International Journal of Innovative Computing, Information and Control
Volume **22**, Number **1**, February **2026**

ICIC International ©2026 ISSN 1349-4198
pp. **79–94**

ADAPTIVE INTERMITTENT CONTROL FOR UNCERTAIN NONLINEAR SYSTEMS: AN EVENT-TRIGGERED APPROACH

Di Lun[1], Yuanyuan Shen[2] and Ning Zhao[1,*]

[1]College of Control Science and Engineering
Bohai University
No. 19, Keji Road, New Songshan District, Jinzhou 121013, P. R. China
lundi_i@163.com; *Corresponding author: zhaoning_hrbeu@163.com

[2]Guangxi Botanical Garden of Medicinal Plants
No. 189, Changgang Road, Nanning 530023, P. R. China
shenyy@gxyyzwy.com

Received April 2025; revised July 2025

Abstract. *This paper focuses on event-triggered adaptive state feedback controller design for nonlinear systems with unknown parameters. Unlike some systems where nonlinear functions satisfy Lipschitz conditions, we consider more general polynomial-growth-constrained nonlinear functions. In order to identify unknown parameters, a parameter estimator is designed. By incorporating event-triggered states and parameter estimation signals, an adaptive intermittent state feedback nonlinear controller is established to achieve remote signal transmission and offset the effects of nonlinear dynamics. Based on this framework, a novel functional is constructed to rigorously prove the global uniform ultimate boundedness of both system states and parameter estimation errors. Finally, two numerical simulation examples are used to characterize the effectiveness of the developed control strategy.*
Keywords: Non-Lipschitz nonlinear systems, Event-triggered control, Intermittent control, Parameter estimation

1. **Introduction.** In recent years, uncertain nonlinear systems have attracted significant attention in the control community due to their widespread applications in various key engineering domains, such as automotive engine control [1], flexible spacecraft attitude regulation [2], and magnetic levitation systems [3]. In such systems, the complexity of the system structure and the presence of unknown parameters make control design particularly challenging. Adaptive control has been recognized as an effective approach [4, 5, 9], where parameter estimators are introduced to identify system uncertainties. Consequently, the development of efficient event-triggered adaptive controllers for uncertain systems has become a pressing research problem.

Event-triggered control (ETC), as a non-periodic transmission decision strategy, has been widely integrated into various advanced control frameworks, including model predictive control [6], fault-tolerant control [7], optimal control [8], disturbance-rejection control [9], and sliding mode control [10]. Its fundamental principle is to release control or measurement signals for transmission only when predefined triggering conditions are satisfied. As noted in [11], this mechanism not only maintains satisfactory control performance but also significantly reduces communication load. However, the implementation of event-triggered mechanisms (ETMs) introduces new challenges, particularly due to the discrete nature of control updates, which are inherently digital rather than analog signals

DOI: 10.24507/ijicic.22.01.79

[12, 13, 14, 15]. This distinction complicates the stability analysis of the closed-loop system. Numerous results have been reported on the application of ETC to nonlinear systems. For instance, in [16], ETMs were designed under the assumption of fully known nonlinear system models satisfying specific function conditions to ensure system stability. Most existing ETM designs adopt a single-ended triggering structure, in which only one triggering condition is applied to each subsystem. While simple to implement, this structure is often insufficient to capture the full dynamics of the system. To improve performance, a few studies have introduced double-ended ETM architectures for remote control [17, 18, 19, 20]. The secure control of networked nonlinear systems was investigated in [24]. The control of nonlinear time-varying systems subject to state constraints was addressed in [25]. Although these approaches show effectiveness in certain contexts, they often lack the adaptability required to cope with system evolution, thereby limiting their practical deployment. A variety of novel ETMs have been proposed. For example, some works aim to avoid continuous controller communication [27], while others focus on reducing persistent monitoring of triggering conditions [28]. However, these designs may still require frequent evaluations or transmissions under certain conditions. To address these limitations, one of the key motivations of this work is to develop a digital controller based on intermittent state and parameter estimation, enabling efficient ETC while enhancing system adaptability and reducing implementation complexity.

In addition, the simultaneous existence of uncertainty and non-Lipschitz nonlinearities significantly increases the complexity of system modeling and stability analysis. Currently, many existing control methods require the nonlinear function to satisfy the Lipschitz condition [26], which is often not satisfied in practical engineering systems. Therefore, to enhance the practical applicability of nonlinear control methods, it is essential to design control strategies that do not depend on these constraints. At present, there are few studies on higher order nonlinear systems, which makes the design of controllers more complicated. To solve these problems, a new adaptive control framework for high order nonlinear systems is developed. The framework can effectively compensate the uncertainty of the system and ensure the closed-loop stability.

The major contribution has three aspects.

- In contrast to [24, 25], an adaptive controller based on parameter estimation and intermittent state is developed. State observation and parameter updates are executed only at discrete event-triggered moments, effectively resolving the mismatch between continuous estimation processes and digital communication constraints.
- In the underlying system, nonlinear term is no longer required to satisfy the strict Lipschitz condition. By using adaptive nonlinear feedback controllers, the impact of uncertainty and strong nonlinearity on system performance is eliminated. This assumption is removed by comparing with the Lipschitz nonlinear system model in [26], and the proposed method successfully solves the adaptive control problem of general nonlinear systems.
- A variety of novel ETMs are proposed. In contrast to existing methods that merely prevent continuous controller communication [27] or persistent monitoring of triggering conditions [28], the proposed ETM enables intermittent controller communication, thereby conserving network resources and reducing the frequent activation of physical components. Furthermore, Zeno behavior is inherently avoided by design.

The paper is structured as follows: In Section 2, the system model is described, two distinct ETMs are proposed, and the associated adaptive intermittent controllers are developed. Section 3 provides the core theoretical contributions, encompassing controller synthesis, stability analysis and the demonstration of Zeno-free behavior. Section 4 presents numerical simulations to validate the proposed method. Finally, Section 5 summarizes the conclusion.

2. Problem Formulation and Preliminaries.

2.1. System description.

Consider a nonlinear system described by

$$\begin{cases} \dot{\varsigma}(t) = A\varsigma(t) + B\left(u(t) + \varpi^T \phi(\varsigma)\right), \\ \varsigma(0) = \varsigma_0, \end{cases} \tag{1}$$

where $\varsigma(t) \in \mathbb{R}^n$ and $u(t) \in \mathbb{R}^m$ are state vector and control input, respectively. A and B are known real matrices, and $\varpi \in \mathbb{R}^{p\times m}$ denotes an unknown constant matrix. The function $\phi(\varsigma)$ is the known nonlinear function that depends on the system state and satisfies $\phi(0) = 0$. The initial condition ς_0 is given. In addition, it is assumed that there is a scalar ρ for which the following inequality holds:

$$\|\phi(\varsigma) - \phi(y)\| \leq \rho \sum_{j=1}^{n_1} \alpha_j \|\varsigma - y\|^j, \tag{2}$$

where n_1 is a positive integer, $\alpha_j \in \{0, 1\}$.

2.2. Event-triggered mechanisms.

Let the sampling period be T. To save sensor-to-controller channel communication resources, two different trigger conditions are designed as

$$\text{Condition 1: } t_{k+1} = \inf\{t \in (t_k, t_k + T] | (\delta_1 > 0) \vee (\delta_2 > 0) \vee (\|\varsigma(t) - \varsigma(t_k)\| > \nu)\}, \tag{3}$$

$$\begin{aligned} \text{Condition 2: } t_{k+1} = \inf\{t \in (t_k, t_k + T] | (\delta_1 > 0) \vee (\delta_2 > 0) \vee (\|\varsigma(t) - \varsigma(t_k)\| \\ > \sigma_2 \|\varsigma(t_k)\|)\}, \end{aligned} \tag{4}$$

where $\delta_1 = \left\|B^T Q\varepsilon(t)\right\|^2 - \sigma_1 \left\|B^T Q\varsigma(t)\right\|^2$, $\delta_2 = \varepsilon^T(t)\psi\varepsilon(t) - \sigma_1 \varsigma^T(t)\psi\varsigma(t)$, $\varepsilon(t) = \varsigma(t) - \varsigma(t_k)$, $\sigma_1, \sigma_2 \in (0, 1)$ are thresholds, and $\psi > 0$ is a weighting matrix. T and ν are two positive constants.

Remark 2.1. *To handle higher-order nonlinear functions, the ETM in* [29] *require the threshold ρ_k to be less than 1, which restricts its applicability. This paper improves the trigger mechanism by removing the strict limitation on the threshold $\nu \in (0, 1)$.*

2.3. Adaptive intermittent controller.

Denote $\hat{\varpi}(t)$ as the estimated value of ϖ. The corresponding adaptive law is given by

$$\dot{\hat{\varpi}}(t) = 2\Gamma\left(\phi(\bar{\varsigma})\bar{x}^T(t)QB - \eta\hat{\varpi}(t)\right), \tag{5}$$

where $\bar{\varsigma}(t) = \varsigma(t_k)$, η is a strictly positive scalar, $\Gamma \in \mathbb{R}^{p\times p}$ and $Q \in \mathbb{R}^{n\times n}$ denote two symmetric positive definite matrices.

An adaptive intermittent controller satisfying Condition 1 is designed by integrating state feedback with a nonlinear compensator, as given below:

$$u(t) = u_1(t) - \bar{\eta} B^T Q\bar{\varsigma}(t)\|\phi(\bar{\varsigma})\|^2, \tag{6}$$

an adaptive intermittent control scheme satisfying Condition 2 is formulated as follows:

$$u(t) = u_1(t) - \bar{\eta} B^T Q\bar{\varsigma}(t)||\phi(\bar{\varsigma})||^2 - \hat{\eta}\left(\sum_{j=1}^{n_1} \alpha_j \sigma_2^j \|\bar{\varsigma}(t)\|^j\right)^2 B^T Q\bar{\varsigma}(t), \tag{7}$$

where $u_1(t) = -K\bar{\varsigma}(t) - \bar{\hat{\varpi}}^T(t)\phi(\bar{\varsigma})$, K is the control gain to be solved; $\bar{\hat{\varpi}}(t) = \hat{\varpi}(t_k)$, $\bar{\eta}$ and $\hat{\eta}$ are both positive scalar parameters.

Let $\tilde{\varpi}(t) = \varpi - \hat{\varpi}(t)$ denote the estimation error. Under triggering Condition 1, by applying the controller in Equation (6) to system (1), the resulting closed-loop system is expressed as follows:

$$\dot{\varsigma}(t) = (A - BK)\varsigma(t) + B\tilde{\varpi}^T(t)\phi(\varsigma) - \bar{\eta}BB^TQ\bar{\varsigma}(t)\|\phi(\bar{\varsigma})\|^2 + B\left(u_1(t) - \hat{u}_1(t)\right). \tag{8}$$

Under triggering Condition 2, the closed-loop system is reformulated as follows:

$$\begin{aligned}\dot{\varsigma}(t) = {} & (A - BK)\varsigma(t) + B\tilde{\varpi}^T(t)\phi(\varsigma) - \bar{\eta}BB^TQ\bar{\varsigma}(t)||\phi(\bar{\varsigma})||^2 \\ & - \hat{\eta}\left(\sum_{j=1}^{n_1} \alpha_j\sigma_2^j\|\bar{\varsigma}(t)\|^j\right)^2 BB^TQ\bar{\varsigma}(t) + B(u_1(t) - \hat{u}_1(t)),\end{aligned} \tag{9}$$

where $\hat{u}_1(t) = -Kx(t) - \hat{\varpi}^T(t)\phi(\varsigma)$.

This work is focused on the proposed control strategy to stabilize the resulting closed-loop system, represented by Equation (8) or (9), achieving global uniform ultimate boundedness; that is,

$$\|\varsigma(t)\| \le \epsilon, \tag{10}$$

where $\epsilon > 0$ denotes a positive constant.

3. **Main Results.** This section mainly presents sufficient conditions that guarantee the stability of systems (8) and (9) under triggering Conditions 1 and 2, respectively. The controller gain is determined using matrix analysis. Moreover, the occurrence of Zeno behavior is effectively prevented.

Theorem 3.1. *For given matrix* Γ *and constants* $T > 0$, $\eta > 0$, $\bar{\eta} > 0$, $r > 0$, $\rho > 0$, $\nu > 0$, $\beta_1 > 0$, $\beta_2 > 0$, $\beta_3 > 0$, $\alpha_0 > 0$, $\sigma_1 > 0$, *the closed-loop system* (8) *under trigger Condition 1 is Globally Uniformly Ultimately Bounded (GUUB), if there exist matrices* $X > 0$ *and* $\bar{\psi} > 0$ *satisfying*

$$a_1 = \bar{\eta}(1 - \sigma_1) - \sigma_1\beta_3 - 8T^2\lambda_{\max}^2(\Gamma)/\beta_1 - \beta_2 \ge 0, \tag{11}$$

$$a_2 = re^{-\alpha_0 T} - 16\eta^2\lambda_{\max}^2(\Gamma)T/\beta_1 \ge 0, \tag{12}$$

$$a_3 = \eta - \frac{2}{\beta_3} - rT - \alpha_0\lambda_{\max}(\Gamma^{-1})/2 \ge 0, \tag{13}$$

$$a_4 = \eta - \frac{1}{\beta_1} \ge 0, \tag{14}$$

$$\bar{\Sigma} = \begin{bmatrix} \bar{\Sigma}_{11} & BY \\ * & -\bar{\psi} \end{bmatrix} < 0, \tag{15}$$

where $\bar{\Sigma}_{11} = \alpha_0 X + AX - BY + (AX - BY)^T + (\beta_1 + \beta_3)\rho^2\left(\sum_{j=1}^{n_1}\alpha_j\nu^j\right)^2 BB^T + \sigma_1\bar{\psi}$. *Furthermore, the control gain is given by* $K = YX^{-1}$, $\psi = X^{-1}\bar{\psi}X^{-1}$ *and Zeno behavior can be avoided.*

Proof: The Lyapunov functional is constructed as

$$V(t) = V_1(t) + V_2(t), \tag{16}$$

where

$$V_1(t) = \varsigma^T(t)Q\varsigma(t) + \frac{1}{2}\mathrm{Tr}\left\{\tilde{\varpi}^T(t)\Gamma^{-1}\tilde{\varpi}(t)\right\},$$

$$V_2(t) = r\int_{t-T}^{t}\int_{\kappa}^{t} e^{-\alpha_0(t-s)}\mathrm{Tr}\left\{\tilde{\varpi}^T(s)\tilde{\varpi}(s)\right\}\mathrm{d}s\mathrm{d}\kappa$$

with $Q > 0$.

Calculating the derivative of $V(t)$, we can obtain

$$\begin{aligned}\dot{V}_1(t)+\alpha_0 V_1(t) &= \alpha_0\varsigma^T(t)Q\varsigma(t)+\frac{1}{2}\alpha_0\mathrm{Tr}\left\{\tilde{\varpi}^T(t)\Gamma^{-1}\tilde{\varpi}(t)\right\}+2\varsigma^T(t)Q\dot{\varsigma}(t)\\ &\quad-\ \mathrm{Tr}\left\{\tilde{\varpi}^T(t)\Gamma^{-1}\dot{\hat{\varpi}}(t)\right\}\\ &\le \Delta_1(t)+2\varsigma^T(t)QB(u_1(t)-\hat{u}(t)),\end{aligned} \tag{17}$$

$$\dot{V}_2(t)+\alpha_0 V_2(t) = rT\mathrm{Tr}\left\{\tilde{\varpi}^T(t)\tilde{\varpi}(t)\right\}-re^{-\alpha_0 T}\int_{t-T}^{t}\mathrm{Tr}\left\{\tilde{\varpi}^T(s)\tilde{\varpi}(s)\right\}\mathrm{d}s, \tag{18}$$

where

$$\begin{aligned}\Delta_1(t) &= \alpha_0\varsigma^T(t)Q\varsigma(t)+\frac{1}{2}\alpha_0\mathrm{Tr}\left\{\tilde{\varpi}^T(t)\Gamma^{-1}\tilde{\varpi}(t)\right\}+\varsigma^T(t)\left[Q(A-BK)+(A-BK)^TQ\right]\varsigma(t)\\ &\quad+2\varsigma^T(t)QB\times\tilde{\varpi}^T(t)\phi(\varsigma)-2\mathrm{Tr}\left\{\tilde{\varpi}^T(t)\phi(\bar{\varsigma})\bar{x}^T(t)QB\right\}+2\eta\mathrm{Tr}\left\{\tilde{\varpi}^T(t)\hat{\varpi}(t)\right\}\\ &\quad-2\bar{\eta}\|\phi(\bar{\varsigma})\|^2\varsigma^T(t)QBB^TQ\bar{\varsigma}(t).\end{aligned}$$

The term $-2\bar{\eta}\|\phi(\bar{\varsigma})\|^2\varsigma^T(t)QBB^TQ\bar{\varsigma}(t)$ can be evaluated as

$$\begin{aligned}-2\bar{\eta}\|\phi(\bar{\varsigma})\|^2\varsigma^T(t)QBB^TQ\bar{\varsigma}(t) &= -2\bar{\eta}\|\phi(\bar{\varsigma})\|^2\varsigma^T(t)QBB^TQ(\varsigma(t)+\bar{\varsigma}(t)-\varsigma(t))\\ &\le -2\bar{\eta}\|\phi(\bar{\varsigma})\|^2\varsigma^T(t)QBB^TQ\varsigma(t)\\ &\quad-2\bar{\eta}\|\phi(\bar{\varsigma})\|^2\varsigma^T(t)QBB^TQ\varepsilon(t)\\ &\le -\bar{\eta}\|\phi(\bar{\varsigma})\|^2\varsigma^T(t)QBB^TQ\varsigma(t)\\ &\quad+\bar{\eta}\|\phi(\bar{\varsigma})\|^2\varepsilon^T(t)QBB^TQ\varepsilon(t).\end{aligned} \tag{19}$$

By virtue of the triggered condition (3), one can get

$$-\bar{\eta}\|\phi(\bar{\varsigma})\|^2\varepsilon^T(t)QBB^TQ\varepsilon(t)+\sigma_1\bar{\eta}\|\phi(\bar{\varsigma})\|^2\varsigma^T(t)QBB^TQ\varsigma(t)\ge 0, \tag{20}$$

$$-\varepsilon^T(t)\psi\varepsilon(t)+\sigma_1\varsigma^T(t)\psi\varsigma(t)\ge 0. \tag{21}$$

The term $2\varsigma^T(t)QB\left(u_1(t)-\hat{u}(t)\right)$ is formulated as

$$\begin{aligned}2\varsigma^T(t)QB\left(u_1(t)-\hat{u}(t)\right) &= 2\varsigma^T(t)QBK\varepsilon(t)+2\varsigma^T(t)QB\left(\hat{\varpi}^T(t)\phi(\varsigma)-\hat{\bar{\varpi}}^T(t)\phi(\bar{\varsigma})\right)\\ &\le\ 2\varsigma^T(t)QBK\varepsilon(t)+\beta_1\rho^2\left(\sum_{j=1}^{n_1}\alpha_j\nu^j\right)^2\left\|B^TQ\varsigma(t)\right\|^2\\ &\quad+\beta_2\|\phi(\bar{\varsigma})\|^2\left\|B^TQ\varsigma(t)\right\|^2+\frac{1}{\beta_2}\left\|\hat{\varpi}(t)-\hat{\bar{\varpi}}(t)\right\|^2\\ &\quad+\frac{1}{\beta_1}\left\|\hat{\varpi}(t)\right\|^2,\end{aligned} \tag{22}$$

where β_1 and β_2 represent positive scalars.

The expression $2\eta\mathrm{Tr}\left\{\tilde{\varpi}^T(t)\hat{\varpi}(t)\right\}$ in Equation (17) is described by

$$2\eta\mathrm{Tr}\left\{\tilde{\varpi}^T(t)\hat{\varpi}(t)\right\}=\eta\left(-\|\tilde{\varpi}(t)\|^2-\|\hat{\varpi}(t)\|^2+\|\varpi\|^2\right). \tag{23}$$

Note that

$$\begin{aligned}\left\|\hat{\varpi}(t)-\hat{\bar{\varpi}}(t)\right\| &\le \int_{t_k}^{t}\left\|\dot{\hat{\varpi}}(s)\right\|\mathrm{d}s\\ &\le 2T\lambda_{\max}(\Gamma)\left\|\phi(\bar{\varsigma})\right\|\left\|\bar{x}^T(t)QB\right\|+2\eta\lambda_{\max}(\Gamma)\int_{t_k}^{t}\left\|\hat{\varpi}(s)\right\|\mathrm{d}s.\end{aligned}$$

Then, it is clear that

$$\left\|\hat{\varpi}(t)-\hat{\bar{\varpi}}(t)\right\|^2\le 8T^2\lambda_{\max}^2(\Gamma)\left\|\phi(\bar{\varsigma})\right\|^2\left\|\bar{x}^T(t)QB\right\|^2$$

$$+ 16\eta^2\lambda^2_{\max}(\Gamma)T\int_{t_k}^{t}\|\tilde{\varpi}(s)\|^2\mathrm{d}s + 16\eta^2\lambda^2_{\max}(\Gamma)T^2\|\varpi\|^2. \tag{24}$$

Noting that $\mathrm{Tr}\left\{a^Tb\right\} = \mathrm{Tr}\left\{ba^T\right\}$, we obtain that

$$2\mathrm{Tr}\left\{\tilde{\varpi}^T(t)\phi(\bar{\varsigma})\bar{x}^T(t)QB\right\} = 2\mathrm{Tr}\left\{\phi(\bar{\varsigma})\bar{x}^T(t)QB\tilde{\varpi}^T(t)\right\}, \tag{25}$$

$$2\varsigma^T(t)QB\tilde{\varpi}^T(t)\phi(\varsigma) = 2\mathrm{Tr}\left\{\varsigma^T(t)QB\tilde{\varpi}^T(t)\phi(\varsigma)\right\} = 2\mathrm{Tr}\left\{\phi(\varsigma)\varsigma^T(t)QB\tilde{\varpi}^T(t)\right\}. \tag{26}$$

Note that

$$\begin{aligned}
&2\mathrm{Tr}\left\{(\phi(\varsigma)\varsigma^T(t) - \phi(\bar{\varsigma})\bar{x}^T(t))QB\tilde{\varpi}^T(t)\right\} \\
&= 2\mathrm{Tr}\left\{(\phi(\varsigma)\varsigma^T(t) - \phi(\bar{\varsigma})x^T(t) + \phi(\bar{\varsigma})x^T(t) - \phi(\bar{\varsigma})\bar{x}^T(t))QB\tilde{\varpi}^T(t)\right\} \\
&\leq \beta_3\|\phi(\varsigma) - \phi(\bar{\varsigma})\|^2\left\|B^TQ\varsigma(t)\right\|^2 + \beta_3\|\phi(\bar{\varsigma})\|^2\left\|B^TQ\varepsilon(t)\right\|^2 + \frac{2}{\beta_3}\mathrm{Tr}\left\{\tilde{\varpi}^T(t)\tilde{\varpi}(t)\right\} \\
&\leq \beta_3\rho^2\left(\sum_{j=1}^{n_1}\alpha_j\nu^j\right)^2\left\|B^TQ\varsigma(t)\right\|^2 + \sigma_1\beta_3\|\phi(\bar{\varsigma})\|^2\left\|B^TQ\varsigma(t)\right\|^2 \\
&\quad + \frac{2}{\beta_3}\mathrm{Tr}\left\{\tilde{\varpi}^T(t)\tilde{\varpi}(t)\right\},
\end{aligned} \tag{27}$$

where $\beta_3 > 0$ is a parameter.

Taking Equations (19)-(27) into Equation (17), it follows that

$$\begin{aligned}
\dot{V}(t) + \alpha_0V(t) \leq{}& \xi^T(t)\Sigma\xi(t) - a_1\|\phi(\bar{\varsigma})\|^2\varsigma^T(t)QBB^TQ\varsigma(t) - a_2\int_{t_k}^{t}\mathrm{Tr}\left\{\tilde{\varpi}^T(s)\tilde{\varpi}(s)\right\}\mathrm{d}s \\
&- a_3\mathrm{Tr}\left\{\tilde{\varpi}^T(t)\tilde{\varpi}(t)\right\} - a_4\mathrm{Tr}\left\{\hat{\varpi}^T(t)\hat{\varpi}(t)\right\} + b,
\end{aligned} \tag{28}$$

where $\Sigma = \begin{bmatrix}\Sigma_{11} & QBK \\ * & -\psi\end{bmatrix} < 0$, $\Sigma_{11} = \alpha_0Q + Q(A - BK) + (A - BK)^TQ + (\beta_1 + \beta_3)\rho^2\left(\sum_{j=1}^{n_1}\alpha_j\nu^j\right)^2QBB^TQ + \sigma_1\psi$, $\xi(t) = \mathrm{col}\{\varsigma(t), \varepsilon(t)\}$, $b = \left(16\eta^2\lambda^2_{\max}(\Gamma)T^2/\beta_1 + \eta\right)\|\varpi\|^2$. Next, we prove $\bar{\Sigma} < 0$. Denote $X = Q^{-1}$, $\bar{\psi} = X\psi X$, $\Upsilon = \mathrm{diag}\{X, X\}$ and $Y = KX$. Pre- and post-multiplying Σ by Υ and Υ^{T}, respectively, yields Equation (15). Subsequently, conditions (11)-(13) lead to

$$\dot{V}(t) + \alpha_0V(t) \leq b. \tag{29}$$

Therefore, it follows that $V(t) \leq e^{-\alpha_0t}V(0) + \frac{b}{\alpha_0}\left(1 - e^{-\alpha_0t}\right)$. From the form of $V(t)$, it follows that

$$\begin{aligned}
&V(t) \geq \varsigma^T(t)Q\varsigma(t) \geq \lambda_{\min}(Q)\|\varsigma(t)\|^2, \\
&V(0) \leq \varsigma^T(0)Q\varsigma(0) + \Delta \leq \lambda_{\max}(Q)\|\varsigma(0)\|^2 + \Delta,
\end{aligned} \tag{30}$$

where $\Delta = \frac{1}{2}\mathrm{Tr}\left\{\tilde{\varpi}^T(0)\Gamma^{-1}\varpi(0)\right\} + \frac{rT^2}{2}\sup_{\rho\in[-T,0]}\|\tilde{\varpi}(\rho)\|^2$. There is a scalar $\ell > 0$, such that $\Delta \leq \ell\|\varsigma(0)\|^2$. Therefore, it follows that $V(0) \leq (\lambda_{\max}(Q) + \ell)\|\varsigma(0)\|^2$. It follows from Equation (30) that

$$\lambda_{\min}(Q)\|\varsigma(t)\|^2 \leq e^{-\alpha_0t}(\lambda_{\max}(Q) + \ell)\|\varsigma(0)\|^2 + \frac{b}{\alpha_0}\left(1 - e^{-\alpha_0t}\right). \tag{31}$$

As $t \to \infty$, it follows that

$$\|\varsigma(t)\| \leq \sqrt{\frac{b}{\alpha_0\lambda_{\min}(Q)}}. \tag{32}$$

This implies that all signals remain bounded.

Next, we prove that the designed trigger mechanism is free of Zeno behavior. Define an auxiliary function as $h_1(t) = \left\|B^T Q\varepsilon(t)\right\|$, whose derivative is given by

$$\dot{h}_1(t) \leq \left\|B^T Q\dot{\varsigma}(t)\right\| \leq \left\|B^T Q\right\| M, \tag{33}$$

where system (8) is considered, and $M = \sup_{t\in[t_k,t_{k+1})} \|\dot{\varsigma}(t)\|$.

After integrating Equation (33) and invoking condition (3), the result is

$$\sqrt{\sigma_1}\left\|B^T Q\varsigma(t_{k+1})\right\| < \left\|B^T Q\varepsilon(t_{k+1})\right\| \leq \left\|B^T Q\right\| M(t_{k+1} - t_k), \tag{34}$$

implying that

$$t_{k+1} - t_k > \frac{\sqrt{\sigma_1}\left\|B^T Q\varsigma(t_{k+1})\right\|}{\left\|B^T Q\right\| M}. \tag{35}$$

Then, the minimum trigger interval κ_1 derived from the condition $\delta_1 > 0$ is greater than zero. In the same way, the minimum trigger intervals $\kappa_2 = \min_{k\in\mathbb{N}} \sqrt{\sigma_1}\left\|\Omega^{\frac{1}{2}}\varsigma(t_{k+1})\right\| \Big/ \left(\left\|\Omega^{\frac{1}{2}}\right\| M\right)$ and $\kappa_3 = \min_{k\in\mathbb{N}} \|\varsigma(t_{k+1})\|/\nu$ corresponding to the conditions $\delta_2 > 0$ and $\|\varsigma(t) - \varsigma(t_k)\| > \nu$ each exceeds zero. As a result, for the Condition 1, the minimum inter-event interval is given by $t_{k+1} - t_k > \kappa = \min\{\kappa_1, \kappa_2, \kappa_3\} \geq 0$. The proof is finished. □

Remark 3.1. *The central challenge in Theorem 3.1 lies in handling* $\left\|\hat{\varpi}(t) - \hat{\bar{\varpi}}(t)\right\|^2$. *By applying Jensen's inequality, we can evaluate it as a single integral using the known estimation equation. The integral term is then effectively eliminated by the Lyapunov functional* $V_2(t)$.

In order to simplify the analysis process, we further modify trigger Condition 1 and propose a new trigger condition:

$$t_{k+1} = \inf\left\{t > t_k \middle| t \text{ satisfying Condition } 1 \vee \left\|\hat{\varpi}(t) - \hat{\bar{\varpi}}(t)\right\| > \sigma_3 \|\hat{\varpi}(t)\|\right\}, \tag{36}$$

thus providing a more concise stability criterion.

Corollary 3.1. *For given matrix* Γ *and constants* ρ, η, $\bar{\eta}$, β_1, β_2, β_3, α_0, σ_1, σ_3, *the closed-loop system* (8) *under trigger condition* (36) *achieves global uniform ultimate boundedness provided that there exist matrices* $X > 0$ *and* $\bar{\psi} > 0$ *satisfying* (15) *along with the following conditions:*

$$\bar{\eta}(1 - \sigma_1) - \sigma_1\beta_3 - \beta_2 \geq 0, \tag{37}$$

$$\eta - \frac{2}{\beta_3} - \alpha_0\lambda_{\max}\left(\Gamma^{-1}\right)/2 \geq 0, \tag{38}$$

$$\eta - \frac{1 - \sigma_3}{\beta_1} \geq 0. \tag{39}$$

Remark 3.2. *In Corollary 3.1, the addition of the new trigger mechanism* (36) *simplifies the stability analysis and eliminates consideration of the term* $\left\|\hat{\varpi}(t) - \hat{\bar{\varpi}}(t)\right\|^2$. *However, this mechanism comes at the cost of consuming more network communication resources. Therefore, it is less conservative to use Corollary 3.1 as the system stability criterion when the network communication bandwidth is allowed.*

Next, the stability criterion of system (9) under trigger Condition 2 is given, and the control gain and the weighted matrix are also provided.

Theorem 3.2. *For given matrix Γ and constants $T > 0$, $\eta > 0$, $\bar{\eta} > 0$, $\hat{\eta} > 0$, r, $\rho > 0$, $\beta_1 > 0$, $\beta_2 > 0$, $\beta_3 > 0$, $\alpha_0 > 0$, $\sigma_1 > 0$, the closed-loop system* (9) *under trigger Condition 2 ensures global uniform ultimate boundedness provided that there exist positive matrices X and $\bar{\psi}$ satisfying Equations* (11)-(14) *together with the following conditions:*

$$\hat{a}_1 = (1 - \sigma_1)\hat{\eta} - (\beta_1 + \beta_3)\rho^2 \geq 0, \tag{40}$$

$$\hat{\hat{\Sigma}} = \begin{bmatrix} \hat{\hat{\Sigma}}_{11} & BY \\ * & -\bar{\psi} \end{bmatrix} < 0, \tag{41}$$

where $\hat{\hat{\Sigma}}_{11} = \alpha_0 X + AX - BY + (AX - BY)^T + \sigma_1\bar{\psi}$. Furthermore, the control gain is given by $K = YX^{-1}$, $\psi = X^{-1}\bar{\psi}X^{-1}$ and the Zeno behavior is effectively avoided.

Proof: Similarly, construct a same Lyapunov functional (16), calculating the derivative of $V(t)$, we can obtain

$$\begin{aligned} \dot{V}_1(t) + \alpha_0 V_1(t) \leq{}& \Delta_1(t) + 2\varsigma^T(t)QB\left(u_1(t) - \hat{u}(t)\right) \\ &- 2\hat{\eta}\left(\sum_{j=1}^{n_1} \alpha_j \sigma_2^j \|\bar{\varsigma}(t)\|^j\right)^2 \varsigma^T(t)QBB^TQ\bar{\varsigma}(t). \end{aligned} \tag{42}$$

The term $-2\hat{\eta}\left(\sum_{j=1}^{n_1} \alpha_j \sigma_2^j \|\bar{\varsigma}(t)\|^j\right)^2 \varsigma^T(t)QBB^TQ\bar{\varsigma}(t)$ can be evaluated as

$$\begin{aligned} &-2\hat{\eta}\left(\sum_{j=1}^{n_1} \alpha_j \sigma_2^j \|\bar{\varsigma}(t)\|^j\right)^2 \varsigma^T(t)QBB^TQ\bar{\varsigma}(t) \\ &= -2\hat{\eta}\left(\sum_{j=1}^{n_1} \alpha_j \sigma_2^j \|\bar{\varsigma}(t)\|^j\right)^2 \varsigma^T(t)QBB^TQ(\varsigma(t) - \varsigma(t) + \bar{\varsigma}(t)) \\ &\leq -2\hat{\eta}\left(\sum_{j=1}^{n_1} \alpha_j \sigma_2^j \|\bar{\varsigma}(t)\|^j\right)^2 \varsigma^T(t)QBB^TQ\varsigma(t) \\ &\quad -2\hat{\eta}\left(\sum_{j=1}^{n_1} \alpha_j \sigma_2^j \|\bar{\varsigma}(t)\|^j\right)^2 \varsigma^T(t)QBB^TQ\varepsilon(t) \\ &\leq -\hat{\eta}\left(\sum_{j=1}^{n_1} \alpha_j \sigma_2^j \|\bar{\varsigma}(t)\|^j\right)^2 \varsigma^T(t)QBB^TQ\varsigma(t) \\ &\quad +\hat{\eta}\left(\sum_{j=1}^{n_1} \alpha_j \sigma_2^j \|\bar{\varsigma}(t)\|^j\right)^2 \varepsilon^T(t)QBB^TQ\varepsilon(t). \end{aligned} \tag{43}$$

By virtue of the triggered condition (4), one can get

$$\begin{aligned} &-\hat{\eta}\left(\sum_{j=1}^{n_1} \alpha_j \sigma_2^j \|\bar{\varsigma}(t)\|^j\right)^2 \varepsilon^T(t)QBB^TQ\varepsilon(t) \\ &+\sigma_1\hat{\eta}\left(\sum_{j=1}^{n_1} \alpha_j \sigma_2^j \|\bar{\varsigma}(t)\|^j\right)^2 \varsigma^T(t)QBB^TQ\varsigma(t) \geq 0. \end{aligned} \tag{44}$$

The term $2\varsigma^T(t)QB\left(u_1(t) - \hat{u}(t)\right)$ is reformulated as

$$2\varsigma^T(t)QB(u_1(t) - \hat{u}(t)) = 2\varsigma^T(t)QBK\varepsilon(t) + 2\varsigma^T(t)QB\left(\hat{\varpi}^T(t)\phi(\varsigma) - \hat{\bar{\varpi}}^T(t)\phi(\bar{\varsigma})\right)$$

$$\leq 2\varsigma^T(t)QBK\varepsilon(t) + \beta_1\rho^2\left(\sum_{j=1}^{n_1}\alpha_j\sigma_2^j\|\bar{\varsigma}(t)\|^j\right)^2\left\|B^TQ\varsigma(t)\right\|^2$$
$$+ \beta_2\|\phi(\bar{\varsigma})\|^2\left\|B^TQ\varsigma(t)\right\|^2 + \frac{1}{\beta_2}\left\|\hat{\varpi}(t) - \hat{\bar{\varpi}}(t)\right\|^2 + \frac{1}{\beta_1}\|\hat{\varpi}(t)\|^2, \tag{45}$$

where $\beta_1 > 0$, $\beta_2 > 0$ are parameters.

Note that

$$\begin{aligned}
&2\mathrm{Tr}\left\{\left(\phi(\varsigma)\varsigma^T(t) - \phi(\bar{\varsigma})\bar{x}^T(t)\right)QB\tilde{\varpi}^T(t)\right\}\\
&= 2\mathrm{Tr}\left\{\left(\phi(\varsigma)\varsigma^T(t) - \phi(\bar{\varsigma})x^T(t) + \phi(\bar{\varsigma})x^T(t) - \phi(\bar{\varsigma})\bar{x}^T(t)\right)QB\tilde{\varpi}^T(t)\right\}\\
&\leq \beta_3\|\phi(\varsigma) - \phi(\bar{\varsigma})\|^2\left\|B^TQ\varsigma(t)\right\|^2 + \beta_3\|\phi(\bar{\varsigma})\|^2\left\|B^TQ\varepsilon(t)\right\|^2 + \frac{2}{\beta_3}\mathrm{Tr}\left\{\tilde{\varpi}^T(t)\tilde{\varpi}(t)\right\}\\
&\leq \beta_3\rho^2\left(\sum_{j=1}^{n_1}\alpha_j\sigma_2^j\|\bar{\varsigma}(t)\|^j\right)^2\left\|B^TQ\varsigma(t)\right\|^2 + \sigma_1\beta_3\|\phi(\bar{\varsigma})\|^2\left\|B^TQ\varsigma(t)\right\|^2\\
&\quad + \frac{2}{\beta_3}\mathrm{Tr}\left\{\tilde{\varpi}^T(t)\tilde{\varpi}(t)\right\},
\end{aligned} \tag{46}$$

where $\beta_3 > 0$ is a parameter.

According to Equations (17)-(27), and Equations (42)-(46), we can get

$$\dot{V}(t) + \alpha_0V(t) \leq \xi^T(t)\hat{\Sigma}\xi(t) - \hat{a}_1\left(\sum_{j=1}^{n_1}\alpha_j\sigma_2^j\|\bar{\varsigma}(t)\|^j\right)^2\left\|B^TQ\varsigma(t)\right\|^2 + b, \tag{47}$$

where $\hat{\Sigma} = \begin{bmatrix}\hat{\Sigma}_{11} & QBK\\ * & -\psi\end{bmatrix} < 0$, $\hat{\Sigma}_{11} = \alpha_0Q + Q(A - BK) + (A - BK)^TQ + \sigma_1\psi$, the interpretation of $\xi(t)$ and b is embodied in Equation (28) and the following proof is the same as in Theorem 3.1. Therefore, the system (9) is GUUB. □

Similarly, we further modify trigger Condition 2 and propose a new trigger condition:

$$t_{k+1} = \inf\left\{t > t_k|t \text{ satisfying Condition } 2 \vee \left\|\hat{\varpi}(t) - \hat{\bar{\varpi}}(t)\right\| > \sigma_3\left\|\hat{\varpi}(t)\right\|\right\}, \tag{48}$$

thus providing a more concise stability criterion.

Corollary 3.2. *For given matrix* Γ *and constants* ρ, η, $\bar{\eta}$, β_1, β_2, β_3, σ_1, α_0, σ_3, *the closed-loop system* (9) *under trigger condition* (48) *is GUUB, if there exist positive matrices* X *and* $\bar{\psi}$ *satisfying Equations* (37)-(41).

Remark 3.3. *In Condition 1, the parameter* ν *is fixed and cannot be flexibly adjusted when making data transfer decisions. Using this condition* $\|\varsigma(t)-\varsigma(t_k)\| > \nu$ *for stability analysis in Theorem 3.1 is simpler than proof of Theorem 3.2, but it brings certain limitations in solving Inequality* (15)*. In contrast,* $\sigma_2\|\varsigma(t_k)\|$ *in Condition 2 depends on the system state, which makes data transfer decisions more flexible, but also increases the complexity of stability analysis. Note that the parameter* σ_2 *appears only in the controller and is independent of the other conditions of Theorem 3.2.*

4. **Simulation.** This section presents two simulation examples to validate the effectiveness of the designed controllers.

Example 4.1. *Consider a second-order numerical example with the following matrices under trigger Condition 1:*

$$A = \begin{bmatrix} 0 & 1 \\ -1 & 1 \end{bmatrix}, \; B = \begin{bmatrix} 0 \\ 1 \end{bmatrix}. \tag{49}$$

In addition, we choose $\varpi = 2$, *and* $\phi(\varsigma) = \varsigma^T\varsigma$. *It can be verified through computation that the pair* (A, B) *is controllable, where* A *is an unstable matrix. To guarantee the applicability of the theorem, the scalars are selected as* $\sigma_1 = 0.4$, $\beta_1 = 100$, $\beta_2 = 0.01$, $\beta_3 = 65$, $\nu = 1$, $\rho = 1$, $T = 0.8$, $\Gamma = 6I_{p\times p}$, $r = 0.05$, $\bar{\eta} = 50$, $\eta = 0.1$, $\alpha_0 = 0.05$, *and then it follows that* $a_1 = 2.1468$, $a_2 = 0.0020$, $a_3 = 0.0251$, $a_4 = 0.0900$, *which verifies that Equations* (11)-(14) *hold. With the aid of the MATLAB toolbox, a feasible solution set can be obtained that satisfies condition* (15), *and the corresponding matrices are given as follows:*

$$K = \begin{bmatrix} 2.6366 & 7.5282 \end{bmatrix}, \; Q = 10^{-3} \times \begin{bmatrix} 0.3226 & 0.1817 \\ 0.1817 & 0.3938 \end{bmatrix}, \; \psi = \begin{bmatrix} 0.0011 & 0.0017 \\ 0.0017 & 0.0038 \end{bmatrix}.$$

Based on the aforementioned data with a discretization step size of 0.01, the simulation results are obtained. The initial conditions are chosen as follows: $\varsigma(0) = [1, 2]^T$, *and* $\hat{\varpi}(0) = 0$. *Figure 1 shows all the event trigger moments within 20 seconds, from which it can be seen that the spacing between any two trigger times is less than or equal to 0.8 seconds, and the number of trigger events occurs 54 times. Compared with time-triggered mechanism, 2000 data needs to be transmitted, which implies the proposed trigger mechanism greatly reduces the update frequency of the controller. Figure 2 depicts the state response curve of the system, from which it can be seen that the system converges near the origin, which demonstrates the efficiency of the proposed controller. Moreover, we give the control input curve, from which we can see that to resist higher-order nonlinearity, a large number of control quantities are needed to stabilize the system at the beginning of the response. Next, we will compare the proposed three different trigger mechanisms. When leaving other parameters unchanged (such as the controller gain, matrices* Q, *and* Ω), *the number of transmitted data packets is shown in Table 1. For Conditions 1, 2 and* (36), *with the event-triggered threshold* σ_1 *increasing, the number of transmitted data decreases accordingly, which may degrade system performance. However, under the same* σ_1, *Table 1 shows that the number of successfully transmitted data packets in Corollary 3.1 is slightly larger than that in Condition 1, which verifies the conclusion of Remark 3.3. Compared to*

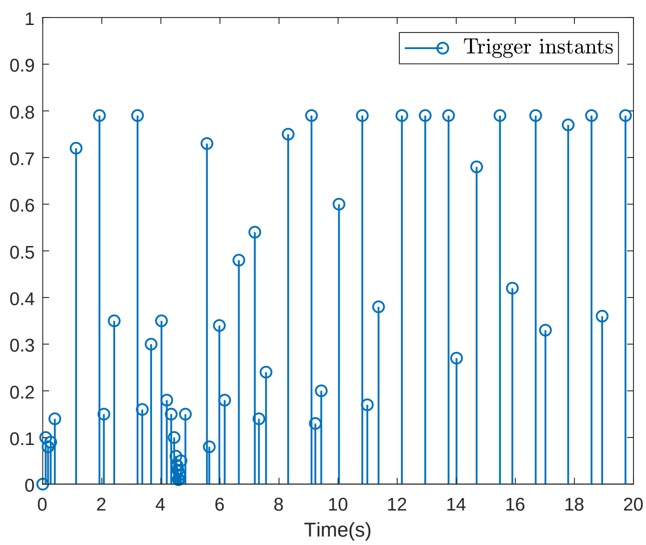


FIGURE 1. Triggered instants t_k in Example 4.1

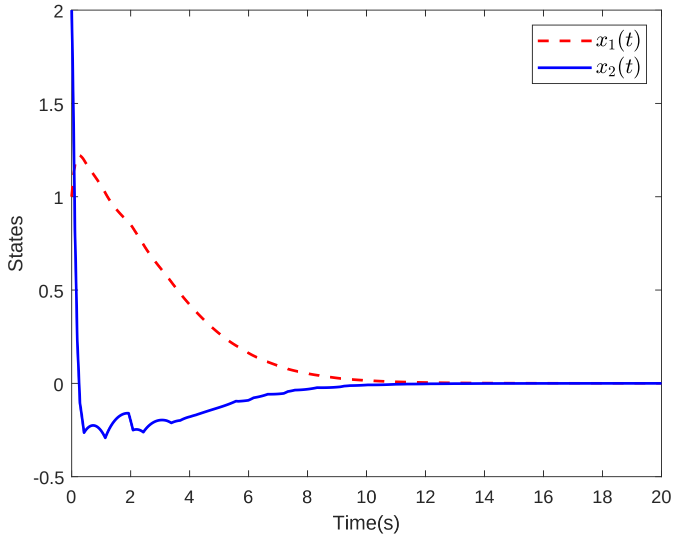


FIGURE 2. State responses of the closed-loop system in Example 4.1

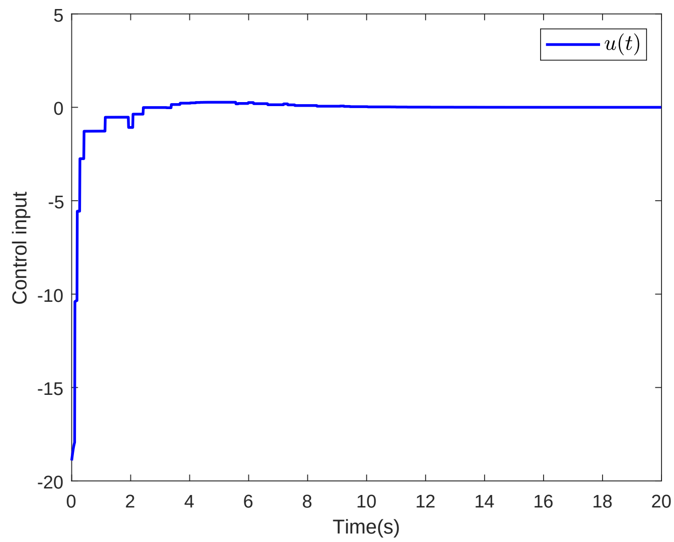


FIGURE 3. Control signal $u(t)$ in Example 4.1

TABLE 1. A number of transmitted packets for different σ_1

σ_1	**0.3**	**0.5**	**0.8**
Condition 1 (Theorem 3.1)	150	98	94
Condition 2 (Theorem 3.2)	163	124	97
Condition (36) (Corollary 3.1)	164	119	95

Condition 1, Condition 2 replaces ν with $\sigma_2 \|\varsigma(t_k)\|$, which makes it more sensitive to the dynamic changes of the system. Additionally, in contrast to Condition 1, Corollary 3.1 adds the condition $\left\|\hat{\varpi}(t) - \hat{\hat{\varpi}}(t)\right\| > \sigma_3 \|\hat{\varpi}(t)\|$, which improves system performance at the cost of an increased number of transmitted data. Based on the above analysis, Condition 1 effectively reduces the number of transmitted data within acceptable control performance.

Example 4.2. *Consider a three-order system with the following matrices under trigger Condition 2:*

$$A = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}, \ B = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}. \tag{50}$$

The parameter ϖ and nonlinear function $\phi(\varsigma)$ are set as $\varpi = 2$ and $\phi(\varsigma) = \sin(\varsigma_1(t)) + \sin(\varsigma_2(t))$. Then, we can obtain $\rho = 1$, $n_1 = 1$, and $\alpha_1 = 1$, which ensures that $|\phi(\varsigma)| \leq \|\varsigma\|_1$. We choose the following parameters: $\sigma_1 = 0.5$, $\sigma_2 = 0.3$, $\beta_1 = 3$, $\beta_2 = 0.01$, $\beta_3 = 6$, $\bar{\eta} = 10$, $\Gamma = 0.02 I_{p\times p}$, $r = 8$, $\eta = 25$, $\alpha_0 = 0.6$, $\hat{\eta} = 50$. The relevant parameters are the same as in Example 4.1.

By solving Inequality (41), we obtain

$$K = \begin{bmatrix} 4.6879 & 11.3110 & 8.9509 \end{bmatrix}, \ Q = 10^{-3} \times \begin{bmatrix} 0.1385 & 0.2468 & 0.1448 \\ 0.2468 & 0.5586 & 0.3377 \\ 0.1448 & 0.3377 & 0.2857 \end{bmatrix},$$

$$\psi = \begin{bmatrix} 0.0012 & 0.0027 & 0.0021 \\ 0.0027 & 0.0064 & 0.0048 \\ 0.0021 & 0.0048 & 0.0037 \end{bmatrix}.$$

The initial conditions are taken as $\hat{\varpi}(0) = 0$ and $\varsigma(0) = [3, 0, 1]^T$. Then, we can give the following simulation results. By observing Figures 4, 5 and 6, we can see that the trigger mechanism saves a lot of communication resources, and all states of the system converge to the neighborhood of the origin attachment under the action of adaptive parameter and controller. This verifies the validity of the proposed method.

Now, we compare Condition 2 and Condition (48), and the number of transmitted data packets is listed in Table 2, from which we can see that the data in Condition 2 is less than that in Condition (48). Note that Condition (48) adds a new condition $\left\|\hat{\varpi}(t) - \hat{\hat{\varpi}}(t)\right\| > \sigma_3 \left\|\hat{\varpi}(t)\right\|$, which causes an increase in the number of transmitted data packets, thereby occupying excessive network channel time. In summary, there are trade-offs in the use of the two event triggering mechanisms. When both mechanisms can guarantee the desired control performance, Condition 2 is more easily adopted by the user to reduce the transmission of packets. When minimum performance is the goal, Condition

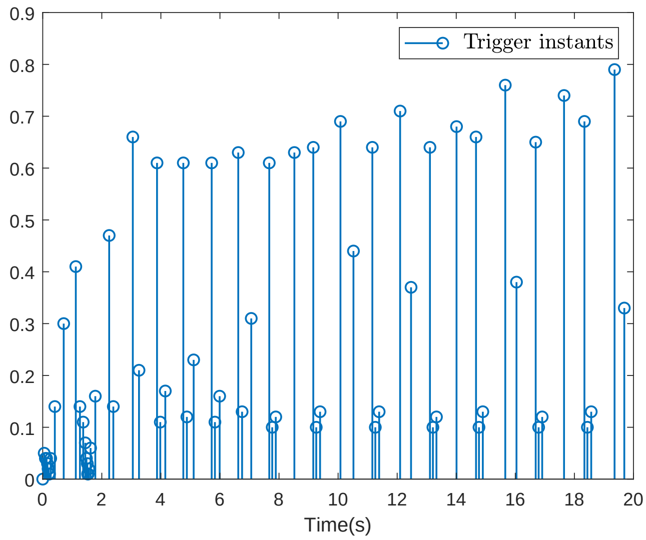


FIGURE 4. Triggered instants t_k in Example 4.2

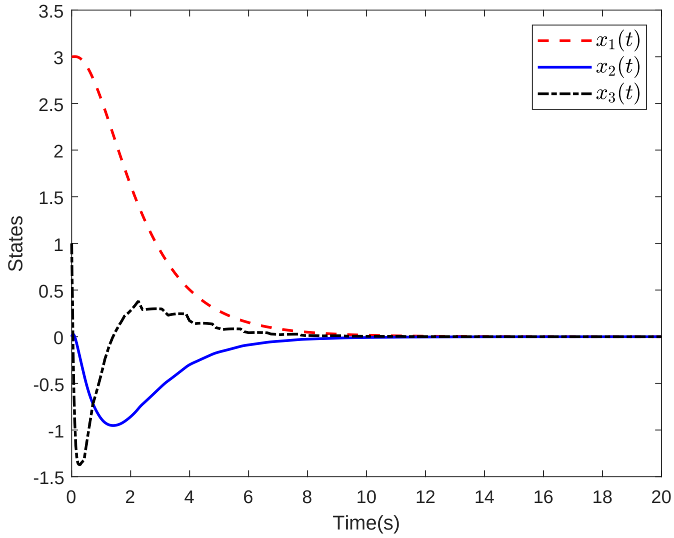


FIGURE 5. State responses of the closed-loop system in Example 4.2

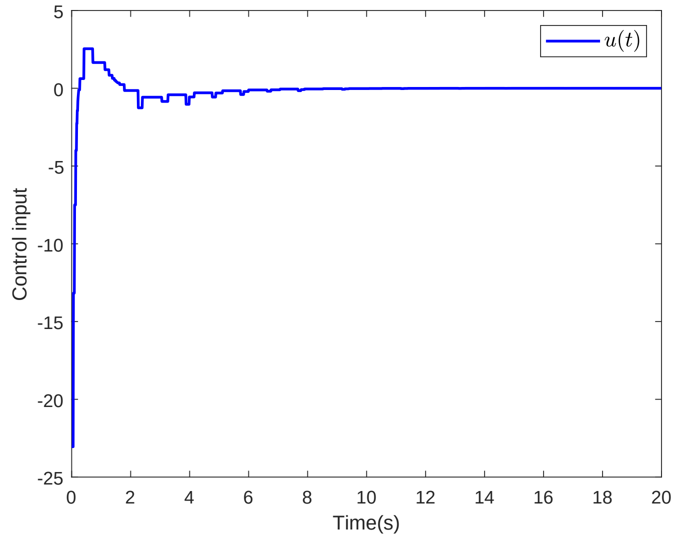


FIGURE 6. Control signal $u(t)$ in Example 4.2

TABLE 2. A number of transmitted packets for different σ_1

σ_1	**0.5**	**0.7**	**0.9**
Condition 2 (Theorem 3.2)	195	160	138
Condition (48) (Corollary 3.2)	262	183	168

(48) *is more likely to be adopted to stabilize the system by increasing the frequency of the controller.*

Remark 4.1. *From Inequalities* (28) *and* (47)*, one can see that the trigger threshold* σ_1 *is typically chosen as a constant slightly less than 1 to ensure that* $1 - \sigma_1 > 0$*. However,* σ_1 *should not be set too small; otherwise, events may be triggered too frequently, which could lead to the Zeno phenomenon. Conversely, if* σ_1 *is too large, the control gain* K *may increase accordingly, potentially causing actuator saturation. Therefore, the selection of*

σ_1 requires trade-offs. To satisfy Inequalities (28) *and* (47)*, it is advisable to make the control gain K and the parameter η as large as possible. This helps accelerate the decay of the Lyapunov function and thereby improves overall control performance.*

5. **Conclusions.** In this paper, the event-triggered adaptive state feedback control for uncertain nonlinear systems has been studied. Several types of state and/or adaptive signal-dependent triggering strategies are developed to decrease communication burden. Furthermore, an adaptive intermittent controller has been designed to reduce its updating frequency. Next, a novel Lyapunov functional has been constructed to ensure that the system converges to a neighborhood of the origin, and a controller design method has been developed. Moreover, a comparative analysis of different mechanisms has been made from the view of control performance and network communication resources, while avoiding the Zeno phenomenon. Finally, two numerical simulations are provided to demonstrate the effectiveness of the developed approach. A potential future research direction is to extend the proposed event-triggered adaptive control framework to multi-agent systems with communication constraints and cooperative tasks.

Acknowledgment. This work was supported in part by the Master's Graduate Innovation Fund Project under Grant YJC2025-010, and in part by the National Natural Science Foundation of China under Grant 62303069.

REFERENCES

[1] Z. Wang, Adaptive fuzzy system compensation based model-free control for steer-by-wire systems with uncertainty, *International Journal of Innovative Computing, Information and Control*, vol.17, no.1, pp.141-152, 2021.
[2] T. Zhao and G.-R. Duan, Fully actuated system approach to attitude control of flexible spacecraft with nonlinear time-varying inertia, *Science China Information Sciences*, vol.65, no.11, 212201, 2022.
[3] Y. P. Asad, A. Shamsi, H. Ivani and J. Tavoosi, Adaptive intelligent inverse control of nonlinear systems with regard to sensor noise and parameter uncertainty (magnetic ball levitation system case study), *International Journal on Smart Sensing and Intelligent Systems*, vol.9, no.1, pp.148-169, 2016.
[4] A. Kanchanaharuthai and E. Mujjalinvimut, Adaptive finite-time synergetic control design for power systems with static var compensator, *International Journal of Innovative Computing, Information and Control*, vol.16, no.3, pp.1007-1020, 2020.
[5] Q. Zhou, Q. Ren, H. Ma, G. Chen and H. Li, Model-free adaptive control for nonlinear systems under dynamic sparse attacks and measurement disturbances, *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol.71, no.10, pp.4731-4741, 2024.
[6] J. Yoo and K. H. Johansson, Event-triggered model predictive control with a statistical learning, *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol.51, no.4, pp.2571-2581, 2021.
[7] X. Wang, Z. Fei, Z. Wang and X. Liu, Event-triggered fault estimation and fault-tolerant control for networked control systems, *Journal of the Franklin Institute*, vol.356, no.8, pp.4420-4441, 2019.
[8] W. Kang, M. Chen, Y. Guan, L. Tang, J. C. Vasquez and J. M. Guerrero, Distributed event-triggered optimal control method for heterogeneous energy storage systems in smart grid, *IEEE Transactions on Sustainable Energy*, vol.13, no.4, pp.1944-1956, 2022.
[9] N. Zhao, H. Zhang, X. Qiu and R. K. Agarwal, Observer-based periodic event-triggered adaptive fuzzy control for networked nonlinear systems, *IEEE Transactions on Cybernetics*, DOI: 10.1109/TCYB.2025.3554702, 2025.
[10] N. Zhao, M. Shi, X. Zhao, G. Zong and H. Zhang, Distributed adaptive sampled-data security tracking control for uncertain heterogeneous multi-agents systems under DoS attacks, *IEEE Transactions on Green Communications and Networking*, vol.8, no.4, pp.1385-1397, 2024.
[11] Z. Gu, D. Yue, J. H. Park and X. Xie, Memory-event-triggered fault detection of networked IT2 T-S fuzzy systems, *IEEE Transactions on Cybernetics*, vol.53, no.2, pp.743-752, 2023.
[12] X. Li, W. Liu, S. Gorbachev and J. Cao, Event-triggered impulsive control for input-to-state stabilization of nonlinear time-delay systems, *IEEE Transactions on Cybernetics*, vol.54, no.4, pp.2536-2544, 2024.

[13] L. Zhang, Z. Shen, B. Niu and N. Zhao, Dynamic-event-based reachable set synthesis for nonlinear delayed hidden semi-Markov jump systems under multiple cyber-attacks, *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol.55, no.1, pp.587-598, 2025.

[14] Z. Shen, L. Zhang, B. Niu and N. Zhao, Event-based reachable set synthesis for delayed nonlinear semi-Markov systems, *Chaos, Solitons & Fractals*, vol.177, 114284, 2023.

[15] M. Liu, L. Zhang, N. Zhao, S. Sharaf and L. Li, Reachable set control of singular semi-Markov jump multi-agent systems with input delay via state decomposition method, *Journal of the Franklin Institute*, vol.361, no.17, 107294, 2024.

[16] R. Postoyan, P. Tabuada, D. Nešić and A. Anta, A framework for the event-triggered stabilization of nonlinear systems, *IEEE Transactions on Automatic Control*, vol.60, no.4, pp.982-996, 2015.

[17] F.-M. Huang and X.-H. Chang, Tracking control of interval type-2 fuzzy systems with improved adaptive event-triggered mechanisms and deception attacks under privacy protection, *Optimal Control Applications and Methods*, 2025.

[18] H. Zhang, N. Zhao, S. Wang and R. K. Agarwal, Improved event-triggered dynamic output feedback control for networked T-S fuzzy systems with actuator failure and deception attacks, *IEEE Transactions on Cybernetics*, vol.53, no.12, pp.7989-7999, 2023.

[19] L. Zhang, Q. Yin, B. Niu, X. Zhao and N. Zhao, Bumpless transfer control and reachable set estimation for Markovian networked systems against DoS attacks, *Information Sciences*, DOI: 10.1016/i.ins.2025.122396, 2025.

[20] Z. Zhao, L. Zhang, S. Yang, N. Zhao and Y. Liu, Dual-triggered scheme for adaptive neural control of MIMO nonlinear switched systems against sensor and actuator attacks, *Communications in Nonlinear Science and Numerical Simulation*, vol.147, 108811, 2025.

[21] X. Mao and L. Szpruch, Strong convergence and stability of implicit numerical methods for stochastic differential equations with non-globally Lipschitz continuous coefficients, *Journal of Computational and Applied Mathematics*, vol.238, pp.14-28, 2013.

[22] J. Simsen, M. S. Simsen and M. R. T. Primo, Continuity of the flow and robustness for evolution equations with non globally Lipschitz forcing term, *São Paulo Journal of Mathematical Sciences*, vol.14, no.1, pp.223-241, 2020.

[23] A. Porretta and E. Priola, Global Lipschitz regularizing effects for linear and nonlinear parabolic equations, *Journal de Mathématiques Pures et Appliquées*, vol.100, no.5, pp.633-686, 2013.

[24] Y. Cao, B. Niu, H. Wang and X. Zhao, Event-based adaptive resilient control for networked nonlinear systems against unknown deception attacks and actuator saturation, *International Journal of Robust and Nonlinear Control*, vol.34, no.7, pp.4769-4786, 2024.

[25] Y.-J. Liu, S. Lu, D. Li and S. Tong, Adaptive controller design-based ABLF for a class of nonlinear time-varying state constraint systems, *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol.47, no.7, pp.1546-1553, 2017.

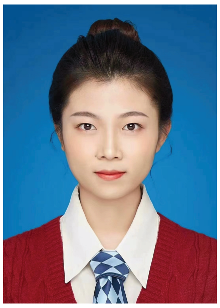
[26] Z. Zhang, C. Wen, L. Xing and Y. Song, Adaptive event-triggered control of uncertain nonlinear systems using intermittent output only, *IEEE Transactions on Automatic Control*, vol.67, no.8, pp.4218-4225, 2022.

[27] B. Cheng and Z. Li, Consensus disturbance rejection with event-triggered communications, *Journal of the Franklin Institute*, vol.356, no.2, pp.956-974, 2019.

[28] Z.-G. Wu, Y. Xu, Y.-J. Pan, H. Su and Y. Tang, Event-triggered control for consensus problem in multi-agent systems with quantized relative state measurements and external disturbance, *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol.65, no.7, pp.2232-2242, 2018.

[29] J. Huang, W. Wang, C. Wen and G. Li, Adaptive event-triggered control of nonlinear systems with controller and parameter estimator triggering, *IEEE Transactions on Automatic Control*, vol.65, no.1, pp.318-324, 2020.

Author Biography



Di Lun received the B.S. degree in Communication Engineering from the Liaoning Institute of Science and Technology, China, in 2023. She is currently pursuing the M.S. degree in Control Science and Engineering at Bohai University, China. Her current research interests include networked control systems, anti-disturbances control, event-triggered control.

Yuanyuan Shen received the M.S. degree from Beijing Forestry University, China, in 2008. She earned a Ph.D. degree in Economics from Zhongnan University of Economics and Law, China, in 2023. She currently serves as the Director of the Foreign Exchange and Cooperation Center of Guangxi Botanical Garden of Medicinal Plants, China. Her research interests include cooperative control, economic modeling, and control theory.

Ning Zhao received the B.S. degree in Mathematics and Applied Mathematics from Hulunbuir University, China, in 2015, the M.S. degree in Mathematics from Heilongjiang University, China, in 2018, and the Ph.D. degree in Control Science and Engineering from Harbin Engineering University, China, in 2022. He is currently an Associate Professor at Bohai University, China. His research interests include networked control systems, event-triggered control, and security control.