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Adaptive decentralized control for large-scale nonlinear systems with finite-time output constraints by multi- dimensional Taylor network

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Abstract

This paper investigates the adaptive decentralized control problem for a class of large-scale nonlinear systems with finite-time output constraints. In order to ensure that the tracking errors are constrained within a predefined boundary in finite time, a novel adaptive barrier Lyapunov function (BLF) control method is proposed by combining the modified finite-time performance function (FTPF) in the first step of backstepping process. Besides, the mean value theorem and regulating functions are employed to handle the difficulties caused by interconnection functions in large-scale systems. Subsequently, with the approximation performance of multi-dimensional Taylor network (MTN), a MTN-based adaptive decentralized tracking control scheme is developed to guarantee that the tracking errors satisfy the prescribed performance and all signals of the closed-loop systems are bounded. Finally, the stability theory analysis and simulation results demonstrate the effectiveness of the proposed method.

KEYWORDS

adaptive control, backstepping technique, finite-time output constraints, large-scale nonlinear systems, multi-dimensional Taylor network

1 | INTRODUCTION

Large-scale systems are a set of interconnected subsystems, which appear widely in actual systems, including power system [1], aerospace system [2], and multi-agent system [3]. Therefore, it is of great practical significance to study the controller design and performance analysis of large-scale systems. Due to such systems with complex correlation functions, it is a technically challenging problem to design a completely centralized controller. In recent years, the decentralized control methods which designed independently for local subsystems, as an important breakthrough, have received widely concerned. Subsequently, many adaptive decentralized control schemes have been proposed for some important classes of nonlinear large-scale systems [4–7], such as dynamic input–output interaction large-scale system [5], output feedback large-scale system [6] and time delay large-scale systems [7]. On the other hand, the model uncertainties also occur inevitably in many industrial systems. To deal with these unknown nonlinearities, some adaptive neural network [8] or fuzzy logic system [9] control schemes were developed and employed popularly in the large-scale systems control [10–14]. However, the problem of computational complexity is ignored in all these aforementioned papers. It is worth noting that when the order of the considered system increases, the adaptive parameters to be estimated will increase accordingly, which makes the control problem of large-scale systems more complex. Therefore, how to design a controller with simple structure and low computational complexity for large-scale systems is a meaningful issue.

In order to resolve the above problems, Yan proposed the multi-dimensional Taylor network (MTN)-based control methods [15], and then applied them to many nonlinear systems such as input constraints nonlinear system [16], stochastic nonlinear system [17], and output feedback nonlinear system [18]. The above literatures have proved that this simple control method can achieve satisfactory control performance under the advantages of low computational complexity and short online learning time. In particular, the literature [19] extended this MTN technology to large-scale interconnected system and proposed an adaptive MTN decentralized control method, which opened a new way for the research of large-scale nonlinear systems. But the abovementioned strategy was developed without considering the output constraints, which is an important factor of degrading system performance. Actually, various forms of practical systems such as fully actuated marine surface vessel system [20] and robotic manipulator system [21] are affected by output constraints. The good news is that the barrier Lyapunov function (BLF) is a powerful tool for coping with constraint problems, and many excellent results have been obtained in recent years [22–24]. For example, the adaptive BLF control approach was presented for time-varying output constraints system in [22]. And another BLF scheme was developed for switched nonlinear system with output constraints in [24]. However, most of the current researches explore that the output errors is limited to a predefined set only when time tends to infinity and ignore the problem of finite-time restriction. Therefore, the existing methods cannot be directly applied to the systems with finite-time output constraints such as mechanical and robotic systems.

Inspired by the above observations, the problem of adaptive decentralized control for large-scale interconnected systems with finite-time output constraints is addressed in this paper. Compared with the existing results, our proposed scheme has the following advantages.

1. The MTN-based adaptive decentralized control technology is introduced into the controller design framework. It should be pointed out that the MTN approximation function in [16–18] cannot be simply used to solve the problem of unknown interconnection function. In order to overcome this obstacle caused by interconnection functions, the mean value theorem and a set of adjustment functions are introduced. Additionally, the main characteristic of the MTN-based control is that they can alleviate the computational burden associated with the NN-based or FLS-based control [10–14].
2. Compared with the traditional tracking control problem of large-scale systems [4–7], this paper introduces BLF into backstepping to make the tracking error of large-scale systems achieve the output constraints objective. Different from the existing output constrains problems [22,23], which achieve the tracking performance as the time tends to infinity, the proposed method makes a breakthrough in tracking the desired trajectory in finite time, so as to accommodate more generic real-life system operations.
3. By employing the finite-time performance function (FTPF) developed in [25] and properly choosing the design parameters, the tracking errors can converge to the predefined arbitrarily small residual sets with the FTPF, and all the signals of the closed-loop system are bounded. In addition, simulation examples and comparative experiments show the effectiveness and superiority of the proposed method.

The paper is organized as follows. Section 2 introduces the nonlinear system we considered, the definitions of FTPF and the properties of the MTN. Section 3 is the detailed controller design process based on adaptive backstepping method and the stability analysis is given in Section 4. A numerical example and a contrasting experiment are presented in Section 5. Section 6 contains the conclusion of this paper and the suggestions for future work.

2 | PROBLEM FORMULATION AND PRELIMINARIES

In this paper, the large-scale interconnected system is considered as follows:

$$\begin{cases} \dot{x}_{i,j} = x_{i,j+1} + f_{i,j}(\bar{\boldsymbol{x}}_{i,j}) + g_{i,j}(\boldsymbol{y}) \\ \dot{x}_{i,n_i} = u_i + f_{i,n_i}(\bar{\boldsymbol{x}}_{i,n_i}) + g_{i,n_i}(\boldsymbol{y}) \\ y_i = x_{i,1} \end{cases} \tag{1}$$

where $j = 1,2,\cdots,n_i - 1$ is the identifier of the state variable in ith subsystem, $i = 1,2,\cdots,N$ indicates there are N subsystems in the large-scale system. $u_i \in \mathbb{R}$ and $y_i \in \mathbb{R}$ are the control input and the control output of the ith subsystem, respectively. $\boldsymbol{y} = [y_1, y_2, \cdots y_N]$

represents the system output of N subsystems and $x_{i,j}$ represents the jth variables of the ith subsystem, $\bar{\boldsymbol{x}}_{i,j} = \left[x_{i,1}, x_{i,2}, \cdots x_{i,j}\right]^{\mathrm{T}}, \bar{\boldsymbol{x}}_{i,n_i} = \left[x_{i,1}, x_{i,2}, \cdots x_{i,n_i}\right]^{\mathrm{T}}$. $f_{i,j}(\cdot)$ are the unknown smooth nonlinear functions with $f_{i,j}(\mathbf{0}) = 0$, $g_{i,j}(\cdot)$ are smooth interconnection functions between the ith subsystem and other subsystems with $g_{i,j}(\mathbf{0}) = 0$.

Remark 1. Compared with the common system [26–28], the controller design process of large-scale system becomes more difficult owing to the complexity of control synthesis and the physical restrictions on information exchange among subsystems.

The control objective is to design a decentralized adaptive MTN control scheme for the system (1), such that the output y_i can track the given reference signal y_{id} and all the signals of large-scale systems are bounded. At the same time, the output y_i can able to satisfy the output constraints in finite time.

Assumption 1. The reference signals $y_{id}(t)$ and their nth derivatives $y_{id}^{(n)}(t)$ are continuous and bounded.

Assumption 2. For the unknown functions $g_{i,j}(\boldsymbol{y})$, there exist the functions $g_{i,j,l}(y_l)$, such that

$$\left|g_{i,j}(\boldsymbol{y})\right|^2 \le \sum_{l=1}^{N} g_{i,j,l}^2(y_l) \tag{2}$$

where $g_{i,j,l}(\cdot)$ is the analytic functions with $g_{i,j,l}(0) = 0$.

Remark 2. $g_{i,j,l}(0) = 0$ implies that the origin is the equilibrium point of system (1). Moreover, by the mean value theorem, there exist the unknown nonlinear functions $\bar{g}_{i,j,l}(\cdot)$, such that.

$$g_{i,j,l}(y_l) = y_l \bar{g}_{i,j,l}(y_l) \tag{3}$$

According to Assumption 2, one has

$$\left|g_{i,j}(\boldsymbol{y})\right|^2 \le \sum_{l=1}^{N} y_l^2 \bar{g}_{i,j,l}^2(y_l) \tag{4}$$

Definition 1. [25]: If the continuous functions $v_i(t)$ satisfy the following three properties, they are named as the FTPF.

1. $v_i(0) > 0$;
2. $\dot{v}_i(t) \le 0$;
3. $\lim_{t \to T_f} v_i(t) = v_{i,T_f} > 0$ and $v_i(t) = v_{i,T_f}$ for any $t \ge T_f$, where v_{i,T_f} and T_f are the arbitrarily small constant and setting time, respectively.

According to Definition 1, a FTPF is defined as

$$v_i(t) = \begin{cases} \left(v_{i,0} - \dfrac{t}{T_f}\right) e^{1 - \frac{T_f}{T_f - t}} + v_{i,T_f}, & t \in \left[0, T_f\right) \\ v_{i,T_f}, & t \in \left[T_f, +\infty\right) \end{cases} \tag{5}$$

where $v_{i,0} > 1$ and $v_{i,T_f} > 0$ are parameters to be designed.

Remark 3. From (5), the functions $v_i(t)$ are continuous and satisfy all the properties in Definition 1, then the initial condition of $v_i(t)$ is $v_i(0) = v_{i,0} + v_{i,T_f}$.

Lemma 1. [25]: For any given positive function $v_i(t)$, when $z_{i,1}(t)$ remains in interval $|z_{i,1}(t)| < v_i(t)$, the following inequality can be obtained:

$$\log \frac{v_i^2(t)}{v_i^2(t) - z_{i,1}^2(t)} \le \frac{z_{i,1}^2(t)}{v_i^2(t) - z_{i,1}^2(t)} \tag{6}$$

where, if and only if $z_{i,1}(t)$ equals 0, the equal sign in the above formula holds.

Due to the existence of unknown functions in the systems, it cannot directly achieve the control goal. Therefore, MTNs can be used to approximate the unknown functions.

In [29], it is shown that for any continuous function $f(\boldsymbol{z}) : \mathbb{R}^m \to \mathbb{R}$ defined on a compact set $\Omega_{\boldsymbol{z}}$ and for any given desired level of accuracy $\varepsilon > 0$, there exists a MTN, such that

$$f(\boldsymbol{z}) = \boldsymbol{\theta}^{*\mathrm{T}} \boldsymbol{S}_{m_n}(\boldsymbol{z}) + \sigma(\boldsymbol{z}),\ \forall \boldsymbol{z} \in \Omega_{\boldsymbol{z}} \tag{7}$$

where $\boldsymbol{\theta}^*$ is the ideal weight vector defined as

$$\boldsymbol{\theta}^* = \underset{\theta \in \mathbb{R}^l}{\operatorname{argmin}} \left\{ \sup \left| f(\boldsymbol{z}) - \boldsymbol{\theta}^{\mathrm{T}} S_{m_n}(\boldsymbol{z}) \right| \right\}$$

and $\boldsymbol{S}_{m_n}(\boldsymbol{z})$ means $\prod_{i,j=1}^{n} s_i^{\sigma_i} s_j^{\sigma_j}$, σ_i and σ_j are non-negative numbers and satisfy $1 \le \sigma_i + \sigma_j \le m$, the form of $\boldsymbol{S}_{m_n}(\boldsymbol{z})$ is as follows:

$$\boldsymbol{S}_{m_n}(\boldsymbol{z}) = \Bigg[\underbrace{z_1, \cdots, z_n}_{1term}, \underbrace{z_1^2, \cdots, z_n^2}_{2term}, \cdots, \underbrace{z_1^m, \cdots, z_n^m}_{mterm}\Bigg]^{\mathrm{T}} \subset \mathbb{R}^l$$

where n denotes the nth state input and m represents the highest power of a polynomial. $\boldsymbol{z}=[z_1,\cdots,z_n]^{\mathrm{T}}\subset\mathbb{R}^n$ is input, $\sigma(\boldsymbol{z})$ means the approximation error and satisfies $|\sigma(\boldsymbol{z})|\le\varepsilon$.

3 | CONTROLLER DESIGN

Firstly, the following change of coordinates will be introduced.

$$\begin{cases} z_{i,1}=y_i-y_{id} \\ z_{i,j}=x_{i,j}-\alpha_{i,j-1},\ j=2,\cdots n_i \end{cases} \tag{8}$$

where $\alpha_{i,j-1}$ is visual control signal, which will be given in $j-1$-th step.

Step i, 1: Considering the ith subsystem in (1) and the coordinate transformation (8) with $j=1$,we have

$$\dot z_{i,1}=\dot y_i-\dot y_{id}=x_{i,2}+f_{i,1}(\bar x_{i,1})+g_{i,1}(\boldsymbol{y})-\dot y_{id} \tag{9}$$

The following Lyapunov function is defined as

$$V_{i,1}=\frac{1}{2}\log\frac{v_i^2(t)}{v_i^2(t)-z_{i,1}^2(t)}+\frac{1}{2}\tilde\theta_{i,1}^{\mathrm{T}}\tilde\theta_{i,1} \tag{10}$$

where $\tilde\theta_{i,1}=\theta_{i,1}-\hat\theta_{i,1}$ is the parameter error.

Subsequently, the derivative of $V_{i,1}$ is

$$\dot V_{i,1}=\frac{z_{i,1}}{v_i^2(t)-z_{i,1}^2}\left(x_{i,2}+f_{i,1}(\bar x_{i,1})+g_{i,1}(\boldsymbol{y})-\dot y_{id}-\frac{v_i(t)\dot v_i(t)}{z_{i,1}}\right)+\frac{\dot v_i(t)}{v_i(t)}-\tilde\theta_{i,1}^{\mathrm{T}}\dot{\hat\theta}_{i,1} \tag{11}$$

By Young's inequality with (4) and $x_{i,2}=z_{i,2}+\alpha_{i,1}$, one gets

$$\dot V_{i,1}\le\frac{z_{i,1}}{v_i^2(t)-z_{i,1}^2}\left(\alpha_{i,1}+\bar f_{i,1}(\bar x_{i,1})-\frac{v_i(t)\dot v_i(t)}{z_{i,1}}-\frac{z_{i,1}}{v_i^2(t)-z_{i,1}^2}\right)+\frac{\dot v_i(t)}{v_i(t)}-\tilde\theta_{i,1}^{\mathrm{T}}\dot{\hat\theta}_{i,1}+\frac{1}{2}\sum_{l=1}^{N}y_l^2\bar g_{i,1,l}^2(y_l)+\frac{1}{2}z_{i,2}^2 \tag{12}$$

where $\bar f_{i,1}(\bar x_{i,1},\dot y_{id},y_{id},v_i)=f_{i,1}(\bar x_{i,1})-\dot y_{id}+\frac{2z_{i,1}}{v_i^2(t)-z_{i,1}^2}$. For the convenience of writing, we will write $f_{i,1}(\bar x_{i,1})$ as $f_{i,1}$ and $\bar f_{i,1}(\bar x_{i,1},\dot y_{id},y_{id},v_i)$ as $\bar f_{i,1}$.

Due to there is an unknown function $f_{i,1}$ in $\bar f_{i,1}$, which makes it impossible to design the controller directly, so the MTN is introduced to estimate it. For $\varepsilon_{i,1}>0$, a MTN $\boldsymbol{\theta}_{i,1}^{\mathrm{T}}S_{i,1}(z_{i,1})$ will be introduced as follows

$$\bar f_{i,1}=\theta_{i,1}^{\mathrm{T}}S_{i,1}(z_{i,1})+\delta_{i,1}(z_{i,1}),|\delta_{i,1}(z_{i,1})|\le\varepsilon_{i,1}$$

where $\delta_{i,1}(z_{i,1})$ being an estimation error and $\varepsilon_{i,1}>0$ being an unknown constant is any accuracy level.

By the Young's inequality, we get

$$\begin{aligned}\dot V_{i,1}\le&\frac{z_{i,1}}{v_i^2(t)-z_{i,1}^2}\left(\alpha_{i,1}-\frac{1}{2}\frac{z_{i,1}}{\left(v_i^2(t)-z_{i,1}^2\right)}+\hat\theta_{i,1}^{\mathrm{T}}S_{i,1}+r_i\dot v_i(t)\right)\\&+\frac{\dot v_i(t)}{v_i(t)}+\frac{1}{2}z_{i,2}^2+\frac{1}{2}\sum_{l=1}^{N}y_l^2\bar g_{i,1,l}^2(y_l)\\&+\frac{z_{i,1}}{v_i^2(t)-z_{i,1}^2}\left(-r_i\dot v_i(t)-\frac{v_i(t)\dot v_i(t)}{z_{i,1}}\right)\\&+\frac{1}{2}\varepsilon_{i,1}^2+\tilde\theta_{i,1}^{\mathrm{T}}\left(\frac{z_{i,1}}{v_i^2(t)-z_{i,1}^2}S_{i,1}-\dot{\hat\theta}_{i,1}\right)\end{aligned} \tag{13}$$

where, r_i is positive parameter to be designed.

Using Young's inequality again, we have

$$\frac{z_{i,1}}{v_i^2(t)-z_{i,1}^2}\left(-r_i\dot v_i(t)-\frac{v_i(t)\dot v_i(t)}{z_{i,1}}\right)\le\frac{1}{2}\left(\frac{z_{i,1}}{v_i^2(t)-z_{i,1}^2}\right)^2+\frac{1}{2}(\dot v_i(t))^2(r_i+1)^2 \tag{14}$$

Furthermore, by the definition of $v_i(t)$ in (5), $v_i(t)$ and $\dot v_i(t)$ are bounded. Then the following result is true.

$$(\dot v_i(t))^2(r_i+1)^2+\frac{\dot v_i(t)}{v_i(t)}\le K_{i,1} \tag{15}$$

where $K_{i,1}$ is an unknown constant. Subsequently, substituting (14) and (15) into (13), we have

$$\begin{aligned}\dot V_{i,1}\le&\frac{z_{i,1}}{v_i^2(t)-z_{i,1}^2}\left(\alpha_{i,1}+\hat\theta_{i,1}^{\mathrm{T}}S_{i,1}+r_i\dot v_i(t)\right)\\&+\frac{1}{2}\sum_{l=1}^{N}y_l^2\bar g_{i,1,l}^2(y_l)+\frac{1}{2}z_{i,2}^2+\frac{1}{2}\varepsilon_{i,1}^2\\&+\tilde\theta_{i,1}^{\mathrm{T}}\left(\frac{z_{i,1}}{v_i^2(t)-z_{i,1}^2}S_{i,1}-\dot{\hat\theta}_{i,1}\right)+K_{i,1}\end{aligned} \tag{16}$$

Now, we design the virtual signal $\alpha_{i,1}$ and the adaptive law $\dot{\hat\theta}_{i,1}$ as

$$\alpha_{i,1}=-k_{i,1}z_{i,1}-\hat\theta_{i,1}^{\mathrm{T}}S_{i,1}-r_i\dot v_i(t) \tag{17}$$

$$\dot{\hat\theta}_{i,1}=\frac{z_{i,1}}{v_i^2(t)-z_{i,1}^2}S_{i,1}-\eta_{i,1}\hat\theta_{i,1} \tag{18}$$

where $k_{i,1}>0$ and $\eta_{i,1}>0$ are parameters to be designed.

Substituting (17) and (18) into (16), one has

$$\dot{V}_{i,1} \leq -\frac{k_{i,1}z_{i,1}^2}{v_i^2(t)-z_{i,1}^2}+\frac{1}{2}\sum_{l=1}^{N}y_l^2\bar{g}_{i,1,l}^2(y_l)+\frac{1}{2}z_{i,2}^2 + \frac{1}{2}\varepsilon_{i,1}^2+\eta_{i,1}\tilde{\theta}_{i,1}^{\mathrm{T}}\hat{\theta}_{i,1}+K_{i,1} \tag{19}$$

Step i,κ**:** Considering the coordinate transformation (8) with $j=\kappa$, we get

$$\dot{z}_{i,\kappa}=\dot{x}_{i,\kappa}-\dot{\alpha}_{i,\kappa-1}=x_{i,\kappa+1}+f_{i,\kappa}(\bar{x}_{i,\kappa})+g_{i,\kappa}(\boldsymbol{y})-\dot{\alpha}_{i,\kappa-1} \tag{20}$$

The following Lyapunov function is defined as

$$V_{i,\kappa}=V_{i,\kappa-1}+\frac{1}{2}z_{i,\kappa}^2+\frac{1}{2}\tilde{\theta}_{i,\kappa}^{\mathrm{T}}\tilde{\theta}_{i,\kappa} \tag{21}$$

where $\tilde{\theta}_{i,\kappa}=\theta_{i,\kappa}-\hat{\theta}_{i,\kappa}$ is the parameter error.

By applying the Young's inequality with (4) and $x_{i,\kappa+1}=z_{i,\kappa+1}+\alpha_{i,\kappa}$, the derivative of $V_{i,\kappa}$ is

$$\dot{V}_{i,\kappa}\leq \dot{V}_{i,\kappa-1}+z_{i,\kappa}\left(z_{i,\kappa+1}+\alpha_{i,\kappa}+\bar{f}_{i,\kappa}(\bar{x}_{i,\kappa})-\frac{3}{2}z_{i,\kappa}\right) -\tilde{\theta}_{i,\kappa}^{\mathrm{T}}\dot{\hat{\theta}}_{i,\kappa}+\frac{1}{2}z_{i,\kappa}^2+\frac{1}{2}\sum_{l=1}^{N}y_l^2\bar{g}_{i,\kappa,l}^2(y_l) \tag{22}$$

where $\bar{f}_{i,\kappa}(\bar{x}_{i,\kappa},\dot{\alpha}_{i,\kappa-1},\alpha_{i,\kappa-1})=f_{i,\kappa}(\bar{x}_{i,\kappa})-\dot{\alpha}_{i,\kappa-1}+\frac{3}{2}z_{i,\kappa}$. For the convenience of writing, we will write $\bar{f}_{i,\kappa}(\bar{x}_{i,\kappa},\dot{\alpha}_{i,\kappa-1},\alpha_{i,\kappa-1})$ as $\bar{f}_{i,\kappa}$.

Similarly, the MTN can be used to estimate the unknown function. Now, we design the virtual signal $\alpha_{i,\kappa}$ and the adaptive law $\dot{\hat{\theta}}_{i,\kappa}$ as

$$\alpha_{i,\kappa}=-k_{i,\kappa}z_{i,\kappa}-\hat{\theta}_{i,\kappa}^{\mathrm{T}}S_{i,\kappa} \tag{23}$$

$$\dot{\hat{\theta}}_{i,\kappa}=z_{i,\kappa}S_{i,\kappa}-\eta_{i,\kappa}\hat{\theta}_{i,\kappa} \tag{24}$$

where $k_{i,\kappa}>0$ and $\eta_{i,\kappa}>0$ are parameters to be designed.

Then, substituting (23) and (24) into (22) and combining MTN, we get

$$\dot{V}_{i,\kappa}\leq -\frac{k_{i,1}z_{i,1}^2}{v_i^2(t)-z_{i,1}^2}-\sum_{j=2}^{\kappa}k_{i,j}z_{i,j}^2+\frac{1}{2}\sum_{j=1}^{\kappa}\sum_{l=1}^{N}y_l^2\bar{g}_{i,j,l}^2(y_l) +\frac{1}{2}\sum_{j=1}^{\kappa}z_{i,j+1}^2+\frac{1}{2}\sum_{j=1}^{\kappa}\varepsilon_{i,j}^2+\sum_{j=1}^{\kappa}\eta_{i,j}\tilde{\theta}_{i,j}^{\mathrm{T}}\hat{\theta}_{i,j}+K_{i,1} \tag{25}$$

Step i,n_i**:** Considering the coordinate transformation (8) with $j=n_i$, we have

$$\dot{z}_{i,n_i}=\dot{x}_{i,n_i}-\dot{\alpha}_{i,n_i-1}=u_i+f_{i,n_i}(\bar{x}_{i,n_i})+g_{i,n_i}(\boldsymbol{y})-\dot{\alpha}_{i,n_i-1} \tag{26}$$

The Lyapunov function is chosen as

$$V_{i,n_i}=V_{i,n_i-1}+\frac{1}{2}z_{i,n_i}^2+\frac{1}{2}\tilde{\theta}_{i,n_i}^{\mathrm{T}}\tilde{\theta}_{i,n_i} \tag{27}$$

where $\tilde{\theta}_{i,n_i}=\theta_{i,n_i}-\hat{\theta}_{i,n_i}$ is the parameter error.

Subsequently, the derivative of V_{i,n_i} is

$$\dot{V}_{i,n_i}\leq \dot{V}_{i,n_i-1}+z_{i,n_i}\left(u_i+f_{i,n_i}(\bar{x}_{i,n_i})-\dot{\alpha}_{i,n_i-1}\right)-\tilde{\theta}_{i,n_i}^{\mathrm{T}}\dot{\hat{\theta}}_{i,n_i} +\frac{1}{2}z_{i,n_i}^2+\frac{1}{2}\sum_{l=1}^{N}y_l^2\bar{g}_{i,n_i,l}^2(y_l) \tag{28}$$

Adding and subtracting $z_{i,n_i}\mu_i(z_{i,n_i})$ at the right-hand side of the above inequality, we have

$$\dot{V}_{i,n_i}\leq \dot{V}_{i,n_i-1}+z_{i,n_i}\left(u_i+\bar{f}_{i,n_i}(\bar{x}_{i,n_i})-z_{i,n_i}-\mu_i(z_{i,n_i})\right)-\tilde{\theta}_{i,n_i}^{\mathrm{T}}\dot{\hat{\theta}}_{i,n_i} +\frac{1}{2}z_{i,n_i}^2+\frac{1}{2}\sum_{l=1}^{N}y_l^2\bar{g}_{i,n_i,l}^2(y_l) \tag{29}$$

where $\bar{f}_{i,n_i}(\bar{x}_{i,n_i})=f_{i,n_i}(\bar{x}_{i,n_i})-\dot{\alpha}_{i,n_i-1}+(1+\mu_i(z_{i,n_i}))z_{i,n_i}$.

Remark 4. $\mu_i(z_{i,n_i})$ is the smooth non-negative regulating function, which is intended to eliminate the interconnection functions in large-scale nonlinear systems. For the convenience of writing, we'll record it later as μ_i.

Similarly, the MTN can be used to estimate the unknown function. Now, we are ready to design the control input u_i and adaptive law $\dot{\hat{\theta}}_{i,n_i}$ as

$$u_i=-k_{i,n_i}z_{i,n_i}-\hat{\theta}_{i,n_i}^{\mathrm{T}}S_{i,n_i} \tag{30}$$

$$\dot{\hat{\theta}}_{i,n_i}=z_{i,n_i}S_{i,n_i}-\eta_{i,n_i}\hat{\theta}_{i,n_i} \tag{31}$$

where $k_{i,n_i}>0$ and $\eta_{i,n_i}>0$ are parameters to be designed.

Substituting (30) and (31) into (29), and combining the MTN, we get

$$\dot{V}_{i,n_i}\leq -\frac{k_{i,1}z_{i,1}^2}{v_i^2(t)-z_{i,1}^2}-\sum_{j=2}^{n_i}k_{i,j}z_{i,j}^2-\sum_{i=1}^{N}z_{i,n_i}^2\mu_i +\frac{1}{2}\sum_{j=1}^{n_i}\sum_{l=1}^{N}y_l^2\bar{g}_{i,j,l}^2(y_l)+\frac{1}{2}\sum_{j=1}^{n_i}\varepsilon_{i,j}^2 +\frac{1}{2}\sum_{j=1}^{n_i-1}z_{i,j+1}^2+\sum_{j=1}^{n_i}\eta_{i,j}\tilde{\theta}_{i,j}^{\mathrm{T}}\hat{\theta}_{i,j}+K_{i,1} \tag{32}$$

4 | STABILITY ANALYSIS

Theorem 1. Considering the interconnected large-scale systems 1 with Assumption 1 and 2. By designing the actual control laws (30), the virtual control signals (17), (23) and choosing the adaptive laws (18), (24), (31), if the initial conditions are bounded with $|z_{i,1}(0)| < v_i(0)$, the following properties are true.

1. All the signals in the closed-loop are semi-globally uniformly bounded.
2. The tracking error $z_{i,1} = y_i - y_{id}$ enters into a prescribed invariant region in finite time.

Proof. Considering the following Lyapunov function

$$V_N = \sum_{i=1}^{N} V_{i,n_i} = \frac{1}{2}\sum_{i=1}^{N}\log\frac{v_i^2(t)}{v_i^2(t)-z_{i,1}^2} + \frac{1}{2}\sum_{i=1}^{N}\sum_{j=2}^{n_i} z_{i,j}^2 + \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{n_i}\tilde{\theta}_{i,j}^{\mathrm{T}}\tilde{\theta}_{i,j} \tag{33}$$

Subsequently, the derivative of V_N is

$$\begin{aligned}\dot{V}_N \le & -\sum_{i=1}^{N}\frac{k_{i,1}z_{i,1}^2}{v_i^2(t)-z_{i,1}^2} - \sum_{i=1}^{N} z_{i,n_i}^2\mu_i - \sum_{i=1}^{N}\sum_{j=2}^{n_i} k_{i,j}z_{i,j}^2 \\ & + \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{n_i}\sum_{l=1}^{N} y_l^2\bar{g}_{i,j,l}^2(y_l) + \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{n_i-1} z_{i,j+1}^2 \\ & + \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{n_i}\varepsilon_{i,j}^2 + \sum_{i=1}^{N}\sum_{j=1}^{n_i}\eta_{i,j}\tilde{\theta}_{i,j}^{\mathrm{T}}\hat{\theta}_{i,j} + \sum_{i=1}^{N} K_{i,1}\end{aligned} \tag{34}$$

By the Lemma 1, we have

$$-\frac{k_{i,1}z_{i,1}^2}{v_i^2(t)-z_{i,1}^2} \le -k_{i,1}\log\frac{v_i^2(t)}{v_i^2(t)-z_{i,1}^2} \tag{35}$$

With the definition of $\tilde{\theta}_{i,j}$ and the Young's inequality, we have

$$\sum_{i=1}^{N}\sum_{j=1}^{n_i}\eta_{i,j}\tilde{\theta}_{i,j}^{\mathrm{T}}\hat{\theta}_{i,j} \le -\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{n_i}\eta_{i,j}\tilde{\theta}_{i,j}^{\mathrm{T}}\tilde{\theta}_{i,j} + \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{n_i}\eta_{i,j}\theta_{i,j}^{\mathrm{T}}\theta_{i,j} \tag{36}$$

The following inequality can be established by choosing a proper smooth non-negative function μ_i

$$-\sum_{i=1}^{N} z_{i,n_i}^2\mu_i + \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{n_i}\sum_{l=1}^{N} y_l^2\bar{g}_{i,j,l}^2(y_l) \le 0 \tag{37}$$

Then, substituting (35) and (36) into (34), we obtain

$$\begin{aligned}\dot{V}_N \le & -\sum_{i=1}^{N} k_{i,1}\log\frac{v_i^2(t)}{v_i^2(t)-z_{i,1}^2} - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=2}^{n_i} k_{i,j}z_{i,j}^2 + \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{n_i}\varepsilon_{i,j}^2 \\ & -\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{n_i}\eta_{i,j}\tilde{\theta}_{i,j}^{\mathrm{T}}\tilde{\theta}_{i,j} + \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{n_i}\eta_{i,j}\theta_{i,j}^{\mathrm{T}}\theta_{i,j} + \sum_{i=1}^{N} K_{i,1}\end{aligned} \tag{38}$$

Let

$$a_i = \min\left\{k_{i,j}, \eta_{i,j}\right\}, 1 \le j \le n_i$$

$$a = \min\{a_1, a_2, \cdots a_N\}$$

$$b = \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{n_i}\varepsilon_{i,j}^2 + \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{n_i}\eta_{i,j}\theta_{i,j}^{\mathrm{T}}\theta_{i,j} + \sum_{i=1}^{N} K_{i,1}$$

Then the inequality (38) can be rewritten in the following form

$$\dot{V}_N \le -aV_N + b \tag{39}$$

Therefore, we can get

$$0 \le V_N(t) \le \left(V_N(0) - \frac{b}{a}\right)e^{-at} + \frac{b}{a} \le V_N(0) + \frac{b}{a}, \forall t \ge 0 \tag{40}$$

It can be seen from (40) that by choosing appropriate design parameters, all the signals in closed-loop are semi-globally bounded.

From (40), it also can be concluded that

$$\log\frac{v_i^2(t)}{v_i^2(t)-z_{i,1}^2} \le 2V_N(0) + \frac{2b}{a} \tag{41}$$

Then,

$$\frac{v_i^2(t)}{v_i^2(t)-z_{i,1}^2} \le e^{2V_N(0)+\frac{2b}{a}} \tag{42}$$

It can be obtained from (42) that

$$|z_{i,1}| \le \sqrt{1 - \frac{1}{e^{2V_N(0)+\frac{2b}{a}}}}|v_i(t)| \le |v_i(t)| \tag{43}$$

where $2V_N(0) + \frac{2b}{a} > 0$.

The proof is thus completed.

5 | SIMULATION RESULTS

In this section, a numerical example and a contrasting experiment are given to demonstrate the validity of the proposed scheme.

Example 1. Considering the following second order large-scale nonlinear system

$$\begin{cases} \dot{x}_{1,1} = x_{1,2} + f_{1,1} + g_{1,1} \\ \dot{x}_{1,2} = u_1 + f_{1,2} + g_{1,2} \\ y_1 = x_{1,1} \\ \dot{x}_{2,1} = x_{2,2} + f_{2,1} + g_{2,1} \\ \dot{x}_{2,2} = u_2 + f_{2,2} + g_{2,2} \\ y_2 = x_{2,1} \end{cases} \tag{44}$$

with the nonlinear functions $f_{1,1} = -2x_{1,1}e^{-0.5x_{1,1}}$, $f_{2,1} = -2x_{2,1}e^{-0.5x_{2,1}}$, $f_{1,2} = -0.5x_{1,1}^2$, $f_{2,2} = -0.8\sin x_{2,1}e^{-0.1x_{2,2}}$ and the interconnection functions $g_{1,1} = -y_1y_2+y_2$, $g_{2,1} = y_1 - y_1y_2$, $g_{1,2} = 0.28y_1y_2$, $g_{2,2} = y_2e^{-y_1}$. The initial conditions of the system is $[x_{1,1}(0), x_{1,2}(0), x_{2,1}(0), x_{2,2}(0)] = [0,0,0,0]$.

By the Theorem 1, the actual control laws are designed as

$$u_i = -k_{i,n_i}z_{i,n_i} - \hat{\theta}_{i,n_i}^{\mathrm{T}}S_{i,n_i} \quad (i = 1,2) \tag{45}$$

The virtual control signals are chosen as

$$\alpha_{i,1} = -k_{i,1}z_{i,1} - \hat{\theta}_{i,1}^{\mathrm{T}}S_{i,1} - r_i\dot{v}_i(t) \quad (i = 1,2) \tag{46}$$

and the adaptive laws are

$$\dot{\hat{\theta}}_{i,1} = \frac{z_{i,1}}{v_i^2(t) - z_{i,1}^2}S_{i,1} - \eta_{i,1}\hat{\theta}_{i,1} \quad (i = 1,2) \tag{47}$$

$$\dot{\hat{\theta}}_{i,2} = z_{i,2}S_{i,2} - \eta_{i,2}\hat{\theta}_{i,2} \quad (i = 1,2) \tag{48}$$

where $z_{i,1} = y_i - y_{id}$ and $z_{i,2} = x_{i,2} - \alpha_{i,1}$. The FTPF is defined as (5) with $i = 1,2$, $v_{i,0} = 2$, $v_{T_f} = 0.1$, $T_f = 3$, and $v_i(0) = v_{i,0} + v_{T_f} = 2.1$.

In the simulation of large-scale system, the design parameters are chosen as $k_{1,1} = 60, k_{2,1} = 40$, $k_{1,2} = 80$, $k_{2,2} = 60$, $r_1 = r_2 = 0.5$, and $\eta_{1,1} = \eta_{2,1} = 4$, $\eta_{1,2} = \eta_{2,2} = 0.1$. The desired reference signals $y_{1d} = 0.5\sin(t), y_{2d} = 0.5(\sin(t) + \sin(0.5t))$. It's easy to get $|z_{i,1}(0)| < v_i(0), i = 1,2$.

With the above conditions and the proposed control scheme, the simulation results of the system (44) are shown in Figures 1–8. Figures 1 and 2 show the trajectories of reference signal and system output of two subsystems. It is obvious that this algorithm has good tracking performance. Figures 3 and 4 plot the trajectories of tracking error of two subsystems. It can be seen that the tracking errors $z_{1,1}$ and $z_{2,1}$ are always kept within the bounds of the predefined performance

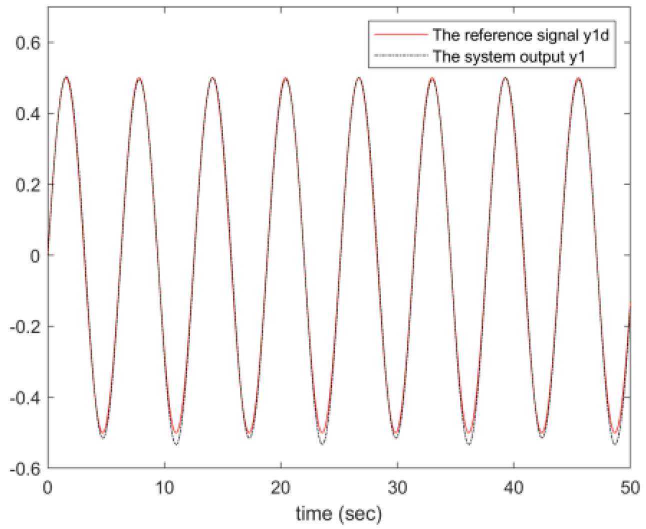

FIGURE 1 The reference signal y_{1d} and the system output y_1 trajectories of the first subsystem

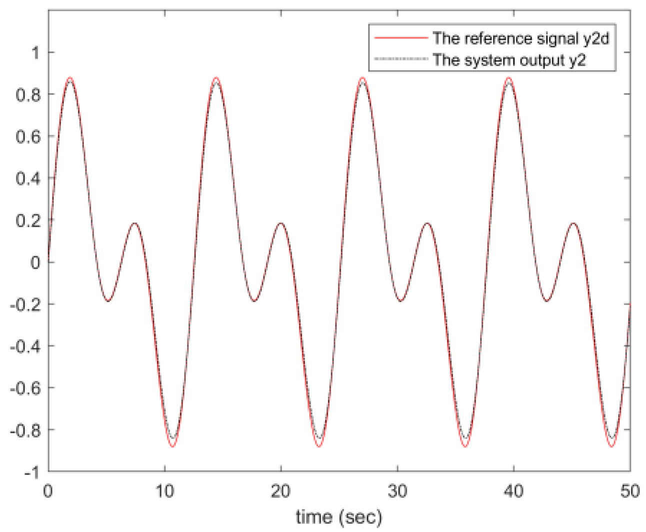

FIGURE 2 The reference signal y_{2d} and the system output y_2 trajectories of the second subsystem

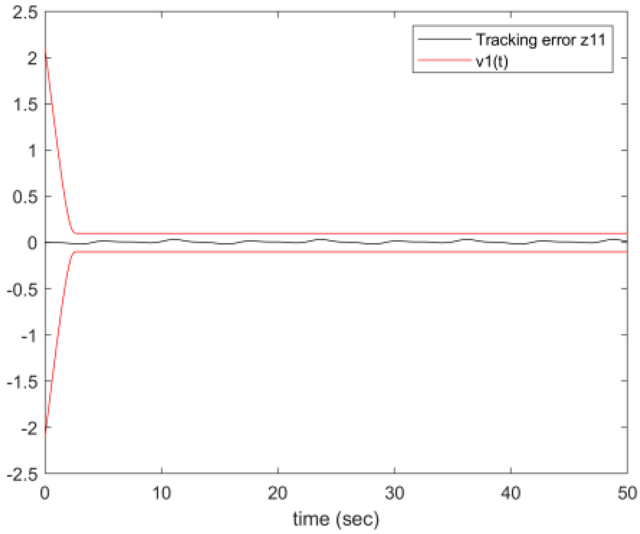

FIGURE 3 The tracking error $z_{1,1} = y_1 - y_{1d}$ trajectory of the first subsystem

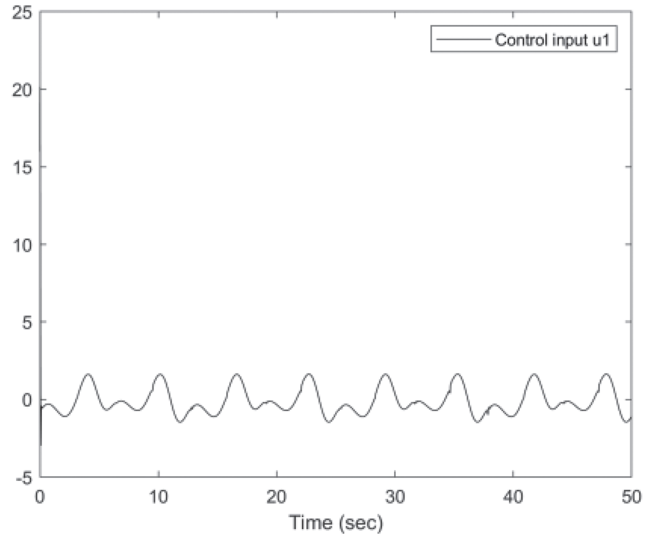

FIGURE 5 The control input u_1 trajectory of the first subsystem

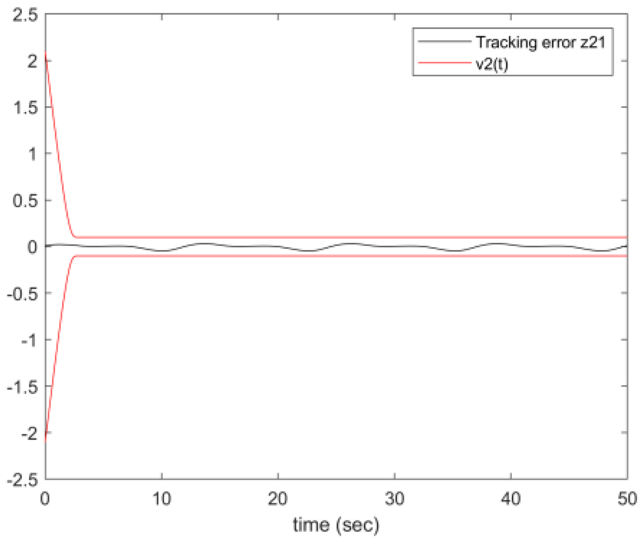

FIGURE 4 The tracking error $z_{2,1} = y_2 - y_{2d}$ trajectory of the second subsystem

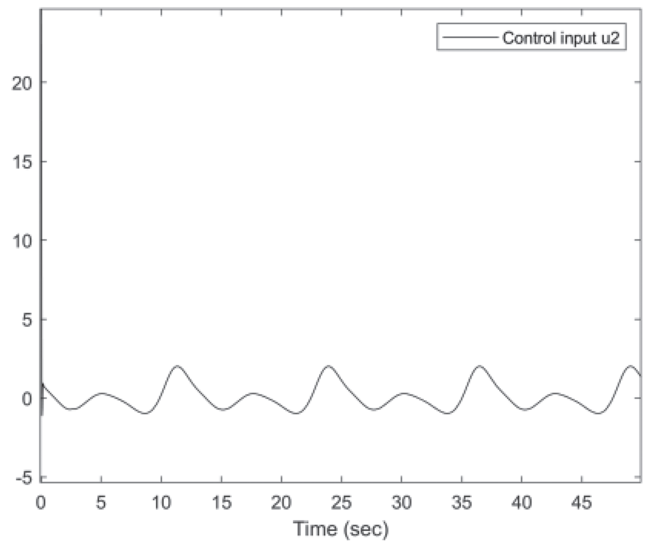

FIGURE 6 The control input u_2 trajectory of the second subsystem

function. The trajectories of control inputs u_1, u_2 and state variables x_{12}, x_{22} in Figures 5–8 show that all the signals are bounded.

Example 2. In order to fully explain the advanced of the proposed scheme, a contrasting experiment has been done in this section. In this experiment, the controllers are constructed by using FTPF and time independent general function respectively. Then, with the help of the system of Example 1, the infinite-time limit function is used in the control scheme for simulation. And the comparison curve of the system output tracking error under the two performance functions is obtained as shown in Figure 9. The infinite-time limit function is $v_{\inf} = \left(v_0 - v'_{tf}\right) e^{-\beta t} + v'_{tf}$, where $v_0 = 2.2$, $v'_{tf} = 0.3$, $\beta = 0.3$.

It can be observed from Figure 9 that the control schemes under the two time performance functions can achieve good tracking effect. Moreover, the control method with FTPF can ensure that the tracking error of

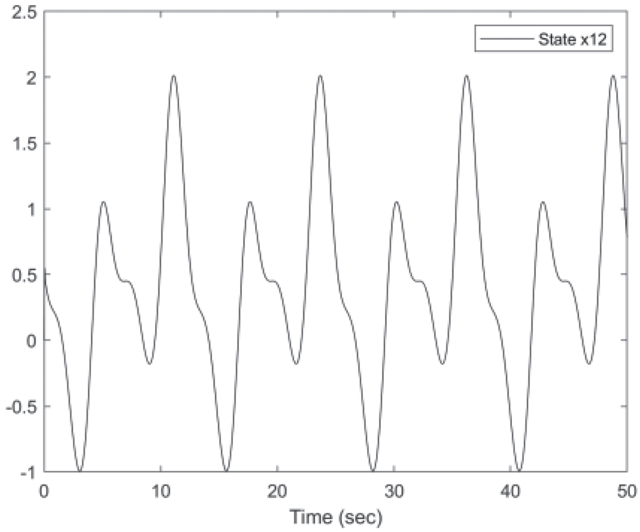

FIGURE 7 The state variables $x_{1,2}$ trajectory of the first subsystem

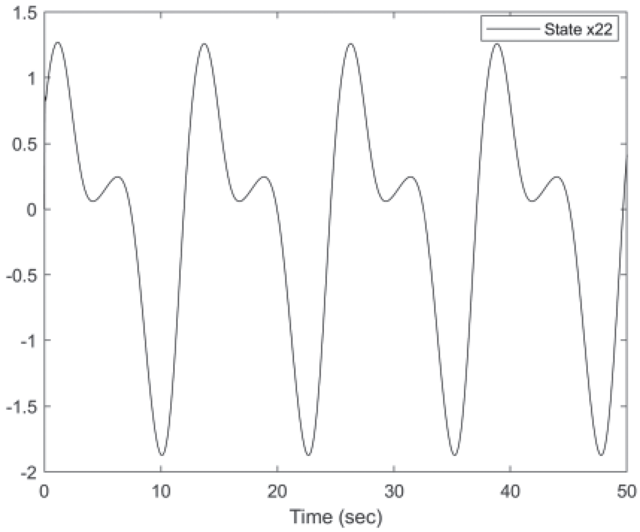

FIGURE 8 The state variables $x_{2,2}$ trajectory of the first subsystem

the system can enter the predefined invariant set with finite time ($t = 3$). However, the infinite-time limit function cannot achieve this goal. Therefore, the comparative experiment results fully illustrate the effectiveness and necessity of the newly defined FTPF in the process of controller design.

6 | CONCLUSION

In this paper, a decentralized adaptive MTN control method has been proposed for a class of large-scale nonlinear systems with finite-time output constraints.

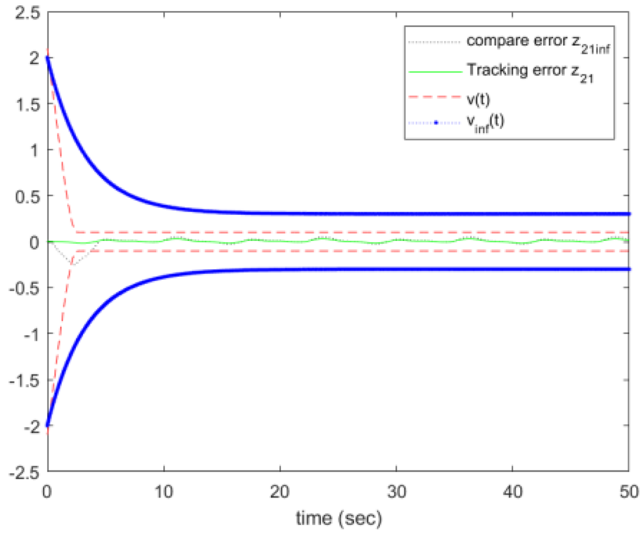

FIGURE 9 Tracking error curve based on finite-time performance function and infinite-time limit function

The restriction of the finite-time output constraints is overcome by introducing the modified finite-time performance function and the BLF in the first step of backstepping design process. The presented control method can ensure that the output tracking errors remain within the boundary of the performance function and all the signals in the systems are bounded. Finally, the theory analysis and simulation results illustrate the rationality of the proposed controller. In our future work, we will try to extend the proposed control scheme to the time-varying full-state constraints nonlinear systems.

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AUTHOR CONTRIBUTIONS

Lei Chu: Formal analysis. **Tian Gao:** Investigation, software. **Mingxin Wang:** Methodology, visualization. **Yuqun Han:** Project administration, supervision. **Shanliang Zhu:** Conceptualization, funding acquisition.

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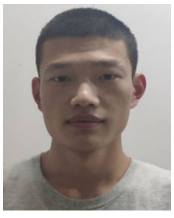

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