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RESEARCH ARTICLE

Observer-Based Event-Triggered Scheme for Finite-Time Control of Discrete-Time Linear Time-Varying Networked Control Systems

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Abstract

This article investigates the finite-time boundedness (FTB) problem for a class of observer-based discrete linear time-varying networked control systems (DLTNCSs). The interval matrix method (IMM) is adopted to handle the bounded time-varying coefficient via an uncertain convex-hull representation, and a maximum absolute value method (MAM) is also established to solve the time-varying coefficient for comparison. An observer-based event-triggered controller (ETC) is then developed, and sufficient linear matrix inequality (LMI) conditions are derived to obtain the admissible controller gain. Moreover, an implementable algorithm is provided for minimizing the energy consumption. Two numerical examples show that the IMM yields smaller estimation errors and lower energy consumption than the MAM.

Keywords: event-triggered controller (ETC), discrete linear time-varying networked control systems (DLTNCSs), finite-time boundedness (FTB), optimization algorithm.

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1 Introduction

Networked control systems (NCSs) have attracted sustained attention owing to their extensive applications in industrial automation, intelligent transportation systems, and cyber-physical systems [1–3]. By using shared communication networks for information exchange among sensors, controllers, and actuators, NCSs offer clear advantages over traditional point-to-point architectures in terms of reduced wiring cost, improved flexibility, and enhanced maintainability and scalability [4–6]. Nevertheless, these advantages are accompanied by network-induced constraints, such as limited bandwidth, transmission delays, packet dropouts, and restricted communication and computation resources, which complicate system analysis and controller design [7, 8]. When the plant further exhibits time-varying characteristics, parameter perturbations and structural variations may intensify the uncertainty of the system dynamics, making the analysis and control of the system a topic of considerable theoretical importance. In practical networked control scenarios, the full state vector is often unavailable and must be

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estimated from limited output measurements. To this end, observer design has been widely employed to reconstruct unmeasurable states and to facilitate the development of output-feedback control laws [9–11]. Zhao et al. [12] developed an observer-based periodic event-triggered adaptive fuzzy control approach for networked nonlinear systems. Ref. [13] has investigated the observer-based adaptive event-triggered control problem for nonlinear networked systems under multiple cyber attacks.

Finite-time analysis and control have received considerable attention because they can characterize the transient behavior of dynamical systems over a prescribed finite horizon [14–16]. In contrast to the conventional asymptotic stability, finite-time boundedness (FTB) emphasizes state constraints during the transient process and is therefore more meaningful for engineering systems with safety margins, transient specifications, and fast response requirements. For discrete-time systems, FTB requires the system state to remain within a bound over a given finite-time interval, and its verification should take into account the recursive evolution of the state trajectory [17–19]. This problem becomes more challenging for linear time-varying NCSs, where parameter variations, observer errors, and event-triggered transmissions are jointly involved in the closed-loop analysis.

Traditional time-triggered control updates the control input according to a fixed sampling schedule, regardless of whether a new control action is actually required by the current system state, which may lead to redundant data transmissions and unnecessary control updates, thus imposing additional communication and computational burdens [20–22]. In contrast, event-triggered control (ETC) executes information transmission and controller updating only when the prescribed triggering condition is met, thereby improving resource utilization while maintaining the desired control performance [23–27]. Although ETC has attracted extensive attention in networked control systems; however, most existing results mainly focus on time-invariant or uncertain systems, whereas the observer-based FTB analysis for DLTNCSs remains insufficiently investigated.

Motivated by the above discussions, this paper investigates observer-based finite-time ETC for DLTNCSs. Simultaneously addressing the time-varying coefficient, observer-based design, and the ETC mechanism leads to coupled time-varying uncertainty, estimation-error, and triggering-error terms in the augmented systems. Such coupling makes the FTB analysis nontrivial. To address this issue, an augmented-system-based framework is developed, under which tractable LMI conditions are derived for the design of the controller gain. The primary contributions of this work are outlined as follows.

(1) The observer-based FTB analysis and event-triggered control problem are investigated for DLTNCSs. By constructing the augmented systems composed of the original system states and the estimation errors, solvable LMI-based sufficient conditions are derived.

(2) The IMM and the MAM are respectively employed to handle the time-varying coefficients of the considered systems. Comparative analyses are conducted in terms of system state responses, estimation errors, and control energy consumption.

(3) An energy consumption performance index related to control energy cost and state performance is introduced, and an implementable optimization algorithm is designed to search for the controller gain and related parameters under the feasibility of derived sufficient conditions.

Figure 1 illustrates the proposed control scheme, while Table 1 lists the main notation used in this paper.

2 Problem Formulation and Preliminaries

In this section, the mathematical model, the event-triggered control scheme, and the interval matrix method (IMM) are presented. The IMM is introduced to characterize the time-varying parameters.

2.1 Model Construction of the Discrete-Time Linear Time-varying Systems

Consider the discrete-time linear time-varying systems (DLTSs) model as follows

$$\begin{cases} \varkappa(\vartheta+1) = \mathcal{A}(\vartheta)\varkappa(\vartheta) + \mathcal{C}u(\vartheta), \\ \omega(\vartheta) = \mathcal{M}\varkappa(\vartheta), \end{cases} \tag{1}$$

where $\varkappa(\vartheta) \in \mathcal{R}^n$ indicates the state of the systems; $\omega(\vartheta) : [0, \infty) \to \mathcal{R}^n$ represents measurement output; $u(\vartheta)$ is the control input; $\mathcal{A}(\vartheta) = (a_{ij}(\vartheta))_{n\times n}$ expresses a time-varying parameter matrix satisfying $\acute{a}_{ij} \leq a_{ij}(\vartheta) \leq \grave{a}_{ij}$; $\mathcal{C}$ and $\mathcal{M}$ characterize constant matrices of the systems.

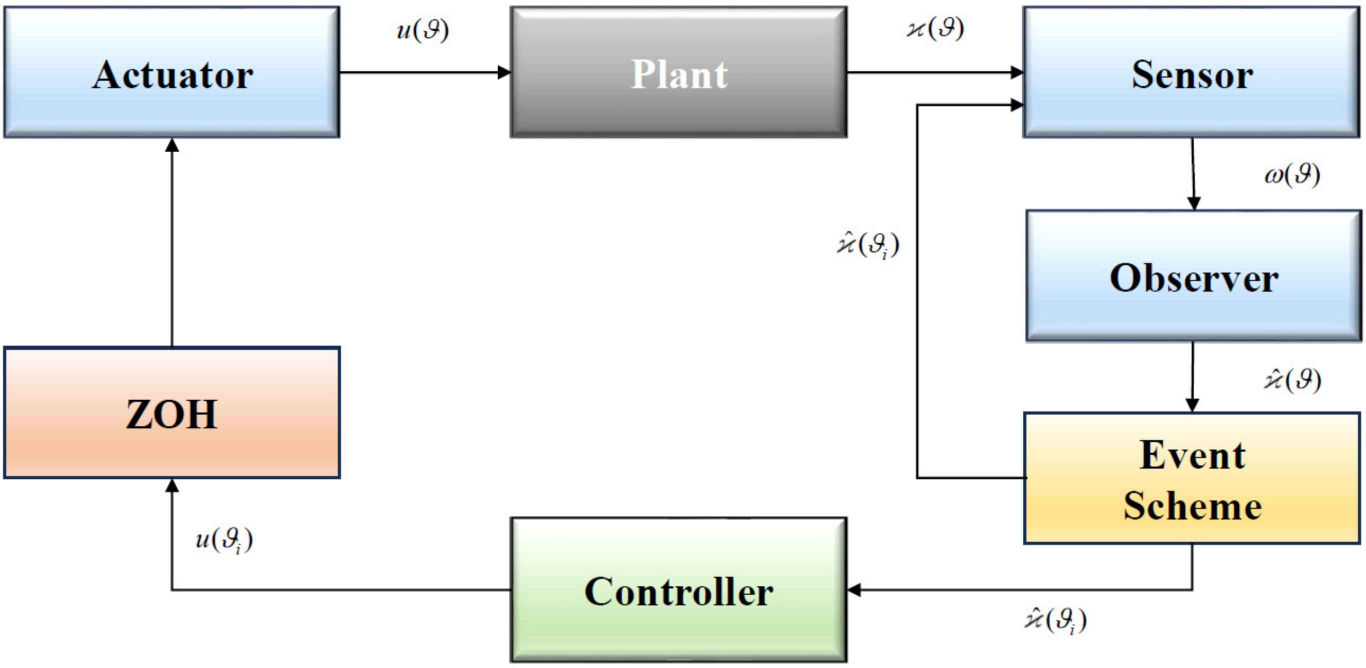

Figure 1. Event-triggered control system.

Table 1. Nomenclature.

Symbol	Description
$\varkappa(\vartheta)$	State vector at instant ϑ
$\hat{\varkappa}(\vartheta)$	Observer state vector at instant ϑ
$u(\vartheta)$	Control input with event-triggered scheme
$\omega(\vartheta)$	The measurement output detected by the sensor
$\mathcal{K}, \mathcal{L}$	The control gain matrix associated with the ETC scheme and the observer gain matrix
$\mathcal{R}^n$	The n-dimensional Euclidean space
$\mathcal{S}^{-1}, \mathcal{S}^T$	The inverse and transpose of matrix $\mathcal{S}$
$\lambda(\mathcal{S})$	The eigenvalues of matrix $\mathcal{S}$
$*$	The symmetric terms in the symmetric matrix

2.2 Model Construction of the Observation Systems

In this subsection, an observer is constructed to estimate the state of systems (1) based on the measurement output $\omega(\vartheta)$, which is given by

$$\hat{\varkappa}(\vartheta+1) = \mathcal{A}\hat{\varkappa}(\vartheta) + \mathcal{C}u(\vartheta) + \mathcal{L}\big(\omega(\vartheta) - \mathcal{M}\hat{\varkappa}(\vartheta)\big), \quad (2)$$

where the constant matrix $\mathcal{A} = \left(\frac{\acute{a}_{ij}+\grave{a}_{ij}}{2}\right)_{n\times n}$ denotes the central matrix of the time-varying coefficient matrix, and $\mathcal{L}$ is the observer gain matrix to be designed. This construction separates the nominal part from the bounded time-varying uncertainty, which facilitates the subsequent derivation of the estimation error systems.

From (1)-(2), we can obtain the following error systems by $\tilde{\varkappa}(\vartheta) = \varkappa(\vartheta) - \hat{\varkappa}(\vartheta)$

$$\begin{aligned}\tilde{\varkappa}(\vartheta+1) &= \varkappa(\vartheta+1) - \hat{\varkappa}(\vartheta+1)\\ &= [\mathcal{A}(\vartheta) - \mathcal{A}]\varkappa(\vartheta) + (\mathcal{A} - \mathcal{L}\mathcal{M})\tilde{\varkappa}(\vartheta).\end{aligned} \quad (3)$$

2.3 Event-Triggered Control Strategy

We investigate an ETC rather than a time-triggered one. The sampling time sequence $\{\vartheta_i\}_{i=0}^{\infty}$ satisfies $0 = \vartheta_0 < \vartheta_1 < \vartheta_2 < \ldots$, and the next sampling instant ϑ_{i+1} can be determined by

$$\vartheta_{i+1} = inf\{\vartheta > \vartheta_i | \epsilon^T(\vartheta)\Omega_1\epsilon(\vartheta) > \delta\hat{\varkappa}^T(\vartheta)\Omega_2\hat{\varkappa}(\vartheta)\}, \quad (4)$$

where $\epsilon(\vartheta) = \hat{\varkappa}(\vartheta) - \hat{\varkappa}_i(\vartheta) = \hat{\varkappa}(\vartheta) - \hat{\varkappa}(\vartheta_i)$, for $\vartheta \in [\vartheta_i, \vartheta_{i+1})$.

The controller considered here is event-driven, and the control input can be described based on the above sampled observer

$$u(\vartheta)=\mathcal{K}\hat{\varkappa}(\vartheta_i), \vartheta\in[\vartheta_i,\vartheta_{i+1}), i\in\mathbb{N}. \quad (5)$$

Substituting $\epsilon(\vartheta)=\hat{\varkappa}(\vartheta)-\hat{\varkappa}(\vartheta_i)$ into DLTSs (1), we can easily get

$$\varkappa(\vartheta+1)=(\mathcal{A}(\vartheta)+\mathcal{C}\mathcal{K})\varkappa(\vartheta)-\mathcal{C}\mathcal{K}\tilde{\varkappa}(\vartheta)-\mathcal{C}\mathcal{K}\epsilon(\vartheta). \quad (6)$$

Remark 1 *Under the event-triggering scheme, the triggering error satisfies the inequality (4). This means that no new event is generated over the interval $[\vartheta_i,\vartheta_{i+1})$, and thus the control input (5) updated at ϑ_i is held constant until the next event occurs. Condition (4) implies that the control input (5) is active in $[\vartheta_i,\vartheta_{i+1})$ for $\epsilon^T(\vartheta)\Omega_1\epsilon(\vartheta)\le\delta\hat{\varkappa}^T(\vartheta)\Omega_2\hat{\varkappa}(\vartheta)$.*

2.4 Interval Matrix Method

We introduce the IMM to solve the challenge for the time-varying parameter $\mathcal{A}(\vartheta)=(\mathfrak{a}_{ij}(\vartheta))_{n\times n}$ with $\acute{\mathfrak{a}}_{ij}\le\mathfrak{a}_{ij}(\vartheta)\le\grave{\mathfrak{a}}_{ij}$, $\acute{\mathcal{A}}=(\acute{\mathfrak{a}}_{ij})_{n\times n}$, $\grave{\mathcal{A}}=(\grave{\mathfrak{a}}_{ij})_{n\times n}$. For the expression $\mathfrak{a}_{ij}(\vartheta)$, we have

$$\begin{aligned}\mathfrak{a}_{ij}(\vartheta)=&\frac{\grave{\mathfrak{a}}_{ij}+\acute{\mathfrak{a}}_{ij}}{2}+\rho_{ij}(\vartheta)\frac{\grave{\mathfrak{a}}_{ij}-\acute{\mathfrak{a}}_{ij}}{2},\\=&\frac{\grave{\mathfrak{a}}_{ij}+\acute{\mathfrak{a}}_{ij}}{2}+\sqrt{\frac{\grave{\mathfrak{a}}_{ij}-\acute{\mathfrak{a}}_{ij}}{2}}\rho_{ij}(\vartheta)\sqrt{\frac{\grave{\mathfrak{a}}_{ij}-\acute{\mathfrak{a}}_{ij}}{2}},\end{aligned} \quad (7)$$

where $\rho_{ij}(\vartheta)\in[-1,1]$. Define $\bar{\mathfrak{a}}_{ij}=\frac{\grave{\mathfrak{a}}_{ij}+\acute{\mathfrak{a}}_{ij}}{2}$, $\hat{\mathfrak{a}}_{ij}=\frac{\grave{\mathfrak{a}}_{ij}-\acute{\mathfrak{a}}_{ij}}{2}$, $\mathcal{A}=(\bar{\mathfrak{a}}_{ij})_{n\times n}$, $\Delta\mathcal{A}(\vartheta)=\rho_{ij}(\vartheta)\frac{\grave{\mathfrak{a}}_{ij}-\acute{\mathfrak{a}}_{ij}}{2}$. Hence, the time-varying system parameter $\mathcal{A}(\vartheta)$ can be described as

$$\mathcal{A}(\vartheta)\in co[\acute{\mathcal{A}},\grave{\mathcal{A}}]=\mathcal{A}+\Delta\mathcal{A}(\vartheta)=\mathcal{A}+\mathcal{H}_a\mathcal{P}_a(\vartheta)\mathcal{L}_a, \quad (8)$$

where

$$\mathcal{H}_a=[\sqrt{\hat{\mathfrak{a}}_{11}}\xi_1,...,\sqrt{\hat{\mathfrak{a}}_{1n}}\xi_1,...,\sqrt{\hat{\mathfrak{a}}_{n1}}\xi_n,...,\sqrt{\hat{\mathfrak{a}}_{nn}}\xi_n]_{n\times n^2},$$
$$\mathcal{L}_a=[\sqrt{\hat{\mathfrak{a}}_{11}}\xi_1^T,...,\sqrt{\hat{\mathfrak{a}}_{1n}}\xi_n^T,...,\sqrt{\hat{\mathfrak{a}}_{n1}}\xi_1^T,...,\sqrt{\hat{\mathfrak{a}}_{nn}}\xi_n^T]_{n\times n^2},$$
$$\mathcal{P}_a(\vartheta)=diag\{\rho_{11}(\vartheta),...\rho_{1n}(\vartheta),...,\rho_{n1}(\vartheta),...,\rho_{nn}(\vartheta)\}_{n^2\times n^2},$$

with ξ_i^T denotes a row vector whose rth element is 1 and all other elements are 0. Taking the aforementioned IMM analysis into account, we can deduce the error systems (3) below

$$\tilde{\varkappa}(\vartheta+1)=\Delta\mathcal{A}(\vartheta)\varkappa(\vartheta)+(\mathcal{A}-\mathcal{L}\mathcal{M})\tilde{\varkappa}(\vartheta). \quad (9)$$

Accordingly, the systems (1) can be reformulated as follows

$$\begin{aligned}\varkappa(\vartheta+1)=&(\mathcal{A}+\mathcal{C}\mathcal{K})\varkappa(\vartheta)+\Delta\mathcal{A}\varkappa(\vartheta)\\&-\mathcal{C}\mathcal{K}\tilde{\varkappa}(\vartheta)-\mathcal{C}\mathcal{K}\epsilon(\vartheta).\end{aligned} \quad (10)$$

Setting $\eta(\vartheta)=\begin{bmatrix}\varkappa(\vartheta)\\\tilde{\varkappa}(\vartheta)\end{bmatrix}$, the augmented error systems are then formulated as follows

$$\eta(\vartheta+1)=(\bar{\mathcal{A}}+\bar{\mathcal{H}}_a\mathcal{P}_a(\vartheta)\bar{\mathcal{L}}_a)\eta(\vartheta)+\bar{\mathcal{C}}\epsilon(\vartheta), \quad (11)$$

where

$$\bar{\mathcal{A}}=\begin{bmatrix}\mathcal{A}+\mathcal{C}\mathcal{K} & -\mathcal{C}\mathcal{K}\\0 & \mathcal{A}-\mathcal{L}\mathcal{M}\end{bmatrix},\bar{\mathcal{C}}=\begin{bmatrix}-\mathcal{C}\mathcal{K}\\0\end{bmatrix},$$
$$\bar{\mathcal{H}}_a=\begin{bmatrix}\mathcal{H}_a\\\mathcal{H}_a\end{bmatrix},\bar{\mathcal{L}}_a=\begin{bmatrix}\mathcal{L}_a & 0\end{bmatrix}.$$

Remark 2 *To overcome the difficulties caused by time-varying coefficients in system analysis and controller design, the IMM is employed to characterize the bounded time-varying coefficient matrix. Specifically, it is first described by the convex hull generated by its lower and upper bound matrices, and is then further decomposed into the sum of a central matrix and a norm-bounded uncertainty term. In this way, the influence of time-varying parameters can be incorporated into a unified uncertainty analysis framework. This treatment avoids directly solving parameter-dependent matrix inequalities and facilitates the derivation of tractable LMI conditions. In addition, by constructing the augmented systems (11) consisting of the original system state and the estimation error, the FTB of both the original system and the error system can be analyzed within a unified framework.*

Moreover, an energy consumption performance index $\mathcal{J}$ is introduced to quantify both the controller energy cost and the stabilization performance of the augmented error systems states.

$$\mathcal{J}=\sum_{\vartheta=0}^{\mathcal{N}}u^T(\vartheta)\mathfrak{R}_1u(\vartheta)+\eta^T(\vartheta)\mathfrak{R}_2\eta(\vartheta), \quad (12)$$

where $\mathfrak{R}_1>0$ and $\mathfrak{R}_2>0$ are given weighting matrices.

To facilitate the FTB analysis of the augmented systems (11), the following definitions and mathematical lemmas are introduced.

Definition 1 [28] *For the closed-loop error system (12), FTB under observer-based event-triggered state feedback associated with $(\upsilon_1,\upsilon_2,\tilde{\mathcal{R}},\mathcal{N})$ is achieved with $0<\upsilon_1<\upsilon_2$, $\tilde{\mathcal{R}}>0$, and $\mathcal{N}$ is a positive integer, if one can construct an observer and an event-triggered state-feedback controller in the forms given by (3) and (5), respectively, such that*

$$\eta^T(0)\tilde{\mathcal{R}}\eta(0)\le\upsilon_1\Rightarrow\eta^T(\vartheta)\tilde{\mathcal{R}}\eta(\vartheta)<\upsilon_2, \quad (13)$$

for all $\vartheta\in\{1,2,...,\mathcal{N}\}$.

Lemma 1 [29] *Let* $\mathcal{U}, \mathcal{V}$, *and* $\mathcal{W}$ *be matrices of compatible dimensions, where* $\mathcal{U}$ *is symmetric. Then, for any matrix* $\mathcal{O}(\kappa)$ *satisfying* $\mathcal{O}^T(\kappa)\mathcal{O}(\kappa) \leq I$ *with* $\kappa \in \mathbb{Z}_+$, *the inequality*

$$\mathcal{U} + [\mathcal{V}\mathcal{O}(\kappa)\mathcal{W}]^T + \mathcal{V}\mathcal{O}(\kappa)\mathcal{W} < 0,$$

is guaranteed if there exists a scalar $\varsigma > 0$ *for which*

$$\mathcal{U} + \varsigma\mathcal{V}\mathcal{V}^T + \varsigma^{-1}\mathcal{W}^T\mathcal{W} < 0.$$

Lemma 2 [30] (*Schur complement*) *For a given symmetric matrix* $\bar{\Psi} = \begin{bmatrix} \bar{\Psi}_{11} & \bar{\Psi}_{12} \\ \bar{\Psi}_{12}^T & \bar{\Psi}_{22} \end{bmatrix}$, *the condition* $\bar{\Psi} < 0$ *is equivalent to either of the following statements:*

$$(i)\ \bar{\Psi}_{11} < 0,\ \bar{\Psi}_{22} - \bar{\Psi}_{12}^T\bar{\Psi}_{11}^{-1}\bar{\Psi}_{12} < 0;$$
$$(ii)\ \bar{\Psi}_{22} < 0,\ \bar{\Psi}_{11} - \bar{\Psi}_{12}\bar{\Psi}_{22}^{-1}\bar{\Psi}_{12}^T < 0.$$

3 Main Results

In this section, an appropriate Lyapunov function is constructed to derive sufficient conditions for the FTB of the augmented systems (11). The resulting conditions are then reformulated into tractable LMI constraints by employing the IMM. In addition, a corollary based on the MAM is established for comparison, and an implementable optimization algorithm is provided.

3.1 FTB Analysis

Theorem 1 *For given the scalars* $\gamma \geq 1$, $\delta > 0$ *and* $\mathcal{N} > 0$, *the systems* (11) *are said to be FTB via the ETC* (5) *w.r.t* $(\upsilon_1, \upsilon_2, \tilde{\mathcal{R}}, \mathcal{N})$ *if there exist positive definite diagonal matrices* $\mathcal{Q} = diag\{\mathcal{Q}_1, \mathcal{Q}_1\}$, Ω_1 *and* Ω_2, *such that the following condition hold*

$$\Theta = \begin{bmatrix} \Theta_{1,1} & \Theta_{1,2} \\ * & \Theta_{2,2} \end{bmatrix} < 0, \tag{14}$$

$$\gamma^{\varsigma}\lambda_2\upsilon_1 < \lambda_1\upsilon_2, \tag{15}$$

where

$$\begin{aligned}\Theta_{1,1} =&(\bar{\mathcal{A}} + \bar{\mathcal{H}}_a\mathcal{P}_a(\vartheta)\bar{\mathcal{L}}_a)^T\mathcal{Q}(\bar{\mathcal{A}} + \bar{\mathcal{H}}_a\mathcal{P}_a(\vartheta)\bar{\mathcal{L}}_a)\\ &- \gamma\mathcal{Q} + \delta\Gamma,\\ \Theta_{1,2} =&(\bar{\mathcal{A}} + \bar{\mathcal{H}}_a\mathcal{P}_a(\vartheta)\bar{\mathcal{L}}_a)^T\mathcal{Q}\bar{\mathcal{C}}, \Theta_{2,2} = \bar{\mathcal{C}}^T\mathcal{Q}\bar{\mathcal{C}} - \Omega_1.\end{aligned}$$

Proof. Considering the following Lyapunov function

$$V(\eta(\vartheta), \vartheta) = \eta^T(\vartheta)\mathcal{Q}\eta(\vartheta), \forall\vartheta \in \{1, 2, ..., N\}. \tag{16}$$

Along the trajectory of systems (11), the forward difference of $V(\eta(\vartheta), \vartheta)$ is derived as follows

$$\begin{aligned}\Delta V(\eta(\vartheta), \vartheta) =&\eta^T(\vartheta + 1)\mathcal{Q}\eta(\vartheta + 1) - \eta^T(\vartheta)\mathcal{Q}\eta(\vartheta)\\ =&[(\bar{\mathcal{A}} + \bar{\mathcal{H}}_a\mathcal{P}_a(\vartheta)\bar{\mathcal{L}}_a)\eta(\vartheta) + \bar{\mathcal{C}}\epsilon(\vartheta)]^T\mathcal{Q}\\ &\times [(\bar{\mathcal{A}} + \bar{\mathcal{H}}_a\mathcal{P}_a(\vartheta)\bar{\mathcal{L}}_a)\eta(\vartheta) + \bar{\mathcal{C}}\epsilon(\vartheta)]\\ &- \eta^T(\vartheta)\mathcal{Q}\eta(\vartheta).\end{aligned} \tag{17}$$

From (17), by setting $\zeta^T(\vartheta) = [\eta^T(\vartheta), \epsilon^T(\vartheta)]$, we have

$$\Delta V(\eta(\vartheta), \vartheta) \leq \zeta^T(\vartheta)\tilde{\Xi}\zeta(\vartheta), \tag{18}$$

where $\tilde{\Xi}$ is a symmetric matrix, and

$$\begin{aligned}\tilde{\Xi}_{1,1} &= (\bar{\mathcal{A}} + \bar{\mathcal{H}}_a\mathcal{P}_a(\vartheta)\bar{\mathcal{L}}_a)^T\mathcal{Q}(\bar{\mathcal{A}} + \bar{\mathcal{H}}_a\mathcal{P}_a(\vartheta)\bar{\mathcal{L}}_a),\\ \tilde{\Xi}_{1,2} &= (\bar{\mathcal{A}} + \bar{\mathcal{H}}_a\mathcal{P}_a(\vartheta)\bar{\mathcal{L}}_a)^T\mathcal{Q}\bar{\mathcal{C}}, \tilde{\Xi}_{2,2} = \bar{\mathcal{C}}^T\mathcal{Q}\bar{\mathcal{C}}.\end{aligned}$$

Combining the event-triggered condition when $\vartheta \in [\vartheta_i, \vartheta_{i+1})$, it is obtained

$$\begin{aligned}\Delta V(\eta(\vartheta), \vartheta) \leq&\zeta^T(\vartheta)\tilde{\Xi}\zeta(\vartheta) + \delta\eta^T(\vartheta)\Gamma\eta(\vartheta)\\ &- \epsilon^T(\vartheta)\Omega_1\epsilon(\vartheta),\end{aligned} \tag{19}$$

with $\Gamma = \begin{bmatrix} I \\ -I \end{bmatrix}\Omega_2\begin{bmatrix} I & -I \end{bmatrix}$.

According to Theorem 1 and the inequality (19), we can obtain

$$\Delta V(\eta(\vartheta), \vartheta) \leq (\gamma - 1)V(\eta(\vartheta), \vartheta). \tag{20}$$

It follows that $V(\eta(\vartheta)) < \gamma V(\eta(\vartheta) - 1)$, i.e. $V(\eta(\vartheta)) < \gamma^{\varsigma}V(\eta(0)), \forall\varsigma \in \{1, 2, ..., \mathcal{N}\}$.

Supposing $\lambda_1 I < \bar{\mathcal{Q}} = \{\tilde{\mathcal{R}}^{-\frac{1}{2}}\mathcal{Q}\tilde{\mathcal{R}}^{-\frac{1}{2}}\} < \lambda_2 I$, thus it's obtained

$$\gamma^{\varsigma}V(0) = \gamma^{\varsigma}\eta^T(0)\tilde{\mathcal{R}}\eta(0) < \gamma^{\varsigma}\lambda_2\upsilon_1. \tag{21}$$

On the other hand, we have

$$\lambda_1\eta^T(\vartheta)\tilde{\mathcal{R}}\eta(\vartheta) < V(\eta(\vartheta)). \tag{22}$$

From (15), it's easily accessible

$$\eta^T(\vartheta)\tilde{\mathcal{R}}\eta(\vartheta) < \frac{\gamma^{\varsigma}\lambda_2\upsilon_1}{\lambda_1} < \upsilon_2. \tag{23}$$

The proof is completed.

3.2 Solution and Comparative Analysis

Theorem 2 *For given the constants $\gamma \geq 1$, $\delta > 0$ and $\mathcal{N} > 0$, the augmented systems (11) are said to be FTB by the controller (5) w.r.t $(\upsilon_1, \upsilon_2, \tilde{\mathcal{R}}, \mathcal{N})$ when the condition (15) is satisfied, if there exist a positive definite scalar matrix $\mathcal{X}_1$, and real matrices $\mathcal{Y}, \mathcal{Z}$, such that*

$$\begin{bmatrix} \Sigma_{1,1} & 0 & \Sigma_{1,3} & \Sigma_{1,4} \\ * & -\tilde{\Omega}_1 & \Sigma_{2,3} & 0 \\ * & * & \Sigma_{3,3} & 0 \\ * & * & * & -\varepsilon_1 I \end{bmatrix} < 0 \tag{24}$$

where

$$\Sigma_{1,1} = -\gamma\mathcal{X} + \delta\tilde{\Gamma},$$
$$\Sigma_{1,3} = \begin{bmatrix} \mathcal{X}_1\mathcal{A}^T + \mathcal{Y}^T\mathcal{C}^T & 0 \\ -\mathcal{Y}^T\mathcal{C}^T & \mathcal{X}_1\mathcal{A}^T - \mathcal{M}^T\mathcal{Z}^T \end{bmatrix},$$
$$\Sigma_{2,3} = \begin{bmatrix} -\mathcal{Y}^T\mathcal{C}^T & 0 \end{bmatrix}, \Sigma_{3,3} = -\mathcal{X} + \bar{\mathcal{H}}_a\bar{\mathcal{H}}_a^T,$$
$$\Sigma_{1,4} = \begin{bmatrix} \mathcal{X}_1\mathcal{L}_a^T \\ 0 \end{bmatrix}, \tilde{\Gamma} = \mathcal{X}\Gamma\mathcal{X}, \tilde{\Omega}_1 = \mathcal{X}_1\Omega_1\mathcal{X}_1.$$

Proof. From the analysis of Theorem 1 above, we obtain

$$\Theta = \Upsilon + \Psi^T\mathcal{Q}\Psi + \Lambda_1^T\mathcal{P}_a^T(\vartheta)\Lambda_2 + \Lambda_2^T\mathcal{P}_a(\vartheta)\Lambda_1 < 0, \tag{25}$$

with

$$\Upsilon = \begin{bmatrix} -\gamma\mathcal{Q} + \delta\Gamma & 0 \\ 0 & -\Omega_1 \end{bmatrix}, \Psi = \begin{bmatrix} \bar{\mathcal{A}} \\ \bar{\mathcal{C}} \end{bmatrix},$$
$$\Lambda_1 = \begin{bmatrix} \bar{\mathcal{L}}_a & 0 \end{bmatrix}, \Lambda_2 = \begin{bmatrix} 0 & \bar{\mathcal{H}}_a^T \end{bmatrix}.$$

By Lemmas 1 and 2, it yields

$$\tilde{\Upsilon} + \varepsilon_1^{-1}\Lambda_1^T\Lambda_1 + \varepsilon_1\Lambda_2^T\Lambda_2 < 0 \tag{26}$$

where

$$\tilde{\Upsilon}_{1,1} = -\gamma\mathcal{Q} + \delta\Gamma, \tilde{\Upsilon}_{1,3} = \bar{\mathcal{A}}, \tilde{\Upsilon}_{2,2} = -\Omega_1,$$
$$\tilde{\Upsilon}_{2,3} = \bar{\mathcal{C}}, \tilde{\Upsilon}_{3,3} = -\mathcal{X}.$$

Let $\mathcal{X} = \mathcal{Q}^{-1} = diag\{\mathcal{X}_1, \mathcal{X}_1\}, \mathcal{Y} = \mathcal{K}\mathcal{X}_1, \mathcal{Z} = \mathcal{L}\mathcal{X}_1$. Then, by reapplying Lemma 1 and pre-multiplying both sides of (26) by $diag\{\mathcal{X}, \mathcal{X}_1, I, I\}$, it can be inferred from condition (24) that (26) holds.

Based on the above results, a comparison case is further developed by applying the MAM to the time-varying coefficients. The corresponding system model and observer structure are constructed accordingly.

Let us denote $\tilde{\mathcal{A}} = (\tilde{\mathfrak{a}}_{ij})_{n\times n}$, where $\tilde{\mathfrak{a}}_{ij} = \max|\mathfrak{a}_{ij}(\vartheta)|$, for $\vartheta \in \{1, 2, ..., \mathcal{N}\}$. The DLTSs (1) can be rewritten as

$$\begin{aligned} \varkappa(\vartheta+1) &= \mathcal{A}(\vartheta)\varkappa(\vartheta) + \mathcal{C}u(\vartheta) \\ &= \tilde{\mathcal{A}}\varkappa(\vartheta) + \mathcal{C}u(\vartheta). \end{aligned} \tag{27}$$

Accordingly, the observer can be configured to

$$\hat{\varkappa}(\vartheta+1) = \tilde{\mathcal{A}}\hat{\varkappa}(\vartheta) + \mathcal{C}u(\vartheta) + \mathcal{L}\big(\omega(\vartheta) - \mathcal{M}\hat{\varkappa}(\vartheta)\big). \tag{28}$$

Therefore, it's easily got

$$\begin{aligned} \tilde{\varkappa}(\vartheta+1) &= \varkappa(\vartheta+1) - \hat{\varkappa}(\vartheta+1) \\ &= (\tilde{\mathcal{A}} - \mathcal{L}\mathcal{M})\tilde{\varkappa}(\vartheta). \end{aligned} \tag{29}$$

From the above analysis, we have

$$\eta(\vartheta+1) = \bar{\mathcal{A}}\eta(\vartheta) + \bar{\mathcal{C}}\epsilon(\vartheta), \tag{30}$$

where

$$\bar{\mathcal{A}} = \begin{bmatrix} \tilde{\mathcal{A}} + \mathcal{C}\mathcal{K} & -\mathcal{C}\mathcal{K} \\ 0 & \tilde{\mathcal{A}} - \mathcal{L}\mathcal{M} \end{bmatrix}, \bar{\mathcal{C}} = \begin{bmatrix} -\mathcal{C}\mathcal{K} \\ 0 \end{bmatrix}.$$

In conjunction with the analysis of Theorem 2, the following corollary is obtained.

Corollary 1 *For given scalars $\gamma \geq 1$, $\delta > 0$, and $\mathcal{N} > 0$, the augmented systems (30) under the controller (5) are FTB w.r.t $(\upsilon_1, \upsilon_2, \tilde{\mathcal{R}}, \mathcal{N})$ provided that the condition (15) holds, if there exist a positive definite matrix $\mathcal{X}_1$ and real matrices $\mathcal{Y}$ and $\mathcal{Z}$ such that*

$$\begin{bmatrix} \Xi_{1,1} & 0 & \Xi_{1,3} \\ * & -\tilde{\Omega}_1 & \Xi_{2,3} \\ * & * & \Xi_{3,3} \end{bmatrix} < 0, \tag{31}$$

where

$$\Xi_{1,1} = -\gamma\mathcal{X} + \delta\tilde{\Gamma},$$
$$\Xi_{1,3} = \begin{bmatrix} \mathcal{X}_1\tilde{\mathcal{A}}^T + \mathcal{Y}^T\mathcal{C}^T & 0 \\ -\mathcal{Y}^T\mathcal{C}^T & \mathcal{X}_1\tilde{\mathcal{A}}^T - \mathcal{M}^T\mathcal{Z}^T \end{bmatrix},$$
$$\Xi_{2,3} = \begin{bmatrix} -\mathcal{Y}^T\mathcal{C}^T & 0 \end{bmatrix}, \Xi_{3,3} = -\mathcal{X}.$$

For practical implementation of the above theorems and corollary, the following algorithmic procedure is provided.

4 Numerical Simulations

In this section, a numerical example is provided to verify the effectiveness of the theorem obtained results.

Example 1. The LDTSs parameters are considered below

$$\mathcal{A}(\vartheta) = \begin{bmatrix} 1.05 + 0.02\sin(0.08\vartheta) & 0.10 \\ 0 & 0.92 + 0.01\cos(0.05\vartheta) \end{bmatrix},$$
$$\mathcal{C} = \begin{bmatrix} 0.25 & 0.5 \\ 0.35 & 0.35 \end{bmatrix}, \mathcal{M} = \begin{bmatrix} 0.25 & 1.6 \\ 1.2 & 0.05 \end{bmatrix}.$$

Consider the initial value of the LDTS (1) by $\varkappa(0) = [0.55, -1.3]^T$, $\hat{\varkappa}(0) = [0.35, -0.15]^T$, and the other

Algorithm 1 Minimization-oriented evaluation of the energy consumption $\mathcal{J}$

Input: The initial value υ_1, the parameters γ_0, δ, and the step size $\Delta\gamma$
Output: The boundedness value υ_2 and the optimal energy consumption index $\mathcal{J}_{min}$.
for $\gamma = \gamma_0 : \Delta\gamma : \gamma_{\max}$ **do**
  if Theorem 2 and Corollary 1 are feasible,
   Compute the performance index $\mathcal{J}_i$.
    if $\mathcal{J}_i$ is the minimum value.
    Set $\mathcal{J}_{\min} = \mathcal{J}_i$.
    Break loop
    end if
  end if
  return $\mathcal{J}_{\min}$ and the corresponding parameters.
end for

parameters are assumed as $\gamma = 1.3, \delta = 0.45, \tilde{\mathcal{R}} = I, \upsilon_1 = 3.355$, $\vartheta = 0, 1, \ldots, \mathcal{N}$ with $\mathcal{N} = 20$ and $\Delta\vartheta = 1$.

The feasible solutions to the LMIs in Theorem 2 are obtained as follows.

$$\mathcal{X}_1 = \begin{bmatrix} 4.2870 & 0 \\ 0 & 4.2870 \end{bmatrix}, \mathcal{Y} = \begin{bmatrix} -25.5981 & 3.7606 \\ 7.4667 & -3.6868 \end{bmatrix},$$
$$\mathcal{Z} = \begin{bmatrix} 0.1422 & 2.5007 \\ 3.7166 & -0.5234 \end{bmatrix}, \Omega_1 = \begin{bmatrix} 0.2663 & 0.0012 \\ 0.0012 & 0.2634 \end{bmatrix},$$
$$\Omega_2 = \begin{bmatrix} 0.0405 & -0.0176 \\ -0.0176 & 0.0848 \end{bmatrix}, \mathcal{K} = \begin{bmatrix} -5.9711 & 0.8772 \\ 1.7417 & -0.8600 \end{bmatrix},$$
$$\mathcal{L} = \begin{bmatrix} 0.0332 & 0.5833 \\ 0.8669 & -0.1221 \end{bmatrix}, \varepsilon_1 = 4.7773, \lambda_1 = 0.2,$$
$$\lambda_2 = 0.25, \upsilon_2 = 797.0207.$$

Figure 2 depicts the behavior of the system (1) in the absence of the controller by the initial value $\varkappa(0) = [0.55, -1.3]^T$. Figure 3 shows that the system states and the estimated states remain stable under the ETC scheme (5). Figure 4 illustrates the difference between the system states and the state estimates. Figure 5 presents the control input trajectories of the ETC (5). It can be observed from Figure 6 that the minimum sampling interval is 1 s. Therefore, a reduction in the control update frequency can be achieved by the ETC scheme, which consequently alleviates the computational burden. The evolution trajectory presented in Figure 7 indicates that $\eta^T(\vartheta)\tilde{\mathcal{R}}\eta(\vartheta) < \upsilon_2 = 797.0207$.

Example 2. For a fair comparison, the same initial conditions and related parameters as those in

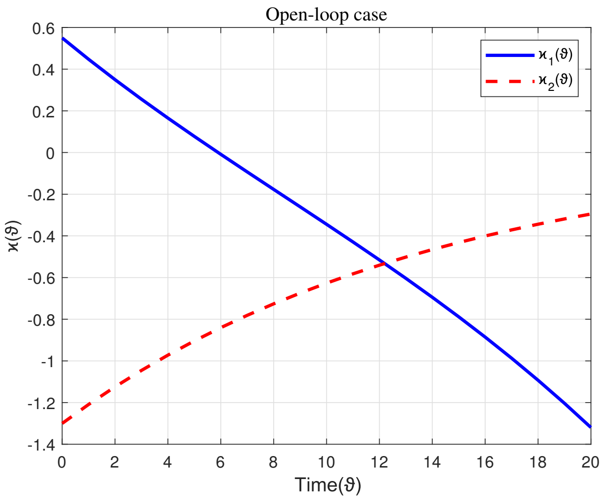

Figure 2. Trajectories of the DLTS (1) without $u(\vartheta)$.

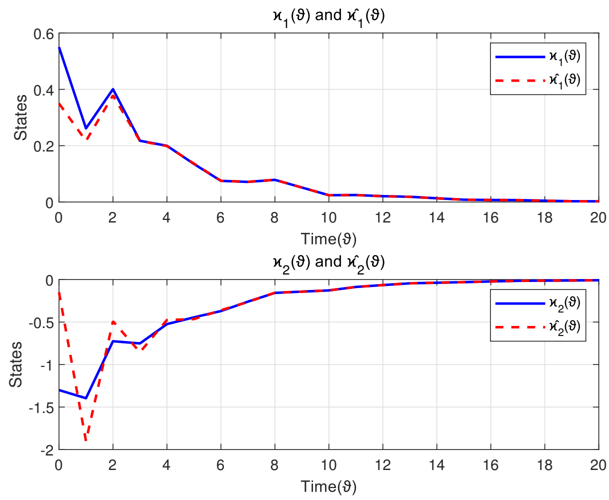

Figure 3. Trajectories of the closed-loop systems (1)-(2) with ETC (5) by $\varkappa(0) = [0.55, -1.3]^T$, $\hat{\varkappa}(0) = [0.35, -0.15]^T$.

Example 1 are adopted in this example. Solving the LMIs in Corollary 1 yields the following feasible solutions.

$$\mathcal{X}_1 = \begin{bmatrix} 4.7586 & 0 \\ 0 & 4.7586 \end{bmatrix}, \mathcal{Y} = \begin{bmatrix} -9.2969 & 4.1402 \\ 8.2019 & -4.0470 \end{bmatrix},$$
$$\mathcal{Z} = \begin{bmatrix} 0.1671 & 2.7772 \\ 4.1686 & -0.5786 \end{bmatrix}, \Omega_1 = \begin{bmatrix} 0.2354 & 0.0010 \\ 0.0010 & 0.2330 \end{bmatrix},$$
$$\Omega_2 = \begin{bmatrix} 0.0384 & -0.0157 \\ -0.0157 & 0.0758 \end{bmatrix}, \mathcal{K} = \begin{bmatrix} -1.9537 & 0.8700 \\ 1.7236 & -0.8505 \end{bmatrix},$$
$$\mathcal{L} = \begin{bmatrix} 0.0351 & 0.5836 \\ 0.8760 & -0.1216 \end{bmatrix}.$$

Figures 8 and 9 show the state trajectories and estimation error trajectories obtained from Theorem 2 and Corollary 1 under the same system parameters, respectively. It can be observed that, compared with

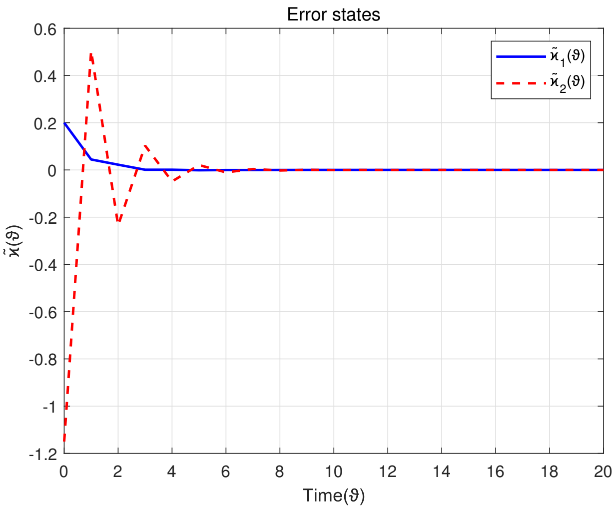

Figure 4. Trajectories of the error system (3) with ETC (5) by $\tilde{x}(0) = [0.2, -1.15]^T$.

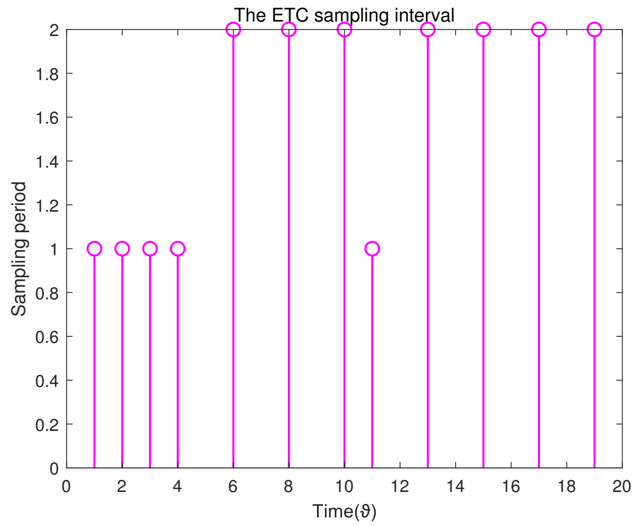

Figure 6. The ETC sampling interval for the DLTS (1).

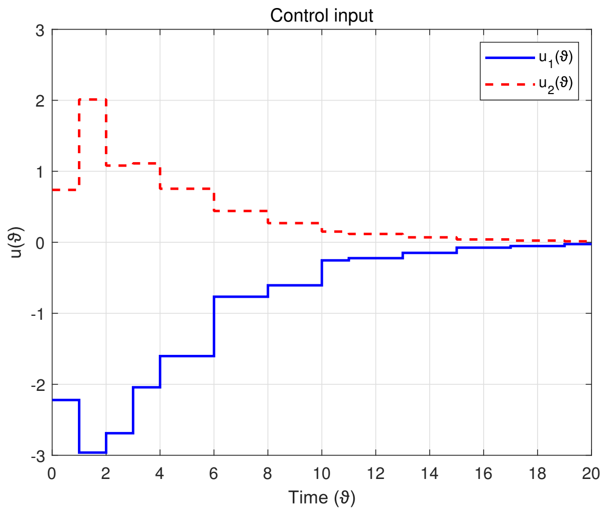

Figure 5. Trajectories of the ETC (5).

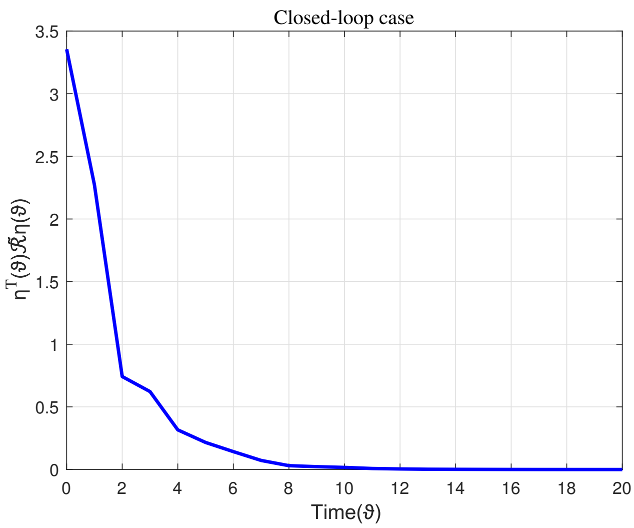

Figure 7. Simulation results for $\eta^T(\vartheta)\tilde{\mathcal{R}}\eta(\vartheta)$.

the MAM for handling time-varying coefficients, the IMM leads to a smoother convergence process for both the system states and the estimation errors. Furthermore, Table 2 presents the comparison results of the performance index under the two methods. The results show that the control scheme corresponding to Theorem 2, derived based on the IMM, yields lower energy consumption, which further verifies the effectiveness of this method in handling time-varying coefficients.

Table 2. Comparison of the energy consumption $\mathcal{J}$ under Theorem 2 and Corollary 1.

Design Criterion	$\mathcal{J}$
Theorem 2	48.9541
Corollary 1	244261.3504

5 Conclusions

In this paper, the FTB problem has been investigated for a class of observer-based DLTNCSs. The IMM has been employed to handle bounded time-varying coefficients by transforming them into uncertain parameter matrices. Based on the observer-generated state estimates, the augmented systems have been constructed to analyze the FTB of both the original systems and the estimation error systems in a unified framework. By using suitable inequality techniques and the ETC strategy, sufficient LMI-based conditions have been established to guarantee the desired FTB performance while reducing unnecessary signal transmissions. Furthermore, a MAM-based corollary has been provided for comparison, and an energy consumption performance index has been introduced to evaluate the control energy cost and

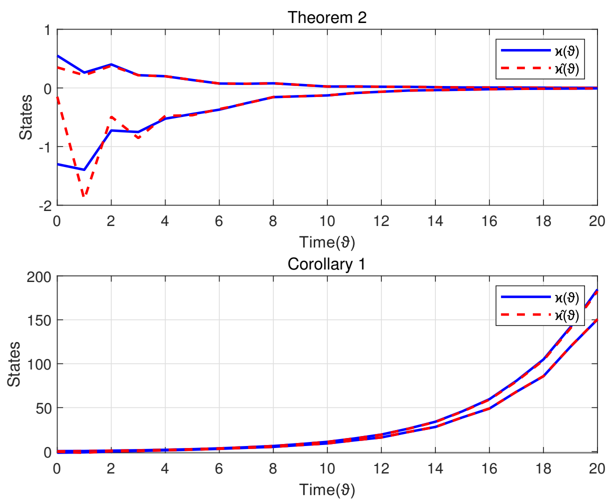

Figure 8. Comparison of the state trajectories for Theorem 2 and Corollary 1.

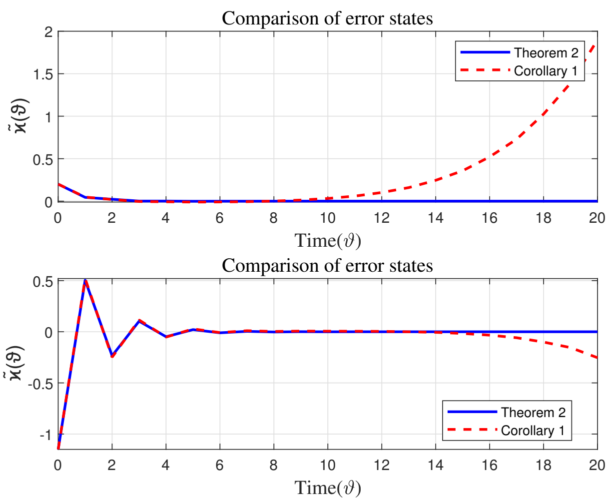

Figure 9. Comparison of the error trajectories for Theorem 2 and Corollary 1.

state performance. An implementable algorithm has also been given to describe the feasible parameter search and the minimization-oriented evaluation of the performance index. Simulation results show that employing IMM yields smoother system responses, smaller estimation errors, and lower energy consumption than the MAM, thereby verifying the effectiveness of the proposed method. Future research will extend the proposed framework to DLTNCSs subject to packet dropouts, communication delays, and cyber attacks.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

Guici Chen served as an Associate Editor of the *Journal of Nonlinear Dynamics and Applications* at the time of manuscript submission. To ensure the integrity of the peer-review process, Guici Chen was not involved in the editorial handling, peer review, or decision-making process for this manuscript, which was handled independently by another editor. The remaining authors declare no conflicts of interest.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable.

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