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Approximation-Based Event-Triggered Control Against Unknown Injection Data in Full States and Actuator of Uncertain Lower-Triangular Nonlinear Systems

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ABSTRACT This paper addresses an approximation-based adaptive event-triggered control problem against unknown injection data in full state measurements and an actuator of systems with unknown strict-feedback nonlinearities. It is assumed that full state variables measured for state-feedback control are corrupted by unknown injection data that denote cyber attacks or fault signals, and all system nonlinearities are unknown. Owing to the corrupted state feedback information, error surfaces using exactly measured state variables become unknown during the recursive control design procedure for strict-feedback nonlinear systems. Thus, they cannot be used to implement the adaptive event-triggered controller. To address this problem, an approximation-based adaptive recursive event-triggered control design using the corrupted state variables is established to ensure that error surfaces using exactly measured state variables converge to an adjustable neighborhood of the origin in the Lyapunov sense. The adaptive controller and its event-triggering law using corrupted states are designed under uncertain injection data where the adaptive injection data compensators using the neural networks are constructed to deal with the unknown injection data effects. The stability of the closed-loop systems and the exclusion of Zeno behavior are analyzed.

INDEX TERMS Event-triggered control, corrupted full state measurements, unknown injection data, dynamic surface design, unknown strict-feedback nonlinearities.

I. INTRODUCTION

The development of information and communication technology has stimulated the tight interaction of control systems and cyber components [1], [2]. Under the network-based control environment, the exact transmission of measured state variables of physical systems is an important problem for ensuring the performance of controllers in the network. During the network transmission of the state information for the feedback control, unexpected time-varying injection data can be added to the state information measured by sensors. The sources of the injection data in the resilient control studies are largely divided into two categories: (i) measurement faults and (ii) adversarial cyber attacks. In the first category, the sensor faults influence the measurement information for the feedback control. Many studies have addressed the resilient control problems of linear and nonlinear systems with measurement faults [3]–[6]. Especially, some limited studies have appeared for the recursive control design of lower-triangular nonlinear systems with measurement faults where backstepping [7] and dynamic surface designs [8], [9] have been used to construct the resilient control systems. In [10], [11], the output functions were regarded as sensor faults, and output-feedback control approaches were presented for nonlinear systems. In [12], an output-feedback stabilizer design problem using a dual-domination approach was addressed for lower-triangular nonlinear systems with unknown measurement sensitivity. In [13], an adaptive

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compensation method of sensor failure was proposed for parametric strict-feedback systems. In [14], a fuzzy adaptive sensor fault compensation approach was studied for nonlinear strict-feedback systems. In [15], an adaptive control method was presented for nonlinear systems with time-varying sensor sensitivities. However, the existing works [10]–[15] for lower-triangular nonlinear systems considered only an output measurement fault. That is, they cannot be applied to state-feedback recursive control design and stability analysis problems in the presence of full state measurement faults because corrupted state variables, instead of exactly measured state variables, should be used to implement virtual and actual controllers. In the second category, the measured state information is stealthily monitored by adversarial attackers and deception attack signals for attackers' desire are maliciously injected into the measured states. Thus, the deception attack signals may depend on the state variables. For known cyber attacks, some resilient control approaches have been presented for linear and nonlinear systems [16]–[21]. To consider unknown cyber attack signals in state variables and an actuator, some adaptive control studies have recently been investigated. In [22], sensor attacks of uncertain linear systems were considered to design adaptive control architectures. An adaptive control methodology was presented in [23] where the time-varying parameters in deception attacks were estimated via the projection algorithm. In [24], an adaptive resilient control approach using Nussbaum functions was studied in the presence of unknown control direction. However, these research results [22]–[24] for compensating for unknown deception attacks in the adaptive control framework are only available for *linear* systems. They cannot be applied to the recursive design problem against unknown injection data in full state measurements of lower-triangular nonlinear systems.

Adaptive control problems of nonlinear lower-triangular systems with uncertainties unmatched to a control input have received great attention in the control design field because of their application to many practical systems such as robot manipulators, biological systems, power systems, flight systems, and traffic control systems. Thus, adaptive recursive control design strategies have been actively developed to deal with unmatched parametric or nonparametric uncertainties. During the early stages of the research, the adaptive technique was combined with the recursive designs to estimate unmatched parametric uncertainties online (see [25]–[31] and references therein). Function approximation techniques using neural networks or fuzzy logic systems have been applied to design approximation-based adaptive control systems, in an attempt to deal with unmatched nonparametric uncertainties (i.e, nonlinear uncertainties) (see [32]–[39] and references therein). In addition, distributed adaptive control approaches have been presented for uncertain multi-agent nonlinear systems in the strict-feedback form [40]–[44]. In these studies, unknown nonlinear functions derived from the recursive control design steps were estimated via radial basis function neural networks (RBFNNs) or fuzzy logic systems. The uncorrupted state feedback information was used as the input for these function approximators. If the state feedback information is corrupted by unknown injection data, the corrupted state feedback information should be used as the input of the function approximators in the adaptive control framework. This problem still persists in the full-state-feedback-based adaptive control field of strict-feedback nonlinear systems.

The event-triggered control technique is particularly popular in the network-based control field of linear and nonlinear systems, for ensuring the efficient use of the network bandwidth [45]–[48]. In event-triggered control, a control input is updated when a triggering law is satisfied. Thus, the computational and communicational resources required for implementing the controller can be conserved. Therefore, event-triggered control problems have been studied for systems with nonlinearities unmatched to the control input. In [49]–[51], adaptive event-triggered control designs were developed for lower-triangular nonlinear systems with parametric uncertainties. In [52], the finite-time stabilization problem of uncertain nonlinear systems was addressed in the event-triggered control framework. In [53]–[56], approximation-based adaptive control techniques for estimating unknown nonlinear uncertainties were combined with event-triggered control designs. Despite these efforts, no studies have been reported thus far on the event-triggered control problem against unknown injection data in full state measurements and an actuator of lower-triangular nonlinear systems.

On the basis of the above discussion, the main difficulties in designing an adaptive event-triggered resilient control scheme against the aforementioned unknown injection data are as follows.

(D1) Because full state measurements for feedback control are corrupted by unknown injection data, the corrupted state variables can be only used in the adaptive control scheme using backstepping or dynamic surface techniques and thus the error surfaces using the exactly measured state variables for the recursive design are unknown for the control design. Accordingly, the first difficulty is *how to design an adaptive controller using the corrupted full state variables to ensure the convergence of the error surfaces using the exactly measured state variables* for achieving the control objective in Lyapunov-based recursive stability analysis.

(D2) Since the exactly measured state variables are not available, the second difficulty is *how to design the triggering law using corrupted state variables* in the adaptive event-triggered control framework. Furthermore, the stability of the closed-loop system and the exclusion of Zeno behavior should be analyzed by the triggering law using the corrupted state variables.

The objective of this paper is to propose a remedy for difficulties (D1) and (D2), that is, to establish an adaptive resilient event-triggered control design strategy using corrupted full state measurements for uncertain nonlinear strict-feedback systems with unknown injection data in full state measurements and an actuator. It is assumed that full state measurements corrupted by unknown injection data are available for feedback, and system nonlinearities are unknown. To overcome difficulties (D1) and (D2), auxiliary signals using corrupted full state variables are designed, and an approximation-based adaptive event-triggered controller and its triggering law are recursively constructed using the auxiliary signals. For the proposed control scheme, dynamic injection data compensators using RBFNNs are designed to compensate for unknown injection data effects. Although the proposed adaptive event-triggered controller is based on corrupted full state variables, it is shown that the convergence of the error surfaces using the exactly measured state variables is ensured for achieving the control objective in the Lyapunov-based stability sense. Finally, simulation examples including a practical application are given for testifying the validity of the proposed theoretical result.

The rest of this paper is outlined as follows. An adaptive resilient event-triggered control problem of uncertain nonlinear strict-feedback systems with unknown injection data in full state measurements and an actuator is formulated in Section 2. The proposed event-triggered control design using corrupted state variables and its stability analysis are presented in Sections 3. Simulation studies are given in Section 4. Finally, we conclude in Section 5.

II. PROBLEM FORMULATION

Let us consider the following uncertain nonlinear strict-feedback systems with unknown injection data in full state measurements and an actuator

$$\begin{aligned}\dot{x}_k &= x_{k+1} + h_k(\bar{x}_k)\\ \dot{x}_n &= u + \kappa_a(t,\bar{x}_n) + h_n(\bar{x}_n)\\ x_{i,a} &= x_i + \kappa_{i,s}(t,x_i)\end{aligned} \tag{1}$$

where $k = 1,\ldots,n-1$, $i = 1,\ldots,n$, $\bar{x}_k = [x_1,x_2,\ldots,x_k]^\top \in \mathbb{R}^k$ are state variable vectors, $h_i(\bar{x}_i) : \mathbb{R}^i \mapsto \mathbb{R}$ are unknown C^1 nonlinear functions, κ_a and $\kappa_{i,s}$ denote injection data in the actuator and the ith state measurement, respectively, $x_{i,a}$ is the corrupted state variables, and $u \in \mathbb{R}$ is an event-triggered control input that is intermittently updated by a triggering law to be designed later. The injection data are represented by $\kappa_{i,s}(t, x_i(t)) = \zeta_i(t)x_i(t)$ and $\kappa_a(t,\bar{x}_n(t)) = \xi(t)\delta(\bar{x}_n(t))$ where ζ_i and ξ are unknown time-varying signals and δ is a continuous nonlinear function.

Assumption 1: Instead of the exactly measured state variables x_i, the corrupted state variables $x_{i,a}$ are available only for the feedback control design.

Assumption 2: [23], [24] There exist unknown constants $\bar{\zeta}_i$, $\bar{\zeta}_{i,d}$, and $\bar{\xi}$ such that $|\zeta_i| \le \bar{\zeta}_i$, $|\dot{\zeta}_i| \le \bar{\zeta}_{i,d}$, and $|\xi| \le \bar{\xi}$.

Assumption 3: [23] The time-varying signals ζ_i satisfy $\zeta_i + 1 \neq 0$ and the sign of $\zeta_i + 1$ is assumed to be positive.

Problem 1: Consider system (1). Our problem is to design an adaptive resilient event-triggered control law u using corrupted state variables so that system (1) is stabilized in the presence of unknown strict-feedback nonlinearities and unknown injection data in full state measurements and an actuator while all other signals remain bounded.

Remark 1 (The following statements are noted): (i) In contrast to the existing resilient control results [23], [24] for linear systems, uncertain nonlinear strict-feedback systems are considered in this paper. A recursive resilient event-triggered control design strategy using the corrupted state variables is established in the presence of unknown injection data in full state measurements and an actuator;

(ii) Assumption 3 is reasonable for ensuring the controllability of the system (1) with injection data in full state measurements [23]. This implies the existence of a nominal solution for Problem 1;

(iii) Contrary to the existing recursive designs [10]–[15] against output measurement faults, this paper considers full state variables corrupted by unknown injection data (i.e, $x_{i,a} = x_i + \kappa_{i,s}(t,x_i)$ in (1)) and the adaptive event-triggered control problem using the corrupted state variables. Thus, Problem 1 is the first trial in the adaptive control branch of uncertain lower-triangular nonlinear systems.

Remark 2: System (1) in the strict-feedback form can represent many nonlinear practical applications such as aircraft wing rock models, jet engines, flight systems, biochemical processes, and flexible-joint robots [7]. The state variables measured for the network-based feedback control of these practical systems can be corrupted by sensor faults or cyber attacks. The resilient event-triggered control strategy proposed in this paper can then be applied to these practical control problems.

III. MAIN RESULTS

A. FUNCTION APPROXIMATION USING RADIAL BASIS FUNCTION NEURAL NETWORKS

In this paper, RBFNNs are employed to approximate unknown continuous nonlinear functions to be specified in the adaptive event-triggered control design procedure. Consider continuous real-valued nonlinear functions $\Psi_i(\gamma_i)$: $\mathbb{R}^{q_i} \mapsto \mathbb{R}$ where $i = 1,\ldots,n$. RBFNNs can approximate $\Psi_i(\gamma_i)$ over a compact set $\Pi_{\gamma_i} \subset \mathbb{R}^{q_i}$ as [57], [58]

$$\Psi_i(\gamma_i) = \theta_i^\top G_i(\gamma_i) + \epsilon_i(\gamma_i) \tag{2}$$

where $i = 1,\ldots,n$, γ_i is the input vector, ϵ_i is the approximation error, $\theta_i \in \mathbb{R}^{l_i}$ is the optimal weighting vector defined as $\theta_i = \arg\min_{\hat{\theta}_i}[\sup_{\gamma_i\in\Pi_{\gamma_i}} |\Psi_i(\gamma_i) - \hat{\theta}_i^\top G_i(\gamma_i)|]$; $\hat{\theta}_i$ is an estimate of θ_i, and $G_i(\gamma_i) = [g_{i,1}(\gamma_i),\ldots,g_{i,l_i}(\gamma_i)]^\top \in \mathbb{R}^{l_i}$; Gaussian functions $g_{i,j}(\gamma_i)$, $j = 1,\ldots,l_i$, are defined as

$$g_{i,j}(\gamma_i) = \exp\left[\frac{-(\gamma_i - o_{i,j})^\top(\gamma_i - o_{i,j})}{r_{i,j}^2}\right] \tag{3}$$

with the center of the receptive field $o_{i,j} \in \mathbb{R}^{q_i}$ and the width of the Gaussian function $r_{i,j} \in \mathbb{R}$.

Assumption 4: [59] θ_i and ϵ_i are bounded as $\|\theta_i\| \le \bar{\theta}_i$ and $|\epsilon_i| \le \bar{\epsilon}_i$, respectively, where $i = 1,\ldots,n$, $\bar{\theta}_i > 0$ and $\bar{\epsilon}_i > 0$ are unknown constants.

Lemma 1: [59] It holds that $\|G_i(\gamma_i)\| \leq \bar{G}_i$ where $i = 1, \ldots, n$ and $\bar{G}_i$ is a constant.

B. RECURSIVE ADAPTIVE EVENT-TRIGGERED CONTROL DESIGN

In this section, a recursive design strategy using the corrupted state feedback information is presented for the adaptive event-triggered control of system (1).

Let us consider the following coordinate transformation on the basis of the dynamic surface design technique

$$e_1 = x_1 \tag{4}$$
$$e_k = x_k - \bar{\nu}_k \tag{5}$$
$$\rho_k = \bar{\nu}_k - \nu_k \tag{6}$$

where $k = 2, \ldots, n$, e_1 and e_k are error surfaces using exactly measured state variables x_1 and x_k, ρ_k and ν_k denote boundary layer errors and virtual control signals, respectively, and $\bar{\nu}_k$ are signals provided by the first-order low-pass filters

$$\tau_k \dot{\bar{\nu}}_k + \bar{\nu}_k = \nu_k, \quad \bar{\nu}_k(0) = \nu_k(0) \tag{7}$$

with small time constants $\tau_k > 0$. Since the exactly measured state variables x_i, $i = 1, \ldots, n$, are corrupted by unknown injection data $\kappa_{i,s}$, the error surfaces e_i, $i = 1, \ldots, n$, are not available for designing the virtual control laws ν_k and the actual control law u. Thus, we propose auxiliary signals using corrupted state variables $x_{i,a}$, $i = 1, \ldots, n$, as follows:

$$\varpi_1 = x_{1,a} \tag{8}$$
$$\varpi_k = x_{k,a} - \bar{\nu}_k - \hat{\zeta}_k \bar{\nu}_k \tag{9}$$

where $k = 2, \ldots, n$, and $\hat{\zeta}_k$ is the estimate of ζ_k which is provided by the injection data compensator to be designed later.

Remark 3: It is well known that the convergence of the error surfaces e_i should be analyzed for stable control design based on the Lyapunov stability theorem in conventional dynamic surface control where $i = 1, \ldots, n$. However, the error surfaces e_i are unknown for our control design because the exactly measured state variables x_i are corrupted during the feedback procedure. Thus, we present a recursive event-triggered control design using the available auxiliary signals ϖ_i, instead of the unknown error surfaces e_i, to ensure the convergence of the error surfaces e_i in the Lyapunov sense.

For the recursive design based on the Lyapunov stability analysis, (8) and (9) can be rewritten as

$$\varpi_1 = \frac{e_1}{\phi_1} \tag{10}$$
$$\begin{aligned}\varpi_k &= e_k + \zeta_k x_k - \hat{\zeta}_k \bar{\nu}_k + \zeta_k \bar{\nu}_k - \zeta_k \bar{\nu}_k \\ &= \frac{e_k}{\phi_k} + \tilde{\zeta}_k \bar{\nu}_k\end{aligned} \tag{11}$$

where $k = 2, \ldots, n$, $\tilde{\zeta}_k = \zeta_k - \hat{\zeta}_k$, and $\phi_k = 1/(1+\zeta_k)$. From Assumption 3, (10) and (11) are well defined. In addition, from Assumption 2, there exist unknown positive constants $\underline{\phi}_i$, $\bar{\phi}_i$, and $\bar{\phi}_{i,d}$ such that $\underline{\phi}_i \leq |\phi_i| \leq \bar{\phi}_i$ and $|\dot{\phi}_i| \leq \bar{\phi}_{i,d}$ where $i = 1, \ldots, n$.

From now on, the approximation-based adaptive event-triggered stabilizer using the auxiliary signals ϖ_i is recursively designed. The control design procedure is based on the Lyapunov stability theorem [7]. This theorem provides a design methodology to deal with the adaptive control design and stability analysis, simultaneously. In the first design step, a Lyapunov function V_1 consisting of the error surface e_1 and the weight estimation error $\tilde{\theta}_1$ for RBFNN is chosen to analyze the convergence of the error surface e_1 and the boundedness of $\tilde{\theta}_1$. In the kth design step, a Lyapunov function V_k consisting of the error surface e_k, weight estimation error $\tilde{\theta}_k$ for RBFNN, and compensation error $\tilde{\zeta}_k$ for the injection data is selected to analyze the convergence of the error surface e_k and the boundedness of $\tilde{\theta}_k$ and $\tilde{\zeta}_k$ where $k = 2, \ldots, n$.

Step 1: Differentiating the first error surface e_1 with respect to time yields

$$\dot{e}_1 = x_2 + h_1(x_1). \tag{12}$$

Consider the Lyapunov function $V_1 = e_1^2/(2\phi_1) + \tilde{\theta}_1^\top \tilde{\theta}_1/(2\lambda_1)$ where $\tilde{\theta}_1 = \theta_1 - \hat{\theta}_1$. Its time derivative is

$$\begin{aligned}\dot{V}_1 &= -\frac{\dot{\phi}_1}{2\phi_1^2} e_1^2 + \frac{1}{\phi_1} e_1(e_2 + \rho_2 + \nu_2 + h_1(x_1)) - \frac{1}{\lambda_1}\tilde{\theta}_1^\top \dot{\hat{\theta}}_1 \\ &\leq \frac{1}{\phi_1} e_1(e_2 + \rho_2 + \nu_2 + \varphi_1) - \frac{1}{\lambda_1}\tilde{\theta}_1^\top \dot{\hat{\theta}}_1\end{aligned} \tag{13}$$

where $\varphi_1 = h_1(x_1) + (\bar{\phi}_{1,d}/(2\phi_1))e_1$.

Then, there exists a continuous nonlinear function $\Psi_1(\gamma_1)$ such that

$$\frac{1}{\phi_1} e_1 \varphi_1 \leq \frac{1}{\phi_1} e_1 \Psi_1(\gamma_1) \tag{14}$$

where $\Psi_1(\gamma_1) = h_1(x_1) + (\bar{\phi}_{1,d}/(2\underline{\phi}_1))e_1$ and $\gamma_1 = e_1$. From (2), employing the RBFNN $\theta_1^\top G_1(\gamma_1)$ to estimate $\Psi_1(\gamma_1)$ yields

$$\Psi_1(\gamma_1) = \theta_1^\top G_1(\gamma_1) + \epsilon_1. \tag{15}$$

Based on the auxiliary signal ϖ_1, the first virtual control law is derived as

$$\nu_2 = -(\beta_1 + m_1)\varpi_1 - \hat{\theta}_1^\top G_1(\gamma_{1,a}) \tag{16}$$
$$\dot{\hat{\theta}}_1 = \lambda_1 \varpi_1 G_1(\gamma_{1,a}) - \lambda_1 \sigma_1 \hat{\theta}_1 \tag{17}$$

where $\beta_1 > 0$, $m_1 > 0$, $\lambda_1 > 0$, and $\sigma_1 > 0$ are design constants, and $\gamma_{1,a} = e_{1,a}$ with $e_{1,a} = x_{1,a}$.

Then, substituting (14) and (15) into (13) gives

$$\dot{V}_1 \leq \frac{1}{\phi_1} e_1(e_2 + \rho_2 + \nu_2 + \theta_1^\top G_1(\gamma_1) + \epsilon_1) - \frac{1}{\lambda_1}\tilde{\theta}_1^\top \dot{\hat{\theta}}_1. \tag{18}$$

From (10), it holds that $e_1 = \phi_1 \varpi_1$. Using (16) and $e_1 = \phi_1 \varpi_1$, (18) becomes

$$\begin{aligned}\dot{V}_1 \leq \frac{1}{\phi_1} e_1(e_2 + \rho_2) + \varpi_1(-(\beta_1 + m_1)\varpi_1 + \tilde{\theta}_1^\top G_1(\gamma_{1,a}) \\ + \theta_1^\top \psi_1 + \epsilon_1) - \frac{1}{\lambda_1}\tilde{\theta}_1^\top \dot{\hat{\theta}}_1\end{aligned} \tag{19}$$

where $\psi_1 = G_1(\gamma_1) - G_1(\gamma_{1,a})$. Adding and subtracting the term $(\beta_1/\phi_1^2)e_1^2$ to (19), and using $e_1 = \phi_1\varpi_1$ and (17) yield

$$\dot{V}_1 \le \frac{1}{\phi_1}e_1(e_2+\rho_2) + \varpi_1(-m_1\varpi_1 + \varsigma_1) - \frac{\beta_1}{\phi_1^2}e_1^2 + \sigma_1\tilde{\theta}_1^\top\hat{\theta}_1 \quad (20)$$

where $\varsigma_1 = \theta_1^\top\psi_1 + \epsilon_1$.

Step k **(**$k = 2, \ldots, n-1$**):** The time derivative of the kth error surface (5) is given by

$$\dot{e}_k = x_{k+1} + h_k(\bar{x}_k) - \dot{\bar{\nu}}_k \quad (21)$$

where $k = 2, \ldots, n-1$.

Consider the Lyapunov function $V_k = e_k^2/(2\phi_k) + \tilde{\zeta}_k^2/2 + \tilde{\theta}_k^\top\tilde{\theta}_k/(2\lambda_k)$ where $k = 2, \ldots, n-1$, $\tilde{\zeta}_k = \zeta_k - \hat{\zeta}_k$, and $\tilde{\theta}_k = \theta_k - \hat{\theta}_k$. Its time derivative along (6) and (21) is represented by

$$\begin{aligned}\dot{V}_k &= -\frac{\dot{\phi}_k}{2\phi_k^2}e_k^2 + \frac{1}{\phi_k}e_k(e_{k+1} + \rho_{k+1} + \nu_{k+1} - \dot{\bar{\nu}}_k + h_k(\bar{x}_k)) \\ &\quad + \tilde{\zeta}_k(\dot{\zeta}_k - \dot{\hat{\zeta}}_k) - \frac{1}{\lambda_k}\tilde{\theta}_k^\top\dot{\hat{\theta}}_k \\ &\le \frac{1}{\phi_k}e_k(e_{k+1} + \rho_{k+1} + \nu_{k+1} - \dot{\bar{\nu}}_k + \varphi_k) - \frac{1}{\phi_{k-1}}e_{k-1}e_k \\ &\quad + \frac{1}{\phi_k}e_k(\beta_k + \iota_k)\bar{\nu}_k\zeta_k + \tilde{\zeta}_k(\dot{\zeta}_k - \dot{\hat{\zeta}}_k) - \frac{1}{\lambda_k}\tilde{\theta}_k^\top\dot{\hat{\theta}}_k \quad (22)\end{aligned}$$

where $\varphi_k = h_k(\bar{x}_k) + (\bar{\phi}_{k,d}/(2\phi_k))e_k + (\phi_k/\phi_{k-1})e_{k-1} - (\beta_k + \iota_k)\bar{\nu}_k\zeta_k$; $\beta_k > 0$ and $\iota_k > 0$ are constants.

From the boundedness of ζ_k, ϕ_k and ϕ_{k-1}, there exists a continuous function $\Psi_k(\gamma_k)$ such that

$$\frac{1}{\phi_k}e_k\varphi_k \le \frac{1}{\phi_k}e_k\Psi_k(\gamma_k) + a_k \quad (23)$$

where $a_k > 0$ is a constant and $\gamma_k = [\bar{x}_k^\top, e_{k-1}, e_k, \bar{\nu}_k, b_k]^\top$ with a constant $b_k > 0$. By employing the RBFNN $\theta_k^\top G_k(\gamma_k)$ to estimate $\Psi_k(\gamma_k)$, we have

$$\Psi_k(\gamma_k) = \theta_k^\top G_k(\gamma_k) + \epsilon_k. \quad (24)$$

An adaptive injection data compensator is presented as

$$\begin{aligned}\dot{\hat{\zeta}}_k &= \hat{\theta}_k^\top G_k(\gamma_{k,a})\bar{\nu}_k - (\beta_k - m_k - (\beta_k + \iota_k)^2\bar{\nu}_k^2)\bar{\nu}_k\varpi_k \\ &\quad - (\beta_k + \iota_k)\bar{\nu}_k^2\hat{\zeta}_k - \alpha_k\hat{\zeta}_k \quad (25)\end{aligned}$$

where $k = 2, \ldots, n$, $\beta_k > 0$, $m_k > 0$, $\iota_k > 0$, and $\alpha_k > 0$ are design parameters, $\gamma_{k,a} = [\bar{x}_{k,a}^\top, e_{k-1,a}, e_{k,a}, \bar{\nu}_k, b_k]^\top$; $\bar{x}_{k,a} = [x_{1,a}, \ldots, x_{k,a}]^\top$, $e_{k-1,a} = x_{k-1,a} - \bar{\nu}_{k-1}$ with $\bar{\nu}_1 = 0$, and $e_{k,a} = x_{k,a} - \bar{\nu}_k$.

The kth virtual control law using the auxiliary signal ϖ_k is designed as

$$\begin{aligned}\nu_{k+1} &= -(\beta_k + m_k + (\beta_k + \iota_k)^2\bar{\nu}_k^2)\varpi_k \\ &\quad - \hat{\theta}_k^\top G_k(\gamma_{k,a}) + \frac{\nu_k - \bar{\nu}_k}{\tau_k} \quad (26)\\ \dot{\hat{\theta}}_k &= \lambda_k\varpi_k G_k(\gamma_{k,a}) - \lambda_k\sigma_k\hat{\theta}_k \quad (27)\end{aligned}$$

where $\lambda_k > 0$ and $\sigma_k > 0$ are design constants.

Using $e_k = \phi_k(\varpi_k - \tilde{\zeta}_k\bar{\nu}_k)$ in (11) and ν_{k+1} in (26), (22) becomes

$$\begin{aligned}&\dot{V}_k \\ &\le \frac{1}{\phi_k}e_k(e_{k+1} + \rho_{k+1}) - \frac{\beta_k}{\phi_k^2}e_k^2 + \frac{\beta_k}{\phi_k^2}e_k^2 \\ &\quad + (\varpi_k - \tilde{\zeta}_k\bar{\nu}_k)\{-(\beta_k + m_k + (\beta_k + \iota_k)^2\bar{\nu}_k^2)\varpi_k \\ &\quad + \tilde{\theta}_k^\top G_k(\gamma_{k,a}) + \theta_k^\top\psi_k + \epsilon_k\} \\ &\quad + \iota_k\tilde{\zeta}_k^2\bar{\nu}_k^2 - \iota_k\tilde{\zeta}_k^2\bar{\nu}_k^2 - \frac{1}{\phi_{k-1}}e_{k-1}e_k + \frac{1}{\phi_k}e_k(\beta_k + \iota_k)\bar{\nu}_k\zeta_k \\ &\quad + \tilde{\zeta}_k(\dot{\zeta}_k - \dot{\hat{\zeta}}_k) - \frac{1}{\lambda_k}\tilde{\theta}_k^\top\dot{\hat{\theta}}_k + a_k \\ &= \frac{1}{\phi_k}e_k(e_{k+1} + \rho_{k+1}) \\ &\quad + \varpi_k\{-(\beta_k + m_k + (\beta_k + \iota_k)^2\bar{\nu}_k^2)\varpi_k + \tilde{\theta}_k^\top G_k(\gamma_{k,a}) + \varsigma_k\} \\ &\quad - \tilde{\zeta}_k\bar{\nu}_k\{-(\beta_k + m_k + (\beta_k + \iota_k)^2\bar{\nu}_k^2)\varpi_k + \tilde{\theta}_k^\top G_k(\gamma_{k,a}) + \varsigma_k\} \\ &\quad - \frac{\beta_k}{\phi_k^2}e_k^2 + \beta_k(\varpi_k^2 - 2\tilde{\zeta}_k\bar{\nu}_k\varpi_k) + (\beta_k + \iota_k)\tilde{\zeta}_k^2\bar{\nu}_k^2 - \iota_k\tilde{\zeta}_k^2\bar{\nu}_k^2 \\ &\quad - \frac{1}{\phi_{k-1}}e_{k-1}e_k + \frac{1}{\phi_k}e_k(\beta_k + \iota_k)\bar{\nu}_k\zeta_k + \tilde{\zeta}_k(\dot{\zeta}_k - \dot{\hat{\zeta}}_k) \\ &\quad - \frac{1}{\lambda_k}\tilde{\theta}_k^\top\dot{\hat{\theta}}_k + a_k \\ &= \frac{1}{\phi_k}e_k(e_{k+1} + \rho_{k+1}) \\ &\quad + \varpi_k\{-m_k\varpi_k - (\beta_k + \iota_k)^2\bar{\nu}_k^2\varpi_k + \tilde{\theta}_k^\top G_k(\gamma_{k,a}) + \varsigma_k\} \\ &\quad - \tilde{\zeta}_k\bar{\nu}_k\{\beta_k\varpi_k - m_k\varpi_k - (\beta_k + \iota_k)^2\bar{\nu}_k^2\varpi_k + (\beta_k + \iota_k)\bar{\nu}_k\hat{\zeta}_k \\ &\quad + \tilde{\theta}_k^\top G_k(\gamma_{k,a}) + \varsigma_k\} - \frac{\beta_k}{\phi_k^2}e_k^2 + (\beta_k + \iota_k)\bar{\nu}_k^2\tilde{\zeta}_k\zeta_k \\ &\quad - \iota_k\tilde{\zeta}_k^2\bar{\nu}_k^2 - \frac{1}{\phi_{k-1}}e_{k-1}e_k + \frac{1}{\phi_k}e_k(\beta_k + \iota_k)\bar{\nu}_k\zeta_k \\ &\quad + \tilde{\zeta}_k(\dot{\zeta}_k - \dot{\hat{\zeta}}_k) - \frac{1}{\lambda_k}\tilde{\theta}_k^\top\dot{\hat{\theta}}_k + a_k \quad (28)\end{aligned}$$

where $\psi_k = G_k(\gamma_k) - G_k(\gamma_{k,a})$ and $\varsigma_k = \theta_k^\top\psi_k + \epsilon_k$.

Then, from $\tilde{\zeta}_k\bar{\nu}_k = \varpi_k - (e_k/\phi_k)$, we have

$$\begin{aligned}(\beta_k + \iota_k)\bar{\nu}_k^2\tilde{\zeta}_k\zeta_k &= (\beta_k + \iota_k)\bar{\nu}_k\zeta_k\left(\varpi_k - \frac{e_k}{\phi_k}\right) \\ &\le (\beta_k + \iota_k)^2\bar{\nu}_k^2\varpi_k^2 + \frac{\zeta_k^2}{4} \\ &\quad - \frac{1}{\phi_k}e_k(\beta_k + \iota_k)\bar{\nu}_k\zeta_k. \quad (29)\end{aligned}$$

Substituting (25), (27), and (29) into (28) yields

$$\begin{aligned}\dot{V}_k &\le \frac{1}{\phi_k}e_k(e_{k+1} + \rho_{k+1}) + \varpi_k(-m_k\varpi_k + \varsigma_k) \\ &\quad - \tilde{\zeta}_k\bar{\nu}_k(\theta_k^\top G_k(\gamma_{k,a}) + \varsigma_k) - \frac{\beta_k}{\phi_k^2}e_k^2 - \iota_k\tilde{\zeta}_k^2\bar{\nu}_k^2 \\ &\quad - \frac{1}{\phi_{k-1}}e_{k-1}e_k + \tilde{\zeta}_k(\dot{\zeta}_k + \alpha_k\hat{\zeta}_k) + \sigma_k\tilde{\theta}_k^\top\hat{\theta}_k \\ &\quad + a_k + \frac{\zeta_k^2}{4}. \quad (30)\end{aligned}$$

Step n: Consider the Lyapunov function $V_n = e_n^2/(2\phi_n) + \tilde{\zeta}_n^2/2 + \tilde{\theta}_n^\top \tilde{\theta}_n/(2\lambda_n)$ with $\tilde{\zeta}_n = \zeta_n - \hat{\zeta}_n$ and $\tilde{\theta}_n = \theta_n - \hat{\theta}_n$. From $\dot{e}_n = u + \xi\phi(\bar{x}_n) + h_n(\bar{x}_n) - \dot{\bar{\nu}}_n$, the time derivative of $\dot{V}_n$ is given by

$$\dot{V}_n \le \frac{1}{\phi_n} e_n(u - \dot{\bar{\nu}}_n + \varphi_n) - \frac{1}{\phi_{n-1}} e_{n-1}e_n + \frac{1}{\phi_n} e_n(\beta_n + \iota_n)\bar{\nu}_n\zeta_n + \tilde{\zeta}_n(\dot{\zeta}_n - \dot{\hat{\zeta}}_n) - \frac{1}{\lambda_n}\tilde{\theta}_n^\top \dot{\hat{\theta}}_n \quad (31)$$

where $\varphi_n = h_n(\bar{x}_n) + \xi\phi(\bar{x}_n) + (\bar{\phi}_{n,d}/(2\phi_n))e_n + (\phi_n/\phi_{n-1})e_{n-1} - (\beta_n + \iota_n)\bar{\nu}_n\zeta_n$; $\beta_n > 0$ and $\iota_n > 0$ are constants.

Due to the boundedness of ϕ_n, ϕ_{n-1}, ζ_n, and ξ, there exists a continuous function $\Psi_n(\gamma_n)$ such that

$$\frac{1}{\phi_n} e_n\varphi_n \le \frac{1}{\phi_n} e_n\Psi_n(\gamma_n) + a_n \quad (32)$$

where $a_n > 0$ is a constant and $\gamma_n = [\bar{x}_n^\top, e_{n-1}, e_n, \bar{\nu}_n, b_n]^\top$ with a constant $b_n > 0$. By employing the RBFNN $\theta_n^\top G_n(\gamma_n)$ to estimate $\Psi_n(\gamma_n)$, we have

$$\Psi_n(\gamma_n) = \theta_n^\top G_n(\gamma_n) + \epsilon_n. \quad (33)$$

The approximation-based adaptive event-triggered control law is presented as

$$u(t) = \bar{u}(t_l), \quad t \in [t_l, t_{l+1}) \quad (34)$$

$$t_{l+1} = \inf\{t > t_l \,|\, |S_u(t)| \ge m_{u,1}|\varpi_n(t)| + m_{u,2}\} \quad (35)$$

where for $l \in \mathbb{Z}^+$, t_l denotes the update time of the controller, $S_u = \bar{u}(t) - u(t)$ is the measurement error due to the triggering, ϖ_n is defined as $\varpi_n = x_{n,a} - \bar{\nu}_n - \hat{\zeta}_n\bar{\nu}_n$ in (9), and $m_{u,1}$ and $m_{u,2}$ are positive design constants. (34) and (35) imply that the control law u is set to $\bar{u}(t_l)$ for $t \in [t_l, t_{l+1})$, and when the triggering law (35) is satisfied, its value is updated at t_{l+1}. Here, the signal $\bar{u}$ with the auxiliary signal ϖ_n and the injection data compensator $\hat{\zeta}_n$ is designed as follows:

$$\bar{u} = -(\beta_n + m_n + (\beta_n + \iota_n)^2\bar{\nu}_n^2)\varpi_n - \hat{\theta}_n^\top G_n(\gamma_{n,a}) + \frac{\nu_n - \bar{\nu}_n}{\tau_n} \quad (36)$$

$$\dot{\hat{\theta}}_n = \lambda_n\varpi_n G_n(\gamma_{n,a}) - \lambda_n\sigma_n\hat{\theta}_n \quad (37)$$

$$\dot{\hat{\zeta}}_n = \hat{\theta}_n^\top G_n(\gamma_{n,a})\bar{\nu}_n - (\beta_n - m_n - (\beta_n + \iota_n)^2\bar{\nu}_n^2)\bar{\nu}_n\varpi_n - (\beta_n + \iota_n)\bar{\nu}_n^2\hat{\zeta}_n - \alpha_n\hat{\zeta}_n \quad (38)$$

where $\varpi_n = x_{n,a} - \bar{\nu}_n - \hat{\zeta}_n\bar{\nu}_n$, $\gamma_{n,a} = [\bar{x}_{n,a}^\top, e_{n-1,a}, e_{n,a}, \bar{\nu}_n, b_n]^\top$; $\bar{x}_{n,a} = [x_{1,a}, \ldots, x_{n,a}]^\top$, $e_{n-1,a} = x_{n-1,a} - \bar{\nu}_{n-1}$, and $e_{n,a} = x_{n,a} - \bar{\nu}_n$, $m_n > 0$ and $\alpha_n > 0$ are design parameters, and $\lambda_n > 0$ and $\sigma_n > 0$ are design constants.

Using $e_n = \phi_n(\varpi_n - \tilde{\zeta}_n\bar{\nu}_n)$ in (11), $S_u = \bar{u}(t) - u(t)$, and (36), (31) becomes

$$\begin{aligned}\dot{V}_n \le\ & \varpi_n\{-(\beta_n + m_n + (\beta_n + \iota_n)^2\bar{\nu}_n^2)\varpi_n + \tilde{\theta}_n^\top G_n(\gamma_{n,a}) + \varsigma_n\} \\ & - \tilde{\zeta}_n\bar{\nu}_n\{-(\beta_n + m_n + (\beta_n + \iota_n)^2\bar{\nu}_n^2)\varpi_n + \tilde{\theta}_n^\top G_n(\gamma_{n,a}) \\ & + \varsigma_n\} - \frac{\beta_n}{\phi_n^2}e_n^2 + \beta_n(\varpi_n^2 - 2\tilde{\zeta}_n\bar{\nu}_n\varpi_n) + (\beta_n + \iota_n)\tilde{\zeta}_n^2\bar{\nu}_n^2 \\ & - \iota_n\tilde{\zeta}_n^2\bar{\nu}_n^2 - \frac{1}{\phi_{n-1}}e_{n-1}e_n + \frac{1}{\phi_n}e_n(\beta_n + \iota_n)\bar{\nu}_n\zeta_n \\ & + \tilde{\zeta}_n(\dot{\zeta}_n - \dot{\hat{\zeta}}_n) - \frac{1}{\lambda_n}\tilde{\theta}_n^\top\dot{\hat{\theta}}_n + a_n - \frac{1}{\phi_n}e_nS_u. \end{aligned} \quad (39)$$

Owing to $S_u(t_l) = 0$ for $l \in \mathbb{Z}^+$ and $\varpi_n(t) = \tilde{\zeta}_n\bar{\nu}_n + (e_n/\phi_n)$, we have

$$\begin{aligned} -\frac{1}{\phi_n}e_nS_u &\le \frac{1}{\phi_n}|e_n|(m_{u,1}|\varpi_n(t)| + m_{u,2}) \\ &\le \frac{m_{u,1}}{\phi_n^2}e_n^2 + \frac{m_{u,1}}{\phi_n}|e_n||\tilde{\zeta}_n\bar{\nu}_n| + \frac{m_{u,2}}{\phi_n}|e_n| \\ &\le \frac{2m_{u,1}}{\phi_n^2}e_n^2 + \frac{m_{u,1}}{4}\tilde{\zeta}_n^2\bar{\nu}_n^2 + \frac{\lambda_u}{\phi_n^2}e_n^2 + \frac{m_{u,2}^2}{4\lambda_u} \end{aligned} \quad (40)$$

where $\lambda_u > 0$ is a constant.

Using (40) and $(\beta_n + \iota_n)\tilde{\zeta}_n^2\bar{\nu}_n^2 = (\beta_n + \iota_n)\tilde{\zeta}_n\bar{\nu}_n^2(\zeta_n - \hat{\zeta}_n)$, we obtain

$$\begin{aligned}\dot{V}_n \le\ & \varpi_n\{-m_n\varpi_n - (\beta_n + \iota_n)^2\bar{\nu}_n^2\varpi_n + \tilde{\theta}_n^\top G_n(\gamma_{n,a}) + \varsigma_n\} \\ & - \tilde{\zeta}_n\bar{\nu}_n\{\beta_n\varpi_n - m_n\varpi_n - (\beta_n + \iota_n)^2\bar{\nu}_n^2\varpi_n \\ & + (\beta_n + \iota_n)\bar{\nu}_n\hat{\zeta}_n + \tilde{\theta}_n^\top G_n(\gamma_{n,a}) + \varsigma_n\} \\ & - (\beta_n - 2m_{u,1} - \lambda_u)\frac{e_n^2}{\phi_n^2} + (\beta_n + \iota_n)\bar{\nu}_n^2\tilde{\zeta}_n\zeta_n \\ & - \left(\iota_n - \frac{m_{u,1}}{4}\right)\tilde{\zeta}_n^2\bar{\nu}_n^2 - \frac{1}{\phi_{n-1}}e_{n-1}e_n \\ & + \frac{1}{\phi_n}e_n(\beta_n + \iota_n)\bar{\nu}_n\zeta_n + \tilde{\zeta}_n(\dot{\zeta}_n - \dot{\hat{\zeta}}_n) \\ & - \frac{1}{\lambda_n}\tilde{\theta}_n^\top\dot{\hat{\theta}}_n + a_n + \frac{m_{u,2}^2}{4\lambda_u} \end{aligned} \quad (41)$$

where $\psi_n = G_n(\gamma_n) - G_n(\gamma_{n,a})$ and $\varsigma_n = \theta_n^\top\psi_n + \epsilon_n$.

Then, using $\tilde{\zeta}_n\bar{\nu}_n = \varpi_n - (e_n/\phi_n)$ gives

$$(\beta_n + \iota_n)\bar{\nu}_n^2\tilde{\zeta}_n\zeta_n \le (\beta_n + \iota_n)^2\bar{\nu}_n^2\varpi_n^2 + \frac{\zeta_n^2}{4} - \frac{1}{\phi_n}e_n(\beta_n + \iota_n)\bar{\nu}_n\zeta_n. \quad (42)$$

Substituting (38), (37), and (42) into (41) yields

$$\begin{aligned}\dot{V}_n \le\ & \varpi_n(-m_n\varpi_n + \varsigma_n) - \tilde{\zeta}_n\bar{\nu}_n(\theta_n^\top G_n(\gamma_{n,a}) + \varsigma_n) \\ & - (\beta_n - 2m_{u,1} - \lambda_u)\frac{e_n^2}{\phi_n^2} - \left(\iota_n - \frac{m_{u,1}}{4}\right)\tilde{\zeta}_n^2\bar{\nu}_n^2 \\ & - \frac{1}{\phi_{n-1}}e_{n-1}e_n + \tilde{\zeta}_n(\dot{\zeta}_n + \alpha_n\hat{\zeta}_n) \\ & + \sigma_n\tilde{\theta}_n^\top\hat{\theta}_n + a_n + \frac{\zeta_n^2}{4} + \frac{m_{u,2}^2}{4\lambda_u}. \end{aligned} \quad (43)$$

Remark 4: Compared with the existing event-triggered control results [53]–[55], this paper considers the event-triggered control problem against unknown injection data in full state measurements and an actuator. Moreover, the adaptive controller (34) and its event-triggering law (35) are designed using the auxiliary signal ϖ_n with the corrupted state variable $x_{n,a}$ and the injection data compensation $\hat{\zeta}_n$.

Although the corrupted state variables are used in the proposed adaptive event-triggered control scheme, the convergence of the error surfaces e_i using the exactly measured state variables x_i, the boundedness of all closed-loop signals, and the exclusion of Zeno behavior are successfully analyzed in the following section.

C. STABILITY ANALYSIS

For the stability analysis, the dynamics of the boundary layer errors (6) are considered as

$$\dot{\rho}_{k+1} = -\frac{\rho_{k+1}}{\tau_{k+1}} + \eta_{k+1}(\bar{e}_{k+1}, \rho_2, \ldots, \rho_{k+1}, \bar{\hat{\theta}}_k, \bar{\hat{\zeta}}_k, \Delta_k) \quad (44)$$

where $k = 1, \ldots, n-1$, $\bar{e}_{k+1} = [e_1, \ldots, e_{k+1}]^\top$, $\bar{\hat{\theta}}_k = [\hat{\theta}_1, \ldots, \hat{\theta}_k]^\top$, $\bar{\hat{\zeta}}_k = [\hat{\zeta}_1, \ldots, \hat{\zeta}_k]^\top$ with $\hat{\zeta}_1 = 0$, $\Delta_k = [\zeta_1, \ldots, \zeta_k, \dot{\zeta}_1, \ldots, \dot{\zeta}_k]^\top$, and $\eta_2 = (\beta_1 + m_1)\dot{\varpi}_1 + \dot{\hat{\theta}}_1^\top G_1 + \hat{\theta}_1^\top(\partial G_1/\partial\gamma_{1,a})\dot{\gamma}_{1,a}$ and $\eta_{k+1} = (\beta_k + m_k + (\beta_k + \iota_k)^2\bar{\nu}_k^2)\dot{\varpi}_k - 2(\beta_k + \iota_k)^2\bar{\nu}_k(\rho_k/\tau_k)\varpi_k + \dot{\hat{\theta}}_k^\top G_k + \hat{\theta}_k^\top(\partial G_k/\partial\gamma_{k,a})\dot{\gamma}_{k,a} + \dot{\rho}_k/\tau_k$ are continuous functions.

A total Lyapunov function V is selected as $V = \sum_{i=1}^n V_i + \sum_{i=1}^{n-1}\rho_{i+1}^2/2$.

Theorem 1: Consider uncertain nonlinear strict-feedback systems (1) with unknown injection data in full state measurements and an actuator. The proposed adaptive event-triggered controller (34)–(38) with an event-triggering condition (35) achieves that for any initial conditions satisfying $V(0) \le \mu$ with a constant $\mu > 0$,

(i) all signals of the closed-loop system are semi-globally uniformly ultimately bounded;

(ii) the error surfaces e_i, $i = 1, \ldots, n$, converge to an adjustable neighborhood of the origin;

(iii) the minimum inter-event time $\underline{t}_l > 0$ satisfying $|t_{l+1} - t_l| \ge \underline{t}_l$ for $l \in \mathbb{Z}^+$ exists.

Proof: The time derivative of V using (20), (30), and (43) is

$$\begin{aligned}\dot{V} \le& \sum_{i=1}^n\left(-\frac{\beta_i}{\phi_i^2}e_i^2 - m_i\varpi_i^2 + \varpi_i\varsigma_i + \sigma_i\tilde{\theta}_i^\top\hat{\theta}_i\right)\\ &+ \sum_{i=2}^n\left(-\tilde{\zeta}_i\bar{\nu}_i\chi_i - \iota_i\tilde{\zeta}_i^2\bar{\nu}_i^2 + \tilde{\zeta}_i(\dot{\zeta}_i + \alpha_i\hat{\zeta}_i) + \frac{\bar{\zeta}_i^2}{4}\right)\\ &+ \sum_{i=1}^{n-1}\left(-\frac{\rho_{i+1}^2}{\tau_{i+1}} + \bar{\eta}_{i+1}\rho_{i+1}\right) + (2m_{u,1} + \lambda_u)\frac{e_n^2}{\phi_n^2}\\ &+ \frac{m_{u,1}}{4}\tilde{\zeta}_n^2\bar{\nu}_n^2 + \frac{m_{u,2}^2}{4\lambda_u} + \sum_{i=2}^n a_i\end{aligned} \quad (45)$$

where $\bar{\eta}_{i+1} = \eta_{i+1} + (1/\phi_i)e_i$ and $\chi_i = \theta_i^\top G_i(\gamma_{i,a}) + \varsigma_i$.

Consider the sets $A_i := \{\sum_{j=1}^i((e_j^2/\phi_j) + (\tilde{\theta}_j^\top\tilde{\theta}_j/\lambda_j)) + \sum_{j=2}^i(\tilde{\zeta}_j^2 + \rho_j^2) \le 2\mu\}$ and $B_i = \{\sum_{j=1}^i(\zeta_j^2 + \dot{\zeta}_j^2) \le d_i\}$ where $i = 1, \ldots, n$ and $d_i = \sum_{j=1}^i(\bar{\zeta}_j^2 + \bar{\zeta}_{j,d}^2)$. A_i and B_i are compact in $\mathbb{R}^{\dim(A_i)}$ and $\mathbb{R}^{2i}$, respectively. Since $A_i \times B_i$ is also compact in $\mathbb{R}^{\dim(A_i)+2i}$, $|\bar{\eta}_{i+1}| \le q_{i+1}$ on $A_i \times B_i$ where $q_{i+1} > 0$ are constants and $\dim(A_i)$ denotes the dimension of the set A_i.

From Assumption 4 and Lemma 1, there exist constants $\bar{\varsigma}_i > 0$ and $\bar{\chi}_i > 0$ such that $|\varsigma_i| \le \bar{\varsigma}_i$ and $|\chi_i| \le \bar{\chi}_i$. Using $\varpi_i\varsigma_i \le m_i\varpi_i^2 + \bar{\varsigma}_i^2/(4m_i)$, $-\tilde{\zeta}_i\bar{\nu}_i\chi_i \le \bar{\iota}_i\tilde{\zeta}_i^2\bar{\nu}_i^2 + \bar{\chi}_i^2/(4\bar{\iota}_i)$ with a constant $\bar{\iota}_i > 0$, $\tilde{\theta}_i^\top\hat{\theta}_i \le -(1/2)\tilde{\theta}_i^\top\tilde{\theta}_i + (1/2)\bar{\theta}_i^\top\bar{\theta}_i$, $\tilde{\zeta}_i\dot{\zeta}_i \le \bar{\iota}_i\tilde{\zeta}_i^2 + \bar{\zeta}_{i,d}^2/(4\bar{\iota}_i)$, $\tilde{\zeta}_i\hat{\zeta}_i \le -(1/2)\tilde{\zeta}_i^2 + (1/2)\bar{\zeta}_i^2$, and $\bar{\eta}_{i+1}\rho_{i+1} \le \bar{\iota}_{i+1}\bar{\eta}_{i+1}^2\rho_{i+1}^2 + 1/(4\bar{\iota}_{i+1})$, and choosing $\beta_i = 2m_{u,1} + \lambda_u + \beta_i^*$ with a constant $\beta_i^* > 0$, $\iota_i = \bar{\iota}_i + m_{u,1}/4$, $\alpha_i = 2\bar{\iota}_i + \alpha_i^*$ with a constant $\alpha_i^* > 0$, and $1/\tau_{i+1} = \bar{\iota}_{i+1}q_{i+1}^2 + \tau_{i+1}^*$ with a constant $\tau_{i+1}^* > 0$ give

$$\begin{aligned}\dot{V} \le& \sum_{i=1}^n\left(-\frac{\beta_i^*}{\phi_i^2}e_i^2 - \frac{\sigma_i}{2}\tilde{\theta}_i^\top\tilde{\theta}_i\right) - \sum_{i=2}^n\frac{\alpha_i^*}{2}\tilde{\zeta}_i^2 + c_0\\ &+ \sum_{i=1}^{n-1}\left(-\tau_{i+1}^*\rho_{i+1}^2 - \left(1 - \frac{\bar{\eta}_{i+1}^2}{q_{i+1}^2}\right)\bar{\iota}_{i+1}q_{i+1}^2\rho_{i+1}^2\right)\end{aligned} \quad (46)$$

where $c_0 = \sum_{i=1}^n(\bar{\varsigma}_i^2/(4m_i) + (\sigma_i/2)\bar{\theta}_i^\top\bar{\theta}_i) + \sum_{i=2}^n a_i + \sum_{i=2}^n(\bar{\chi}_i^2/(4\bar{\iota}_i) + \bar{\zeta}_{i,d}^2/(4\bar{\iota}_i) + (\alpha_i/2)\bar{\zeta}_i^2 + \bar{\zeta}_i^2/4 + 1/(4\bar{\iota}_i)) + m_{u,2}^2/(4\lambda_u)$.

Owing to $|\bar{\eta}_{i+1}| \le q_{i+1}$ on $V = \mu$, (46) becomes $\dot{V} \le -c_1V + c_0$ with $0 < c_1 < \min\{2(\beta_1^*/\bar{\phi}_1), \ldots, 2(\beta_n^*/\bar{\phi}_n), 2\tau_2^*, \ldots, 2\tau_n^*, \sigma_1\lambda_1, \ldots, \sigma_n\lambda_n, \alpha_2^*, \ldots, \alpha_n^*\}$. Thus, $\dot{V} < 0$ on $V = \mu$ when $c_1 > c_0/\mu$. This implies that $V \le \mu$ is an invariant set, i.e., if $V(0) \le \mu$, then $V(t) \le \mu$ for all $t \ge 0$. Integrating both sides of $\dot{V} \le -c_1V + c_0$ with respect to time yields $V(t) \le e^{-c_1t}V(0) + (c_0/c_1)(1 - e^{-c_1t})$. Using $(1/\bar{\phi}_M)\sum_{i=1}^n e_i^2/2 \le V(t)$ with $\bar{\phi}_M = \max_{i=1,\ldots,n}\{\bar{\phi}_i\}$, the stabilization error vector $e = [e_1, \ldots, e_n]^\top$ is exponentially bounded to the compact set $\Omega = \{e \| \|e\| \le \sqrt{2\bar{\phi}_Mc_0/c_1}\}$ where the set Ω can be adjusted arbitrarily small by c_1. Thus, Theorems 1-(i) and 1-(ii) are ensured. This completes the proofs of Theorems 1-(i) and 1-(ii).

The existence of the minimum inter-event time $\underline{t}_l$ satisfying $|t_{l+1} - t_l| \ge \underline{t}_l$ is checked to show the exclusion of Zeno behavior. Differentiating the measurement error $S_u(t)$, $\forall t \in [t_l, t_{l+1})$, with respect to time, it holds that $d|S_u|/dt = \mathrm{sgn}(S_u)\dot{S}_u \le |\dot{\bar{u}}|$ where $\mathrm{sgn}(S_u)$ is the sign of S_u and $\dot{\bar{u}}$ is defined as

$$\begin{aligned}\dot{\bar{u}} =& -(\beta_n + m_n + (\beta_n + \iota_n)^2 2\bar{\nu}_n\dot{\bar{\nu}}_n)\varpi_n\\ &- (\beta_n + m_n + (\beta_n + \iota_n)^2\bar{\nu}_n^2)\dot{\varpi}_n\\ &- \dot{\hat{\theta}}_n^\top G_n - \hat{\theta}_n^\top\dot{G}_n + \frac{\dot{\nu}_n - \dot{\bar{\nu}}_n}{\tau_n}.\end{aligned} \quad (47)$$

From the proofs of Theorems 1-(i) and 1-(ii), all closed-loop signals are bounded. Therefore, we obtain $|\dot{\bar{u}}| \le \bar{d}_u$ where $\bar{d}_u$ is a constant. Let us integrate $|\dot{\bar{u}}| \le \bar{d}_u$ during $t \in [t_l, t_{l+1})$ and use the event-triggering law (35). Then, the inter-execution times $t_{l+1} - t_l$ satisfy $|t_{l+1} - t_l| \ge (m_{u,1}|\varpi_n(t)| + m_{u,2})/\bar{d}_u \ge m_{u,2}/\bar{d}_u$. Thus, the minimum inter-event time is defined as $\underline{t}_l = m_{u,2}/\bar{d}_u$. This completes the proof of Theorem 1-(iii). ■

Remark 5: From the proof of Theorem 1, the stabilization performance can be improved by reducing the compact set Ω. From this standpoint, the design parameters can be selected. The choice of the design parameters is only a sufficient condition for Theorem 1. The guidelines for the choice of the design parameters are as follows.

(i) Increasing the design parameters β_i, $i = 1, \ldots, n$ helps to increasing of the convergence rate of the error surfaces e_i (i.e., increasing c_1), and thus Ω can be reduced.

(ii) As the design parameters m_i, $i = 1, \ldots, n$ and ι_j, $j = 2, \ldots, n$ increase, c_0 is reduced. Therefore, Ω can be reduced.

(iii) As the design parameters λ_i denoting the tuning rate increase and the design parameters σ_i for the σ-modification are fixed as small values, the tuning speed of the adaptive parameters $\hat{\theta}_i$ can be increased where $i = 1, \ldots, n$.

(iv) According to the limited resources of the network, the number of released data during the transient and steady-state responses can be adjusted by choosing the design parameters $m_{u,1}$ and $m_{u,2}$ in the event-triggering law (35).

Remark 6: The control gain functions and the event-triggered state variables are not considered in the strict-feedback nonlinear systems (1). The problems caused by the control gain functions reported in [60] and the event-triggered state variables reported in [61] should be reformulated under the state feedback information corrupted by unknown injection data. Thus, the proposed approach cannot be applied in a straightforward manner to these problems. Future work can explore the extension of the proposed approach to complex systems in the strict-feedback form.

IV. SIMULATION RESULTS

Two simulation studies including a wing rock model with ailerons are presented to illustrate the validity of the proposed theoretical result against unknown injection data in full states and an actuator. In these simulations, the triggering law (35) is checked periodically with the sampling time 1 ms.

Example 1: Consider the following second-order nonlinear system with unknown injection data in full state measurements and an actuator:

$$\begin{aligned} \dot{x}_1 &= x_2 + h_1(x_1) \\ \dot{x}_2 &= u + \kappa_a(t, \bar{x}_2) + h_2(\bar{x}_2) \\ x_{i,a} &= x_i + \kappa_{i,s}(t, x_i) \end{aligned} \tag{48}$$

where $i = 1, 2$, $h_1 = x_1^2 \sin(x_1) + x_2$, and $h_2 = x_1 x_2 + x_2 \cos(x_1)$. Then, the injection data are given by $\kappa_{1,s} = (0.5 + \cos(1.2t))x_1$, $\kappa_{2,s} = (0.5 + \sin(1.8t))x_2$, and $\kappa_a = x_1 x_2 \cos(t)$. It is assumed that the inherent nonlinearities h_1 and h_2, and the injection data $\kappa_{1,s}$, $\kappa_{2,s}$, and κ_a are unknown. The initial values are set to $x_1(0) = 1.5$ and $x_2(0) = -1$ where $i = 1, 2$. The design parameters are selected as $\beta_1 = \beta_2 = 1$, $m_1 = 1$, $m_2 = 4$, $\iota_2 = 0.1$, $b_2 = 0.1$, $\tau_2 = 0.001$, $\lambda_1 = \lambda_2 = 0.02$, $\sigma_1 = \sigma_2 = 0.001$, $\alpha_2 = 0.5$, $m_{u,1} = 0.4$, and $m_{u,2} = 0.04$.

Fig. 1 shows the stabilization result and the event-triggered control input. Fig. 2 displays the outputs of RBFNNs and the injection data compensator. The inter-execution times and the cumulative number of events are displayed in Fig. 3. The total triggering number is 163 and thus only 1.087% of the total 15000 sampled data are used to implement the proposed adaptive controller. Thus, the control efforts can be reduced using the event-triggering laws. Although the corrupted state variables are only used in the controller and its event-triggering law, the proposed recursive event-triggered design against unknown injection data in full state measurements and an actuator achieves the stabilization of uncertain nonlinear strict-feedback systems.

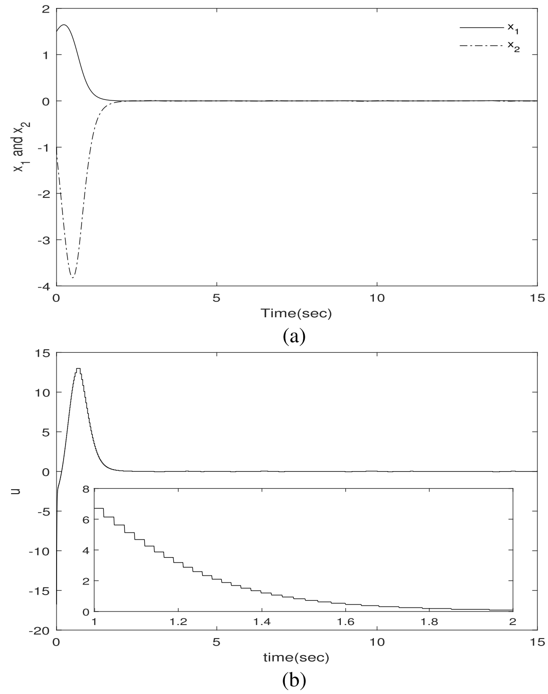

FIGURE 1. Control results and input for example 1 (a) x_1 and x_2 (b) u.

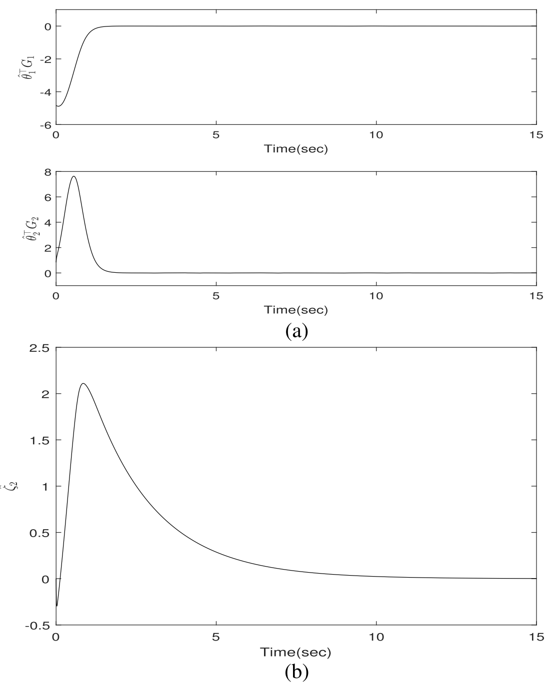

FIGURE 2. Outputs of RBFNNs and injection data compensator for example 1 (a) $\hat{\theta}_1^{\top} G_1$ and $\hat{\theta}_2^{\top} G_2$ (b) $\hat{\xi}_2$.

Example 2: The stabilization problem of the wing rock model with ailerons in the presence of unknown injection data

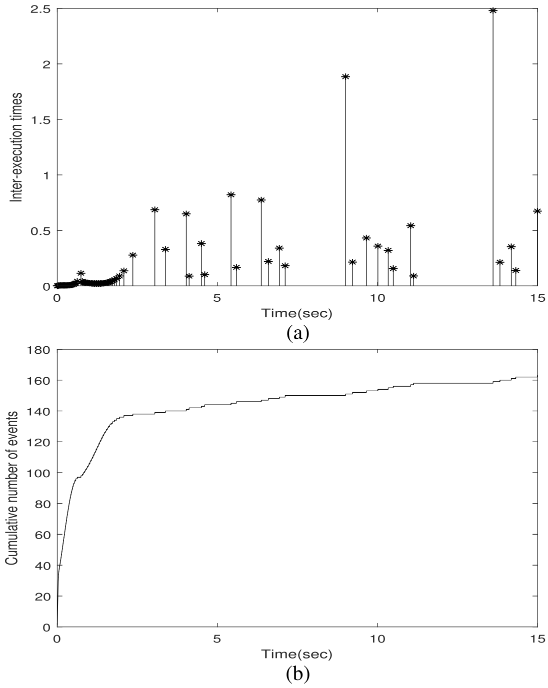

FIGURE 3. Inter-execution times and the cumulative number of events for example 1 (a) inter-execution times $t_{l+1} - t_l$ (b) the cumulative number of events.

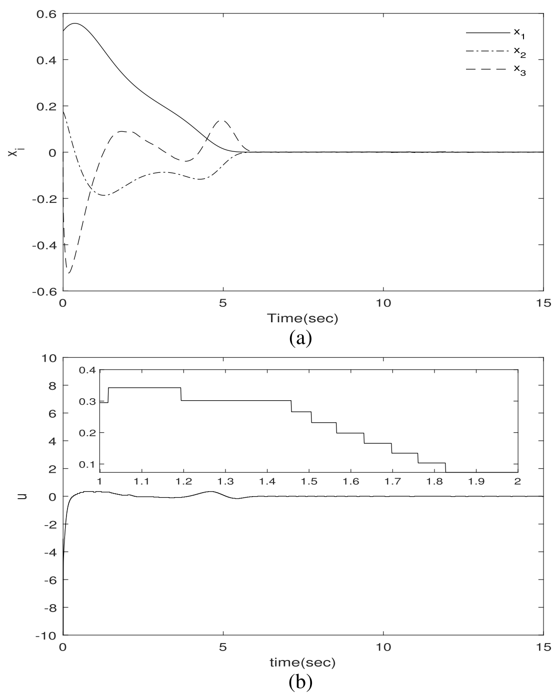

FIGURE 4. Control results and input for example 2 (a) x_i, $i = 1, 2, 3$ (b) u.

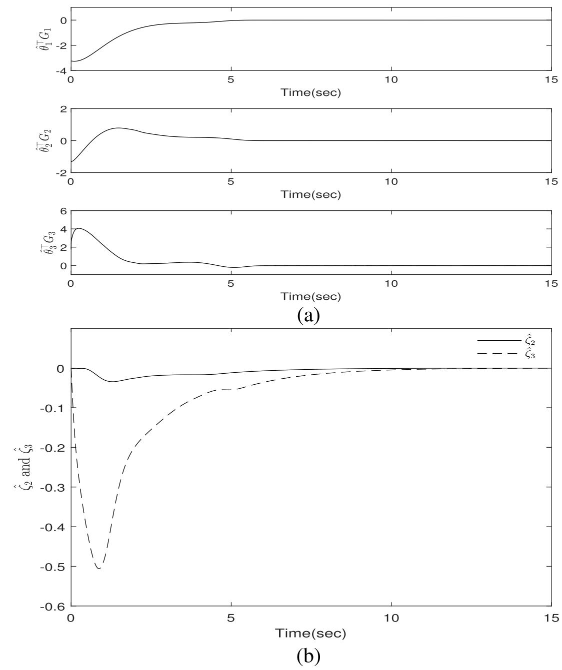

FIGURE 5. Outputs of RBFNNs and injection data compensators for example 2 (a) $\hat{\theta}_1^\top G_1$, $\hat{\theta}_2^\top G_2$, and $\hat{\theta}_3^\top G_3$ (b) $\hat{\xi}_2$ and $\hat{\xi}_3$.

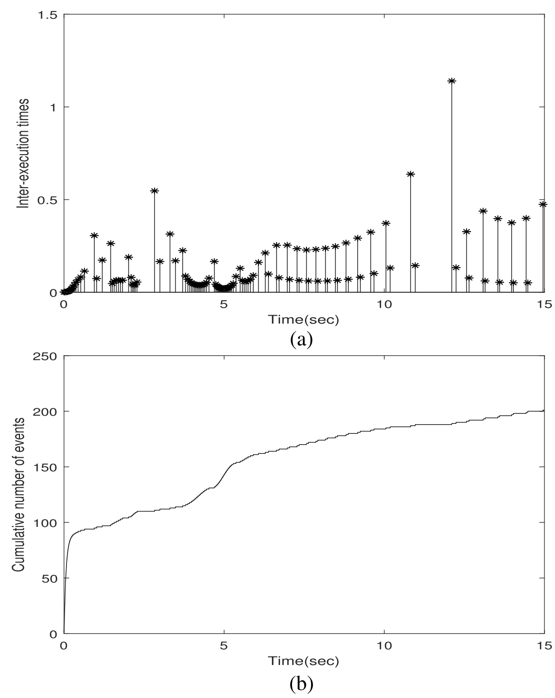

FIGURE 6. Inter-execution times and the cumulative number of events for example 2 (a) inter-execution times $t_{l+1} - t_l$ (b) the cumulative number of events.

in full state measurements and an actuator is considered in this example. The model dynamics is described by

$$
\begin{aligned}
\dot{x}_1 &= x_2 + h_1(x_1) \\
\dot{x}_2 &= x_3 + h_2(\bar{x}_2) \\
\dot{x}_3 &= u + \kappa_a(t, \bar{x}_3) + h_3(\bar{x}_3) \\
x_{i,a} &= x_i + \kappa_{i,s}(t, x_i)
\end{aligned} \tag{49}
$$

where $i = 1, 2, 3$, x_1 is the roll angle, x_2 is the roll rate, x_3 is the aileron deflection angle, $h_1 = 0$,

$h_2 = p_1x_1 + p_2x_2 + p_3|x_1|x_2 + p_4|x_2|x_2 + p_5x_1^3$, and $h_3 = -x_3$. Here, the model parameters of the delta wing for a 25^o angle of attack are set to $p_1 = -0.01859521$, $p_2 = 0.015162375$, $p_3 = -0.06245153$, $p_4 = 0.00954708$, and $p_5 = 0.02145291$ [62]. The unknown injection data $\kappa_{1,s} = (1 + \cos(t))x_1$, $\kappa_{2,s} = (1 + \sin(t))x_2$, $\kappa_{3,s} = (1 + \sin(t))x_3$, and $\kappa_a = (x_1^2)x_3 \sin(x_2t)\cos(t)$ influence the system (49). It is assumed that h_2, h_3, $\kappa_{i,s}$, $i = 1, 2, 3$, and κ_a are unknown for the adaptive event-triggered control design. In the uncontrolled system (49) with $u = 0$, the roll angle x_1 is divergent for the large initial condition [62]. Thus, the large initial conditions are chosen as $x_1(0) = 0.52359$ rad, $x_2(0) = 0.17453$ rad, and $x_3(0) = 0$ rad. The design parameters for the proposed event-triggered controller are chosen as $\beta_i = 1$, $m_1 = 1$, $m_2 = m_3 = 5$, $\iota_2 = \iota_3 = 0.2$, $b_2 = b_3 = 0.1$, $\tau_2 = \tau_3 = 0.001$, $\lambda_1 = 0.06$, $\lambda_2 = \lambda_3 = 0.02$, $\sigma_i = 0.001$, $\alpha_2 = \alpha_3 = 0.5$, $m_{u,1} = 0.1$, and $m_{u,2} = 0.01$ where $i = 1, 2, 3$.

The control result and event-triggered input are displayed in Fig. 4. Fig. 5 shows the outputs of RBFNN and the injection data compensators. Fig. 6 displays the inter-execution times and the cumulative number of events where the total triggering number is 243. Therefore, only 1.62% of the 15000 sampled data are used to achieve good stabilization performance against unknown injection data in full state measurements and an actuator, and unknown system nonlinearities.

V. CONCLUSION

An adaptive event-triggered control approach has been proposed for uncertain nonlinear strict-feedback systems with unknown injection data in full state measurements and an actuator. The approximation-based adaptive controller and its event-triggering condition have been constructed using state variables corrupted by unknown injection data in full state measurements. To this end, auxiliary signals using corrupted state variables and dynamic injection data compensators using neural networks have been designed to compensate for unknown injection data effects. It has been shown that the proposed event-triggered control scheme using corrupted state variables ensures the convergence of the error surfaces using exactly measured state variables. Further extension to the decentralized resilient event-triggered control problem of interconnected nonlinear systems with unknown injection data is conceivable. This remains as a meaningful subject for future research.

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