

ADAPTIVE SELF-TRIGGERED SECURITY CONTROL FOR NONLINEAR CPSS UNDER INPUT SATURATION AND DECEPTION ATTACKS

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ABSTRACT. *This paper proposes the single-parameter-learning-method-based adaptive self-triggered resilient control strategy for nonlinear cyber-physical systems (CPSs) in presence of input saturation and deception attacks. In the design framework of the controller, by combining the single parameter learning method (SPLM) and backstepping method, the parameters with multiple unknown variables such as external disturbance, unknown sensor attack signals and weight vector are transformed into the form of only single parameter, which greatly reduces the algorithm complexity of the controller. In addition, the problem of complexity explosion can be solved according to command filtering method. Furthermore, the proposed adaptive self-triggered control scheme can not only solve the problem of continuous monitoring of the triggering threshold, but also the communication resources and performance of control in the CPSs can be coordinated. In the end, the effectiveness of the proposed control approach is presented via a practical example.*

Keywords: Nonlinear CPSs, Deception attacks, Single parameter learning method, Adaptive self-triggered control, Input saturation

1. Introduction. In past years, the system that uses networked space to manipulate a physical entity remotely, reliably, in real time, securely, and collaboratively through human-computer interaction interfaces with physical processes is known as cyber-physical systems (CPSs). Due to the integration of the physical world and the information world, the CPSs play an irreplaceable role in many practical engineering and critical facilities, such as network control systems, power systems and transportation systems [1, 2, 3]. Nevertheless, the communication between different physical elements in CPSs is delivered through wireless channels, and the wireless channels are vulnerable to malicious attackers,

which renders the performance of the studied control system degraded or even unstable, which thus potentially lead to unpredictable losses. Generally, the attack types can be divided into deception attacks [4, 5], replay attacks [6] and denial-of-service attacks [7]. The first one is to send false data information to the user's real sensor to block the communication channel such that the users cannot obtain the required information; the second is that repeatedly transmitting and receiving the same information makes the system unstable; the third type is to block the communication channel so that users do not get the information they need. Thus, how to maintain a certain performance for systems under attacks has become a wide range of industry research.

Note that the system is attacked by unknown attack signals, which makes the original state information will become unavailable in the design of the controller, and at this time only the post-attack state information can be embedded in the framework of adaptive control. Therefore, how to ensure the stability of the system against deception attacks is difficult. There have been a lot of research results on system against deception attacks in the literature. A dynamic surface technique based on neural network and a sensor compensation mechanism have been designed for the uncertain system with nonlinear time-delay to eliminate the impact caused by sensor attacks [5]. Note that a new coordinate transformation was proposed for non-strict feedback nonlinear CPSs with time-delay to deal with actuator faults and malicious deception attacks [8]. However, the aforementioned results need multiple parameters to estimate different adaptive laws, which greatly increases the complexity of controller design. Therefore, it is a challenge to design a low-complexity design algorithm program in order to reduce the complexity of the design algorithm. On the other hand, it should be noted that the many practical systems possess constraints on their inputs or states, which make it impossible to directly use input or state in controller design. The problem of adaptive fuzzy control for uncertain nonlinear systems with input saturation based on a designed auxiliary system was investigated in [9]. Moreover, event-triggered mechanism (ETM) has been widely studied as an effective control method to reduce the load of communication transmission [10]. Its essence is to generate aperiodic time series by constructing appropriate trigger condition to reduce the resource consumption of the corresponding channel. However, due to the fact that the ETM requires continuous monitoring of measurement errors by hardware, this is a challenge to implement in practice. To address this obstacle, a self-triggered strategy has been proposed in [11]. Unfortunately, there are few results about self-triggered adaptive resilient control of nonlinear CPSs in the presence of input saturation and deception attacks.

Inspired by the above discussion, this paper mainly focuses on solving the problem of adaptive self-triggered resilient control for nonlinear CPSs in the presence of input saturation and deception attacks. The contributions of this paper are as follows.

- This paper investigates a novel adaptive self-triggered resilient control scheme for nonlinear CPSs with input saturation and deception attacks. Compared with [4, 5] with multiple unknown parameters to be estimated, the SPLM is incorporated into the nonlinear CPSs with input saturation and deception attacks. Specifically, the unknown sensor attack signals, external disturbance and weight vector are transformed into the form of only single parameter, which will greatly reduce the complexity of the controller design algorithm.
- Due to the fact that the CPSs are threatened by sensor attacks, which makes the information of original state unavailable, in order to make the system more robust, the state information of post-attack is adopted to construct a novel coordinate transformation to deal with the unavailable state.

- The self-triggered mechanism is embedded to reduce the load of communication transmission. Compared with the ETM [10], the self-triggered mechanism does not need to continuously monitor the event error, and achieves a good tradeoff between the utilization of communication bandwidth and system performance.

The rest of the paper is arranged as follows. In Section 2, the system model and some preliminaries are presented. In Section 3, the adaptive self-triggered control scheme and stability analysis are given. Section 4 shows a simulation study for verification. Finally, the conclusions are given in Section 5.

2. Preliminaries.

2.1. CPSs with input saturation. Consider a class of the nonlinear CPSs with input saturation as

$$\begin{aligned}\dot{x}_1 &= x_2 + g_1(x_1) + w_1(t), \\ \dot{x}_i &= x_{i+1} + g_i(\bar{x}_i) + w_i(t), \quad i = 2, \dots, n-1, \\ \dot{x}_n &= \nu(u(t)) + g_n(\bar{x}_n) + w_n(t),\end{aligned}\tag{1}$$

where $\bar{x}_i = [x_1, \dots, x_i]^T \in R^i$ is state variable of system, $\nu(u(t)) \in R$ is system input, $g_i(\bar{x}_i) : R^i \rightarrow R$ represents unknown nonlinear smooth function and $w_i(t)$ stands for external disturbance.

Assumption 2.1. *The disturbance $w_i(t)$ is bounded by a positive constant $\bar{w}_i$, i.e., $|w_i(t)| \leq \bar{w}_i$.*

In this work, the input saturation model, which is greatly investigated in [9], can be defined as

$$\nu(u(t)) = \text{Sat}(u(t)) = \begin{cases} u(t), & |u(t)| \leq \nu_M \\ \text{sign}(u(t))\nu_M, & |u(t)| > \nu_M \end{cases},\tag{2}$$

where ν_M is the bound of $u(t)$. It is clear that the relation between the operated control input $\nu(u(t))$ and the control input $u(t)$ has a sharp corner when $\nu(u(t)) = \nu_M$. Therefore, $\nu(u(t))$ cannot be used directly in the frame of the backstepping design. In accordance with [9], the input saturation can be approximated by a smooth function as

$$q(u) = \tanh\left(\frac{u}{\nu_M}\right) \times \nu_M = \frac{e^{\frac{u}{\nu_M}} - e^{-\frac{u}{\nu_M}}}{e^{\frac{u}{\nu_M}} + e^{-\frac{u}{\nu_M}}} \nu_M.\tag{3}$$

Furthermore, $\text{Sat}(u(t))$ in (2) can be reformulated as $\text{Sat}(u) = q(u) + p(u) = \tanh\left(\frac{u}{\nu_M}\right) \times \nu_M + p(u)$, where $p(u) = \text{Sat}(u) - q(u)$ is a bounded function and it can be written as $|p(u)| = |\text{Sat}(u) - q(u)| \leq (1 - \tanh(1)) \bullet \nu_M = \bar{C}$. It is obvious that in $0 \leq |u| \leq \nu_M$ the bound $p(u)$ decreases from $\bar{C}$ to 0 as u changes from ν_M to 0, and beyond the range the bound $p(u)$ increases from 0 to $\bar{C}$.

Remark 2.1. *It should be noted that if system (1) does not consider deception attacks and input saturation, in which case the system state is available in the frame of backstepping, it will be a nonlinear system as investigated in [12]. However, this article will study nonlinear CPSs with deception attacks and input saturation, in which system states are unmeasurable for controller synthesis. Therefore, the stability of the closed-loop system (CLS) will become more challenging compared with [12].*

Remark 2.2. *Deception attacks destabilize CPSs by injecting false signals, and mitigating stronger attacks demands larger control inputs. However, practical actuators are constrained by input saturation, limiting the available compensation input. Thus, they are analyzed simultaneously to ensure the control scheme's resilience and practicality.*

2.2. Deception attacks. The state attacked by the deception attacks can be defined as follows:

$$\tilde{x}_i = x_i + \theta_i x_i = \zeta_i x_i, \quad i = 1, \dots, n, \quad (4)$$

where $\tilde{x}_i$ is the available state of system by attacks and θ_i is the type of deception attacks, which is time-varying signal. According to (4), one can obtain that $\zeta_i = 1 + \theta_i$.

Assumption 2.2. We assume that the attack signal θ_i is an unknown but bounded time-varying signal and the signal ζ_i satisfies $\zeta_i > 0$. Furthermore, we assume that there exist unknown positive upper bound constants $\bar{\zeta}_i$ and $\tilde{\zeta}_i$ such that $|\zeta_i| \leq \bar{\zeta}_i$ and $|\dot{\zeta}_i| \leq \tilde{\zeta}_i$, respectively.

Lemma 2.1. For any variables $\Lambda, \Xi \in R$, the following inequality holds:

$$\Lambda^T \Xi \leq \frac{s^{\lambda_1}}{\lambda_1} \|\Lambda\|^{\lambda_1} + \frac{1}{\lambda_2 s^{\lambda_2}} \|\Xi\|^{\lambda_2}, \quad (5)$$

where s , λ_1 and λ_2 are positive constants.

3. Main Results. In this section, different from the previous results [9, 12] with the continuous control, the adaptive self-triggered resilient control for nonlinear CPSs based on single-parameter learning method and framework of backstepping was proposed, which transforms the deception attack and uncertain disturbance into a form with single parameter, which renders the computation greatly reduced. In addition, the stability analysis proves that all signals of the CLS are bounded.

3.1. Controller design. Considering the following coordinate transformations as

$$\begin{aligned} r_1 &= \tilde{x}_1, \\ r_i &= \tilde{x}_i - \lambda_i, \quad i = 2, \dots, n-1, \\ r_n &= \tilde{x}_n - \lambda_n - \varsigma, \end{aligned} \quad (6)$$

where r_i is an error surface, and ς will be given later. λ_i is a new variable constructed by a first-order filter, which can be expressed as $a_i \dot{\lambda}_i + \lambda_i = \alpha_{i-1}$ and $\lambda_i(0) = \alpha_{i-1}(0)$, where $a_i > 0$ is a constant, and α_i is the constructed virtual controller. Moreover, we define the $e_i = \lambda_i - \alpha_{i-1}$, and one has $\dot{\lambda}_i = -\frac{e_i}{a_i}$.

Step 1: From (1) and (6), one has

$$\dot{r}_1 = \dot{\zeta}_1 \zeta_1^{-1} \tilde{x}_1 + \zeta_1 \zeta_2^{-1} r_2 + \zeta_1 \zeta_2^{-1} e_2 + \zeta_1 \zeta_2^{-1} \alpha_1 + \zeta_1 g_1(\zeta_1^{-1} \tilde{x}_1) + \zeta_1 w_1(t). \quad (7)$$

In accordance with Lemma 2.1 in [13], we have

$$g_1(\zeta_1^{-1} \tilde{x}_1) \leq h_1(\zeta_1^{-1}) \tilde{g}_1(\tilde{x}_1), \quad (8)$$

where $h_1(\zeta_1^{-1})$ and $\tilde{g}_1(\tilde{x}_1)$ are smooth functions.

According to the approximation properties of FLS, $\tilde{g}_1(\tilde{x}_1)$ can be written as

$$\tilde{g}_1(\tilde{x}_1) = \xi_1^T \sigma_1(\tilde{x}_1) + \varepsilon_1. \quad (9)$$

Let $\aleph_1 = \dot{\zeta}_1 \zeta_1^{-1} \tilde{x}_1 + \zeta_1 h_1(\zeta_1^{-1}) [\xi_1^T \sigma_1(\tilde{x}_1) + \varepsilon_1] + \zeta_1 w_1(t)$. According to Lemma 2.1, we have

$$\|\aleph_1\| \leq \left| \dot{\zeta}_1 \zeta_1^{-1} \right| |\tilde{x}_1| + |\zeta_1 h_1(\zeta_1^{-1})| \|\xi_1\| \|\sigma_1(\tilde{x}_1)\| + |\zeta_1 h_1(\zeta_1^{-1})| \bar{\varepsilon}_1 + \zeta_1 \bar{w}_1 \leq \varphi_1 \vartheta_1(v_1), \quad (10)$$

where $\varphi_1 = \max \left\{ \left| \dot{\zeta}_1 \zeta_1^{-1} \right|, |\zeta_1 h_1(\zeta_1^{-1})| \|\xi_1\|, |\zeta_1 h_1(\zeta_1^{-1})| \bar{\varepsilon}_1 + \zeta_1 \bar{w}_1 \right\}$ and $\vartheta_1(v_1) = |\tilde{x}_1| + \|\sigma_1(\tilde{x}_1)\| + 1$ with $v_1 = \tilde{x}_1$. In accordance with Lemma 2 in [14] and Assumptions 2.1 and 2.2, we can get that $\dot{\zeta}_1$ and ζ_1^{-1} are bounded, i.e., φ_1 is a constant.

Remark 3.1. According to a series of operations (7)-(10), the multiple uncertain parameters have been transformed into a linear parameterized form with single parameter. The result of this process is to greatly reduce the complexity of the controller design algorithm.

In accordance with (7) and (10), we have

$$r_1 \dot{r}_1 \leq |r_1| \varphi_1 \vartheta_1(v_1) + r_1 \zeta_1 \zeta_2^{-1} r_2 + r_1 \zeta_1 \zeta_2^{-1} \alpha_1 + r_1 \zeta_1 \zeta_2^{-1} e_2. \quad (11)$$

Further, in line with Lemma 2.1, the first term $|r_1| \varphi_1 \vartheta_1(v_1)$ in (11) can be evaluated as

$$|r_1| \varphi_1 \vartheta_1(v_1) \leq k_1 \varphi_1 r_1^2 \vartheta_1^2(v_1) + \frac{\varphi_1}{4k_1}, \quad (12)$$

where $k_1 > 0$ is a constant.

The virtual controller α_1 and the adaptive law $\dot{\hat{\varphi}}_1$ are designed as follows:

$$\alpha_1 = -c_1 r_1 - k_1 \hat{\varphi}_1 r_1 \vartheta_1^2(v_1), \quad (13)$$

$$\dot{\hat{\varphi}}_1 = k_1 r_1^2 \vartheta_1^2(v_1) - \rho_1 \hat{\varphi}_1, \quad (14)$$

where $c_1 > 0$ and $\rho_1 > 0$ are constants. In accordance with Assumption 2.2, we can get that there exist two positive constants ϕ_1 and $\bar{\phi}_1$ such that $\phi_1 \leq |\zeta_i \zeta_{i+1}^{-1}| \leq \bar{\phi}_1$.

The Lyapunov function is constructed as

$$V_1 = \frac{1}{2} r_1^2 + \frac{1}{2\phi_1} (\varphi_1 - \phi_1 \hat{\varphi}_1)^2 + \frac{1}{2} e_2^2. \quad (15)$$

From (13) and (14), the derivative of V_1 satisfies

$$\begin{aligned} \dot{V}_1 &\leq r_1 \zeta_1 \zeta_2^{-1} r_2 - c_1 \phi_1 r_1^2 + r_1 \zeta_1 \zeta_2^{-1} e_2 + k_1 (\varphi_1 - \phi_1 \hat{\varphi}_1) r_1^2 \vartheta_1^2(v_1) + \rho_1 (\varphi_1 - \phi_1 \hat{\varphi}_1) \hat{\varphi}_1 \\ &\quad - k_1 (\varphi_1 - \phi_1 \hat{\varphi}_1) r_1^2 \vartheta_1^2(v_1) + e_2 \dot{e}_2 + \frac{\varphi_1}{4k_1}. \end{aligned} \quad (16)$$

In accordance with (6), we have $\dot{e}_2 = -\frac{e_2}{a_2} - M_1(\tilde{x}_1, \hat{\varphi}_1, v_1)$ with $M_1 = \dot{\alpha}_1$. From Lemma 2 in [14], M_1 is bounded by an upper bound $\bar{M}_1$. Furthermore, in accordance with Lemma 2.1, we have

$$e_2 M_1 \leq \frac{1}{2} e_2^2 + \frac{1}{2} \bar{M}_1^2, \quad r_1 \zeta_1 \zeta_2^{-1} e_2 \leq \frac{1}{2} \phi_1 r_1^2 + \frac{1}{2\phi_1} \bar{\phi}_1^2 e_2^2, \quad (17)$$

$$\rho_1 (\varphi_1 - \phi_1 \hat{\varphi}_1) \hat{\varphi}_1 \leq -\frac{1}{2} \rho_1 \phi_1^{-1} (\varphi_1 - \phi_1 \hat{\varphi}_1)^2 + \frac{1}{2} \rho_1 \phi_1^{-1} \varphi_1^2. \quad (18)$$

Combining (16)-(18), one has

$$\begin{aligned} \dot{V} &\leq -\left(c_1 - \frac{1}{2}\right) \phi_1 r_1^2 - \frac{1}{2} \rho_1 \phi_1^{-1} (\varphi_1 - \phi_1 \hat{\varphi}_1)^2 - \left(\frac{1}{a_2} - \frac{1}{2} - \frac{1}{2\phi_1} \bar{\phi}_1^2\right) e_2^2 \\ &\quad + r_1 \zeta_1 \zeta_2^{-1} r_2 + \frac{\varphi_1}{4k_1} + \frac{1}{2} \bar{M}_1^2 + \frac{1}{2} \rho_1 \phi_1^{-1} \varphi_1^2. \end{aligned} \quad (19)$$

Step i: Let $\mathfrak{S}_i = \text{diag}(\zeta_1^{-1}, \zeta_2^{-1}, \dots, \zeta_i^{-1})$, according to (1) and (6), we have

$$\dot{r}_i = \dot{\zeta}_i \zeta_i^{-1} \tilde{x}_i + \zeta_i \zeta_{i+1}^{-1} r_{i+1} + \zeta_i \zeta_{i+1}^{-1} e_{i+1} + \zeta_i \zeta_{i+1}^{-1} \alpha_i + \zeta_i g_i(\mathfrak{S}_i \tilde{x}_i) + \zeta_i w_i(t) - \dot{\lambda}_i. \quad (20)$$

With similar way in (8), one has $g_i(\mathfrak{S}_i \tilde{x}_i) \leq h_i(\mathfrak{S}_i) \tilde{g}_i(\tilde{x}_i)$, it is obvious that the nonlinear function $\tilde{g}_i(\tilde{x}_i)$ is available, and employing the properties of FLS, one has $\tilde{g}_i(\tilde{x}_i) = \xi_i^T \sigma_i(\tilde{x}_i) + \varepsilon_i$.

Let $\mathfrak{N}_i = \dot{\zeta}_i \zeta_i^{-1} \bar{x}_i + \zeta_i h_i(\mathfrak{S}_i) \xi_i^T \sigma_i(\bar{x}_i) + \zeta_i h_i(\mathfrak{S}_i) \varepsilon_i + \zeta_i w_i(t) - \dot{\lambda}_i + r_{i-1} \zeta_{i-1} \zeta_i^{-1}$. In accordance with Assumption 2.1, we have

$$\begin{aligned} \|\mathfrak{N}_i\| &\leq \left| \dot{\zeta}_i \zeta_i^{-1} \right| |\bar{x}_i| + |\zeta_i h_i(\mathfrak{S}_i)| \|\xi_i\| \left\| \sigma_i(\bar{x}_i) \right\| + |\zeta_i h_i(\mathfrak{S}_i)| \bar{\varepsilon}_i + \zeta_i \bar{w}_i + \tilde{\lambda}_i + |r_{i-1}| |\zeta_{i-1} \zeta_i^{-1}| \\ &\leq \varphi_i \vartheta_i(v_i), \end{aligned} \quad (21)$$

where $\varphi_i = \max \left\{ \left| \dot{\zeta}_i \zeta_i^{-1} \right|, |\zeta_i h_i(\mathfrak{S}_i)| \|\xi_i\|, |\zeta_i h_i(\mathfrak{S}_i)| \bar{\varepsilon}_i + \zeta_i \bar{w}_i + \tilde{\lambda}_i, |\zeta_{i-1} \zeta_i^{-1}| \right\}$, $\vartheta_i(v_i) = \left| \bar{x}_i \right| + \left\| \sigma_i(\bar{x}_i) \right\| + 1 + |r_{i-1}|$ with $v_i = \left[\bar{x}_i^T, r_{i-1} \right]^T$ and $\tilde{\lambda}_i > 0$ is a constant such that $\left| \dot{\lambda}_i \right| \leq \tilde{\lambda}_i$. Furthermore, one can obtain that φ_i is also a constant.

In accordance with (20) and (21), one can get

$$r_i \dot{r}_i \leq |r_i| \varphi_i \vartheta_i(v_i) + r_i \zeta_i \zeta_{i+1}^{-1} r_{i+1} + r_i \zeta_i \zeta_{i+1}^{-1} \alpha_i + r_i \zeta_i \zeta_{i+1}^{-1} e_{i+1} - r_{i-1} \zeta_{i-1} \zeta_i^{-1} r_i. \quad (22)$$

The virtual control α_i and adaptive law $\dot{\hat{\varphi}}_i$ are designed as

$$\alpha_i = -c_i r_i - k_i \hat{\varphi}_i r_i \vartheta_i^2(v_i), \quad (23)$$

$$\dot{\hat{\varphi}}_i = k_i r_i^2 \vartheta_i^2(v_i) - \rho_i \hat{\varphi}_i, \quad (24)$$

where $c_i > 0$ and $\rho_i > 0$ are constants.

Substituting (23) and (24) into (22) leads to

$$\begin{aligned} r_i \dot{r}_i &\leq r_i \zeta_i \zeta_{i+1}^{-1} r_{i+1} - c_i \phi_i r_i^2 + r_i \zeta_i \zeta_{i+1}^{-1} e_{i+1} - r_{i-1} \zeta_{i-1} \zeta_i^{-1} r_i + k_i (\varphi_i - \phi_i \hat{\varphi}_i) r_i^2 \vartheta_i^2(v_i) \\ &\quad + \frac{\varphi_i}{4k_i}. \end{aligned} \quad (25)$$

The following Lyapunov function is constructed:

$$V_i = V_{i-1} + \frac{1}{2} r_i^2 + \frac{1}{2\phi_i} (\varphi_i - \phi_i \hat{\varphi}_i)^2 + \frac{1}{2} e_{i+1}^2. \quad (26)$$

From (25) and (26), the derivative of V_i is calculated as

$$\begin{aligned} \dot{V}_i &\leq - \sum_{z=1}^i \left[\left(c_z - \frac{1}{2} \right) \phi_z r_z^2 + \frac{1}{2} \rho_z \phi_z^{-1} (\varphi_z - \phi_z \hat{\varphi}_z)^2 + \left(\frac{1}{a_{z+1}} - \frac{1}{2} - \frac{1}{2\phi_z} \bar{\phi}_z^2 \right) e_{z+1}^2 \right] \\ &\quad + \sum_{z=1}^i \left[\frac{\varphi_z}{4k_z} + \frac{1}{2} \bar{M}_z^2 + \frac{1}{2} \rho_z \phi_z^{-1} \varphi_z^2 \right] + r_z \zeta_z \zeta_{z+1}^{-1} r_{z+1}. \end{aligned} \quad (27)$$

Step n: Let $\mathfrak{S}_n = \text{diag}(\zeta_1^{-1}, \zeta_2^{-1}, \dots, \zeta_n^{-1})$, according to (1) and (6), we have

$$\dot{r}_n = \dot{\zeta}_n \zeta_n^{-1} \bar{x}_n + \zeta_n \tau(u) + \zeta_n g_n(\mathfrak{S}_n \bar{x}_n) + \zeta_n w_n(t) - \dot{\lambda}_n - \varsigma. \quad (28)$$

Furthermore, we can derive $g_n(\mathfrak{S}_n \bar{x}_n) \leq h_n(\mathfrak{S}_n) \tilde{g}_n(\bar{x}_n)$. Then, $\tilde{g}_n(\bar{x}_n)$ can be reformulated as

$$\tilde{g}_n(\bar{x}_n) = \xi_n^T \sigma_n(\bar{x}_n) + \varepsilon_n. \quad (29)$$

Define the following dynamic system:

$$\dot{\varsigma} = -\varsigma + \zeta_n(q(u) - u). \quad (30)$$

In accordance with (29) and (30), (28) can be written as

$$\begin{aligned} \dot{r}_n &= \dot{\zeta}_n \zeta_n^{-1} \bar{x}_n + \zeta_n q(u) + \zeta_n h_n(\mathfrak{S}_n) \xi_n^T \sigma_n(\bar{x}_n) + \zeta_n h_n(\mathfrak{S}_n) \varepsilon_n + \zeta_n w_n(t) - \dot{\lambda}_n + \varsigma \\ &\quad - \zeta_n(q(u) - u). \end{aligned} \quad (31)$$

Let $\aleph_n = \dot{\zeta}_n \zeta_n^{-1} \tilde{x}_n + \zeta_n h_n(\mathfrak{S}_n) \xi_n^T \sigma_n(\tilde{x}_n) + \zeta_n h_n(\mathfrak{S}_n) \varepsilon_n + \zeta_n w_n(t) - \dot{\lambda}_n + \varsigma + r_{n-1} \zeta_{n-1} \zeta_n^{-1}$. In accordance with Assumption 2.1, we have

$$\begin{aligned} \|\aleph_n\| &\leq \left| \dot{\zeta}_n \zeta_n^{-1} \right| |\tilde{x}_n| + |\zeta_n h_n(\mathfrak{S}_n)| \|\xi_n\| \left\| \sigma_n(\tilde{x}_n) \right\| + |\zeta_n h_n(\mathfrak{S}_n)| \bar{\varepsilon}_n + \zeta_n \bar{w}_n + \tilde{\lambda}_n + |\varsigma| \\ &\quad + |r_{n-1}| |\zeta_{n-1} \zeta_n^{-1}| \\ &\leq \varphi_n \vartheta_n(v_n), \end{aligned} \quad (32)$$

where $\varphi_n = \max \left\{ \left| \dot{\zeta}_n \zeta_n^{-1} \right|, |\zeta_n h_n(\mathfrak{S}_n)| \|\xi_n\|, |\zeta_n h_n(\mathfrak{S}_n)| \bar{\varepsilon}_n + \zeta_n \bar{w}_n + \tilde{\lambda}_n + |\varsigma|, |\zeta_{n-1} \zeta_n^{-1}| \right\}$, $\vartheta_n(v_n) = |\tilde{x}_n| + \left\| \sigma_n(\tilde{x}_n) \right\| + 1 + |r_{n-1}|$ with $v_n = \left[\tilde{x}_n^T, r_{n-1} \right]^T$ and $\tilde{\lambda}_n > 0$ is a constant such that $|\lambda_n| \leq \tilde{\lambda}_n$. Furthermore, we can obtain that φ_n is also a constant.

In accordance with (28) and (32), we have

$$r_n \dot{r}_n \leq |r_n| \varphi_n \vartheta_n(v_n) + r_n \zeta_n u - r_{n-1} \zeta_{n-1} \zeta_n^{-1} r_n. \quad (33)$$

The control command u_0 and the adaptive law $\hat{\varphi}_n$ are designed as

$$u_0 = -c_n r_n - k_n r_n \hat{\varphi}_n \vartheta_n^2(v_n), \quad (34)$$

$$\dot{\hat{\varphi}}_n = k_n r_n^2 \vartheta_n^2(v_n) - \rho_n \hat{\varphi}_n, \quad (35)$$

where $c_n > 0$ and $\rho_n > 0$ are constants.

The self-triggered strategy is given as

$$u(t) = u_0(t_k), \quad \forall t \in [t_k, t_{k+1}), \quad (36)$$

$$t_{k+1} = t_k + \frac{\iota |u(t)| + \Delta}{\max\{\Upsilon, |\tilde{u}(t)|\}}, \quad (37)$$

where $0 < \iota < 1$, Δ and Υ are positive constants. Δ and $|\tilde{u}(t)|$ are change rates of control signal interval; $\iota |u(t)| + \Delta$ stands for control signal interval between two successive triggered instants and $\tilde{u}(t) = \dot{u}_0(t)|_{t=t_k}$.

When (37) is triggered, $u(t) = u_0(t_k)$ will be applied to the system (1) at once. The next trigger point t_{k+1} will be obtained, and control signal $u(t)$ holds as a constant $u_0(t_k)$ on the time interval $[t_k, t_{k+1})$.

According to (36) and (37), one can get $|u(t_{k+1}) - u(t)| \leq \iota |u(t)| + \Delta$. Let $\omega_1(t_k) = \omega_2(t_k) = 0$, $\omega_1(t_{k+1}) = \omega_2(t_{k+1}) = \pm 1$ and $|\omega_1(t)| \leq 1$, $\omega_2(t) \leq 1$, $\forall t \in t_k, t_{k+1}$. Further, one has

$$u(t) = \frac{u_0(t) - \omega_2(t) \Delta}{1 + \omega_1(t) \iota}, \quad t \in [t_k, t_{k+1}). \quad (38)$$

The total Lyapunov function is constructed as

$$V_n = V_{n-1} + \frac{1}{2} r_n^2 + \frac{1}{2 \phi_n} (\varphi_n - \phi_n \hat{\varphi}_n)^2. \quad (39)$$

According to (33)-(35), the derivative of V_n satisfies

$$\dot{V}_n \leq \dot{V}_{n-1} + r_n \zeta_n (u - u_0) - c_n \phi_n r_n^2 - r_{n-1} \zeta_{n-1} \zeta_n r_n + \rho_n (\varphi_n - \phi_n \hat{\varphi}_n) \hat{\varphi}_n + \frac{\varphi_n}{4k_n}. \quad (40)$$

In accordance with Assumption 2.2 and self-triggered strategy, there exists a positive constant such that $|u - u_0| \leq \mu$, i.e., $r_n \zeta_n (u - u_0) \leq |r_n| \phi_n \mu$. In addition, using Lemma 2.1, one has

$$r_n \phi_n \mu \leq \frac{\phi_n}{2} r_n^2 + \frac{\bar{\phi}_n^2}{2 \phi_n} \mu^2, \quad (41)$$

$$\rho_n (\varphi_n - \phi_n \hat{\varphi}_n) \hat{\varphi}_n \leq -\frac{1}{2} \rho_n \phi_n^{-1} (\varphi_n - \phi_n \hat{\varphi}_n)^2 + \frac{1}{2} \rho_n \phi_n^{-1} \varphi_n^2. \quad (42)$$

Substituting (41) and (42) into (40) leads to

$$\begin{aligned} \dot{V}_n &\leq \sum_{z=1}^n \left[\left(c_z - \frac{1}{2} \right) \phi_z r_z^2 + \rho_z \phi_z^{-1} (\varphi_z - \phi_z \hat{\varphi}_z)^2 \right] + \sum_{z=1}^{n-1} \left[\left(a_{z+1}^{-1} - \frac{1}{2} - \frac{1}{2} \rho_z \phi_z^{-1} \right) e_{z+1}^2 \right] \\ &\quad + \sum_{z=1}^n \left[\frac{1}{2} \rho_z \phi_z^{-1} \hat{\varphi}_z^2 + \frac{\varphi_z}{4k_z} \right] + \sum_{z=1}^{n-1} \frac{1}{2} \bar{M}_z^2 + \frac{\bar{\varphi}_n^2}{2\phi_n} \mu^2 \\ &\leq -\bar{A}V_n + A_0, \end{aligned} \quad (43)$$

where $\bar{A} = \min \left\{ \left(2c_z - \frac{1}{2} \right) \phi_z, \rho_z, 2a_{z+1}^{-1} - \rho_z \phi_z^{-1} - 1 \right\}$, $A_0 = \sum_{z=1}^n \left[\frac{1}{2} \rho_z \phi_z^{-1} \hat{\varphi}_z^2 + \frac{\varphi_z}{4k_z} \right] + \sum_{z=1}^{n-1} \frac{1}{2} \bar{M}_z^2 + \frac{\bar{\varphi}_n^2}{2\phi_n} \mu^2$ and $\phi_n = \zeta_n$.

3.2. Stability analysis.

Theorem 3.1. *Considering the nonlinear CPSs (1) with input saturation and unknown deception attacks under Assumptions 2.1 and 2.2, the SPLM-based adaptive self-triggered resilient control scheme with the virtual laws (13) and (23), the adaptive laws (14), (24) and (35), and the self-triggered strategy (36) and (37) can ensure that all the signals in the CLS are bounded and the Zeno phenomenon is avoided.*

Proof: By using Inequation (43) and integrating both sides of Inequation (43) with respect to time, we have

$$V_n \leq \left(V_n(0) - \frac{A_0}{\bar{A}} \right) e^{-\bar{A}t} + \frac{A_0}{\bar{A}}. \quad (44)$$

In accordance with (44) and stability theory of Lyapunov function, one can get that $V_n \leq \frac{A_0}{\bar{A}}$ as $t \rightarrow \infty$ and V_n is bounded. Moreover, according to (39), we can obtain that r_i , $\varphi_i - \phi_i \hat{\varphi}_i$ and e_{i+1} are bounded, and due to the boundedness of the weight φ_i , we can further get the boundedness of $\hat{\varphi}_i$. In accordance with (6), the boundedness of available state $\tilde{x}_1$ can be induced from the boundedness of r_1 . Furthermore, according to the boundedness of r_1 and $\hat{\varphi}_1$, we can get that v_1 and α_1 are bounded, which implies that variables of filter λ_2 and $\hat{\lambda}_2$ are bounded. In a similar procedure, r_i , e_i , φ_i , λ_i and $\hat{\lambda}_i$ as well as α_{i+1} are also bounded. Additionally, according to the boundedness of r_n , λ_n , $\hat{\lambda}_n$ and φ_n , we can deduce that $\tilde{x}_n$ and v_n are bounded. Finally, the boundedness of u_0 can be rolled out. Thus, all signals in CLS can be ensured to be bounded.

The next step is to show that Zeno phenomenon does not happen. Note that the boundedness of control command u is guaranteed, and the item $(\iota|u(t)| + \Delta) / \max\{\Upsilon, |\tilde{u}(t)|\}$ can be ensured to be bounded. Therefore, the lower bounded of the time interval $\tilde{t}$ satisfies $\tilde{t} = t_{k+1} - t_k > 0$, that is, the Zeno phenomenon is avoided. $\square$

Remark 3.2. *Compared with multi-parameter estimation in [5, 8], our SPLM reduces computational complexity by converting multiple unknowns into one parameter, while ensuring closed-loop system boundedness under deception attacks. Unlike event-triggered mechanisms in [10, 11] requiring continuous monitoring, our self-triggered mechanism guarantees a positive lower bound for inter-trigger intervals, avoiding continuous detection and saving communication resources for CPSs.*

4. Simulation Example. In this section, a two-stage chemical reactor system is considered [5]:

$$\dot{x}_1 = - \left(W_1 + \frac{1}{M_1} \right) x_1 + \frac{1 - L_1}{B_1} x_2 + w_1,$$

$$\dot{x}_2 = -W_2 x_2 - \frac{1}{M_1} x_2^2 - \frac{2K_e}{M_2} + \frac{B_f}{B_2} \nu(u(t)) + w_2, \quad (45)$$

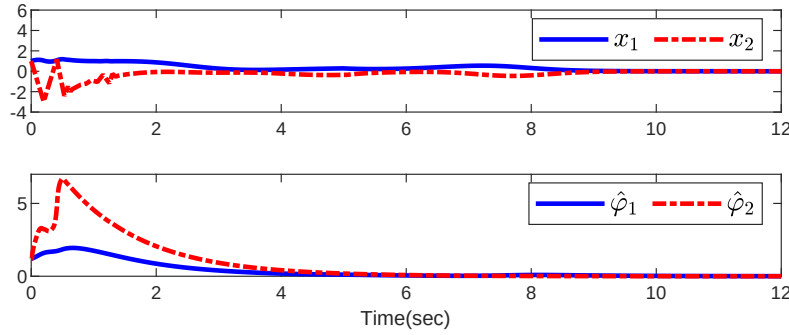
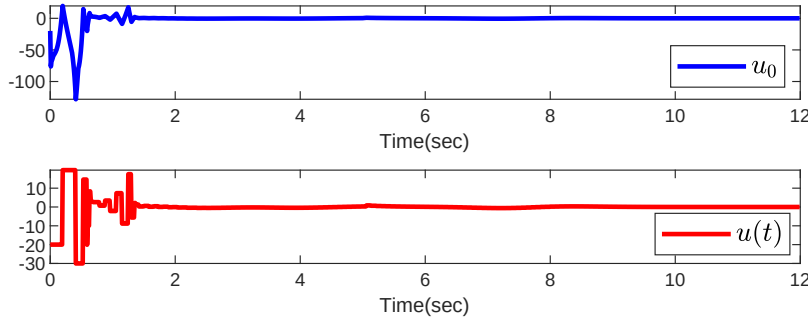
where x_1 and x_2 are reactor's produce streams, the other parameters M_1 , M_2 , W_1 , W_2 , B_1 , B_2 , B_f , K_e and L_1 are intrinsic (see [5]), and w_1 and w_2 are bounded external disturbance. In accordance with [5], we select $B_f = 0.5$, $M_1 = M_2 = 2$, $B_1 = B_2 = 0.5$, $W_1 = W_2 = 0.5$, $L_1 = 0.5$ and $K_e = 7/3$. In addition, taking deception attacks in the system into account, the system (45) can be modeled as follows:

$$\begin{aligned} \dot{x}_1 &= x_2 + g_1(x_1) + w_1, \\ \dot{x}_2 &= \nu(u(t)) + g_2(\bar{x}_2) + w_2 \end{aligned} \quad (46)$$

with the attack model being $\tilde{x}_z = x_z + \theta_z x_z$, $z = 1, 2$, where $\theta_1 = \cos(1.5t) + 0.3$, $\theta_2 = 0.2 \sin(t) + 0.6$, $w_1 = 0.6 \cos(0.8t) \sin(t)$, $w_2 = 0.3 \sin(0.6t)$, $g_1(x_1) = -x_1$ and $g_2(\bar{x}_2) = -(7/3 + 0.5)x_2 - 0.5x_2^2$.

In the matlab simulation, the initial of system states and adaptive laws as well as the sampling period are designed as $[1, 1]^T$, $[1.2, 1.2]^T$ and 0.01 second, respectively. The parameters are chosen as $k_1 = k_2 = 0.04$, $c_1 = 1$, $c_2 = 13$, $\rho_1 = \rho_2 = 0.8$, $\iota = 0.95$, $\Delta = 0.35$, $\nu_M = 30$ and $\Upsilon = 5$.

Figure 1 plots the trajectories of the system state x_1 , x_2 and adaptive laws $\hat{\varphi}_1$ and $\hat{\varphi}_2$; Figure 2 depicts the trajectories of the control command u_0 and actual control $u(t)$. Additionally, in accordance with Figure 3, we can obtain that the triggered numbers are 160, which indicates that the adaptive resilient self-trigger control scheme proposed in this paper can save more resources and reduce the communication load in the process of communication. Furthermore, the simulation results distinctly show that the boundedness of all signals in the CLS can be remained even if the input saturation and deception attacks exist. Besides, the Zeno phenomenon is avoided.


 FIGURE 1. Trajectories of x_1 , x_2 , $\hat{\varphi}_1$ and $\hat{\varphi}_2$

 FIGURE 2. Trajectories of u_0 and $u(t)$

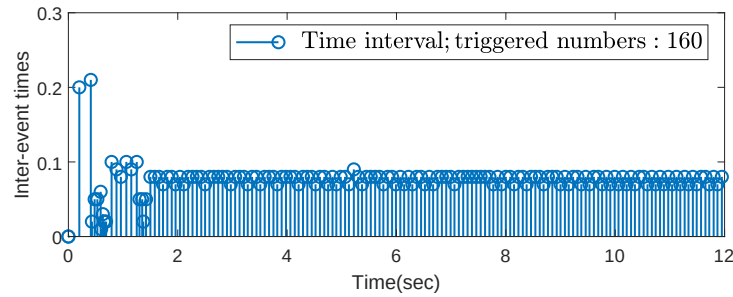


FIGURE 3. The triggered numbers

5. Conclusions. This paper proposes the problem of adaptive resilient self-triggered control based on the SPLM for nonlinear CPSs in the presence of input saturation and deception attacks. The SPLM is integrated into the design framework of backstepping, and multiple uncertain terms are cleverly transformed into the form of single parameter, which greatly reduces the complexity of controller design. Moreover, the proposed self-triggered control scheme can determine the next triggering moment only through the current system information rather than monitoring the triggering condition continuously. The designed control strategy ensures that all the signals of the CLS are bounded in the presence of input saturation and deception attacks.

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