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Decentralized Fault Estimation and Distributed Fault-tolerant Tracking Control Co-design for Sensor Faulty Multi-agent Systems with Bi-directional Couplings

Chun Liu*, Zhengyan Yu, and Ron J. Patton

Abstract: This study proposes a co-design framework of decentralized fault estimation and distributed fault-tolerant tracking control schemes of Lipschitz nonlinear multi-agent systems with external disturbances and unpredicted sensor faults. To begin with, the sensor fault is actively hidden in the extended state through augmented transformation, and the decentralized unknown input observer based on extended dynamics is applied in synchronously estimating system state and sensor fault. Then, the updated link-based fault-tolerant tracking control protocol is proposed by virtue of the estimated information from estimation dynamics and the relative output signal from neighboring agents in a distributed fashion. The proposed co-designed algorithm guarantees the state consensus tracking property and overcomes the bi-directional couplings between the estimation and tolerance systems. Simulation example of multi-machine power systems verifies the effectiveness of the proposed co-designed algorithm.

Keywords: Decentralized fault estimation, distributed fault-tolerant tracking control, Lipschitz nonlinear multi-agent systems, sensor faults, bi-directional couplings.

1. INTRODUCTION

Consensus, coordination, synchronization and formation control of multi-agent systems have attracted great attention and progressed rapidly in recent years [1–3]. Multi-agent systems have significant advantages over an individual agent, especially in multiple unmanned aerial vehicles [4], intelligent grid systems [5], social networks [6], etc. Leaderless consensus and leader-following consensus tracking are two significant research directions in cooperation and coordination of multi-agent systems. In practice, considering the complexity and dynamics of leaders, it is necessary to apply consensus tracking algorithms to maintain the desired goals [7]. The estimator-based distributed leader-following tracking control scheme is developed for multi-agent systems with measuring noises and interconnections [8]. The distributed bipartite tracking consensus issues for linear leader-following multi-agent systems commanded by an individual leader in [9] and multi-agent systems with Lipschitz nonlinearities in [10, 11] are investigated.

Generally, the actuators and sensors in multi-agent systems are usually not redundant but are susceptible to physical or networked constraints such as mechanical noise, chattering or vibration, as well as system nonlinearities that cannot be accurately modelled [12]. Multi-agent systems are prone to sensor faults, such as deviation, drift, and noise, leading to a degraded measurement accuracy and weakened control performance, and even fatal accidents [13]. Therefore, fault-tolerant control and fault estimation schemes of the faulty multi-agent systems have significantly emerged in order to improve stability and reliability [14–16], especially in maintaining accurate tracking characteristics of the leader-following sensor faulty multi-agent systems. A distributed structure-based fault estimation observer is applied in the fault-tolerant consensus controller to evaluate the actuator faults and resist the external disturbances [14]. In [15], a novel consensus tracking protocol is developed for multi-agent systems with multiplicative faults through the event-triggered fault-tolerant mechanism. An active fault-tolerant tracking scheme is proposed for Markov multi-agent systems to compensate actuator faults and address the switching topology issue [16]. However, the studies of the consensus tracking protocol of multi-agent systems focus on the actuator fault compensation and ignore the complicated sensor fault-resisting in the measuring channel. Therefore, it is significant and challenging to manage the tracking prob-

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lem of the leader-following multi-agent systems in spite of system nonlinearity, sensor faults and external disturbances via the application of fault estimation and fault-tolerant tracking control strategy.

In addition, on the one hand, most of the fault-tolerant tracking control studies focus on linear multi-agent systems and deal with independent actuator faults [17, 18], while the study of consensus tracking control with fault tolerance for sensor faults in leader-following nonlinear multi-agent systems [19, 20] is limited. On the other hand, excluding existing studies that focus only on separated fault estimation or separated fault-tolerant control schemes [21,22], there are limited results that consider the bi-directional couplings between estimation and tolerance dynamics, and even fewer results that explore whether the direct application of the faulty signal from the estimated systems to counteract faults can superimpose cycles that cause worse consequences. In spite of the unmodelled nonlinearities, external disturbances, and physical faults in the existing multi-agent systems, introducing the estimated fault information directly into the fault-tolerant tracking control systems to compensate the physical faults also affects the robustness and performance to some extent in dynamical systems [23, 24]. Therefore, considering the advantages of decentralized control structures that do not require interaction with neighboring agents, and the simplicity of the distributed control design with low cost and easy implementation in large-scale multi-agent systems, inspired by our preliminary studies on integrated fault-tolerant control and fault estimation designs [25, 26], we aim to develop a co-design of decentralized fault estimation and distributed fault-tolerant tracking algorithm for bi-directionally coupled Lipschitz nonlinear multi-agent systems despite sensor faults and external disturbances.

The main contributions of this study are summarized as follows. (i) Compared with the leader-following tracking control of linear multi-agent systems with independent actuator faults [17, 18], [27] in control channel, this study attempts to effectively combine anti-disturbance and sensor fault-tolerant technologies in a class of Lipschitz nonlinear leader-following multi-agent systems. (ii) By applying the unknown input observers [25] to estimate fault and state information, and devising the time-varying link-based distributed law to deal with dynamical weights or switching topologies [16], [28], it is a challenging attempt to address the bi-directional couplings between fault-tolerant tracking and fault estimation systems in a co-designed framework. Such a co-designed approach can effectively circumvent the vicious circularity caused by the flow of fault information from the estimated dynamics to fault-tolerant tracking control systems. (iii) Motivated by the previous constant gain-/node-based protocols [26] in focusing on agent itself, a completely distributed link-based distributed fault-tolerant tracking control protocol is replenished into the co-designed framework with an easy reduction/expansion of connected edges and deconstruction of communication loads.

The remainder of this study is organized as follows. Multi-agent systems modelling is introduced in Section 2. Section 3 proposes the decentralized fault estimation, and Section 4 is devoted to the link-based distributed fault-tolerant tracking design. Simulation results verify the effectiveness of the co-designed algorithm of the sensor faulty multi-agent systems with bi-directional couplings in Section 5. Finally, Section 6 presents the conclusion.

Notation $\mathbb{R}^n$ represents the n-dimensional Euclidean space, $\mathbb{R}^{n\times m}$ denotes the set of all $n\times m$ real matrices, the symbol $\dagger$ representss the pseudo-inverse, $\otimes$ denotes the Kronecker product of matrices, $\mathrm{He}(X) = X + X^T$, and $\star$ denotes the symmetric item of the specific matrix.

2. MULTI-AGENT SYSTEMS MODELLING

Consider a set of undirected graphs $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{A})$ connected by N agent, where $\mathcal{V} = \{1, 2, \dots, N\}$ denotes the node set, $\mathcal{E} \subseteq \{(i, j), i, j \in \mathcal{V}\}$ denotes the edge set, and $\mathcal{A} \in \mathbb{R}^{N\times N}$ denotes the adjacency matrix. The adjacency matrix $\mathcal{A} = [a_{ij}]_{N\times N}$ represents a constant topology-based matrix, where the element a_{ij} denotes the weight coefficient of each edge (i, j). Each element $a_{ii} = 0$ for $i = 1, 2, \cdots, N$, $a_{ij} > 0$ for $(i, j) \in \mathcal{E}$, and $a_{ij} = 0$, otherwise.

The dynamics of the i-th following agent are modelled with the following Lipschitz nonlinearity, external disturbance and sensor fault,

$$\begin{aligned} &\dot{x}_i(t) = Ax_i(t) + Bu_i(t) + g(x_i(t), t) + Dd_i \\ &(t)\ y_i(t) = Cx_i(t) + Ff_{si}(t), i = 1, \cdots, N \end{aligned} \tag{1}$$

where $x_i(t) \in \mathbb{R}^n, u_i(t) \in \mathbb{R}^m, y_i(t) \in \mathbb{R}^p, d_i(t) \in \mathbb{R}^q$ and $f_{si}(t) \in \mathbb{R}^r$ denote the system state, control input, system output, external disturbance, and sensor fault, respectively. The system nonlinearity $g(x_i(t), t) \in \mathbb{R}^n$ is satisfied with the locally Lipschitz condition, and A, B, C, D, F denote system gains with compatible dimensions.

The dynamic motion of the leading agent tagged with 0 is modelled as

$$\begin{aligned} &\dot{x}_0(t) = Ax_0(t) + Bu_0(t) + g(x_0(t), t) + Dd_0(t) \\ &y_0(t) = Cx_0(t) \end{aligned} \tag{2}$$

where $x_0(t) \in \mathbb{R}^n, u_0(t) \in \mathbb{R}^m, y_0(t) \in \mathbb{R}^p, d_0(t) \in \mathbb{R}^q$ and $g(x_0(t), t) \in \mathbb{R}^n$ denote the state vector, input vector, output vector, external disturbance, and system Lipschitz nonlinearity of the leading agent, respectively.

Assumption 1 It is controllable and observable for the pairs (A, B) and (A, C), respectively.

Assumption 2 (i) The sensor fault $f_{si}(t)$ of the considered multi-agent systems (1) in the output channel is differentiable after the fault occurring time instant. (ii) Compared with the quadratic nonlinear constraint [26], the considered Lipschitz nonlinearity is constrained within the following condition, i.e., $\|g(x_i(t),t)-g(x_0(t),t)\| \leq \mathbb{L}\|x_i(t)-x_0(t)\|$. (iii) The external disturbance $d_0(t)$ of the leading agent is $\mathcal{L}_2[0,\infty)$ bounded.

3. DECENTRALIZED FAULT ESTIMATION

According to the differentiable sensor fault $f_{si}(t)$ in (1), the sensor fault can be actively hidden in the extended state through the following augmented transformation. The dynamics of the following one are extended as

$$\begin{aligned} \dot{\bar{x}}_i(t) &= \bar{A}\bar{x}_i(t) + \bar{B}u_i(t) + \bar{g}(\bar{x}_i(t),t) + \bar{D}d_i(t) \\ y_i(t) &= \bar{C}\bar{x}_i(t) \end{aligned} \tag{3}$$

where the extended state is denoted as $\bar{x}_i(t) = [x_i^T(t)\ f_{si}^T(t)]^T$ and the augmented nonlinearity is denoted as $\bar{g}(\bar{x}_i(t),t) = [g^T(x_i(t),t)\ 0_{r\times 1}]^T$. The gain matrices in (3) are modelled as

$$\bar{A} = \begin{bmatrix} A & 0_{n\times r} \\ 0_{r\times n} & 0_{r\times r} \end{bmatrix}, \bar{B} = \begin{bmatrix} B \\ 0_{r\times m} \end{bmatrix}, \bar{D} = \begin{bmatrix} D \\ 0_{r\times q} \end{bmatrix},$$
$$\bar{C} = [C\ \ F]$$

The extended state $\bar{x}_i(t)$ requires to be evaluated by the i-th decentralized unknown input observer, which means that the sensor fault and state information is simultaneously evaluated by its corresponding observer rather than the connected observers.

In this study, the i-th decentralized unknown input observer is devised as

$$\begin{aligned} \hat{\bar{x}}_i(t) &= z_i(t) + Hy_i(t) \\ \dot{z}_i(t) &= Mz_i(t) + Gu_i(t) + Jy_i(t) + \Gamma\bar{g}(\hat{\bar{x}}_i(t),t) \end{aligned} \tag{4}$$

where $z_i(t)$ denotes the state of the i-th unknown input observer, and $\hat{\bar{x}}_i(t) = [\hat{x}_i^T(t)\ \hat{f}_{si}^T(t)]^T$ denotes the estimated value of $\bar{x}_i(t)$, where $\hat{x}_i(t)$ and $\hat{f}_{si}(t)$ denote the respective estimations of $x_i(t)$ and $f_{si}(t)$, and $\bar{g}(\hat{\bar{x}}_i(t),t)$ denotes the estimation of $\bar{g}(\bar{x}_i(t),t)$ with the estimated state $\hat{\bar{x}}_i(t)$. Matrices M,G,J,Γ and H are of compatible dimensions to be computed in the unknown input observer design.

Denote the estimation error $\bar{e}_i(t) = \bar{x}_i(t) - \hat{\bar{x}}_i(t) = [e_{xi}^T(t)\ e_{si}^T(t)]^T$ with the state estimation error $e_{xi}(t) = x_i(t) - \hat{x}_i(t)$ and the sensor fault estimation error $e_{si}(t) = f_{si}(t) - \hat{f}_{si}(t)$.

Then, on the basis of the extended dynamics (3) and the unknown input observer (4), the estimation error dynamics are derived as

$$\begin{aligned} \dot{\bar{e}}_i(t) = &\left(\Gamma\bar{A} - J_1\bar{C}\right)\bar{e}_i(t) + \left(\Gamma\bar{A} - J_1\bar{C} - M\right)z_i(t) \\ &+ \Gamma\Delta\bar{g}(\bar{e}_i(t),t) + (\Gamma\bar{B} - G)u_i(t) \\ &+ \Gamma\bar{D}d_i(t) + \left(\left(\Gamma\bar{A} - J_1\bar{C}\right)H - J_2\right)y_i(t) \end{aligned} \tag{5}$$

where $\Gamma = I_{n+r} - H\bar{C}, J = J_1 + J_2$ and $\Delta\bar{g}(\bar{e}_i(t),t) = \bar{g}(\bar{x}_i(t),t) - \bar{g}(\hat{\bar{x}}_i(t),t)$.

According to the following equation constraints,

$$\begin{cases} \Gamma\bar{A} - J_1\bar{C} = M \\ \Gamma\bar{B} = G \\ \left(\Gamma\bar{A} - J_1\bar{C}\right)H = J_2 \end{cases} \tag{6}$$

Then, the estimation error systems (5) are modified as

$$\dot{\bar{e}}_i(t) = M\bar{e}_i(t) + \Gamma\Delta\bar{g}(\bar{e}_i(t),t) + \Gamma\bar{D}d_i(t) \tag{7}$$

Remark 1 On the basis of the estimation error system (5), since M is Hurwitz and $\Gamma\Delta\bar{g}(\bar{e}_i(t),t) = 0, \Gamma\bar{D}d_i(t) = 0$, then $\dot{\bar{e}}_i(t) = M\bar{e}_i(t)$ is obtained, and the estimated error dynamics are robustly asymptotically stable, i.e., $\lim_{t\to\infty}\bar{e}_i(t) = 0$. Therefore, this implies that if the estimation error system is asymptotically robust under the considered equation constraints (6), the unknown input observer exists in the extended dynamics (3). Furthermore, it indicates from (5) and (7) that the performance of fault estimation is influenced by the nonlinearity $g(x_i(t),t)$ and the external disturbance $d_i(t)$.

Remark 2 The nonlinear error $\Delta\bar{g}(\bar{e}_i(t),t) \neq 0$ and the external disturbance item $d_i(t) \neq 0$ are considered. Then, matrices Γ, M, G and J_2 are computed with the derived J_1 and H, i.e., $\Gamma = I_{n+r} - H\bar{C}, M = (I_{n+r} - H\bar{C})\bar{A} - J_1\bar{C}, J_2 = ((I_{n+r} - H\bar{C})\bar{A} - J_1\bar{C})H$ and $G = (I_{n+r} - H\bar{C})\bar{B}$. Hence, the objective of unknown input observer in the decentralized fault estimation design is to compute J_1 and H such that the estimated error dynamics (5) and (7) are asymptotically robustly stable in spite of the nonlinear errors $\Delta\bar{g}(\bar{e}_i(t),t)$ and external disturbances $d_i(t)$.

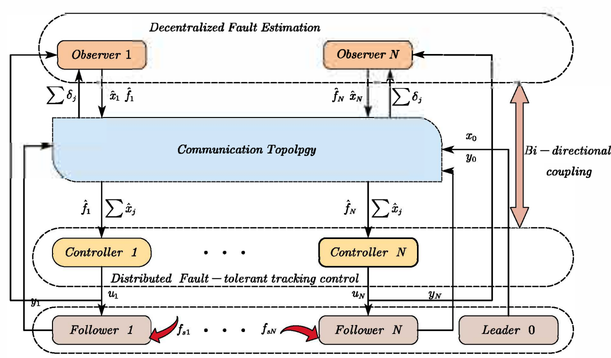

Fig. 1. The co-designed structure with decentralized fault estimation and distributed fault-tolerant tracking control.

4. DISTRIBUTED FAULT-TOLERANT TRACKING CONTROL

The co-designed framework of fault estimation and fault-tolerant tracking control is proposed in Fig. 1 on the basis of the following two parts, i.e., the sensor fault com-pensation (SFC) item which contains the overall estima-tion information of the full-ordered unknown input ob-server (4), and the consensus tracking item which consists of the relative output signal of the neighboring agents and the estimated sensor faults through an updated link-based distributed tracking control law.

The link-based distributed fault-tolerant tracking con-troller $u_i(t)$ in (1) is designed as

$$\begin{aligned} u_i(t) = & -\overbrace{K_f \hat{\bar{x}}_i(t)}^{\text{SFC item}} \\ & \underbrace{+ K_l \delta_{ij}(t) \sum_{j=1}^{N} a_{ij} \left(y_i(t) - F\hat{f}_{si}(t) - y_j(t) + F\hat{f}_{sj}(t) \right)}_{\text{consensus tracking item}} \end{aligned} \tag{8}$$

where $K_f = [K_s \; 0_{m\times r}]$ is the SFC matrix with the state compensation matrix K_s, K_l is the updated link gain matrix, a_{ij} denotes the (i,j)-th entry of the adjacency matrix $\mathcal{A}$, and $\delta_{ij}(t)$ represents the weight coefficient between the i-th and the j-th agents with $\delta_{ij}(t) = \delta_{ji}(t)$ and $\delta_{ii}(t) = 0$. Furthermore, $\delta_{ij}(t)$ is restricted to $\delta_{ij}(t)a_{ik} = \delta_{ij}(t)a_{ij}$ when $j = k$, otherwise, $\delta_{ij}(t)a_{ik} = 0$ when $j \neq k$.

The updated link-based distributed tracking control law of the weight coefficient $\delta_{ij}(t)$ in (8) is designed as follows

$$\begin{aligned} \dot{\delta}_{ij}(t) = & \tau_{ij} a_{ij} \left(y_i(t) - y_j(t) \right)^T \Pi \left(y_i(t) - F\hat{f}_{si}(t) \right. \\ & \left. - y_j(t) + F\hat{f}_{sj}(t) \right) \end{aligned} \tag{9}$$

where τ_{ij} is a positive scalar and Π denotes the inter-link gain matrix.

Substituting the link-based distributed fault-tolerant tracking controller (8) into the original dynamics (1) yields

$$\begin{aligned} \dot{x}_i(t) = & (A - BK_s)x_i(t) + BK_f \bar{e}_i(t) + g(x_i(t),t) \\ & + BK_l \delta_{ij}(t) \textstyle\sum_{j=1}^{N} a_{ij}(C(x_i(t) - x_j(t)) \\ & + F(e_{si}(t) - e_{sj}(t)) + Dd_i(t) \end{aligned} \tag{10}$$

Consider the healthy sensor measuring information in the leading agent, the control input of the leading agent is traditionally designed as $u_0(t) = -K_o y_0(t)$ with $K_o = K_s C^{\dagger}$.

Subsequently, denote the state consensus tracking error as $e_i(t) = x_i(t) - x_0(t)$, and the state consensus tracking error dynamics are derived by

$$\begin{aligned} \dot{e}_i(t) = & (A - BK_s)e_i(t) + BK_f \bar{e}_i(t) + F(e_{si}(t) - e_{sj}(t)) \\ & + BK_l \delta_{ij}(t) \textstyle\sum_{j=1}^{N} a_{ij}(C(x_i(t) - x_j(t)) \\ & + \Delta g(e_i(t),t) + D\Delta d_i(t) \\ = & (A - BK_s)e_i(t) + BK_f \bar{e}_i(t) + F\Phi(\bar{e}_i(t) - \bar{e}_j(t)) \\ & + BK_l \delta_{ij}(t) \textstyle\sum_{i=1}^{N} a_{ij}(C(e_i(t) - e_j(t)) \\ & + \Delta g(e_i(t),t) + D\Delta d_i(t) \end{aligned} \tag{11}$$

where the nonlinear error $\Delta g(e_i(t),t) = g(x_i(t),t) - g(x_0(t),t)$, the disturbance error $\Delta d_i(t) = d_i(t) - d_0(t)$, and $\Phi = [0_{r\times n} \;\; I_r]$.

In comparison with the separated estimation error dynamics and another separated state consensus tracking error dynamics via the updated link-based distributed tracking control algorithm in (8) and (9), it follows that

$$\begin{cases} \dot{\bar{e}}_i(t) = M\bar{e}_i(t) + \Gamma\Delta\bar{g}(\bar{e}_i(t),t) + \Gamma\bar{D}d_i(t) \\ \dot{e}_i(t) = (A - BK_s)e_i(t) + \Delta g(e_i(t),t) + D\Delta d_i(t) \\ \qquad + BK_l \delta_{ij}(t) \sum_{i=1}^{N} a_{ij}(C(e_i(t) - e_j(t))) \end{cases} \tag{12}$$

Notably, the separated estimation error and state consensus tracking error dynamics in (12) do not take the bi-directional couplings between the estimation and tolerance systems into consideration. Specifically, both the Lipschitz nonlinear errors in $\Gamma\Delta\bar{g}(\bar{e}_i(t),t)$ and $\Delta g(e_i(t),t)$ and the disturbance errors in $\Gamma\bar{D}d_i(t)$ and $D\Delta d_i(t)$ exist in the estimation and tolerance systems. Furthermore, the estimation error items $BK_f\bar{e}_i(t)$ and $BK_l\delta_{ij}(t)\sum_{i=1}^{N} a_{ij}(F\Phi(\bar{e}_i(t) - \bar{e}_j(t)))$ have an obvious influence on the state consensus tracking dynamics.

Thus, the proposed estimation error and state consensus tracking error systems with the bi-directional couplings $\bar{g}(\bar{e}_i(t),t), g(e_i(t),t), d_i(t), \Delta d_i(t)$ and $\bar{e}_i(t)$ in a co-designed framework yield the following expressions,

$$\begin{cases} \dot{\bar{e}}(t) = \left(I_N \otimes \left(\Gamma\bar{A} - J_1\bar{C}\right)\right)\bar{e}(t) + (I_N \otimes \Gamma)\Delta\bar{g}(\bar{e}(t),t) \\ \qquad + (I_N \otimes \Gamma\bar{D})d(t) \\ \dot{e}(t) = (I_N \otimes (A - BK_s) - (\Delta\delta(t) \circ \mathcal{L}) \otimes BK_lC)e(t) \\ \qquad + \Delta g(e(t),t) + (I_N \otimes D)\Delta d(t) \\ \qquad + (I_N \otimes BK_f - (\Delta\delta(t)\mathcal{L}) \otimes BK_lF\Phi)\bar{e}(t) \\ z(t) = (I_N \otimes C_{\bar{e}})\bar{e}(t) + (I_N \otimes C_e)e(t) \end{cases} \tag{13}$$

with the following global vectors,

$$\begin{aligned} & \bar{e}(t) = [\bar{e}_1^T(t), \cdots, \bar{e}_N^T(t)]^T, e(t) = [e_1^T(t), \cdots, e_N^T(t)]^T, \\ & \Delta\bar{g}(\bar{e}(t),t) = [\Delta\bar{g}^T(\bar{e}_1(t),t), \cdots, \Delta\bar{g}^T(\bar{e}_N(t),t)]^T, \\ & \Delta g(e(t),t) = [\Delta g^T(e_1(t),t), \cdots, \Delta g^T(e_N(t),t)]^T, \\ & d(t) = [d_1^T(t), \cdots, d_N^T(t)]^T, \\ & \Delta d(t) = [\Delta d_1^T(t), \cdots, \Delta d_N^T(t)]^T \end{aligned}$$

and $z(t) \in \mathbb{R}^{\bar{r}}$ is the expected output with matrices $C_{\bar{e}} \in \mathbb{R}^{\bar{r}\times(n+r)}$ and $C_e \in \mathbb{R}^{\bar{r}\times n}$. The symbol $\mathcal{L}$ denotes the Laplacian matrix, and $\otimes$ and $\circ$ denote the Kronecker product and entrywise product, respectively.

Furthermore, matrix $\Delta\delta(t) = [\Delta\delta_{ij}(t)] \in \mathbb{R}^{N\times N}$, where $\Delta\delta_{ij}(t)$ is the element of matrix $\Delta\delta(t)$ satisfying with

$$\Delta\delta_{ij}(t) = \begin{cases} \delta_{ij}(t), & \text{if } i \neq j \\ \sum_{k=1}^{N} \delta_{ik}(t), & \text{if } i = j \end{cases} \tag{14}$$

Given a positive scalar γ, the decentralized fault estimation and distributed fault-tolerant tracking control co-design for the sensor faulty multi-agent systems with bi-directional couplings can realize an H_∞ robust performance index no greater than γ, if the following inequality holds

$$\int_0^\infty z^T(t)z(t)\mathrm{d}t \le \gamma^2 \int_0^\infty d^T(t)d(t)\mathrm{d}t \tag{15}$$

The main objective of the co-designed fault estimation and fault-tolerant tracking control through the updated link-based distributed law is to compute K_s, K_l, J_1 and H to guarantee the robust stability of the estimation error and state consensus tracking error dynamics (7) and (11) in the considered multi-agent systems in the presence of Lipschitz nonlinearity, external disturbance, sensor fault as well as the bi-directional couplings between the estimation and tolerance systems. Thus, the leader-following consensus tracking property of the considered multi-agent systems is realized.

Theorem 1 Given the positive scalars $\varepsilon_f, \varepsilon_1, \varepsilon_2, \eta, \gamma$ and matrices $C_{\bar{e}}, C_e$, the considered estimation error and state consensus tracking error dynamics (13) are robustly stable and the leader-following consensus tracking issue with an H_∞ performance index are solved through the co-design of the decentralized fault estimation and distributed fault-tolerant tracking control strategy, if there exist symmetric positive definite matrices $\bar{P}, Q_1, Q_2$ and Q_3, and matrices $K_l, X_1, X_2, X_3, X_4, X_5, X_6$ and X_7 such that

$$\begin{bmatrix} \Xi_{11} & \Xi_{12} & D & \bar{P} & \bar{P}C_e^T & BK_lC & 0 \\ \star & \Xi_{22} & \Xi_{23} & 0 & 0 & 0 & \Xi_{27} \\ \star & \star & \Xi_{33} & 0 & 0 & 0 & 0 \\ \star & \star & \star & \Xi_{44} & 0 & 0 & 0 \\ \star & \star & \star & \star & \Xi_{55} & 0 & 0 \\ \star & \star & \star & \star & \star & \Xi_{66} & 0 \\ \star & \star & \star & \star & \star & \star & \Xi_{77} \end{bmatrix} < 0 \tag{16}$$

with

$$\begin{aligned} &\Xi_{11} = \mathrm{He}(A\bar{P} - BX_1) + \varepsilon_1^{-1}I_n + \varepsilon_2^{-1}NDD^T, \\ &\Xi_{12} = BK_f - \eta\lambda_{\min}BK_lF\Phi + \bar{P}C_e^TC_{\bar{e}}, \\ &\Xi_{22} = \begin{bmatrix} \hat{\Xi}_{11} & \hat{\Xi}_{12} & \hat{\Xi}_{13} \\ \star & \mathrm{He}(-X_4CB) & -X_5 - B^TC^TX_6^T \\ \star & \star & \mathrm{He}(-X_7) \end{bmatrix} \\ &\quad + \varepsilon_f\mathbb{L}^2I_{n+r} + C_{\bar{e}}^TC_{\bar{e}}, \\ &\Xi_{23} = \begin{bmatrix} Q_1D - X_2CD & 0 & -X_2 \\ -X_4CD & Q_2 & -X_4 \\ -X_6CD & 0 & Q_3 - X_6 \end{bmatrix}, \\ &\Xi_{27} = \begin{bmatrix} Q_1 - X_2C & 0 & -X_2 \\ -X_4C & Q_2 & -X_4 \\ -X_6C & 0 & Q_3 - X_6 \end{bmatrix}, \\ &\Xi_{33} = -\gamma^2I_{n+q}, \Xi_{44} = -(\varepsilon_1\mathbb{L}^2 + \eta^2\lambda_{\min}^2)^{-1}I_n, \\ &\Xi_{55} = -I_n, \Xi_{66} = -I_n, \Xi_{77} = -\varepsilon_fI_{n+r} \end{aligned}$$

where $\hat{\Xi}_{11} = \mathrm{He}(Q_1A - X_2CA - X_3C), \hat{\Xi}_{12} = Q_1B - X_2CB - A^TC^TX_4^T - C^TX_5^T, \hat{\Xi}_{13} = -X_3 - A^TC^TX_6^T - C^TX_7^T$, and $\lambda_{\min}$ is the minimum non-zero eigenvalue of the graph $\mathcal{L}$. The symbol $\star$ denotes the symmetric entries and $\mathrm{He}(\mathrm{X}) = \mathrm{X} + \mathrm{X}^\mathrm{T}$.

Thus, the designed matrices in fault estimation and fault-tolerant tracking control co-design are derived as $K_s = X_1\bar{P}^{-1}, H_1 = Q_1^{-1}X_2, J_{11} = Q_1^{-1}X_3, H_2 = Q_2^{-1}X_4, J_{12} = Q_2^{-1}X_5, H_3 = Q_3^{-1}X_6$ and $J_{13} = Q_3^{-1}X_7$. The inter-link gain matrix is derived as $\Pi = (C^T)^\dagger\bar{P}^{-1}BK_l$.

Proof Consider the following Lyapunov function candidate $V_1(t)$ with a symmetric positive definite matrix Q,

$$V_1(t) = \bar{e}^T(t)(I_N \otimes Q)\bar{e}(t) \tag{17}$$

On the basis of the Lipschitz condition of $g(x_i(t), t)$ in Assumption 2, $\|\bar{g}(\bar{x}_i(t), t) - \bar{g}(\hat{\bar{x}}_i(t), t)\| \le \mathbb{L}^2\|\bar{e}_i(t)\|^2$ is derived. For a positive scalar ε_f, it is derived as

$$\begin{aligned} &2\bar{e}_i^T(t)Q\Gamma\Delta\bar{g}(\bar{e}_i(t), t) \\ &\le \varepsilon_f^{-1}\bar{e}_i^T(t)Q\Gamma\Gamma^TQ\bar{e}_i(t) + \varepsilon_f\mathbb{L}^2\|\bar{e}_i(t)\|^2 \end{aligned} \tag{18}$$

The derivative of $V_1(t)$ in (17) is given as follows

$$\begin{aligned} \dot{V}_1(t) \le\ &\bar{e}^T(t)(I_N \otimes (\mathrm{He}(Q(\Gamma\bar{A} - J_1\bar{C})) \\ &+ \varepsilon_f^{-1}Q\Gamma\Gamma^TQ + \varepsilon_f\mathbb{L}^2I_{n+r}))\bar{e}(t) \\ &+ 2\bar{e}^T(t)(I_N \otimes Q\Gamma\bar{D})d(t) \end{aligned} \tag{19}$$

Subsequently, given a positive scalar η and a symmetric positive matrix P, consider the following Lyapunov function $V_2(t)$

$$V_2(t) = e^T(t)(I_N \otimes P)e(t) + \sum_{i=1}^N \sum_{j=1}^N \frac{(\delta_{ij}(t) - \eta)^2}{\tau_{ij}} \tag{20}$$

where τ_{ij} is a positive scalar and $\delta_{ij}(t)$ is the weight coefficient in the updated link-based distributed tracking control law.

Define the inverse matrix $\bar{P} = P^{-1}$. Since $\Pi = (C^T)^\dagger\bar{P}^{-1}BK_l$ is satisfied, $PBK_l = C^T\Pi$ is realized. It then follows that

$$\begin{aligned} &-2e^T(t)(\Delta\delta(t) \circ \mathcal{L}) \otimes (PBK_lCe(t) + PBK_lF\Phi\bar{e}(t)) \\ &+ \sum_{i=1}^N \sum_{j=1}^N (\delta_{ij}(t) - \eta)a_{ij}(y_i(t) - y_j(t))^T \\ &\times \Pi(y_i(t) - F\hat{f}_{si}(t) - y_j(t) + F\hat{f}_{sj}(t)) \\ = &-2\eta\sum_{i=1}^N \sum_{j=1}^N e_i^T(t)a_{ij}PBK_l(C(x_i(t) - x_j(t)) \\ &+ F(e_{si}(t) - e_{sj}(t)) \end{aligned} \tag{21}$$

where $\Delta\delta_{ij}(t)$ is the element of matrix $\Delta\delta(t)$.

Then, the derivative of $V_2(t)$ in (20) is obtained with the positive constants ε_1 and ε_2 as follows

$$\begin{aligned} \dot{V}_2(t) \le\ &\sum_{i=1}^N e_i^T(t)(\mathrm{He}(P(A - BK_s)) + \varepsilon_1^{-1}PP + \varepsilon_1\mathbb{L}^2I_n \\ &- 2\eta\lambda_{\min}PBK_lC + \varepsilon_2^{-1}NPDD^TP)e_i(t) \\ &+ 2\sum_{i=1}^N e_i^T(t)(PBK_f - \eta\lambda_{\min}PBK_lF\Phi)\bar{e}_i(t) \\ &+ 2\sum_{i=1}^N e_i^T(t)PD\Delta d_i(t) \end{aligned} \tag{22}$$

where $\lambda_{\min}$ is the minimum non-zero eigenvalue of $\mathcal{L}$.

It thus follows that

$$\begin{aligned}
&z^T(t)z(t)-\gamma^2 d^T(t)d(t)+\dot V_1(t)+\dot V_2(t)\\
\le\ &\bar e^T(t)(I_N\otimes(\mathrm{He}(Q(\Gamma\bar A-J_1\bar C))+\varepsilon_f^{-1}Q\Gamma\Gamma^TQ\\
&+\varepsilon_f\mathbb{L}^2I_{n+r}+C_{\bar e}^TC_{\bar e}))\bar e(t)-2\eta\lambda_{\min}PBK_lC\\
&+2e^T(t)\left(I_N\otimes(PBK_f-\eta\lambda_{\min}PBK_lF\Phi+C_e^TC_{\bar e})\right)\bar e(t)\\
&+e^T(t)(I_N\otimes(\mathrm{He}(P(A-BK_s))+\varepsilon_1^{-1}PP+\varepsilon_1\mathbb{L}^2I_n\\
&+\varepsilon_2^{-1}NPDD^TP+C_e^TC_e))e(t)-\gamma^2d^T(t)d(t)
\end{aligned}\tag{23}$$

However, the equality constraint $PBK_l=C^T\Pi$ is difficult to address in consideration of the computational freedom. Thus, to overcome the equality constraint, the following expression is illustrated.

$$\begin{aligned}
&\textstyle\sum_{i=1}^N e_i^T(t)\left(-2\eta\lambda_{\min}BK_lC\bar P\right)e_i(t)\\
\le&\textstyle\sum_{i=1}^N e_i^T(t)(BK_lCC^TK_l^TB^T+\eta^2\lambda_{\min}^2\bar P\bar P)e_i(t)
\end{aligned}\tag{24}$$

Subsequently, the sufficient condition of achieving an H_∞ performance index no greater than γ is $z^T(t)z(t)-\gamma^2d^T(t)d(t)+\dot V_1(t)+\dot V_2(t)<0$.

Denote $X_1=K_s\bar P$ and define the global vector $\zeta(t)=[e^T(t)\ \bar e^T(t)\ d^T(t)]^T$, pre-multiplying and post-multiplying both sides with the diagonal matrix $\mathrm{diag}(I_N\otimes\bar P,I_{N(n+r)},I_{qN})$ yields

$$\zeta^T(t)\bar\Omega\zeta(t)<0\tag{25}$$

with

$$\bar\Omega=\begin{bmatrix}\Omega_{11} & BK_f+\bar PC_e^TC_{\bar e}-\eta\lambda_{\min}BK_lF\Phi & D\\ \star & \Omega_{22} & Q\Gamma\bar D\\ \star & \star & -\gamma^2I_{qN}\end{bmatrix}$$

where the elements $\Omega_{11}=\mathrm{He}(A\bar P-BX_1)+\varepsilon_1^{-1}I_n+(\varepsilon_1\mathbb{L}^2+\eta^2\lambda_{\min}^2)\bar P\bar P+BK_lCC^TK_l^TB^T+\bar PC_e^TC_e\bar P+\varepsilon_2^{-1}NDD^T$ and $\Omega_{22}=\mathrm{He}(Q(\Gamma\bar A-J_1\bar C))+\varepsilon_f^{-1}Q\Gamma\Gamma^TQ+\varepsilon_f\mathbb{L}^2I_{n+r}+C_{\bar e}^TC_{\bar e}$.

Since $\bar\Omega<0$ holds, it follows that $\zeta^T(t)\bar\Omega\zeta(t)\le-\bar\lambda_{\min}(-\bar\Omega)\|\zeta(t)\|^2<0$, where $\bar\lambda_{\min}(-\bar\Omega)$ is the minimum eigenvalue of matrix $-\bar\Omega$.

Finally, define $Q=\mathrm{diag}(Q_1,Q_2,Q_3),H=[H_1^T\ H_2^T\ H_3^T]^T$ and $J_1=[J_{11}^T\ J_{12}^T\ J_{13}^T]^T$ with $X_2=Q_1H_1,X_3=Q_1J_{11},X_4=Q_2H_2,X_5=Q_2J_{12},X_6=Q_3H_3$ and $X_7=Q_3J_{13}$. Therefore, the inequality $\bar\Omega<0$ can be converted to the linear matrix inequality form in (16) using Schur lemma without the optimization approach of the equality constraint, i.e., $PBK_l=C^T\Pi$. Hence, the considered estimation error and state consensus tracking error dynamics (13) are robustly stable and the leader-following consensus tracking problem with the H_∞ index γ is addressed.

Remark 3 The main difference between the developed updated link-based distributed fault-tolerant tracking control design and other decentralized control scheme [23, 24] or the traditional distributed control scheme [15] lies in the dynamic collection of the distributed data from mutually exclusive neighbors in the case of dealing with switching topologies in networked multi-agent systems. Compared with the separated fault-tolerant control and fault estimation designs that do not consider system nonlinearity and estimation errors [17, 18], this co-design approach proposed in this study can effectively circumvent the problem of loop superposition and deterioration of fault information introduced into the fault-tolerant tracking system from the estimation system.

5. SIMULATION RESULTS

In this section, the case of multi-machine power systems with Lipschitz nonlinear interconnections and sensor faults in the rotor angle and relative speed measuring instruments is presented to validate the efficiency of the developed co-design of decentralized fault estimation and distributed fault-tolerant tracking algorithm.

The considered Lipschitz nonlinear model in three-machine power control field [26] is characterized by the system matrices $\{A,B,C\}$, the disturbance distribution matrix D, the sensor fault distribution matrix F as follows:

$$\begin{aligned}
A&=\begin{bmatrix}0&1&0&0\\0&-0.2941&30.7999&0\\0&0&-2.8571&2.8571\\0&0.6366&0&-10\end{bmatrix},\\
B&=\begin{bmatrix}0\\0\\0\\10\end{bmatrix},\quad C=\begin{bmatrix}1&0&0&0\\0&1&0&0\end{bmatrix},\\
D&=\begin{bmatrix}0.8&0.9&0&1\end{bmatrix}^T,\quad F=\begin{bmatrix}0.5&1\end{bmatrix}^T
\end{aligned}\tag{26}$$

The Laplacian matrix $\mathcal{L}$ of three-machine power systems is formulated as

$$\mathcal{L}=\begin{bmatrix}2&-1&-1\\-1&2&-1\\-1&-1&2\end{bmatrix}\tag{27}$$

The state vector of each machine in three-machine power systems is denoted as $x_i(t)=[\Delta\sigma_i{}^T\ \Delta\omega_i{}^T\ \Delta P_{mi}^T\ \Delta X_{e_i}^T]^T,i=0,\cdots,3$, where $\Delta\omega_i$ is the relative speed, $\Delta\sigma_i$ is the deviation of rotor angle, ΔX_{e_i} is the deviation per unit steam orifice diameter, and ΔP_{mi} is the deviation per unit mechanical power.

The Lipschitz nonlinear interconnection item is modelled as $g(x_i(t),t)=[\sum_{j=1}^3\alpha_{ij}\sin(\Delta\sigma_i-\Delta\sigma_j)\ 0\ 0\ 0]^T$ with $\alpha_{ij}=1,i,j=1,2,3$ on the basis of the given Laplacian matrix $\mathcal{L}$. Furthermore, the three-machine power dynamics are set with the sensor fault noise in rotor angle and relative speed instruments, i.e., $f_{s1}(t)$ with the band-limited white noise (noise power: 0.1, sample time: 1, time period of occurrence: 0s-20s, and upper bound: 0.05 between 20s-80s) and $f_{s2}(t)$ with the band-limited white noise (noise power: 0.5, sample time: 0.5, time period of

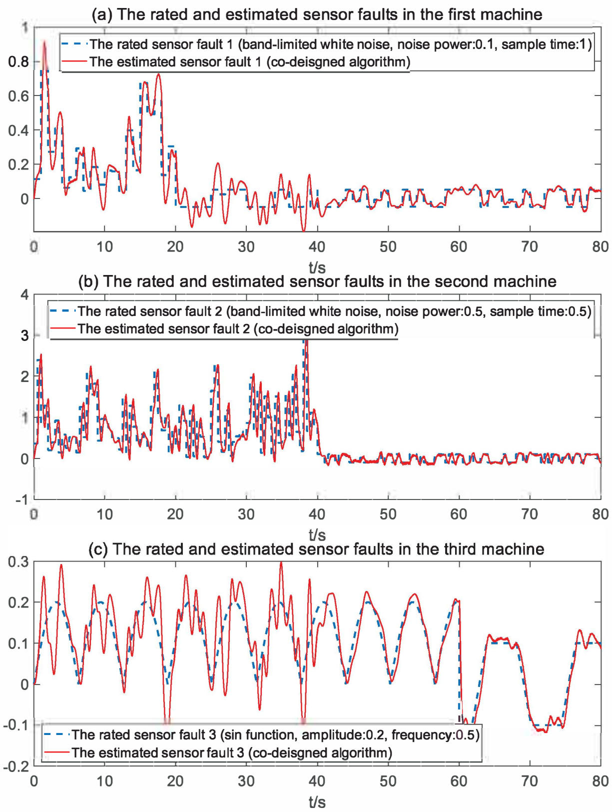

Fig. 2. The rated and estimated sensor faults in the three-machine power systems with the co-designed algorithm

occurrence: 0s-40s, and upper bound: 0.1 between 40s-80s). The settled sensor fault in the third machine is given as follows:

$$f_3 = \begin{cases} |0.2\sin(0.5t)|, t \leq 60 \\ 0.1\mathrm{sat}\left(0.2\sin\left(0.5t\right)\right), t > 60 \end{cases} \tag{28}$$

In the presence of white-noise sensor faults with restrictions for both the first and second machines, and the time-varying sensor faults combining $\sin(\cdot)$ and saturation $\mathrm{sat}(\cdot)$ functions for the third machine in the three-machine power systems, all the results in Figs. 2-7 show the effectiveness of the decentralized fault estimation and distributed fault-tolerant tracking control co-design through an updated link-based tracking control law.

Fig. 2 shows the rated and estimated sensor faults for the multi-machine power systems. The mixed sensor fault noise in the rotor angle and relative speed measurement channels can be accurately, timely and effectively estimated by the decentralized unknown input observers, and the estimated curves almost coincides with the rated curves. Furthermore, despite the bi-directional couplings between the estimation and tolerance systems, all estimated sensor faults achieve good tracking of the rated values simulated by the proposed co-designed fault estima-

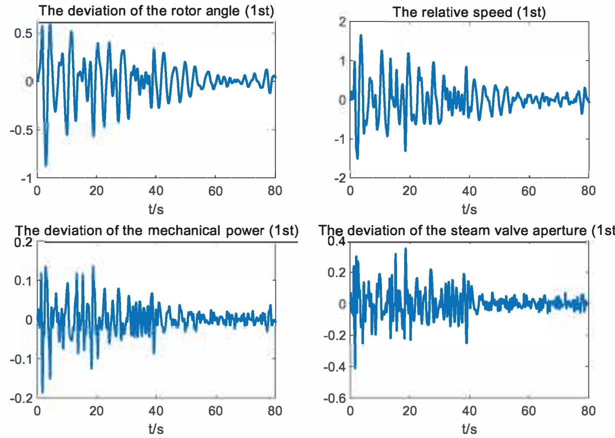

Fig. 3. The rotor angle, speed, mechanical power and steam valve aperture states in the first machine

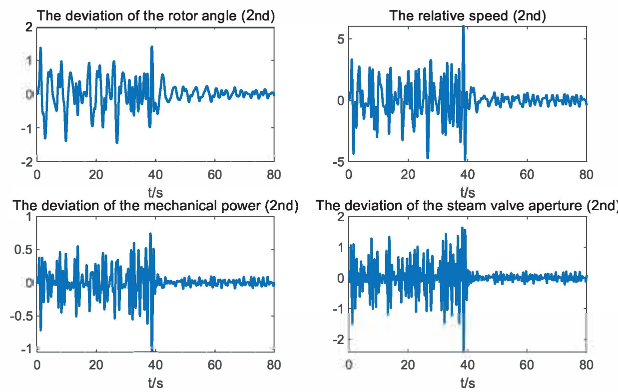

Fig. 4. The rotor angle, speed, mechanical power and steam valve aperture states in the second machine

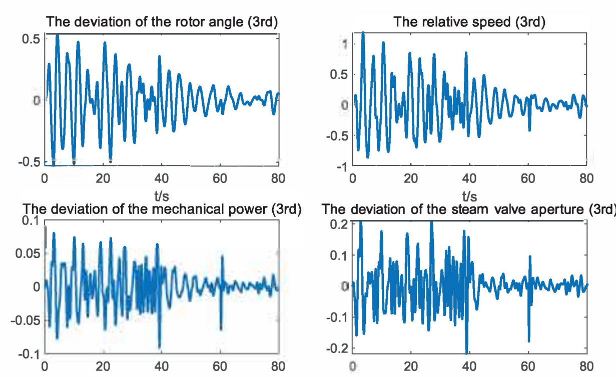

Fig. 5. The rotor angle, speed, mechanical power and steam valve aperture states in the third machine

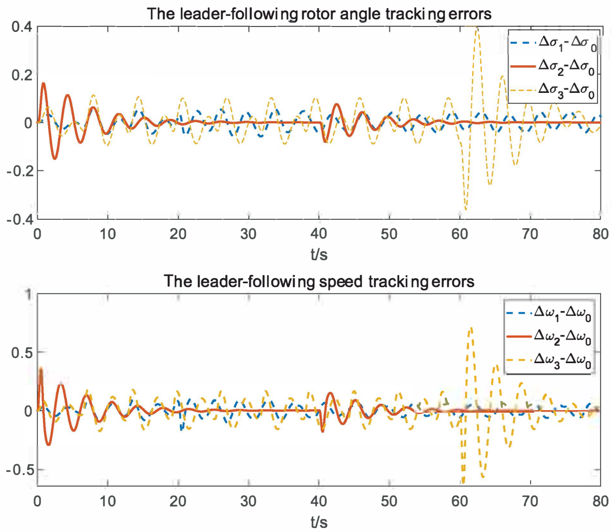

Fig. 6. The leader-following rotor angle and speed tracking errors in the three-machine power systems

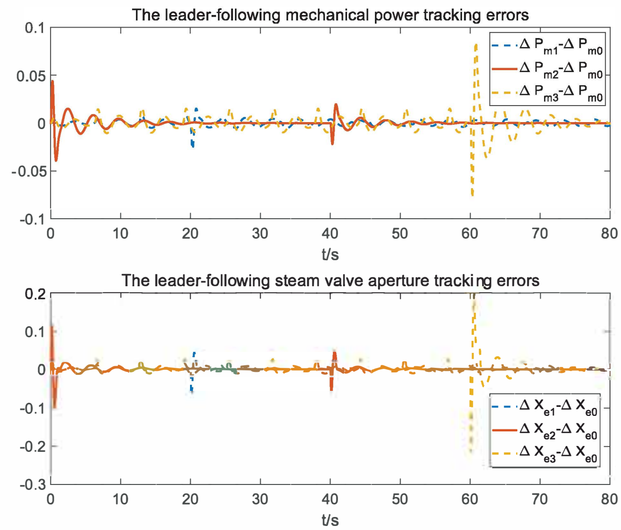

Fig. 7. The leader-following mechanical power and steam valve aperture tracking errors in the three-machine power systems

tion and fault-tolerant tracking algorithm.

The respective state evolutions of the speed $\Delta\omega$, rotor angle $\Delta\sigma$, mechanical power ΔP_m, and steam valve orifice diameter ΔX_e for each machine in Figs. 3-5 illustrate the robustness of the power systems of the three following machines. Notably, the first machine drops the fault during 0s-20s at lower noise power and the second machine fails during 0s-40s at higher noise power. The third machine suffers a sin function sensor failure during the period of 0s-60s and a saturation sensor failure within the period of 60s-80s.

Furthermore, the leader-following rotor angle tracking errors, speed tracking errors, mechanical power tracking errors, and steam valve aperture tracking errors are illustrated in Fig. 6 and Fig. 7, which implies that the state consensus tracking errors converge to some extent for the multi-machine power systems in spite of the Lipschitz nonlinearities, external disturbances, sensor faults as well as the bi-directional couplings.

6. CONCLUSION

The co-designed algorithm of the decentralized fault estimation and distributed fault-tolerant tracking control strategies is proposed for a class of Lipschitz nonlinear multi-agent systems in spite of external disturbances and sensor faults. The main innovation is the exploration of the bi-directional couplings between the considered estimation and tolerance dynamics. Decentralized fault estimation scheme is developed to evaluate sensor faults and states, and an updated link-based distributed fault-tolerant tracking strategy is developed to efficiently handle the dynamical and switching topologies based on the current output and estimated collections. Simulation example of three-machine power systems validates the ef-fectiveness of the proposed co-design algorithm. Future studies of general nonlinear multi-agent systems towards more effective tolerance capabilities in the face of actua-tor/sensor faults in physical layer and communication de-lays or cyber-attacks in networked layer are highlighted. More challenges of the cooperative tracking control issues with better robustness and lower bandwidth requirements should be further addressed by the improved integration of cooperative fault estimation and fault-tolerant tracking control co-design in dealing with the presence of multiple sources of nodes and links, reciprocal delays and multiple communication resource consumption.

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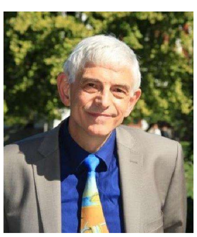

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