzzy systems under asynchronous network communications," *IEEE Trans. Fuzzy Syst.*, vol. 28, no. 2, pp. 390–399, Feb. 2020.

[23] H. Li, Z. Zhang, H. Yan, and X. Xie, "Adaptive event-triggered fuzzy control for uncertain active suspension systems," *IEEE Trans. Cybern.*, vol. 49, no. 12, pp. 4388–4397, Dec. 2019.

[24] Z. Gu, T. Zhang, F. Yang, H. Zhao, and M. Shen, "A novel event-triggered mechanism for networked cascade control system with stochastic nonlinearities and actuator failures," *J. Franklin Inst.*, vol. 356, no. 4, pp. 1955–1974, 2019.

[25] Y. Gu, Z. Sun, L.-W. Li, J. H. Park, and M. Shen, "Event-triggered security adaptive control of uncertain multi-area power systems with cyber attacks," *Appl. Math. Comput.*, vol. 432, 2022, Art. no. 127344.

[26] J. Wu, C. Peng, J. Zhang, and B. Zhang, "Event-triggered finite-time H_∞ filtering for networked systems under deception attacks," *J. Franklin Inst.*, vol. 357, no. 6, pp. 3792–3808, 2020.

[27] Y. Xu, G. Guo, and S. Yu, "Resilient observer-based sliding mode control of connected vehicles with denial-of-service attacks," *J. Franklin Inst.*, vol. 359, no. 7, pp. 2886–2905, 2022.

[28] X. Li and D. Ye, "Asynchronous event-triggered control for networked interval type-2 fuzzy systems against DoS attacks," *IEEE Trans. Fuzzy Syst.*, vol. 29, no. 2, pp. 262–274, Feb. 2021.

[29] P. Shi, H. Wang, and C.-C. Lim, "Network-based event-triggered control for singular systems with quantizations," *IEEE Trans. Ind. Electron.*, vol. 63, no. 2, pp. 1230–1238, Feb. 2016.

[30] J. Liu, Y. Gu, X. Xie, D. Yue, and J. H. Park, "Hybrid-driven-based H_∞ control for networked cascade control systems with actuator saturations and stochastic cyber attacks," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 49, no. 12, pp. 2452–2463, Dec. 2019.

[31] C. Deng and C. Wen, "Distributed resilient observer-based fault-tolerant control for heterogeneous multiagent systems under actuator faults and DoS attacks," *IEEE Trans. Control Netw. Syst.*, vol. 7, no. 3, pp. 1308–1318, Sep. 2020.

[32] J. Cheng, Y. Wang, J. H. Park, J. Cao, and K. Shi, "Static output feedback quantized control for fuzzy Markovian switching singularly perturbed systems with deception attacks," *IEEE Trans. Fuzzy Syst.*, vol. 30, no. 4, pp. 1036–1047, Apr. 2022.

[33] Q. Zhang, H. Yan, H. Zhang, S. Chen, and M. Wang, "H_∞ control of singular system based on stochastic cyber-attacks and dynamic event-triggered mechanism," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 51, no. 12, pp. 7510–7516, Dec. 2021.

[34] T. Li, X. Tang, H. Zhang, and S. Fei, "Improved event-triggered control for networked control systems under stochastic cyber-attacks," *Neurocomputing*, vol. 350, pp. 33–43, 2019.