Adaptive Sliding Mode Control for Optimal H_2 -gain Performance of Interconnected Large-scale Cyber Physical Systems Under FDIAs Environments

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Adaptive sliding mode control for optimal $\mathcal{L}_2$ -gain performance of interconnected large-scale cyber physical systems under FDIAs environments

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Abstract

Aiming at a class of large-scale cyber physical systems(LSCPSs) with multiple subsystems nonlinearly interconnected under false data injection attacks(FDIAs), the problems of $\mathcal{L}_2$ -gain performance analysis and sliding mode control are studied. First, the quadratical stability criteria with $\mathcal{L}_2$ -gain performance of the sliding dynamics of LSCPSs are derived by linear matrix inequalities(LMIs) technology. Then adaptive integral sliding mode controllers are designed, which include two parts: one part is designed for suppressing the influences of FDIAs on the systems, and the other part is used to deal with factors such as quantization errors, external interferences, nonlinear interconnections, and model uncertainties. Finally, the comparison results of simulation examples show the effectiveness and superiority of the established methods.

Keywords: sliding mode control, large-scale cyber-physical systems(LSCPSs), false data injection attacks(FDIAs), optimal $\mathcal{L}_2$ -gain performance

1 Introduction

The mutual fusion relationships between the information networks and the physical networks produce a class of systems of mutual fusion, which are called the cyber physical systems [1], [2]. People control physical networks through information networks, so that cyber physical systems are widely used in the fields of industrial automation for urban constructions, [3], [4], [5], [6].

With the development of science and technology, the amount of data in physical networks have increased sharply, and the scales of cyber physical systems have gradually become more modernized, industrialized, and networked, so that the existing methods need significant rethinking. The control problems of large-scale cyber physical systems (LSCPSs) with nonlinear interconnection [7] between multiple subsystems have become more difficult. References [8], [9] discussed the design of controllers for model problems, the papers [10], [11], [12] improved on traditional algorithms. This paper focuses on the researches in context of the combined LSCPSs.

On the other hand, security problems caused by cyber attacks are very important. The infrastructures based on national information system play great roles in modern society, and successful attacks on the national information system will hinder the construction of key infrastructure and produce unexpected consequences [13]. The attackers use leakage of the communication network to obtain the real-time state of the physical system, and destroy the performance and integrity of the system by manipulating the sensor measurement or controller input, so as to achieve illegal purposes such as economic benefits [14]. Therefore, the defense against attacks under the background of LSCPSs, which has important practical significance and application values.

Many researchers have done a lot of works on the security problems caused by FDIAs from different angles, the existing robust control methods, such as H_∞ control [15], [16], [17], have a certain defense effect against FDIAs. Some references [18], [19], [20], [21] focus on estimating the state of attackers when using the information, and give the corresponding detection methods. Different from other network attacks (such as sneak attack, secret attack, zero dynamic attack, etc.), FDIAs, as one of typical deception attacks, have strong concealment [22], [23] and can hardly be detected by general passive defense methods. Attackers need to collect enough information about the target systems from the accessible network communication before performing destructive activities. Therefore, FDIAs have become research hotspot of network security. In this paper, by the combination of sliding mode control [24], [25] and adaptive control, an adaptive sliding mode control algorithm will be shown to defend the FSIAs in real time.

Besides FDIAs, this paper also considers factors such as quantization encoder/decoder parameters mismatch, external interferences and model uncertainty in the transmission networks, and studies the control problems of LSCPSs with nonlinear interconnections between multiple subsystems. The main contributions of this paper are as follows:

(1) Quadratical stability criterions of the sliding dynamics of the LSCPSs are derived using LMIs technique, and the optimal gain matrices are obtained, which ensure that the LSCPSs can maintain quadratical stability and achieve the optimal $\mathcal{L}_2$ -gain performance after reaching the desired integral sliding surfaces.

(2) The adaptive integral sliding mode controllers are designed for ensuring the reachability of the specified integral sliding surfaces, where the controllers are designed into two parts: one part is designed for suppressing the influences of FDIAs on the systems, and the other part is used to deal with factors such as quantization errors, external interferences, nonlinear interconnections, and model uncertainties.

(3) Through Simulations of Matlab, comparison results verify feasibility and superiority of the control algorithm in this paper.

The rest of this paper is organized as follows. In Section 2, the problem statement and preliminaries are described. The main results, including the designs of the switching surfaces and the sliding mode reaching control laws are presented in Section 3. Section 4 show comparison results to verify feasibility and superiority of the control algorithm with an example. Finally, Section 5 concludes the paper.

2 Problem statement and preliminaries

2.1 System model

In this paper, the nonlinear LSCPSs defined by N interconnected subsystems are described as

$$\begin{cases} \dot{x}_i(t) = (A_i + \Delta A_i(t))x_i(t) + B_i u_i(t) + B_i f_i(t, x, p) + D_i \omega_i(t) \\ y_i(t) = C_i x_i(t) + H_i \omega_i(t) \end{cases} \quad (1)$$

where $x_i \in \mathbb{R}^{n_i}$, $u_i \in \mathbb{R}^{m_i}$ and $y_i \in \mathbb{R}^{p_i}$ are the states, the control inputs and outputs of the i th subsystem, respectively; $i = 1, 2, \dots, N$. $\omega_i(t) \in \mathbb{R}^{q_i}$ are the external disturbance. $\Delta A_i(t) \in \mathbb{R}^{n_i \times n_i}$ are the unknown mismatched time varying model uncertainties in the i th subsystem. $f_i(t, x, p) \in \mathbb{R}^{m_i}$ describe the nonlinear interconnected terms affecting the i th subsystem, where $x = [x_1^T, x_2^T, \dots, x_N^T]^T$ and $p \in \mathbb{R}^r$ are uncertain system parameters.

Suppose that (A_i, B_i) are controllable, the system state variables are observable, and can be used for feedback control design.

First, the following three assumptions are given.

Assumption 1 [26] Time varying uncertainties $\Delta A_i(t)$ satisfy

$$\Delta A_i(t) = F_i \Delta_i(t) E_i, \quad \Delta_i(t) \Delta_i^T(t) \leq I \quad (2)$$

where F_i and E_i are known real constant matrices with appropriate dimensions, $\Delta_i(t)$ are unknown time varying matrix functions.

Assumption 2 [27] The interconnected terms $f_i(t, x, p)$ satisfy

$$\|f_i(t, x, p)\| \leq b_i + \sum_{k=1}^N c_{ik} \|x_k\| + \sum_{k=1}^N d_{ik} \|x_i\| \|x_k\| \quad (3)$$

Among them, b_i , c_{ik} and d_{ik} are unknown positive constants, which represent the strength of interaction between subsystems, that is, the strength of interconnection.

Assumption 3 [28] External disturbance $\omega_i(t) \in \mathcal{L}_2[0, T]$, satisfy the square integrable and $\int_0^T \omega_i^T(t) \omega_i(t) dt < \infty$.

2.2 Quantization parameter mismatch

The process of signal quantization can be regarded as the process of encoding and decoding by the quantizers. Quantizers are defined by the rounding functions $q_i(\cdot)$, and the quantized signals are expressed as

$$Q_i(u_i(t)) = \mu_{di}(t) \text{round} \left(\frac{u_i(t)}{\mu_{ci}(t)} \right) \triangleq \mu_{di}(t) q_i \left(\frac{u_i(t)}{\mu_{ci}(t)} \right) \quad (4)$$

Among them, $\mu_{ci}(t)$ and $\mu_{di}(t)$ are the quantization sensitivity parameters of the encoder side and decoder side of the i th subsystem, respectively. In practical applications, the noise disturbance caused by hardware conditions are often inevitable, and parameters matching of quantization encoder and decoder under ideal conditions almost do not exist in reality, so here assumes that $\mu_{di}(t) \neq \mu_{ci}(t)$ and $\mu_{di}(t)$ and $\mu_{ci}(t)$ are time-varying [29], [30].

Establishing quantization time-varying ratio parameter models of the i th subsystem

$$r_i(t) = \frac{\mu_{di}(t)}{\mu_{ci}(t)} \quad (5)$$

where $r_i(t) \in (r_{i\min}, r_{i\max})$, $r_{i\min}$ and $r_{i\max}$ are unknown positive scalars and satisfying $r_{i\max} \geq r_{i\min}$.

According to quantized signal (4) and quantized ratio model (5), one can get

$$Q_i(u_i(t)) = r_i(t) (u_i(t) + e_{\mu_{ci}}(t)) \quad (6)$$

where the quantization error is

$$e_{\mu_{ci}}(t) = \mu_{ci}(t) q_i \left(\frac{u_i(t)}{\mu_{ci}(t)} \right) - u_i(t) \quad (7)$$

It is not difficult to get that the quantization error $e_{\mu_{ci}}(t)$ satisfy

$$\|e_{\mu_{ci}}(t)\| \leq \frac{\sqrt{m_i}}{2} \mu_{ci}(t) \quad (8)$$

2.3 False data injection attacks

The large-scale systems under FDIAs environments are as follows

$$\tilde{u}_i(t) = u_i(t) + a_i(t, x_i(t)) \quad (9)$$

where $\tilde{u}_i(t)$ represents the control signals of actual damage, $a_i(t, x_i(t))$ are actuator attacks related to obtain time-varying states.

The expressions for $a_i(t, x_i(t))$ are

$$a_i(t, x_i(t)) = \Lambda_i(t)\varphi_i(t, x_i(t)) \quad (10)$$

where $\Lambda_i(t)$ represents the unknown weighting matrices, and $\varphi_i(t, x_i(t))$ represents the system information applied by the attackers.

Assumption 4 In practical applications, information injected by attackers are usually limited by physical constraints such as channel capacity and amplitude. Therefore, $\varphi_i(t, x_i(t))$ can be defined by some positive functions with known structure, and the norm of weighting matrices $\Lambda_i(t)$ are unknown normal number. Therefore, FDIAs meet the following requirements

$$\|\Lambda_i(t)\| \leq \lambda_i, \quad \|\varphi_i(t, x_i(t))\| \leq \phi_i(t, x_i(t)) \quad (11)$$

Remark 1 The attack model considered in LSCPSs has been investigated in [31], hackers can destroy the measurement outputs or control commands by modifying the data transmitted via the channels. Therefore, it is reasonable to assume that opponents can obtain complete state information in the system, and they can be used to design deception attack signals [32]. $a_i(t, x_i(t))$ parameterizations can be considered.

Since actuators of system are affected by FDIAs and occur in the quantization channels, LSCPSs with mismatched encoder/decoder parameters are represented as

$$\begin{cases} \dot{x}_i(t) = (A_i + \Delta A_i(t))x_i(t) + B_i Q_i(\tilde{u}_i(t)) + B_i f_i(t, x, p) + D_i \omega_i(t) \\ y_i(t) = C_i x_i(t) + H_i \omega_i(t) \end{cases} \quad (12)$$

where $Q_i(\tilde{u}_i(t))$ represent the quantized mismatch input signals attacked by FDIAs, and their expressions are

$$Q_i(\tilde{u}_i(t)) = \mu_{di}(t) \left[q_i \left(\frac{u_i(t)}{\mu_{ci}(t)} \right) + a_i(t, x_i(t)) \right] \quad (13)$$

Definition 1 ($\mathcal{L}_2$ gain performance [33]) For given positive scalars γ_i , if $\omega_i(t) = 0$, the nonlinear LSCPSs (12) are quadratical stability; and under zero initial condition, when $\omega_i(t) \neq 0$, if LSCPSs satisfy the following inequalities

$$\sum_{i=1}^N \int_0^\infty y_i^T(t) y_i(t) dt < \sum_{i=1}^N \gamma_i^2 \int_0^\infty \omega_i^T(t) \omega_i(t) dt \quad (14)$$

LSCPSs are said to have quadratical stability with bounded gain performance γ_i .

3 Main results

Sliding mode control has very strong robustness, and its control performance is significantly better than general fixed structure control methods in dealing with uncertainties and unknown disturbances in nonlinear systems. Corresponding to the two processes of the sliding mode control, the design problem of sliding mode control consists of two steps: one is the design of the switching function, and the other is the design of the control law. The design purpose of the switching function is to design a switching surface to ensure that when the trajectory of the controlled system is stable on the switching surface, the dynamical system is stable and has the desired performance. The control law is designed to make the system reach the switching surface.

3.1 Design of switching functions

First, the following integral switching functions are constructed

$$s_i(t) = G_i x_i(t) - \int_0^t G_i (A_i - B_i K_i) x_i(\tau_i) d\tau_i \quad (15)$$

where $G_i = B_i^+$, i.e., the pseudo inverse of B_i . And the parameters $K_i \in \mathbb{R}^{m_i \times n_i}$ are real matrices to be designed.

According to sliding mode control theory, one can obtain the equivalent control for the i th subsystem by taking $\dot{s}_i(t) = 0$

$$\begin{aligned} Q_{eqi}(u_i(t)) = & - (G_i B_i)^{-1} G_i \Delta A_i(t) x_i(t) - f_i(t, x, p) \\ & - (G_i B_i)^{-1} G_i D_i \omega_i(t) - K_i x_i(t) \end{aligned} \quad (16)$$

Bring the equivalent control $Q_{eqi}(u_i(t))$ into nonlinear LSCPSs (12), sliding dynamics of nonlinear interconnected LSCPSs (12) are expressed as

$$\begin{cases} \dot{x}_i(t) = (\bar{A}_i + \Delta \bar{A}_i(t)) x_i(t) + \bar{D}_i \omega_i(t) \\ y_i(t) = \bar{C}_i x_i(t) + \bar{H}_i \omega_i(t) \end{cases} \quad (17)$$

where $\bar{A}_i = A_i - B_i K_i$, $\bar{G}_i = I - B_i (G_i B_i)^{-1} G_i$, $\Delta \bar{A}_i(t) = \bar{G}_i \Delta A_i(t)$, $\bar{D}_i = \bar{G}_i D_i$.

Quadratic stability of the sliding dynamics (17) with $\mathcal{L}_2$ -gain performance are now shown in Theorem 1.

Theorem 1 For the sliding dynamics of LSCPSs (17), if there are symmetric positive definite matrices X_i , regular matrices W_i and positive scalars ε_i , such that the following optimization problems of LMIs can be solved,

$$\min_{\alpha_i} \begin{bmatrix} \text{He}[A_i X_i - B_i W_i] + \varepsilon_i \bar{G}_i F_i F_i^T \bar{G}_i^T & X_i C_i^T & X_i E_i^T & \bar{D}_i + X_i C_i^T H_i \\ * & -I & 0 & 0 \\ * & * & -\varepsilon_i I & 0 \\ * & * & * & H_i^T H_i - \alpha_i I \end{bmatrix} < 0 \quad (18)$$

then the sliding dynamics of LSCPSs are quadratical stability, satisfying the $\mathcal{L}_2$ -gain performance, with a minimum upper bounds $\gamma_{i\text{opt}} = \sqrt{\alpha_i}$, where the optimal gain matrices K_i in (15) can be determined by

$$K_i = W_i X_i^{-1} \quad (19)$$

Proof of Theorem 1 Considering a Lyapunov function candidate, where $P_i > 0$.

$$\bar{V}(t) = \sum_{i=1}^N \bar{V}_i(t) = \sum_{i=1}^N x_i^T(t) P_i x_i(t) \quad (20)$$

Derivating $\bar{V}(t)$ along the sliding dynamics of the nonlinear interconnected LSCPSs (17), one can get

$$\dot{\bar{V}}(t) = \sum_{i=1}^N x_i^T(t) \text{He} \left[(\bar{A}_i + \Delta \bar{A}_i(t))^T P_i \right] x_i(t) + \sum_{i=1}^N 2x_i^T(t) P_i \bar{D}_i \omega_i(t) \quad (21)$$

Furthermore, we have

$$\dot{\bar{V}}(t) + \sum_{i=1}^N y_i^T(t) y_i(t) - \alpha_i \sum_{i=1}^N \omega_i^T(t) \omega_i(t) = \sum_{i=1}^N \xi_i^T(t) \Gamma_i \xi_i(t) \quad (22)$$

where $\xi_i(t) \triangleq [x_i^T(t) \ \omega_i^T(t)]^T$, $\Gamma_i \triangleq \begin{bmatrix} \text{He}[(\bar{A}_i + \Delta \bar{A}_i(t))^T P_i] + C_i^T C_i & P_i \bar{D}_i + C_i^T H_i \\ * & H_i^T H_i - \alpha_i I_i \end{bmatrix}$.

Now, multiplying both sides of $\Gamma_i < 0$ by matrices $\text{diag}\{P_i^{-1}, I_i\}$ at the same time, and letting $P_i^{-1} = X_i$ and $W_i = K_i X_i$, one can get $\Gamma_i < 0$ hold if and only if the following inequalities

$$\begin{bmatrix} \Psi_i & \bar{D}_i + X_i C_i^T H_i \\ * & H_i^T H_i - \alpha_i I_i \end{bmatrix} < 0 \quad (23)$$

hold, where $\Psi_i = \text{He}[A_i X_i - B_i W_i] + X_i C_i^T C_i X_i + \text{He}[\bar{G}_i F_i \Delta_i(t) E_i X_i]$. By the utilization of Schur Complement Lemma [34], one can further get that $\Gamma_i < 0$ hold if and only if LMIs (18) hold. Thus quadratical stability of the sliding dynamics are established.

Next, under the inequalities $\xi_i^T(t) \Gamma_i \xi_i(t) < 0$, integrating both sides of equation (22) on time $[0, T]$, we can get

$$\bar{V}(x(T)) - \bar{V}(x(0)) + \sum_{i=1}^N \int_0^T y_i^T(t) y_i(t) dt - \sum_{i=1}^N \alpha_i \int_0^T \omega_i^T(t) \omega_i(t) dt < 0 \quad (24)$$

Under zero initial conditions, and $\bar{V}(x(T)) = \sum_{i=1}^N x_i^T(t) P_i x_i(t) \geq 0$, we can get

$$\sum_{i=1}^N \int_0^T y_i^T(t) y_i(t) dt < \sum_{i=1}^N \alpha_i \int_0^T \omega_i^T(t) \omega_i(t) dt \quad (25)$$

Letting $\alpha_i = \gamma_i^2$, the criterions satisfying $\mathcal{L}_2$ -gain performance can be obtained

$$\sum_{i=1}^N \int_0^T y_i^T(t) y_i(t) dt < \sum_{i=1}^N \gamma_i^2 \int_0^T \omega_i^T(t) \omega_i(t) dt \quad (26)$$

Taking the time limit $T \rightarrow \infty$ on both sides of the above inequalities to obtain equations (14), that is, the condition of the $\mathcal{L}_2$ gain performance is achieved.

It is not difficult to see from Definition 1 that it reflects the stability performance indexes of the system outputs when LSCPSs are subjected to the same serious external interferences. The LMIs are designed to minimize the $\mathcal{L}_2$ -gain coefficients γ_i , and the optimization values $\sqrt{\alpha_i}$ are the best indexes of $\mathcal{L}_2$ -gain performance of LSCPSs. Since values of γ_i are the smallest at this time, gain matrices of sliding functions are the best at this time. Under actions of any external disturbances belonging to $\mathcal{L}_2$ -gain in interval $[0, T]$, when the inequalities of Definition 1 are established, the gain matrices solved by LMIs can realize the optimal control of state parameters, produce the best suppression effect on external interference, and the nonlinear interconnected LSCPSs are quadratic stability. Therefore, the proof of Theorem 1 is completed. $\square$

3.2 Design of Adaptive Integral Sliding Mode Controllers

In this paper, the adaptive integral sliding mode controllers are designed as follows.

$$u_i^j(t) = u_{ei}^j(t) + u_{ai}^j(t), \quad (27)$$

$$\begin{aligned} u_{ei}^j(t) = & -\{\beta_i [\hat{l}_i(t) + \hat{\rho}_i(t)] + [\|G_i F_i\| \|E_i\| + \|K_i\|] \|x_i(t)\| \} \text{sign}(s_i^j(t)) \hat{r}_i(t) \\ & - \frac{\sqrt{m_i}}{2} \mu_{ci}(t) \text{sign}(s_i^j(t)), \end{aligned} \quad (28)$$

$$u_{ai}^j(t) = -\beta_i \hat{r}_i(t) \text{sign}(s_i^j(t)) \hat{\delta}_i(t) \phi_i(t, x_i(t)), \quad (29)$$

where $\beta_i > 1$, $j = 1, 2, \dots, m_i$; $u_{ei}^j(t)$ are the parts to handle quantization parameter mismatch, nonlinear interconnection terms and external disturbances, and $u_{ai}^j(t)$ are the parts to handle FDIAs.

The parameters $\hat{\zeta}_i(t)$, $\hat{\rho}_i(t)$, $\hat{\delta}_i(t)$ and $\hat{r}_i(t)$ are the estimations of $\zeta_i(t)$, $\rho_i(t)$, $\delta_i(t)$ and $r_i(t)$, respectively. And they are derived from the designed adaptive laws. The initial values $\hat{\zeta}_i(0)$, $\hat{\rho}_i(0)$, $\hat{\delta}_i(0)$ and $\hat{r}_i(0)$ are greater than zero.

$$\dot{\hat{\zeta}}_i(t) = \frac{1}{\eta_{1i}} \|s_i(t)\|, \quad (30)$$

$$\dot{\rho}_i(t) = \frac{1}{\eta_{2i}} \|s_i(t)\|, \quad (31)$$

$$\dot{\delta}_i(t) = \frac{1}{\eta_{3i}} \phi_i(t, x_i(t)) \|s_i(t)\|, \quad (32)$$

$$\begin{aligned} \dot{r}_i(t) = & \frac{1}{\eta_{4i}} \|s_i(t)\| \hat{r}_i^3(t) \left\{ \beta_i [\hat{\zeta}_i(t) + \hat{\rho}_i(t) + \hat{\delta}_i(t) \phi_i(t, x_i(t))] \right. \\ & \left. + [\|G_i F_i\| \|E_i\| + \|K_i\|] \|x_i(t)\| \right\}. \end{aligned} \quad (33)$$

Theorem 2 For the nonlinear interconnected LSCPSs (12) that satisfy Assumptions 1-4 and are simultaneously attacked by FDIAs, quantized encoder/decoder parameters mismatch and unknown external disturbances, when the LSCPSs are controlled by action of the sliding mode controllers (27)-(29) with adaptive laws (30)-(33), the state trajectories of the nonlinear interconnected LSCPSs can reach the desired integral sliding surfaces $s_i(t) = 0$ and achieve robust quadratical stability with $\mathcal{L}_2$ -gain performance.

Proof of Theorem 2 The Lyapunov functions $V_i^j(t) = \frac{1}{2} s_i^j T(t) s_i^j(t)$ are constructed related to the i th-subsystem and their derivations are obtained along the system state trajectories (12)

$$\begin{aligned} \dot{V}_i^j(t) = & s_i^{jT}(t) \left[G_i \Delta A_i(t) x_i(t) + G_i B_i K_i x_i(t) + G_i B_i Q_i \left(u_i^j(t) \right) \right. \\ & \left. + G_i B_i \mu_{di}(t) a_i(t, x_i(t)) + G_i B_i f_i(t, x, p) + G_i D_i \omega_i(t) \right] \end{aligned} \quad (34)$$

Noticing $G_i = B_i^+$, quantization error in (7), and according to the Assumptions 1-4, one can get

$$\begin{aligned} \dot{V}_i^j(t) \leq & \|s_i(t)\| [\|G_i F_i\| \|E_i\| + \|K_i\|] \|x_i(t)\| + \|s_i(t)\| \mu_{di}(t) \lambda_i \phi_i(t, x_i(t)) \\ & + s_i^{jT}(t) r_i(t) \left(u_i^j(t) + e_{\mu_{ci}}^j(t) \right) + \|s_i(t)\| \|G_i D_i\| \|\omega_i(t)\| \\ & + \|s_i(t)\| \left[b_i + \sum_{k=1}^N c_{ik} \|x_k\| + \sum_{k=1}^N d_{ik} \|x_i\| \|x_k\| \right] \end{aligned} \quad (35)$$

Letting $\delta_i(t) = \mu_{di}(t) \lambda_i$, and $\zeta_i(t)$, $\rho_i(t)$ such that

$$\zeta_i(t) \geq \|G_i D_i\| \|\omega_i(t)\| \quad (36)$$

$$\rho_i(t) \geq b_i + \sum_{k=1}^N c_{ik} \|x_k\| + \sum_{k=1}^N d_{ik} \|x_i\| \|x_k\| \quad (37)$$

Then $\dot{V}_i^j(t)$ can be expressed as

$$\begin{aligned} \dot{V}_i^j(t) \leq & s_i^{jT}(t) r_i(t) \left(u_i^j(t) + e_{\mu_{ci}}^j(t) \right) + \|s_i(t)\| [\|G_i F_i\| \|E_i\| + \|K_i\|] \|x_i(t)\| \\ & + \|s_i(t)\| \delta_i(t) \phi_i(t, x_i(t)) + \|s_i(t)\| \zeta_i(t) + \|s_i(t)\| \rho_i(t) \end{aligned} \quad (38)$$

Considering the Lyapunov functions

$$\tilde{V}(t) = \sum_{i=1}^N \sum_{j=1}^m V_i^j(t) + \frac{\eta_{1i}}{2} \sum_{i=1}^N \tilde{\zeta}_i^2(t) + \frac{\eta_{2i}}{2} \sum_{i=1}^N \tilde{\rho}_i^2(t) + \frac{\eta_{3i}}{2} \sum_{i=1}^N \tilde{\delta}_i^2(t) + \frac{\eta_{4i}}{2} \sum_{i=1}^N \tilde{r}_i^2(t) \quad (39)$$

where $\tilde{\zeta}_i(t) = \zeta_i(t) - \hat{\zeta}_i(t)$, $\tilde{\rho}_i(t) = \rho_i(t) - \hat{\rho}_i(t)$, $\tilde{\delta}_i(t) = \delta_i(t) - \hat{\delta}_i(t)$, $\tilde{r}_i(t) = r_i(t) - \hat{r}_i^{-1}(t)$.

Taking the derivations of both sides of the above Lyapunov functions along the trajectories of the nonlinear interconnected LSCPSs (12) and combining the adaptive laws (30)-(33), one can get

$$\begin{aligned} \dot{\tilde{V}} &= \sum_{i=1}^N \sum_{j=1}^m s_i^{jT}(t) r_i(t) \left(w_i^j(t) + e_{\mu_{ci}}^j(t) \right) \\ &+ \sum_{i=1}^N \|s_i(t)\| \left\{ [\|G_i F_i\| \|E_i\| + \|K_i\|] \|x_i(t)\| + \hat{\zeta}_i(t) + \hat{\rho}_i(t) + \hat{\delta}_i(t) \phi_i(t, x_i(t)) \right\} \\ &+ \sum_{i=1}^N \left\{ \beta_i \left[\hat{\zeta}_i(t) + \hat{\rho}_i(t) + \hat{\delta}_i(t) \phi_i(t, x_i(t)) \right] + [\|G_i F_i\| \|E_i\| + \|K_i\|] \|x_i(t)\| \right\} \\ &\times \|s_i(t)\| \tilde{r}_i(t) \hat{r}_i(t) \end{aligned} \quad (40)$$

Bringing the controller equation (27)-(29) into (40) and combining $\|e_{\mu_{ci}}(t)\| \leq \frac{\sqrt{m_i}}{2} \mu_{ci}(t)$, one can get that

$$\begin{aligned} \dot{\tilde{V}} &\leq \sum_{i=1}^N \sum_{j=1}^m s_i^{jT}(t) r_i(t) \left\{ -\hat{r}_i(t) \operatorname{sign} \left(s_i^j(t) \right) [\|G_i F_i\| \|E_i\| + \|K_i\|] \|x_i(t)\| \right. \\ &+ \beta_i \left[\hat{\zeta}_i(t) + \hat{\rho}_i(t) + \hat{\delta}_i(t) \phi_i(t, x_i(t)) \right] - \frac{\sqrt{m_i}}{2} \mu_{ci}(t) \operatorname{sign} \left(s_i^j(t) \right) + \frac{\sqrt{m_i}}{2} \mu_{ci}(t) \left. \right\} \\ &+ \sum_{i=1}^N \|s_i(t)\| \left[[\|G_i F_i\| \|E_i\| + \|K_i\|] \|x_i(t)\| + \hat{\zeta}_i(t) + \hat{\rho}_i(t) + \hat{\delta}_i(t) \phi_i(t, x_i(t)) \right] \\ &+ \sum_{i=1}^N \left\{ \left[\beta_i \left[\hat{\zeta}_i(t) + \hat{\rho}_i(t) + \hat{\delta}_i(t) \phi_i(t, x_i(t)) \right] + [\|G_i F_i\| \|E_i\| + \|K_i\|] \|x_i(t)\| \right] \right\} \\ &\times \|s_i(t)\| \tilde{r}_i(t) \hat{r}_i(t) \end{aligned} \quad (41)$$

By the combination of $r_i(t) = \frac{\mu_{di}(t)}{\mu_{ci}(t)}$ and the properties of symbolic function $\operatorname{sign}(\cdot)$, the following results are obtained

$$\begin{aligned} \dot{\tilde{V}} &\leq - \sum_{i=1}^N \|s_i(t)\|_1 r_i(t) \hat{r}_i(t) [\|G_i F_i\| \|E_i\| + \|K_i\|] \|x_i(t)\| \\ &+ \beta_i [\hat{\zeta}_i(t) + \hat{\rho}_i(t) + \hat{\delta}_i(t) \phi_i(t, x_i(t))] - \frac{\sqrt{m_i}}{2} \mu_{di}(t) \|s_i(t)\|_1 + \frac{\sqrt{m_i}}{2} \mu_{di}(t) \|s_i(t)\| \\ &+ \sum_{i=1}^N \|s_i(t)\| \left[[\|G_i F_i\| \|E_i\| + \|K_i\|] \|x_i(t)\| + \hat{\zeta}_i(t) + \hat{\rho}_i(t) + \hat{\delta}_i(t) \phi_i(t, x_i(t)) \right] \\ &+ \sum_{i=1}^N \left\{ \left[\beta_i [\hat{\zeta}_i(t) + \hat{\rho}_i(t) + \hat{\delta}_i(t) \phi_i(t, x_i(t))] + [\|G_i F_i\| \|E_i\| + \|K_i\|] \|x_i(t)\| \right] \right\} \end{aligned}$$

$$\times \|s_i(t)\| \tilde{r}_i(t) \hat{r}_i(t) \quad (42)$$

Since the inequality $\|s_i(t)\|_1 > \|s_i(t)\|$, after sorting out (42), one can get

$$\begin{aligned} \dot{\tilde{V}} &\leq - \sum_{i=1}^N \|s_i(t)\| r_i(t) \hat{r}_i(t) \left[[\|G_i F_i\| \|E_i\| + \|K_i\|] \|x_i(t)\| \right. \\ &\quad \left. + \beta_i [\hat{\zeta}_i(t) + \hat{\rho}_i(t) + \hat{\delta}_i(t) \phi_i(t, x_i(t))] \right] \\ &\quad + \sum_{i=1}^N \|s_i(t)\| \left[[\|G_i F_i\| \|E_i\| + \|K_i\|] \|x_i(t)\| + \hat{\zeta}_i(t) + \hat{\rho}_i(t) + \hat{\delta}_i(t) \phi_i(t, x_i(t)) \right] \\ &\quad + \sum_{i=1}^N \left\{ \left[\beta_i [\hat{\zeta}_i(t) + \hat{\rho}_i(t) + \hat{\delta}_i(t) \phi_i(t, x_i(t))] + [\|G_i F_i\| \|E_i\| + \|K_i\|] \|x_i(t)\| \right] \right\} \\ &\quad \times \|s_i(t)\| \tilde{r}_i(t) \hat{r}_i(t) \\ &\leq (1 - \beta_i) \|s_i(t)\| \left[\hat{\zeta}_i(t) + \hat{\rho}_i(t) + \hat{\delta}_i(t) \phi_i(t, x_i(t)) \right] < 0 \end{aligned} \quad (43)$$

Integrating both sides of above inequalities on time $[0, T]$, and taking the limit of the upper limit T of the integrals, and arranging the inequalities to get

$$\sum_{i=1}^N \int_0^\infty (\beta_i - 1) \|s_i(\tau)\| \left[\hat{\zeta}_i(\tau) + \hat{\rho}_i(\tau) + \hat{\delta}_i(\tau) \phi_i(\tau, x_i(\tau)) \right] d\tau \leq \tilde{V}(0) < +\infty \quad (44)$$

It's easy to see $s_i(t)$, $\hat{\zeta}_i(t)$, $\hat{\rho}_i(t)$ and $\hat{\delta}_i(t)$ are all uniformly continuous, and equations $\lim_{t \rightarrow \infty} \sum_{i=1}^N \int_0^t (1 - \beta_i) \|s_i(\tau)\| \left[\hat{\zeta}_i(\tau) + \hat{\rho}_i(\tau) + \hat{\delta}_i(\tau) \phi_i(\tau, x_i(\tau)) \right] d\tau$ exist and are bounded, then we can get that the above equations is zero, so when t tends to infinity, we can get $\lim_{t \rightarrow \infty} \|s_i(t)\| = 0$. Therefore, the proof of Theorem 2 is completed. $\square$

4 Simulation example

This paper uses matlab/simulink experimental simulation to verify the feasibility and superiority of the adaptive integral sliding mode control design of the quantized mismatched nonlinear LSCPSs under the FDIAs.

Selecting i as 1, 2, the system parameter matrices of the nonlinear LSCPSs (12) are selected as follows

$$\begin{aligned} A_1 &= \begin{bmatrix} 2 & 3 \\ 5 & 6 \end{bmatrix}, & A_2 &= \begin{bmatrix} 2 & 1 \\ 3 & 2 \end{bmatrix}, \\ B_1 &= \begin{bmatrix} 1 \\ 2 \end{bmatrix}, & B_2 &= \begin{bmatrix} 10 \\ 6 \end{bmatrix}, \\ C_1 &= [0.5 \ 1], & C_2 &= [2 \ 1], \\ D_1 &= \begin{bmatrix} 0.2 \\ 3 \end{bmatrix}, & D_2 &= \begin{bmatrix} 3 \\ 0.2 \end{bmatrix}, \\ H_1 &= 2, & H_2 &= 2. \end{aligned}$$

The time-varying uncertain parameter matrices that satisfy the Assumption 1 are selected as

$$\begin{aligned} F_1 &= \begin{bmatrix} 2 \\ 3 \end{bmatrix}, & F_2 &= \begin{bmatrix} 2 \\ 1 \end{bmatrix}, \\ E_1 &= \begin{bmatrix} 2 & 2 \end{bmatrix}, & E_2 &= \begin{bmatrix} 1 & 3 \end{bmatrix}, \\ \Delta_1 &= 0.5e^{-t}, & \Delta_2 &= 0.2e^{-2t}. \end{aligned}$$

The nonlinear interconnection terms that satisfy the Assumption 2 are selected as

$$\begin{aligned} f_1(t, x, p) &= 0.2x_{12}x_{22} + 0.1x_{21} + 0.2x_{22}, \\ f_2(t, x, p) &= 0.2x_{12}x_{22} + 0.2x_{11} + 0.2x_{12}. \end{aligned}$$

The external disturbances are

$$\omega_1(t) = 0.2e^{-t}, \quad \omega_2(t) = 0.3e^{-t}.$$

In addition, in the simulation, the initial states are

$$x_1(0) = [1; 3], \quad x_2(0) = [2; 1].$$

Selecting $G_1 = [0.2 \ 0.4]$ and $G_2 = [0.0735 \ 0.0441]$ so that G_i are the pseudo inverse matrices of B_i .

According to Theorem 1, using the LMIs toolbox to solve

$$\begin{aligned} K_1 &= [12.5150 \ 23.2118], & K_2 &= [-21.3544 \ 301.6499], \\ \gamma_{1opt} &= 10.8900, & \gamma_{2opt} &= 16.0000. \end{aligned}$$

The selections of quantization sensitivity parameters in case of mismatch are as follows. At the same time, this paper considers that actuators are subjected to malicious FDIAs during the communication transmission process. The FDIAs that satisfy the Assumption 4 are expressed as follows, correspondingly the known-structure functions of the system used by attackers are $\phi_1(t, x_1(t)) = 5\|C_1x_1(t)\| + 25$, $\phi_2(t, x_2(t)) = 5\|C_2x_2(t)\| + 25$.

$$\begin{aligned} \delta_{a1} &= 5\|C_1x_1(t)\| \sin(t) + 20, \\ \delta_{a2} &= 5\|C_2x_2(t)\| \cos(t) + 20. \end{aligned}$$

$$\begin{aligned} \mu_{c1}(t) &= \begin{cases} 1, & t \leq 0.6 \\ 0.8, & 0.6 < t \leq 4 \\ 0.7, & 4 < t \leq 7 \\ 0.5, & t > 7 \end{cases}, & \mu_{d1}(t) &= \begin{cases} 0.8, & t \leq 0.3 \\ 0.7, & 0.3 < t \leq 3 \\ 0.6, & 3 < t \leq 5 \\ 0.4, & t > 5 \end{cases}, \\ \mu_{c2}(t) &= \begin{cases} 1, & t \leq 0.5 \\ 0.9, & 0.5 < t \leq 2 \\ 0.5, & 2 < t \leq 5 \\ 0.45, & t > 5 \end{cases}, & \mu_{d2}(t) &= \begin{cases} 1.2, & t \leq 0.4 \\ 1, & 0.4 < t \leq 2.5 \\ 0.6, & 2.5 < t \leq 6 \\ 0.5, & t > 6 \end{cases}. \end{aligned}$$

Fig. 1: The response curves of subsystem 1 states

For the adaptive integral sliding mode controllers, the adjustable parameters β_i are selected as $\beta_1 = 2$, $\beta_2 = 2$, and the initial states and adjustable gains in the adaptive laws are respectively taken as follows.

$$\begin{aligned} \hat{l}_1(0) &= 0.3, & \hat{l}_2(0) &= 0.1, & \eta_{11} &= 50, & \eta_{12} &= 60, \\ \hat{\rho}_1(0) &= 0.1, & \hat{\rho}_2(0) &= 0.1, & \eta_{21} &= 40, & \eta_{22} &= 70, \\ \hat{\delta}_1(0) &= 0.1, & \hat{\delta}_2(0) &= 0.8, & \eta_{31} &= 20, & \eta_{32} &= 50, \\ \hat{r}_1(0) &= 6, & \hat{r}_2(0) &= 8, & \eta_{41} &= 150, & \eta_{42} &= 450. \end{aligned}$$

Since the images of the hyperbolic tangent function $\tanh\left(\frac{s_i^j(t)}{\kappa_i}\right)$ are close to the switching function $\text{sign}\left(s_i^j(t)\right)$ and $\left\|\text{sign}\left(s_i^j(t)\right)\right\| = 1$, refer to the practice of [35], the use of hyperbolic tangent functions instead of the switching functions in the simulation can not only reduce the chattering phenomenons generated by the control input signals, but also make the sliding mode functions converge quickly when they are close to the equilibrium points, where κ_i should be much smaller than 1, $\kappa_1 = 0.005$, $\kappa_2 = 0.005$.

In order to demonstrate the effectiveness and superiority of the algorithm in this paper to defend against FDIAs of actuator attacks, the simulations consider the following two cases.

Case 1. The defense algorithms against FDIAs is designed in the controllers. Figure 1 and Figure 2 respectively show the convergence of the two subsystems and achieve stable $\mathcal{L}_2$ -gain performance. Figure 3 shows that the system sliding mode functions can quickly converge to the origins, the system state trajectories can quickly reach the designed sliding surfaces.

Case 2. The controller does not consider the defense algorithm for FDIAs, that is, the controller $u_i^j(t) = u_{ei}^j(t)$, the estimated value $\hat{r}_i(t)$ does not have the part related to $\hat{\delta}_i(t)$. Figures 4 and 5 respectively show that the state

Fig. 2: The response curves of subsystem 2 states **Fig. 3:** The response curves of sliding mode functions

responses of the two subsystems have not converged and the control performance is poor. Figure 3 shows that the sliding function of the system cannot converge to the origins and the system cannot reach the desired sliding surface.

The comparison results show the effectiveness and superiority of the proposed control algorithm in this paper.

5 Conclusions

In this paper, the problems of $\mathcal{L}_2$ -gain performance analysis and sliding mode control design are studied for a class of large-scale cyber physical systems(LSCPSs) with multiple subsystems nonlinearly interconnected under false data injection attacks(FDIAs). First, by the utilization of linear matrix inequalities technology, the quadratical stability of the sliding dynamics with

Fig. 4: The response curves of subsystem 1 states

Fig. 5: The response curves of subsystem 2 states

$\mathcal{L}_2$ -gain performance are established. Second, adaptive integral sliding mode controllers are developed to effectively deal with the influences of FDIAs, quantization parameter mismatch, external disturbances, nonlinear interconnections and model uncertainties. Finally, the comparison results of simulation examples show the effectiveness and superiority of the established control algorithm.

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Fig. 6: The response curves of sliding mode functions

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