Dynamic Event-Triggered Low-Computation Neural Adaptive Output-Feedback Control for Strict-Feedback Nonlinear Systems with Prescribed Performance

Haibo Xu, Xinyu Ouyang, Nannan Zhao

***Abstract*—This paper addresses the low-computation neural output feedback control issue for a class of strict-feedback nonlinear systems (SFNS) with dynamic event-triggered. Based on the prescribed performance technology, a novel state observer based on the radial basis function neural networks (RBFNNs) is introduced, such that the proposed low-computation method can ensure that all signals in the closed-loop system are bounded. Different from the existing results, RBFNNs only receive system state estimation as input. In this way, the explosion of complexity problem in backstepping and RBFNNs methods is avoided without using dynamic surface control and filtered commands. On the other hand, in order to reduce the number of system communications, this paper also reconstructs the event condition based on the function of error transformation. The effectiveness of the provided method is demonstrated through numerical simulation.**

***keywords*—Nonlinear systems, neural adaptive control, low-computation, output-feedback, dynamic event-triggered, prescribed performance control (PPC)**

I. Introduction

In order to guarantee the transient performance of the control system, Bechlioulisa et al. [1] proposed a PPC approach for the first time to keep the tracking error within a given range. With the continuous development of the PPC method, it is widely applied in various types of nonlinear system control [2]–[6]. In [2], Hua and Li proposed a different state transformation based on the output feedback and PPC for a class of time-delay systems with unknown Prandtlshlinskii hysteresis. In [3], the PPC method was applied to a class of switched nonstrict-feedback nonlinear uncertain systems and the problem of adaptive NNs-based decentralized PPC was solved. In the work of Tang et al. [4], the authors solved the PPC problem of multi-input multi-output nonlinear systems with actuator failure and provided a new error transformation. The work in [5] solved the PPC problem based on high-order stochastic nonlinear systems, and designed a new variable of error transformation . Further, based on the work in [5], Zhang et al. [6] studied the PPC for high-order nonlinear multi-agent systems.

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Since most state variables of nonlinear systems in practical systems are unmeasurable, the development of the output feedback controller is necessary. In this case, output feedback control methods have achieved significant progress in fields such as uncertain nonlinear systems [7]–[9], switched nonlinear systems [10]–[12] and nonlinear multi-agent systems [13]–[15]. In [7], Zhou et al. designed a dynamic feedback control strategy that is based on fuzzy logic system and output feedback controller. In [8], the control problem of non-triangular stochastic nonlinear systems with unmodeled dynamics was further developed by using the robust adaptive output-feedback control. The work in [10] developed a new output-feedback control strategy with PPC for the nonstrict-feedback switched nonlinear systems. In this strategy, the uncertain states were estimated by a linear state observer. In [14], a design method of distributed controller based on output feedback control was proposed. By introducing m cascaded compensators, the leader-follower consensus problem of a multi-agent system with output delay was solved.

Despite the maturity of output feedback control, the problem of exploding computational complexity caused by the backstepping method remains an open issue. Aiming at this problem, Swaroop et al. [16] designed a dynamic surface control method based on low-pass filters to avoid the complexity caused by the explosive growth of terminology. In addition, Dong et al. [17], [18] designed a command filtered method based on backstepping technology. However, due to the addition of filters, the structure of the controller becomes complex, which in turn increase the burden of calculation. Therefore, Zhang et al. [19] designed a backstepping-like control scheme based on PPC. This scheme solved the exploding computational complexity problem by proving the boundedness of each order closed-loop signal under the constraint of PPC. In [20], the author extended this low-complexity control method to the unknown nonlinear system with an actuator dead zone and added 2-bit-triggered tracking control to reduce the number of communications.

In data transmission, two main methods are usually used, namely periodic sampling and ETC, to determine the transmission and sampling time to achieve control of the system and ensure its stability. As a traditional method of data transmission, the periodic sampling strategy will result in an increase in the cost of communication resource of system data transmission. But, ETC is an effective control strategy, which can reduce control frequency and avoid unnecessary waste of resources. The control instants of the ETC systems are resolved by the occurrence of the wittily designing event conditions that are related to the previous state of the system [21]–[27]. The authors in [21] designed an event-triggered controller for tracking the desired value of nonlinear systems with exogenous inputs. In [22] Xing et al. designed a new switching threshold strategy, which was formed by concatenating the fixed and relative threshold strategy. In addition, Xing et al. [23] designed an encoding-decoding method in which only a one-bit signal transmitted between the actuator and controller, thus occupying less channel bandwidth. With the development of event-triggered control, the DETC [28]–[30] scheme, which can dynamically adjust event conditions, is favored by researchers. In [31], the authors proposed a DETC scheme for SFNS to achieve zero tracking error.

Based on the motivation of the above analyses, this brief investigates a low-computation neural output feedback dynamic event-triggered control for a class of SFNS with unmatched disturbances. This scheme avoids the explosive growth of terminology and saves communication resources. The highlights of this study, in contrast to the prior research, are as follows:

(1) Inspired by [19], [20], this paper realizes the low-complexity calculation of nonlinear systems with unknown states without using dynamic surfaces and command filters.

(2) Compared with [7]–[9], RBFNNs only receive system state estimation as input. In order to realize the low-computation control scheme, the state observer is reconstructed based on this method.

(3) To adapt to the low-complexity control scheme, this paper reconstructs the dynamic event-triggered condition based on the function of error conversion , which can further extend the trigger time interval compared with [22].

II. PROBLEM DESCRIPTION AND BASIC KNOWLEDGE

The plant is a continuous-time strict-feedback nonlinear system described by

$$\begin{cases} \dot{x}_i = f_i(\bar{x}_i) + \lambda_i(t) + x_{i+1} \\ \dot{x}_n = f_n(\bar{x}_n) + \lambda_n(t) + u \\ y = x_1 \end{cases} \tag{1}$$

where $\bar{x}_i = [x_1, x_2, \cdots, x_i]^T \in \mathbb{R}^i$ $(i = 1, 2, \cdots, n)$ denotes the state vector, $y \in \mathbb{R}$ and u denote the output and input respectively. $f_i(\cdot), i = 1, 2, \cdots, n$ represent the unknown smooth system functions with $f_i(0) = 0$. $\lambda_i(t)(i = 1, \cdots, n)$ are the system's unmatched disturbance, which satisfies $|\lambda_i(t)| \le \bar{\lambda}_i$, $\bar{\lambda}_i$ is constant. Assuming that only x_1 is measurable, while the other states $x_i, i = 2, \ldots, n$ are unmeasurable. Set the following coordinate transformation:

$$\begin{cases} z_1 = x_1 - y_r \\ z_i = \hat{x}_i - \alpha_{i-1} \end{cases} \quad i = 2, \cdots, n \tag{2}$$

where $\hat{x}_i$ is the estimate of x_i, y_r and α_{i-1} denote the trajectory signal and the virtual control law respectively. In order to constrain $z_i, i = 1, \cdots, n$, the boundary function $\psi_i(t)$ defined as

$$\psi_i(t) = (\psi_{i_0} - \psi_{i_\infty})e^{-\tau_i t} + \psi_{i_\infty}, \quad i = 1, \cdots, n \tag{3}$$

where ψ_{i_0}, ψ_{i_∞} and ψ_i are positive constants, $\psi_{i_0} > \psi_{i_\infty}$, ψ_{i_0} is the starting value, ψ_{i_∞} is the maximum allowable size of steady-state error, and τ_i is the convergence rate of prescribed tracking error. For the PPC scheme, the following holds:

$$|z_i(t)| < \psi_i(t), \quad i = 1, \ldots, n, \quad t > 0. \tag{4}$$

Further, (4) can be expressed as the following equation:

$$z_i(t) = \psi_i(t) K(\xi(t)). \tag{5}$$

And the function of error transformation $\xi(t)$ is

$$\xi(t) = K^{-1}(\frac{z_i(t)}{\psi_i(t)}). \tag{6}$$

Next, an auxiliary smooth function $K^{-1}(\iota)$ is selected, such that

$$\lim_{\iota \to -1} K^{-1}(\iota) = -\infty \quad \lim_{\iota \to 1} K^{-1}(\iota) = \infty. \tag{7}$$

For instance, $K^{-1}(\iota) = 2\tanh^{-1}(\iota) = \ln(\frac{1+\iota}{1-\iota})$ or $K^{-1}(\iota) = \tan(\frac{\pi}{2}\iota)$ can be a candidate for $K^{-1}(\iota)$. Based on $K^{-1}(\iota)$, the function of error transformation is designed as

$$\xi_i(t) = K^{-1}(\iota) = K^{-1}(\frac{z_i(t)}{\psi_i(t)}) = \ln(\frac{\psi_i + z_i}{\psi_i - z_i}). \tag{8}$$

The dynamics of $\xi_i(t)$ is defined by

$$\dot{\xi}_i(t) = 2\Gamma_i(\dot{z}_i - \frac{\dot{\psi}_i z_i}{\psi_i}) \tag{9}$$

where $\Gamma_i = \frac{\psi_i}{\psi_i^2 - z_i^2}$.

Remark 1. *It can be seen from the property of hyperbolic tangent function that if $K^{-1}(\iota)$ is bounded, then $|\iota| < 1$ holds. When $\iota = \frac{z_i(t)}{\psi_i(t)}$, under the initial condition $|z_i(0)| < |\psi_i(0)|$ the value of $z_i(t)$ can be limited by the $\psi_1(t)$ for $t > 0$. In this paper a suitable Lyapunov function V_n will be constructed, when V_n is proved to be bounded, it is easy to deduce that ξ_i^2 is bounded, then the inequality $|\frac{z_i(t)}{\psi_1(t)}| < 1$ holds.*

The control objective of this article is steering the output y to track the desired value y_r. In addition the system output error and state error are constrained within the boundary function. To achieve this goal, the following lemmas and assumptions are given.

Assumption 1. *The trajectory signal $y_r(t)$ is continuous and bounded, together with its time derivative $\dot{y}_r(t)$.*

Lemma 1. *Based on RBFNNs [32]–[36], the unknown nonlinear function $F(\hat{X}) = [f_1(\hat{\bar{x}}_1), f_2(\hat{\bar{x}}_2), \cdots, f_n(\hat{\bar{x}}_n)]^T$ defined on a compact set Ω_Z can be appropriated as below*

$$F(\hat{X}) = \theta^T \Psi(\hat{X}) + \varepsilon(\hat{X}), \ |\varepsilon(\hat{X})| \le \bar{\varepsilon}^* \tag{10}$$

where $\Psi(\hat{X}) = [\Psi_1(\hat{\bar{x}}_1), \Psi_2(\hat{\bar{x}}_2), \cdots, \Psi_n(\hat{\bar{x}}_n)]^T$ denotes the basis function with n being the node number of RBFNNs, $\hat{\bar{x}}_i$ is the estimated value of the states $\bar{x}_i$, $\theta = [\theta_1, \theta_2, \ldots, \theta_i]^T$ and $\varepsilon(\hat{X}), \bar{\varepsilon}^* > 0$ denote the weight vector and the approximation error respectively. We select the basis function as *below:*

$$\Psi_i(\hat{\bar{x}}_i) = \exp\left[\frac{-(\hat{\bar{x}}_i - \vartheta_i)^T(\hat{\bar{x}}_i - \vartheta_i)}{\varpi^2}\right], \quad i = 1, 2, \cdots, n \tag{11}$$

where $\Psi_i(\hat{\bar{x}}_i)$ is the Gauss functions, $\vartheta_i = [\vartheta_{i1}, \vartheta_{i2}, \cdots, \vartheta_{ij}]^T$ is the center vectors, and ϖ is the width of $\Psi_i(\hat{\bar{x}}_i)$.

Remark 2. *Compared with the traditional output feedback control [7]–[10], in this paper, RBFNNs only take the system state estimation as input. This can improve the accuracy of approximation and reduce the computational complexity. At the same time, only the tracking signal and the first derivative of it need to be considered, making it easier to realize in practical control.*

III. Main design

A. Design of the state observer

Since the states $x_i, i = 2, \ldots, n$ are unmeasurable, in order to reconstruct the unmeasurable system states, the state observer is designed as follows:

$$\begin{aligned} \dot{\hat{x}}_i &= \hat{x}_{i+1} + \hat{\theta}_i^T \Psi_i(\hat{\bar{x}}_i) + b_i(y - \hat{x}_1) \\ \dot{\hat{x}}_n &= u + \hat{\theta}_n^T \Psi_n(\hat{\bar{x}}_n) + b_n(y - \hat{x}_1) \\ i &= 1, 2, \cdots, n-1 \end{aligned} \tag{12}$$

where b_i is the designed parameters of the filter. Define $e_i = x_i - \hat{x}_i$, $\tilde{\theta} = \theta - \hat{\theta}$, based on (1) and (12), we get

$$\begin{aligned} \dot{e}_i &= e_{i+1} - b_i e_1 + \varepsilon_i + \lambda_i + \tilde{\theta}_i^T \Psi_i(\hat{\bar{x}}_i) \\ &\quad + \theta_i^T(\Psi_i(\bar{x}_i) - \Psi_i(\hat{\bar{x}}_i)) \\ i &= 1, 2, \cdots, n-1. \end{aligned} \tag{13}$$

Define $e = [e_1, e_2, \cdots, e_n]^T$, $\Lambda(t) = [\lambda_1, \cdots, \lambda_n]^T$, $\varepsilon = [\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_n]^T$, $C = [0, \ldots, 1]^T$, $C_i = [0, \ldots, 1, \ldots, 0]^T$,$M = [b_1, b_2, \ldots, b_n]^T$and

$$B = \begin{bmatrix} -b_1 & \\ \vdots & I_{n-1} \\ -b_n & 0 \cdots 0 \end{bmatrix},$$

where the ith element of the vector B_i is 1. Then, it follows from (1), (12) and (13) that

$$\begin{aligned} \dot{e} &= Be + \Lambda + \varepsilon + \sum_{i=1}^{n} C_i \tilde{\theta}_i^T \Psi_i(\hat{\bar{x}}_i) \\ &\quad + \sum_{i=1}^{n} C_i \theta_i^T(\Psi_i(\bar{x}_i) - \Psi_i(\hat{\bar{x}}_i)) \\ \dot{\hat{x}} &= B\hat{x} + Cu + \sum_{i=1}^{n} C_i \hat{\theta}_i^T \Psi_i(\hat{\bar{x}}_i) + My. \end{aligned} \tag{14}$$

Here b_i is chosen such that the matrix B is a strict Hurwitz matrix, that is, there exists positive symmetric matrix Q and P such that

$$B^T P + PB = -Q. \tag{15}$$

B. Controller Design

In this subsection, the low-Computation neural network output-feedback controller and the DETC method are presented. The update law is chosen as

$$\dot{\hat{\theta}}_i(t) = a_i \Gamma_i \xi_i \Psi_i(\hat{\bar{x}}_i) - \Gamma_i \hat{\theta}_i, \tag{16}$$

where $a_1 > 0$, and $0 < a_i < 1 (i = 2, \cdots, n)$ are design arguments, ξ_i is the abbreviation of $\xi_i(t)$. In addition, construct the virtual control law α_i as

$$\alpha_i = -\hat{\theta}_i^T \Psi_i(\hat{\bar{x}}_i) - c_i \xi_i \tag{17}$$

where c_1 and $c_i > 1, (i = 2, \ldots, n)$ are design positive constants. In this case, the adaptive controller is defined as

$$\omega(t) = \alpha_n. \tag{18}$$

Next, we will present the proposed DETC scheme. Firstly, the auxiliary dynamic variable δ is updated by the following formula

$$\dot{\delta} = -\beta\delta + \mu\Gamma_n(\eta \frac{2c_n - 3}{4} \xi_n^2 - \epsilon^2), \tag{19}$$

in which $\delta(0) > 0$, $\beta > 0$, $\eta \in (0, 1)$ and $\mu \in [0, 1]$ are positive constants. The DETC strategy is given as

$$\begin{aligned} \hat{u}(t) &= \omega(t_k), \quad \forall t \in [t_k, t_{k+1}) \\ t_{k+1} &= \inf\left\{t \in \middle| \rho\Gamma_n(\epsilon(t)^2 - \eta \frac{2c_n - 3}{4} \xi_n^2) \geq \delta\right\} \end{aligned} \tag{20}$$

where $\epsilon(t) = u - \omega(t_k)$. From (20) we can obtain

$$\dot{\delta} \geq -\beta\delta - \frac{\mu}{\rho}\delta = -(\beta + \frac{\mu}{\rho})\delta. \tag{21}$$

Furtermore, we get

$$\delta \geq \delta(0) \mathrm{e}^{-(\beta + \frac{\mu}{\rho})t} > 0. \tag{22}$$

IV. Stability analysis

Lemma 2. *If $|z_i(t)| < \psi_i(t)$, then the observer error $e = [e_1, e_2, \cdots, e_n]^T$ is bounded.*

Proof: Construct the Lyapunov function candidate as follows:

$$V_0 = e^T P e. \tag{23}$$

By combining (14) and (15), one gets

$$\begin{aligned} \dot{V}_0 = &-e^T Q e + 2e^T P(\Lambda + \varepsilon) + 2e^T P \sum_{i=1}^{n} C_i \tilde{\theta}_i^T \Psi_i(\hat{\bar{x}}_i) \\ &+ 2e^T P \sum_{i=1}^{n} C_i \theta_i^T(\Psi_i(\bar{x}_i) - \Psi_i(\hat{\bar{x}}_i)). \end{aligned} \tag{24}$$

As $\Psi_i^T \Psi_i \leq 1$, by invoking the Young's inequality, we have:

$$2e^T P(\Lambda + \varepsilon) \leq ||P||^2(||\Lambda||^2 + ||\varepsilon||^2) + 2||e||^2 \tag{25a}$$

$$2e^T P \sum_{i=1}^{n} C_i \tilde{\theta}_i^T \Psi_i(\hat{\bar{x}}_i) \leq ||P||^2 \sum_{i=1}^{n} ||\tilde{\theta}_i||^2 + ||e||^2 \tag{25b}$$

$$\begin{aligned} 2e^T P \sum_{i=1}^{n} C_i \theta_i^T(\Psi_i(\bar{x}_i) - \Psi_i(\hat{\bar{x}}_i)) \leq &||P||^2 \sum_{i=1}^{n} ||\theta_i||^2 \\ &+ ||e||^2. \end{aligned} \tag{25c}$$

By substituting (25) into (24), it holds

$$\begin{aligned}\dot{V}_0 \leq &-(\lambda_{min}(Q)-4)||e||^2 + ||P||^2\sum_{i=1}^{n}||\tilde{\theta}_i||^2 \\ &+ ||P||^2(||\Lambda||^2 + ||\varepsilon||^2 + \sum_{i=1}^{n}||\theta_i||^2).\end{aligned} \tag{26}$$

Based on (16), if $|z_i(t)| < \psi_i(t)$, $||\tilde{\theta}_i||$ and $||\dot{\tilde{\theta}}_i||$ are bounded. Denote $\Delta = ||P||^2(||\Lambda||^2 + ||\varepsilon||^2 + \sum_{i=1}^{n}||\theta_i||^2) + ||P||^2\sum_{i=1}^{n}||\tilde{\theta}_i||^2$, we can get Δ is bounded and (26) can be written as

$$\dot{V}_0 \leq -(\lambda_{min}(Q)-4)||e||^2 + \Delta. \tag{27}$$

Therefor $e \in L^\infty$. The proof is completed. ∎

Lemma 3. *If $\dot{x}_i$ is bounded, and for each $i = 1, 2, \ldots, n$, inequality (4), $||\hat{\bar{x}}_i|| \in L^\infty$ and $||\dot{\hat{\bar{x}}}_i|| \in L^\infty$ hold, then $\dot{\alpha}_i \in L^\infty$ also holds.*

Proof. *The derivative of (17) gives*

$$\dot{\alpha}_i = -\dot{\hat{\theta}}_i^T\Psi_i(\hat{\bar{x}}_i) - c_i\dot{\xi}_i - \hat{\theta}_i^T\frac{\partial\Psi_i}{\partial\hat{\bar{x}}_i}\dot{\hat{\bar{x}}}_i. \tag{28}$$

From the proof of Lemma 2, if $|z_i(t)| < \psi_i(t)$, $||\tilde{\theta}_i|| \in L^\infty$ and $||\dot{\tilde{\theta}}_i|| \in L^\infty$ hold.

First, differentiating z_1 yields

$$\dot{z}_1 = \dot{x}_1 - \dot{y}_d. \tag{29}$$

Based on Assumption 1 and (4), it is easy to obtain $\dot{z}_1$ and $\dot{\psi}_1$ are bounded. According to the design of (10), $||\Psi_i(\bar{x}_i)|| \in L^\infty$ and $||\frac{\partial\Psi_i}{\partial\bar{x}_i}|| \in L^\infty$also holds. Finally, $\dot{\alpha}_1$ is bounded as $||\dot{\hat{x}}_1||_\infty \in L^\infty$.

Second, the derivative of z_i we can obtain

$$\dot{z}_i = \dot{\hat{x}}_i - \dot{\alpha}_{i-1}, \quad i = 2, \ldots, n. \tag{30}$$

With $\dot{\alpha}_1 \in L^\infty$, we can obtain that $\dot{z}_2$, $\dot{\xi}_2$ and $\dot{\alpha}_2$ are bounded. Through recursion, we can obtain $\dot{\alpha}_i$ is bounded.

Next, the main result of this paper are summarized as follow:

Theorem 1. *Consider system (1) and the given initial conditions (4), with the support of (10) and Lemma 2 the control scheme guarantees that*

(1) The output tracking error asymptotically falls into the residual set $(-\psi_{i_\infty}, \psi_{i_\infty})$;

(2) The boundedness of all other signals of the closed-loop system is guaranteed;

(3) The Zeno behavior is avoided.

Proof. *By seeking a contradiction, it can be proved that (4) holds when $\forall t \geq 0$. Define $t \triangleq t_k$ to denote the time instant such that exists as follows:*

$$|z_k(t_k)| \geq \psi_k(t_k), \quad k \in \{1, 2, \ldots, n\}. \tag{31}$$

Define the time at which (4) is first violated as $t_1 \triangleq min\{t_k\}$. For $t < t_1$, it results in

$$|z_i(t)| < \psi_i(t), \quad i = 1, \ldots, n \tag{32}$$

and that there must exist z_j guarantees that

$$\lim_{t\to t_1^-}|z_j(t)| = \lim_{t\to t_1^-}|\psi_j(t)|, \quad j \in \{1, \ldots, n\}. \tag{33}$$

Then, (33) is sufficient and necessary conditions for (34)

$$\lim_{t\to t_1^-}|\xi_j(t)| = \infty, \quad j \in \{1, 2, \ldots, n\}. \tag{34}$$

For $t \in [0, t_1)$, the above situation does not exist.

***Step** 1: Construct the Lyapunov function candidate as below:*

$$V_1 = \frac{1}{4}\xi_1^2 + \frac{1}{2a_1}\tilde{\theta}_1^T\tilde{\theta}_1. \tag{35}$$

From Assumption 1, the boundedness of x_1 on $[0, t_1)$ is ensured. According to (9) and $\dot{z}_1 = f_1 + e_2 + \hat{x}_2 + \lambda_1 - \dot{y}_r$, we have

$$\dot{V}_1 = \xi_1\Gamma_1\left(f_1 + e_2 + \hat{x}_2 + \lambda_1 - \dot{y}_r - \frac{\dot{\psi}_1 z_1}{\psi_1}\right) - \frac{1}{a_1}\tilde{\theta}_1^T\dot{\hat{\theta}}_1. \tag{36}$$

By analyzing (10), one gets

$$\dot{V}_1 = \xi_1\Gamma_1(\theta_1^T\Delta\Psi_1 + \Delta_1) + \frac{1}{a_1}\tilde{\theta}_1^T\hat{\theta}_1 \tag{37}$$

where $\Delta\Psi_1 = \Psi_1(x_1) - \Psi_1(\hat{x}_1)$, $\Delta_1 = \varepsilon_1 + \lambda_1 - \dot{y}_d + e_2 + z_2 - \frac{\dot{\psi}_1 z_1}{\psi_1}$. In view of $|\lambda_i(t)| \leq \bar{\lambda}_i$, (3), (32) and Lemma 1, we can obtain that there exists a positive constant $\bar{\Delta}_1$ such that

$$\Delta_1 \leq \bar{\Delta}_1. \tag{38}$$

Next, as $\Psi_i^T\Psi_i \leq 1$, by invoking the Young's inequality, we have:

$$\xi_1\Gamma_1\theta_1^T\Delta\Psi_1 \leq \frac{c_1\Gamma_1}{4}\xi_1^2 + \frac{\Gamma_1}{c_1}||\theta_1||^2, \tag{39a}$$

$$\xi_1\Gamma_1\Delta_1 \leq \frac{c_1\Gamma_1}{4}\xi_1^2 + \frac{\Gamma_1}{c_1}\bar{\Delta}_1^2, \tag{39b}$$

$$\tilde{\theta}_1^T\hat{\theta}_1 \leq -\frac{||\tilde{\theta}_1||^2}{2} + \frac{||\theta_1||^2}{2}. \tag{39c}$$

By substituting (39) into (37), it holds

$$\begin{aligned}\dot{V}_1 \leq &-\frac{c_1\Gamma_1}{2}\xi_1^2 + \Gamma_1(\frac{1}{c_1}\bar{\Delta}_1^2 + (\frac{1}{2a_1} + \frac{1}{c_1})||\theta_1||^2) \\ &- \frac{\Gamma_1}{2a_1}\tilde{\theta}_1^T\tilde{\theta}_1.\end{aligned} \tag{40}$$

For $t \in [0, t_1)$, based on (4) and Γ_1, one has

$$\Gamma_1 \geq \frac{1}{\psi_1} \geq \frac{1}{\psi_{1,0}}. \tag{41}$$

Finally, the boundedness of V_1 is illustrated from two different cases

***Case** 1: $\frac{1}{c_1}\bar{\Delta}_1^2 + (\frac{1}{2a_1} + \frac{1}{c_1})||\theta_1||^2 \geq \frac{c_1}{4}\xi_1^2$. Define*

$$\begin{aligned}C_{11} &\triangleq min\left\{\frac{1}{\psi_{1,0}}, \frac{c_1}{\psi_{1,0}}\right\}, \\ \varsigma_1 &\triangleq sup\left\{\Gamma_1(\frac{1}{c_1}\bar{\Delta}_1^2 + (\frac{1}{2a_1} + \frac{1}{c_1})||\theta_1||^2)\right\},\end{aligned} \tag{42}$$

we can obtain that

$$\dot{V}_1 \leq -C_{11}V_1 + \varsigma_1. \tag{43}$$

***Case** 2: $\frac{1}{c_1}\bar{\Delta}_1^2 + (\frac{1}{2a_1} + \frac{1}{c_1})||\theta_1||^2 < \frac{c_1}{4}\xi_1^2$. Define*

$$C_{12} \triangleq min\left\{\frac{1}{\psi_{1,0}}, \frac{2c_1}{\psi_{1,0}}\right\}, \tag{44}$$

one gets

$$\dot{V}_1 \leq -C_{12}V_1. \tag{45}$$

Based on (43) and (45), through categorical discussions, we can obtain

$$\dot{V}_1 \leq -C_1V_1 + \varsigma_1 \tag{46}$$

where $C_1 \triangleq min\{C_{11}, C_{12}\}$.

***Step** 2: From (2), (17) and (46), it is clear that* ξ_1, α_1 *and* $\hat{x}_2$ *are bounded. Then, construct the Lyapunov function as*

$$V_2 = \frac{1}{4}\xi_2^2 + \frac{1}{2a_2}\tilde{\theta}_2^T\tilde{\theta}_2. \tag{47}$$

According to (2) and (12), we can get

$$\begin{aligned}\dot{V}_2 =&\xi_2\Gamma_2(\alpha_2 - b_2\hat{x} + z_3 - \frac{\dot{\psi}_2 z_2}{\psi_2} + \hat{\theta}_2^T\Psi_2(\hat{\bar{x}}_2)\\ &- \dot{\alpha}_1) - \frac{1}{a_2}\tilde{\theta}_2^T\dot{\hat{\theta}}_2.\end{aligned} \tag{48}$$

By analyzing (10), one gets

$$\dot{V}_2 =\xi_2\Gamma_2(-c_2\xi_2 + \Delta_2) + \frac{\Gamma_2}{a_2}\tilde{\theta}_2^T\hat{\theta}_2 - \Gamma_2\xi_2\tilde{\theta}_2^T\Psi_2(\hat{\bar{x}}_2) \tag{49}$$

where $\Delta_2 = -b_2\hat{x}_1 + z_3 - \frac{\dot{\psi}_2 z_2}{\psi_2} - \dot{\alpha}_1$. *Based on* $x_1 \in L^\infty$, $\hat{\bar{x}}_2 \in L^\infty$*and Lemma 3, when* $t < t_1$, $\dot{\alpha}_1 \in L^\infty$ *can be deduced. Similar to (38), we can obtain* $\Delta_2 \leq \bar{\Delta}_2$, *where* $\bar{\Delta}_2$ *is a positive constant. Next by invoking the Young's inequality, we have:*

$$\Gamma_2\xi_2\tilde{\theta}_2^T\Psi_2(\hat{\bar{x}}_2) \leq \frac{\Gamma_2}{2}\xi_2^2 + \frac{\Gamma_2}{2}||\tilde{\theta}_2||^2 \tag{50a}$$

$$\xi_2\Gamma_2\Delta_2 \leq \frac{c_2\Gamma_2}{2}\xi_2^2 + \frac{\Gamma_2}{2c_2}\bar{\Delta}_2^2 \tag{50b}$$

$$\tilde{\theta}_2^T\hat{\theta}_2 \leq -\frac{||\tilde{\theta}_2||^2}{2} + \frac{||\theta_2||^2}{2}. \tag{50c}$$

Substituting (50) into (49) one gets

$$\begin{aligned}\dot{V}_2 \leq& -\frac{c_2 - 1}{2}\Gamma_2\xi_2^2 + \Gamma_2(\frac{1}{2c_2}\bar{\Delta}_2^2 + \frac{1}{2a_2}||\theta_2||^2)\\ &- \frac{1 - a_2}{2a_2}\Gamma_2\tilde{\theta}_2^T\tilde{\theta}_2.\end{aligned} \tag{51}$$

According to (4) and Γ_1, *for* $t \in [0, t_1)$ *we can obtain*

$$\Gamma_2 \geq \frac{1}{\psi_2} \geq \frac{1}{\psi_{2,0}}. \tag{52}$$

***Case** 1:* $\frac{1}{2c_2}\bar{\Delta}_2^2 + \frac{1}{2a_2}||\theta_2||^2 \geq \frac{c_2 - 1}{4}\xi_2^2$. *Based on* $\Gamma_2 \in L^\infty$, *denote*

$$\begin{aligned}C_{21} \triangleq& min\Big\{\frac{1 - a_2}{\psi_{2,0}}, \frac{2c_2 - 2}{\psi_{2,0}}\Big\},\\ \varsigma_2 \triangleq& sup\Big\{\Gamma_2(\frac{1}{2c_2}\bar{\Delta}_2^2 + \frac{1}{2a_2}||\theta_2||^2)\Big\},\end{aligned} \tag{53}$$

one has

$$\dot{V}_2 \leq -C_{21}V_2 + \varsigma_2. \tag{54}$$

***Case** 2:* $\frac{1}{2c_2}\bar{\Delta}_2^2 + \frac{1}{2a_2}||\theta_2||^2 < \frac{c_2 - 1}{4}\xi_2^2$. *Denote*

$$C_{22} \triangleq min\Big\{\frac{1 - a_2}{\psi_{2,0}}, \frac{c_2 - 1}{\psi_{2,0}}\Big\}, \tag{55}$$

one further deduces that

$$\dot{V}_2 \leq -C_{22}V_2. \tag{56}$$

Denote $C_2 = min\{C_{21}, C_{22}\}$, *one has*

$$\dot{V}_2 \leq -C_2V_2 + \varsigma_2. \tag{57}$$

***Step** i: By repeating the procedure similar to Step 2, it is obtained that* α_{i-1}, $\dot{\alpha}_{i-1}$ *and* x_i *are bounded on* $[0, t_1)$. *Construct the Lyapunov function as*

$$V_i = \frac{1}{4}\xi_i^2 + \frac{1}{2a_i}\tilde{\theta}_i^T\tilde{\theta}_i. \tag{58}$$

Consider (2) and (12), we can get

$$\begin{aligned}\dot{V}_i =&\xi_i\Gamma_i(\alpha_i - b_i\hat{x}_1 + z_{i+1} - \frac{\dot{\psi}_i z_i}{\psi_i} + \hat{\theta}_i^T\Psi_i(\hat{\bar{x}}_i)\\ &- \dot{\alpha}_{i-1}) - \frac{1}{a_i}\tilde{\theta}_i^T\dot{\hat{\theta}}_i.\end{aligned} \tag{59}$$

By analyzing (10), one gets

$$\dot{V}_i =\xi_i\Gamma_i(-c_i\xi_i + \Delta_i) + \frac{\Gamma_i}{a_i}\tilde{\theta}_i^T\hat{\theta}_i - \Gamma_i\xi_i\tilde{\theta}_i^T\Psi_i(\hat{\bar{x}}_i) \tag{60}$$

where $\Delta_i = -b_i\hat{x} + z_{i+1} - \frac{\dot{\psi}_i z_i}{\psi_i} - \dot{\alpha}_{i-1}$. *Be similar to last Step, it is clear that* $\Delta_i < \bar{\Delta}_i$. *Then, the following inequalities hold:*

$$\Gamma_i\xi_i\tilde{\theta}_i^T\Psi_i(\hat{\bar{x}}_i) \leq \frac{\Gamma_i}{2}\xi_i^2 + \frac{\Gamma_i}{2}||\tilde{\theta}_i||^2 \tag{61a}$$

$$\xi_i\Gamma_i\Delta_i \leq \frac{c_i\Gamma_i}{2}\xi_i^2 + \frac{\Gamma_i}{2c_i}\bar{\Delta}_i^2 \tag{61b}$$

$$\tilde{\theta}_i^T\hat{\theta}_i \leq -\frac{||\tilde{\theta}_i||^2}{2} + \frac{||\theta_i||^2}{2}. \tag{61c}$$

Substituting (61) into (60) we have

$$\begin{aligned}\dot{V}_i \leq& -\frac{c_i - 1}{2}\Gamma_i\xi_i^2 + \Gamma_i(\frac{1}{2c_i}\bar{\Delta}_i^2 + \frac{1}{2a_i}||\theta_i||^2)\\ &- \frac{1 - a_i}{2a_i}\Gamma_i\tilde{\theta}_i^T\tilde{\theta}_i.\end{aligned} \tag{62}$$

Applying the same method as Step 2, we can derive

$$\dot{V}_i \leq -C_iV_i + \varsigma_i \tag{63}$$

where $C_i \triangleq min\{\frac{1-a_i}{\psi_{i,0}}, \frac{c_i-1}{\psi_{i,0}}\}$, $\varsigma_i \triangleq sup\{\Gamma_i(\frac{1}{2c_i}\bar{\Delta}_i^2 + \frac{1}{2a_i}||\theta_i||^2)\}$.

***Step** n: According to the analysis in Step i,* $x_n \in L^\infty$ *is ensured. Choosing the Lyapunov function as*

$$V_n = \frac{1}{4}\xi_n^2 + \frac{1}{2a_n}\tilde{\theta}_n^T\tilde{\theta}_n + \delta. \tag{64}$$

Differentiating (64) yields

$$\begin{aligned}\dot{V}_n =&\xi_n\Gamma_n(u - b_n\hat{x}_1 - \frac{\dot{\psi}_n z_n}{\psi_n} - \dot{\alpha}_{n-1} + \hat{\theta}_n^T\Psi_n(\hat{\bar{x}}_n))\\ &- \frac{1}{a_n}\tilde{\theta}_n^T\dot{\hat{\theta}}_n + \dot{\delta}.\end{aligned} \tag{65}$$

By taking (18) and $u(t) = \omega(t) - \epsilon(t)$ *into considered, one gets*

$$\begin{aligned}\dot{V}_n =&\xi_n\Gamma_n(\omega(t) - \epsilon(t) - \frac{\dot{\psi}_n z_n}{\psi_n} - \dot{\alpha}_{n-1}\\ &- \frac{1}{a_n}\tilde{\theta}_n^T\dot{\hat{\theta}}_n + \dot{\delta},\end{aligned} \tag{66}$$

ultimately we have

$$\begin{aligned}\dot{V}_n =&\xi_n\Gamma_n(-c_n\xi_n - \epsilon + \Delta_n) + \frac{\Gamma_n}{a_n}\tilde{\theta}_n^T\hat{\theta}_n\\ &- \Gamma_n\xi_n\tilde{\theta}_n^T\Psi_n(\hat{\bar{x}}_n) + \dot{\delta}\end{aligned} \tag{67}$$

where $\Delta_n = b_n e_1 - \frac{\dot{\psi}_n z_n}{\psi_n} - \dot{\alpha}_{n-1}$. *Be similar to last Step, it is clear that* $\Delta_n < \bar{\Delta}_n$. *Then, the following inequalities hold:*

$$\xi_n \Gamma_n \Delta_n \le \frac{c_n \Gamma_n}{2}\xi_n^2 + \frac{\Gamma_n}{2c_n}\bar{\Delta}_n^2 \tag{68a}$$

$$\tilde{\theta}_n^T \hat{\theta}_n \le -\frac{||\tilde{\theta}_n||^2}{2} + \frac{||\theta_n||^2}{2} \tag{68b}$$

$$\Gamma_n \xi_n \tilde{\theta}_n^T \Psi_n(\hat{\bar{x}}_n) \le \frac{\Gamma_n}{2}\xi_n^2 + \frac{\Gamma_n}{2}||\tilde{\theta}_n||^2 \tag{68c}$$

$$\Gamma_n \xi_n \epsilon \le \frac{1}{4}\Gamma_n \xi_n^2 + \Gamma_n \epsilon^2. \tag{68d}$$

Substituting (68) into (67) one gets

$$\begin{aligned}\dot{V}_n \le & -\frac{2c_n - 3}{4}\Gamma_n \xi_n^2 + \Gamma_n(\frac{1}{2c_n}\bar{\Delta}_n^2 + \frac{1}{2a_n}||\theta_n||^2) \\ & -\frac{1-a_n}{2a_n}\Gamma_n \tilde{\theta}_n^T \tilde{\theta}_n + \dot{\delta} + \Gamma_n \epsilon^2.\end{aligned} \tag{69}$$

Inserting (19) into (69), one gets

$$\begin{aligned}\dot{V}_n \le & -(1-\mu\eta)\frac{2c_n - 3}{4}\Gamma_n \xi_n^2 + \Gamma_n(\frac{1}{2c_n}\bar{\Delta}_n^2 + \frac{1}{2a_n}||\theta_n||^2) \\ & -\frac{1-a_n}{2a_n}\Gamma_n \tilde{\theta}_n^T \tilde{\theta}_n + (1-\mu)\Gamma_n \epsilon^2 - \beta\delta.\end{aligned} \tag{70}$$

From (20) we have $\epsilon^2 \le \frac{\delta}{\rho\Gamma_n} + \eta\frac{2c_n-3}{4}\xi_n^2$. *In addition, since* $\mu \in [0,1]$, $\eta \in (0,1)$, *and* $\rho > \frac{1-\xi}{\beta}$,

$$\begin{aligned}\dot{V}_n \le & -(1-\eta)\frac{2c_n - 3}{4}\Gamma_n \xi_n^2 + \Gamma_n(\frac{1}{2c_n}\bar{\Delta}_n^2 + \frac{1}{2a_n}||\theta_n||^2) \\ & -\frac{1-a_n}{2a_n}\Gamma_n \tilde{\theta}_n^T \tilde{\theta}_n + (\frac{1-\mu}{\rho} - \beta)\delta.\end{aligned} \tag{71}$$

Applying the same method as Step i, we can derive

$$\dot{V}_n \le -C_n V_i + \varsigma_n \tag{72}$$

where $C_n \triangleq min\{\frac{1-a_n}{\psi_{n,0}}, \frac{2c_n-3}{\psi_{n,0},}, \frac{1-\mu-\rho\beta}{\rho}\}$, $\varsigma_i = sup\{\Gamma_n(\frac{1}{2c_n}\bar{\Delta}_n^2 + \frac{1}{2a_n}||\theta_n||^2\}$. *According to (46), (57), (63) and (72), one has*

$$V_i \le (V_i(0) - \varsigma_i), \quad i = 1, \ldots, n. \tag{73}$$

By analyzing (35), (47), (58) and (72), we have

$$\xi_i \le 2\sqrt{V}_i(0), \quad t < t_1, i = 1, \ldots, n. \tag{74}$$

In summary, ξ_i *is bounded, which contradicts the definition of* ξ_i *in (34). Thus, (4) is proved. Therefore, based on Lemma 2 and Lemma 3 and the derivation of each step, all the closed-loop signals are bounded.*

Consider the nonlinear systems (1) under the event-trigger mechanism (20). Therefore, assuming that Zeno behavior occurs in Theorem 1, there must exist a finite time $T > 0$ *that satisfies*

$$\lim_{t\to\infty} t_k = T, \quad k \in \mathbf{z}^+. \tag{75}$$

That is, in the finite time interval $[0, T]$, *there are infinite triggering events. Since* $\epsilon(t) = u - \hat{u}$, *where* $\hat{u}$ *is a constant, we can get*

$$\dot{\epsilon} = \dot{u}, \quad \forall k \in \mathbf{z}^+, \quad t \in [t_k, t_{k+1}). \tag{76}$$

Define $\bar{t} \in [t_k, t_{k+1})$ *such that*

$$|\epsilon(\bar{t})| = 0, \quad |\epsilon(\tilde{t})| > 0, \quad \forall \tilde{t} \in (\bar{t}, t_{k+1}). \tag{77}$$

Based on (77), one has

$$\frac{d|\epsilon|}{dt} = \frac{d\sqrt{\epsilon^2}}{dt} = \frac{\epsilon\dot{\epsilon}}{\sqrt{\epsilon^2}} \le \frac{|\epsilon||\dot{\epsilon}|}{|\epsilon|} = |\dot{u}|, t \in (\bar{t}, t_{k+1}). \tag{78}$$

As $f_i(\cdot), i = 1, \cdots, n$ *are at least* $(n+1-i)$*th-order smooth functions, then* $\dot{u} \in L^\infty$ *holds. Therefore, there exists a positive constant* $\varrho > 0$, *such that*

$$\frac{d|\epsilon|}{dt} \le |\dot{u}| \le \varrho, \quad t \in (\bar{t}, t_{k+1}). \tag{79}$$

Based on (19) and (20), the following inequality holds:

$$|\epsilon| \le \sqrt{\frac{\delta(0)}{\rho}\mathbf{e}^{-(\beta+\frac{\mu}{\rho})t}}. \tag{80}$$

Since $\epsilon(\bar{t}) = 0$, *we have*

$$t_{k+1} - t_k \ge t_{k+1} - \bar{t} \ge \sqrt{\frac{\delta(0)}{\rho}\mathbf{e}^{-(\beta+\frac{\mu}{\rho})t}}/\varrho. \tag{81}$$

As $t \in [t_k, t_{k+1}) \in [0, T]$, *one gets*

$$t_{k+1} - t_k \ge \sqrt{\frac{\delta(0)}{\rho}\mathbf{e}^{-(\beta+\frac{\mu}{\rho})T}}/\varrho = \nu > 0. \tag{82}$$

Therefore, there is a minimum value ν *between any* t_k *and* t_{k+1}. *Due to* $t \in [t_k, t_{k+1}) \in [0, T]$, *when* k *satisfies*

$$k \ge \lceil \frac{T}{\nu} \rceil + 1, \tag{83}$$

where $\lceil \frac{T}{\nu} \rceil$ *denote the smallest integer that is larger than* $\frac{T}{\nu}$. *Then, we can get* $t_k > T$, *which is contrary to the assumption in (75). This means that the number of events within the time interval* $[0, T]$ *is limited. Therefore,the Zeno behavior does not exist, then the proof is complete.*

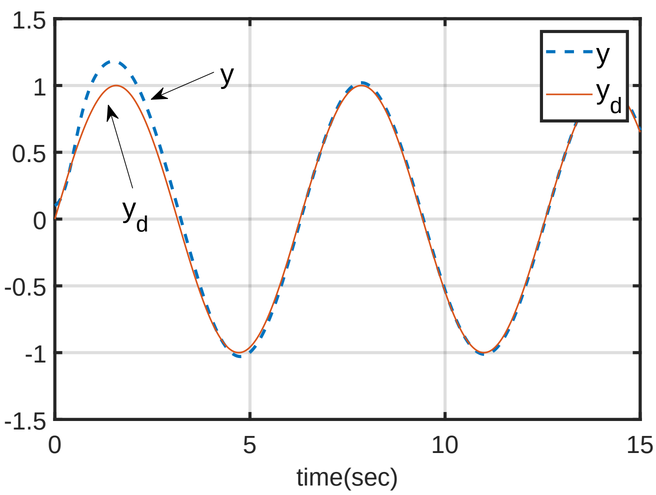

Fig. 1. System output $y(t)$ and its desired value $y_r(t)$.

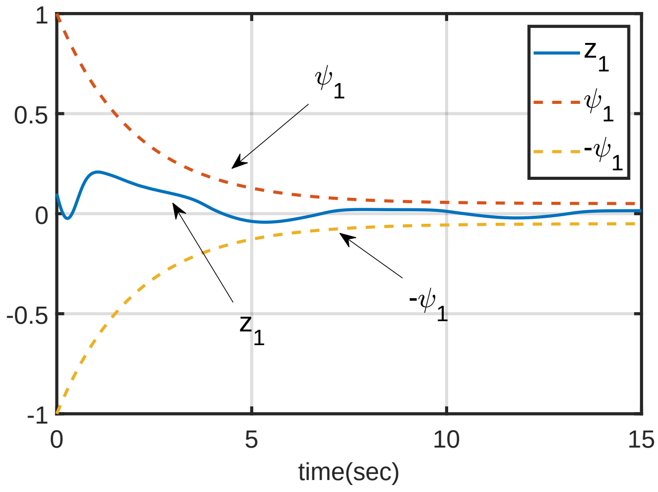

Fig. 2. Tracking error z_1 under the prescribed performance constraint ψ_1.

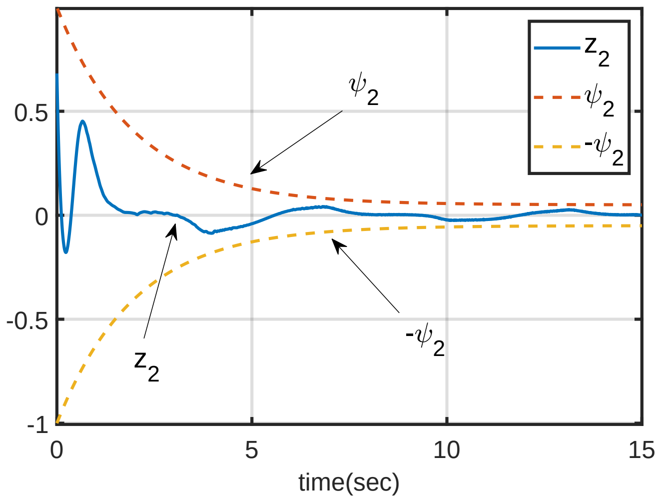

Fig. 3. State error z_2 under the prescribed performance constraint ψ_2.

V. SIMULATION STUDY

In this section, the effectiveness of the proposed controller is demonstrated via a simulation example.

A second-order nonlinear system is considered as follows:

$$\begin{aligned} \dot{x}_1 &= f_1(\bar{x}_1) + \lambda_1(t) + x_2 \\ \dot{x}_2 &= f_2(\bar{x}_2) + \lambda_2(t) + u \\ y &= x_1 \end{aligned} \tag{84}$$

where $f_1(\bar{x}_1) = sin(x_1)$, $f_2(\bar{x}_2) = \dfrac{x_1}{x_1^2 + x_2^2}$, $\lambda_1 = 0.2sin(t)$, and $\lambda_2 = cos(2t)$. Next, the simulation parameters are chosen as $b_1 = 2$, $b_2 = 0.2$, $c_1 = 2.9$, $c_2 = 3$, $a_1 = 0.2$, $a_2 = 0.2$, $\beta = 0.1$, $\mu = 0.12$, $\eta = 0.49$, $\rho = 3$. The desired value $y_r(t) = \sin(t)$. Meanwhile, the PPC functions are $\varphi_1 = (1 - 0.05)e^{-1t} + 0.05$ and $\varphi_2 = (1 - 0.05)e^{-1t} + 0.05$. The initial condition is $[x_1(0), x_2(0), \hat{x}_1(0), \hat{x}_2(0), \delta(0), \hat{\theta}_1, \hat{\theta}_2]^T = [0, 0, 0.1, 0.1, 0.1, 0.1, 0.2]^T$. In addition, based on Lemma 1 , the RBFNNs basis of the Gaussian function is

$$\Psi_i(\hat{\bar{x}}_i) = \exp\left[\frac{-(\hat{\bar{x}}_i - r_{i,j})^T(\hat{\bar{x}}_i - r_{i,j})}{\varpi_{i,j}^2}\right], \quad i = 1, 2, \quad j = 1, 2, \cdots, 5 \tag{85}$$

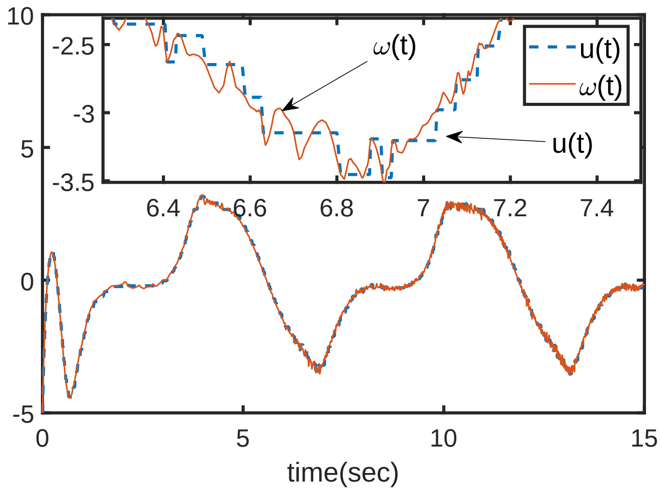

Fig. 4. Control signal with the proposed scheme.

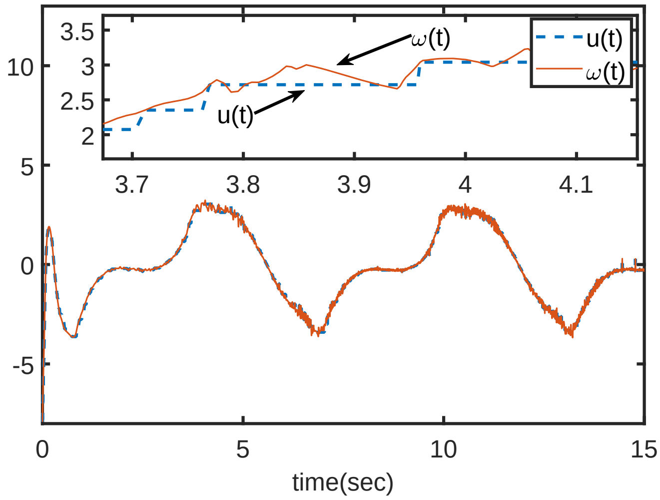

Fig. 5. Control signal with the relative threshold strategy (Redraw according to the relative threshold method in reference [22] under different parameters and system conditions).

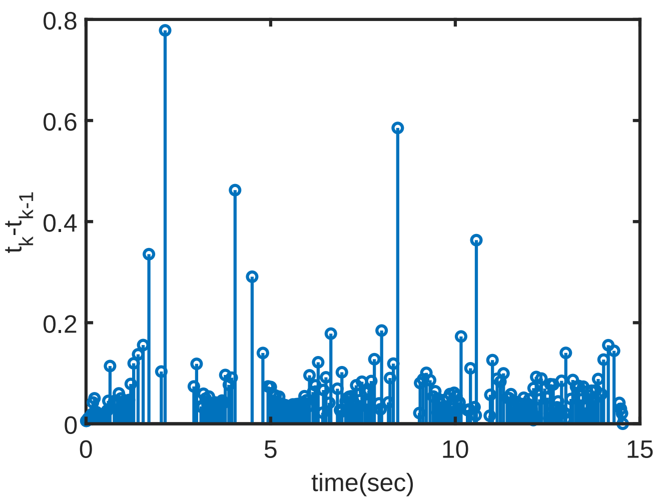

Fig. 6. Time interval with the proposed scheme.

where $\varpi_{i,j} = 2$, $r_{1,j} = -3 + j$, $r_{2,j} = [-3 + j, -3 - j]$. The other design parameters for the relative threshold strategy are set as $m_1 = 0.05$, $\bar{m}_1 = 2$, $\delta = 0.1$, $\varepsilon = 0.5$.

The simulation results are shown in Figs.1-7. Fig. 1

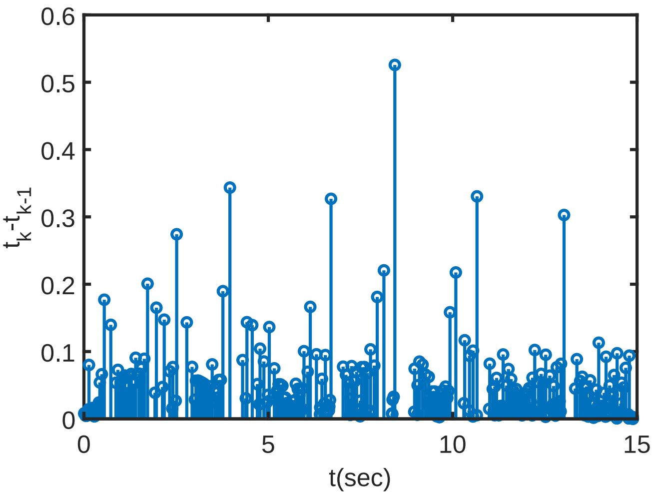

Fig. 7. Time interval with the relative threshold strategy (Redraw according to the relative threshold method in reference [22] under different parameters and system conditions).

displays system output $y(t)$ and its desired value $y_r(t)$. The tracking error z_1, the state error z_2 and their boundaries are shown in Figs. 2 and 3, respectively. And the control signal is shown in Fig.4 and 5. In addition, in Fig. 6 the number of event triggering for the DETC in this paper is 246, while in Fig.7 the number of event triggering with relative threshold strategy is 341. Through the comparison of Fig. 6 and 7, we can clearly see that compared with the relative threshold scheme in [22], the scheme designed in this paper can significantly reduce the number of communications.

VI. Conclusion

In this paper, a low-computation neural adaptive output-feedback prescribed performance controller with dynamic event-triggered has been first proposed for a class of SFNS with unmatched disturbances. A backstepping-like method based on PPC has been used to solve the complexity explosion problem caused by the traditional backstepping method. In this method, the high-order derivative information of the reference signal is not required. In addition, RBFNNs only accept the system state estimation as input, which simplifies the calculation and makes it easier to be implemented in practice. In addition, the DETC scheme we designed reduces the communication burden of the system. Finally, the effectiveness of the proposed method is verified by numerical simulation. In the near future, a DETC that is more consistent with the PPC needs our attention and study.

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