Distributed Fault Detection of Nonlinear Process Systems with Senor Failures ⋆

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Abstract: A distributed fault detection scheme is presented in this work to deal with the senor failures in a nonlinear process system. Firstly, a residual generator is derived, in which the fault signal is generated by introducing a residual signal. Then, a distributed extended Kalman Filter (EKF) is designed to estimate the unmeasurable system states. Finally, the proposed distributed EKF is used for the fault detection and isolation in a distributed framework. By applying the distributed fault detection scheme to a completely stirred tank reactor process, it is shown that the proposed scheme has ability to monitor the sensor faults automatically.

Keywords: Distributed fault detection, Distributed extended Kalman Filter, Sensor faults, Completely stirred tank reactor.

1. INTRODUCTION

In practical applications, from the perspective of large-scale systems framework has become one of hot topics for research and engineering Chen et al. (2016); Song et al. (2017); Tang et al. (2018). In virtue of the rapid developments in computer science and hardware/software technology, the large-scale systems framework can bring a lot of benefits to the society, and the environment in different applications. A large-scale industrial process is a system composed of many components which may interact with each other with physical connections. It is not easy to estimate/monitor the states with a centralized structure due to the computational burden Zhang et al. (2019b,a). Recently, there has been increasing interest in distributed state estimation and control, whose analyses of feasibility, optimality and stability have been widely investigated Taşçıkaraoglu et al. (2015).

Fault tolerance control has become an important topic in modern control system and practical application Zhang and Jiang (2008). Modern control systems are required to meet high control performance and safety requirements. For a complex system, there may exist failures in sensors Xu et al. (2017), actuators Ye and Yang (2006) or other system components Patan (2014). To deal with the possible faults, many fault tolerance control approaches have been investigated to maintain the desirable stability and performance requirements Zarch et al. (2018). These approaches are known as fault tolerant control systems, which can handle the effects of faults automatically while ensuring the required control performance. The fault tolerance control system are general divided into two types Gao et al. (2015). One is known as passive fault tolerant control, in which controller are robustly designed to deal with the presumed faults Patwardhan et al. (2006). Another one is the active fault tolerant control, which can reconfigure control inputs to maintain the acceptable control performance. In this approach, the fault tolerance control performance greatly depends on the most recent system information Patwardhan and Shah (2005).

In the last decades, many attentions have been paid to the fault detection and isolation schemes. However, little attention has been attracted to the distributed fault tolerance control. The distributed fault tolerance control scheme is derived in this paper to deal with the senor failures of nonlinear systems. The approach is designed by utilizing the advantages of the distributed estimator. The system states are estimated by a Distributed EKF in a distributed framework. Such a distributed fault detection an isolation structure has the ability to monitor the effects of faults automatically.

The outline of this paper is: in Section II, problem formulations of this work are introduced. The fault detection scheme is derived under the distributed EKF framework in Section III. The proposed method is applied to a CSTR process in Section IV to show the effectiveness. Finally, Section V draws the conclusion of this paper.

2. PROBLEM FORMULATIONS

The following nonlinear system is considered:

$$\dot{x}(t) = f(x(t), u(t), w(t)) \tag{1a}$$
$$y(t) = h(x(t), v(t)) \tag{1b}$$

where the vector $x \in \mathbb{R}^n$ denotes the system state, $y \in \mathbb{R}^m$ denotes the measured outputs, $w(t)$ denotes random process noise/disturbances, v denotes a measurement noise vector, f and h are respectively refer to the dynamics of the nonlinear system and the output relation, respectively.

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Table 1. Nomenclatures

Variable	Description
x_i, u_i, y_i	state, input and output of subsystem $i, i = 1, \cdots, M$
$u_j(t_k)$	input received from subsystem $j, j = 1, \cdots, M, j \neq i$
$x_l(t_k)$	estimators of the subsystem $l, l = 1, \cdots, M$
$x_i^p(t_k)$	predicted future state based on p-th sensor
$r_i(t_k)$	residual signal of subsystem $i, i = 1, \cdots, M$
A^T	the transpose of A
(x_s, u_s)	the operation-point

To design a distributed fault tolerance control scheme, the system (2) is required to be divided into subsystems. Specifically, the model of i-th subsystem is represented as:

$$\dot{x}_i(t) = f_i(x_i(t), u_i(t), \bar{x}_i(t), \bar{u}_i(t), w_i(t)) \quad (2a)$$
$$y_i(t) = h_i(x_i(t), v_i(t)) \quad (2b)$$

where $x_i \in \mathbb{R}^{n_i}$ is the state of the i-th subsystem, $y_i \in \mathbb{R}^{m_i}$ is the output of the i-th subsystem, $\bar{x}_i$ is a vector of the neighbor subsystems of subsystem i directly, $i = 1, \cdots, M$, with M being the number of the total subsystems, $\bar{u}_i$ is a vector of neighbor subsystems of subsystem i directly. w_i denotes the process noise and v_i denotes the measurement noise of subsystem i.

The observability are checked by linearizing the nonlinear model (2) at different points. The linearized model of the system at (x_s, u_s) is described in the form of:

$$\dot{x}_i(t) = A_i x_i(t) + B_i u_i(t) + \sum_{j=1, j\neq i}^{M} (A_j x_j(t) + B_j u_j(t)) \quad (3a)$$
$$y_i(t) = C_i x_i(t) + v_i(t) \quad (3b)$$

where the system matrices are obtained by taking the Jacobian of (2) at (x_s, u_s), respectively, as:

$$A_{ii} = \left[\frac{\partial f_i}{\partial x_i}\right]_{(x_s,u_s)}, \; B_{ii} = \left[\frac{\partial f_i}{\partial u_i}\right]_{(x_s,u_s)}, \; C_i = \left[\frac{\partial h_i}{\partial x_i}\right]_{(x_s,u_s)},$$
$$A_{ij} = \left[\frac{\partial f_i}{\partial x_j}\right]_{(x_s,u_s)}, \; B_{ij} = \left[\frac{\partial f_i}{\partial u_j}\right]_{(x_s,u_s)}.$$

It should be noted that the linearization of the nonlinear system at (x_s, u_s) is given by $\Delta x = x - x_s$, $\Delta u = u - u_s$, $\Delta y = x - x_s$. Specifically, a new coordinates Δx, Δu and Δy represent the variations of x, u and y from their equilibrium values x_s, u_s and y_s. The sign 'Δ' is simplified here. Then, for subsystem i, its observability is checked based on the pair (A_{ii}, C_i). More specifically, the full rank conditions are required with $rank(O_{i,c}) = n_i$, where $O_{i,c}$ represents the observability matrix.

Sensor faults mean that some system-operating information are not available for the system control and state estimation. The control performance can be degraded or even lead to the instability of the system due to the possible sensor faults. The sensor output $y_f(t) \in \mathbb{R}^{n_y}$ with possible faults at time k is expressed equivalently by:

$$y_f(t) = F_y(t)y(k) = (I + \gamma(t))y(k) \quad (4)$$

where $\gamma(t) = \text{diag}\{\gamma_1(t), \cdots, \gamma_M(t)\}$, $F_y(t) = \text{diag}\{I_{n_{y_1}} + \gamma_1(t), \cdots, I_{n_{y_M}} + \gamma_M(t)\}$. Then, the sensor fault for the subsystem i is denoted as

$$y_{i,f}(t) = F_{i,f}(t)y(t) = (I_{n_{y_i}} + \gamma_i(t))y_i(t) \quad (5)$$

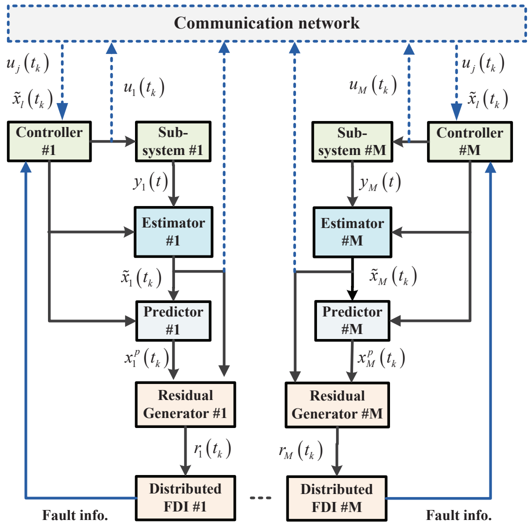

Fig. 1. Diagram of the distributed fault diagnosis

where $\gamma_i \in [-1, 0], i = 1, \cdots, M$ are sensor effectiveness factors. The fault-free and the complete sensor failure are are represented as $\gamma_i = 0$ and $\gamma_i = -1$ respectively.

In this work, we consider the sensor failures that are significant to the system safety and control performance. To deal with the possible failures to the important sensors, it is assumed that there are two sets of identical sensors to measure the outputs. The l-th measurement in subsystem i from the p-th sensor set is denoted by $y_{i,l}^p$.

3. MAIN RESULTS

The diagram of the distributed fault diagnosis is given as Fig. 1. The main components of this control structure include the distributed state estimation, the FDI modules and fault tolerance. The distributed fault detection and diagnosis module is derived by proposing residual generator, in which the fault signal is generated by introducing a residual signal. The fault compensating strategy is developed by proposing a distributed EKF for estimating of the unmeasurable states. The possible sensor faults are detected and isolated by a local FDI modules. Two estimated states are independently obtained by applying the distributed estimators with the measured outputs. The sensor faults will be dealt by the two distributed estimators. Specifically, the backup of the sensor measurement can provide a reliable state estimated states of the system even if the sensor fails. Also, the potential sensor faults can be diagnosed.

3.1 Distributed state estimation

The EKFs are discrete time filters by successive linearizing the nonlinear system Zeng et al. (2016). In this section, the distributed EKFs are designed for the nonlinear system (2) to provide the full states for the state feedback control. There are two steps for EKF, i.e., prediction step and update step. Each subsystem is associated with a local EKF at each time t_k. Specifically, the local filter for subsystem i at t_k is:

1) Prediction step:

$$\hat{x}_{(i)}(t_k|t_{k-1}) = \hat{x}_{(i)}(t_{k-1}) + \int_{t_{k-1}}^{t_k} f_{(i)}(x_{(i)}(t), \bar{X}_{(i)}(t_{k-1}))dt \quad (6a)$$

$$P_i(t_k|t_{k-1}) = \Phi_i(t_k, t_{k-1})P_i(t_{k-1}|t_{k-1})\Phi_i(t_k, t_{k-1})^T + \int_{t_{k-1}}^{t_k} \Phi_i(s, t_{k-1})Q_i\Phi_i(s, t_{k-1})^T ds \quad (6b)$$

2) Update step:

$$K_i(t_k) = P_i(t_k|t_{k-1})H_i(t_k)^T \times \left[H_i(t_k)P_i(t_k|t_{k-1})H_i(t_k)^T + R_i\right]^{-1} \quad (7a)$$

$$\hat{x}_{(i)}(t_k|t_k) = \hat{x}_{(i)}(t_k|t_{k-1}) + K_i(t_k) \times \left[y_{(i)}(t_k) - h_{(i)}\left(\hat{x}_{(i)}(t_k|t_{k-1})\right)\right] \quad (7b)$$

$$P_i(t_k|t_k) = \left[I - K_i(t_k)H_i(t_k)\right]P_i(t_k|t_{k-1}) \quad (7c)$$

where $\hat{x}_{(i)}(t_k|t_{k-1})$ is the state prediction at t_k, the error covariance matrix of $x_{(i)}(t_{k-1})$ is denoted by $P_i(t_{k-1}|t_{k-1})$ and the predicted error covariance matrix for time t_k is denoted by $P_i(t_k|t_{k-1})$. The matrices Q_i and R_i are the covariances of process noise and measurement of subsystem i, respectively; $\Phi_i(s, t_{k-1})$ is the state transition matrix, which can be expressed as $\Phi_i(s, t_{k-1}) = e^{F_i(t_{k-1})\cdot(s-t_{k-1})}$, $F_i(t_{k-1})$ is the Jacobian of $f_{(i)}$ with respect to $x_{(i)}$ at time t_{k-1}, given by $F_i(t_{k-1}) = \left[\frac{\partial f_{(i)}(x_{(i)}(t), \bar{X}_{(i)}(t_{k-1}))}{\partial x_{(i)}}\right]_{x_{(i)}=\hat{x}_{(i)}(t_{k-1}|t_{k-1})}$, $H_i(t_k) = \left[\frac{\partial h_{(i)}(x_{(i)}(t))}{\partial x_{(i)}}\right]_{x_{(i)}=\hat{x}_{(i)}(t_k|t_k)}$, and $K_i(t_k)$ is the filter gain at t_k. $\bar{X}_{(i)}(t_{k-1})$ denotes the latest subsystem estimate information of $X_{(i)}(t)$ for time $t \in [t_{k-1}, t_k]$ available to filter i.

To perform the distributed EKF for the subsystem i, the states of neighbor subsystems are necessary. Thus, an iterative algorithm is used for the distributed state estimators to coordinate with the neighbor subsystems. The subsystems communicate with each other for every n sampling periods. That is, the communication interval is $n\Delta$. The distributed EKF algorithm is implemented with following steps:

- Step 1: At $t_0 = 0$, given $x_{(i)}(0), P_i(t_0|t_0), i = 1, \ldots, p$.
- Step 2: For $t_k > 0$, each local EKF i gets the measurement of the subsystem i, i.e., $y_{(i)}(t_k)$.
- Step 3: If $\mathrm{mod}(k, n) = 0$, each estimator receives the state estimates (i.e., $\bar{X}_{(i)}(t_{k-1}) = \hat{X}_{(i)}(t_{k-1})$) of the neighbor subsystems at the time t_{k-1}.
- Step 4: With $\bar{X}_{(i)}(t_{k-1})$, each estimator i calculates the $\hat{x}_{(i)}(t_k), i = 1, \cdots, p$. The estimated state of the global system is $\hat{x}(t_k) = \left[\hat{x}_{(1)}(t_k)^T \ \ldots \ \hat{x}_{(p)}(t_k)^T\right]^T$.
- Step 5: At $k = k + 1$, go to Step 2.

The system input information is treated as known to the distributed EKFs. The computation burden will increase with iteration increases. Hence, there is a trade-off between the computation burden and the estimation performance. The $x_j(t)$ for $t \in [t_k - 1, t_k)$ in (6) is approximated by the prediction step of EKF i at t_k, $\hat{x}_j(t_k - 1)$.

3.2 Distributed Fault Detection and Diagnosis

In many practical systems, the sensors may experience abrupt faults. This section deals with the possible sensor failures by using the distributed state estimation Section 3.1. It is necessary to derive a fault detection and diagnosis module to detect and isolate the sensor faults. To deal with the possible failures to the important sensors, it is assumed that there are two sets of identical sensors to measure the outputs, named as 1 and 2 respectively. The l-th measurement in subsystem i from the p-th sensor set is denoted by $y_{i,l}^p, p = 1, 2, l = 1, \cdots, n_i$.

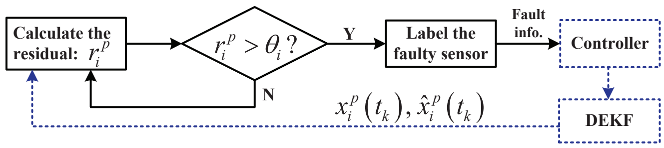

Fig. 2. The procedure for the fault diagnosis

Assume there is only one sensor failure in the system at one time. Accordingly, a distributed fault detection module is derived to deal with the abrupt sensor faults by taking the advantages of the distributed EKF. A fault detection module is proposed for each subsystem, and each module is composed by several key components: a local EKF, and a residual generator. Fig. 2 presents the structure of the local fault detection module for subsystem i.

The state predictor is used to provide a reference state trajectory for the residual generator. The state predictor for each subsystem $i, i = 1, \cdots, M$, is developed based on the nominal model:

$$\dot{x}_i^p(t) = f_i(x_i^p(t), u_i(t), \bar{x}_i(t), \bar{u}_i(t), 0) \quad (8)$$

where $x_i^p(t)$ is the open-loop prediction of the state of the subsystem $i, i = 1, \cdots, M$, p denotes the copy of the state prediction, $p = 1, 2$.

In each fault detection module for subsystem $i, i = 1, \cdots, M$, the residual generator calculates the differences of prediction $x_i^p(t)$ and state estimate $\hat{x}_i^p(t)$:

$$\overline{r}_i^p(t_k) = x_i^p(t) - \hat{x}_i^p(t) \quad (9)$$

where $p = 1, 2$.

Then, for the n_i states in subsystem i, the residual sequence is $\overline{r}_i^p(t_k) = [\overline{r}_{i,1}^p(t_k), \cdots, \overline{r}_{i,n_i}^p(t_k)]^T$. It is assumed that there exist $\overline{r}_{i,l}^{p,max}, l = 1, \cdots, n_i$ such that $r_{i,l}^p \leq \overline{r}_{i,l}^{p,max}, l = 1, \cdots, n_i$ if the is no sensor fault. Then, the residual generator generates a residual signal sequence for each subsystem $i, i = 1, \cdots, M$:

$$r_i^p(t_k) = \sqrt{\left(\frac{\overline{r}_{i,1}^p(t_k)}{\overline{r}_{i,1}^{p,max}}\right)^2 + \cdots + \left(\frac{\overline{r}_{i,n_i}^p(t_k)}{\overline{r}_{i,n_i}^{p,max}}\right)^2} \quad (10)$$

If there is no sensor fault, each residual will stay below a certain threshold, i.e., θ_i for $r_i^p(t_k), i = 1, \cdots, M$. When any of the residual signals exceed the corresponding thresholds, it indicates that there is a sensor fault.

The steps for the fault diagnosis mechanism in this work is presented as:

1) For $t_k \geq 0$, the each fault diagnosis module $i, i = 1, \cdots, M$ receives $r_{i,l}^p, p = 1, 2, l = 1, \cdots, n_i$.

2) Check the conditions $r_i^p(t_k) > \theta_i, i = 1, \cdots, M, p = 1, 2$ hold or not. A sensor fault has occurred if any of the residual signals exceeds its threshold.
3) Mark the fault agent as c_f-th copy, where $c_f \in \{1, 2\}$. The fault is in one of the measurements $y_i^{c_f}, i = 1, \cdots, M$. The copy without fault is marked as the c_n-th copy.
4) Calculate $y_i^{c_f} - y_i^{c_n}$ and compare it with a threshold $\rho_i > 0, i = 1, \cdots, M$. If $|y_i^{c_f} - y_i^{c_n}| > \rho_i$, then $y_i^{c_f}$ is the faulty sensor.

In Step 3), a prescribed scalar $\rho_i, i = 1, \cdots, M$ is derived for the sensor fault isolation. Since the measurement noise $v_i(t)$ is bounded, $|y_i^{c_f} - y_i^{c_n}|$ is always bounded without sensor faults. A same upper bound on $|y_i^{c_f} - y_i^{c_n}|$ can be defined as $\rho_i, i = 1, \cdots, M$. If $|y_i^{c_f} - y_i^{c_n}| > \rho_l$, it means that there must be a fault for either $y_i^{c_f}$ or $y_i^{c_n}$. According to step 2), the fault must be the $y_i^{c_f}, i = 1, \cdots, M$.

4. APPLICATION TO THE CSTR PROCESS

A three-vessel process Liu et al. (2009) with two CSTRs and a flash tank separator are investigated (see Fig. 3). The first vessel contains the reactant J with a feed stream F_{10} and then is transformed to outcome K. Then, outcome K is converted to outcome L.

The dynamic system is given as follows Liu et al. (2009):

$$\dot{x}_{A1} = \frac{F_{10}}{V_1}(x_{A10} - x_{A1}) + \frac{F_r}{V_1}(x_{Ar} - x_{A1}) - k_1 e^{\frac{-E_1}{RT_1}} x_{A1} \tag{11a}$$

$$\dot{x}_{B1} = \frac{F_{10}}{V_1}(x_{B10} - x_{B1}) + \frac{F_r}{V_1}(x_{Br} - x_{B1}) + k_1 e^{\frac{-E_1}{RT_1}} x_{A1} - k_2 e^{\frac{-E_2}{RT_1}} x_{B1} \tag{11b}$$

$$\dot{T}_1 = \frac{F_{10}}{V_1}(T_{10} - T_1) + \frac{F_r}{V_1}(T_3 - T_1) - \frac{\Delta H_1}{C_p} k_1 e^{\frac{-E_1}{RT_1}} x_{A1} - \frac{\Delta H_2}{C_p} k_2 e^{\frac{-E_2}{RT_1}} x_{B1} + \frac{Q_1}{\rho C_p V_1} \tag{11c}$$

$$\dot{x}_{A2} = \frac{F_1}{V_2}(x_{A1} - x_{A2}) + \frac{F_{20}}{V_2}(x_{A20} - x_{A2}) - k_1 e^{\frac{-E_1}{RT_2}} x_{A2} \tag{11d}$$

$$\dot{x}_{B2} = \frac{F_1}{V_2}(x_{B1} - x_{B2}) + \frac{F_{20}}{V_2}(x_{B20} - x_{B2}) + k_1 e^{\frac{-E_1}{RT_2}} x_{A2} - k_2 e^{\frac{-E_2}{RT_2}} x_{B2} \tag{11e}$$

$$\dot{T}_2 = \frac{F_1}{V_2}(T_1 - T_2) + \frac{F_{20}}{V_2}(T_{20} - T_2) - \frac{\Delta H_1}{C_p} k_1 e^{\frac{-E_1}{RT_2}} x_{A2} - \frac{\Delta H_2}{C_p} k_2 e^{\frac{-E_2}{RT_2}} x_{B2} + \frac{Q_2}{\rho C_p V_2} \tag{11f}$$

$$\dot{x}_{A3} = \frac{F_2}{V_3}(x_{A2} - x_{A3}) - \frac{F_r + F_p}{V_3}(x_{Ar} - x_{A3}) \tag{11g}$$

$$\dot{x}_{B3} = \frac{F_2}{V_3}(x_{B2} - x_{B3}) - \frac{F_r + F_p}{V_3}(x_{Br} - x_{B3}) \tag{11h}$$

$$\dot{T}_3 = \frac{F_2}{V_3}(T_2 - T_3) + \frac{Q_3}{\rho C_p V_3} \tag{11i}$$

where x_{Ai}, x_{Bi} respectively are the mass fractions of J, K in the vessel $i, i = 1, 2, 3$; x_{C3} are the mass fractions of L in vessel 3; T_i are temperatures in the vessel i; T_{10}, T_{20} are the temperatures of the feed stream to vessels 1 and 2; F_1, F_2 are the effluent flow rate from vessels 1 and 2; F_{10}, F_{20} are the steady-state feed stream flow rates to vessels 1 and 2; F_r, F_p are the Flow rates of the recycle and purge; V_i are Volumes of vessel i; E_1 and E_2 are the activation energy for reactions 1 and 2; k_1 and k_2 are the pre-exponential values for reactions 1 and 2; ΔH_1 and ΔH_2 are the heats of reaction for reactions 1 and 2; $\alpha_A, \alpha_B, \alpha_C$ are the relative volatilities of J, K, L, Q_1, Q_2, Q_3 are the heat inputs into vessel i; C_p is the heat capacity; R is the gas constant and ρ is the solution density.

To deal with the possible sensor faults for the process, a distributed fault detection scheme is developed. Firstly, the fault signal is generated by introducing a residual signal; Then, the distributed EKF is used to estimate the unmeasurable system states; Finally, the proposed DEKF is presented for fault tolerant detection problem in a distributed framework.

Table 2. Model parameters.

Variables	Value	Variables	Value
T_{10}, T_{20}	300 K	α_A	3.5
F_{10}, F_{20}	5.04 m^3/h	α_B	1
F_r	50.4 m^3/h	α_C	0.5
E_1	50 KJ/mol	ΔH_1	-240 KJ/mol
E_2	60 KJ/mol	ΔH_2	-280 KJ/mol
k_1	9.972 $\times 10^6$ h^{-1}	R	8.314
k_2	9.36 $\times 10^6$ h^{-1}	x_{A10}	1
ΔH_{v1}	-3.53 $\times 10^4$ kJ/kmol	x_{B10}	1
ΔH_{v2}	-1.57 $\times 10^4$ kJ/kmol	x_{A20}	0
ΔH_{v3}	-4.068 $\times 10^4$ kJ/kmol	x_{B20}	0
F_p	0.504 m^3/h	C_p	4.2 $\times 10^3$
ρ	1000 kg/m^3	Q_1	2900 MJ/h
Q_2	1000 MJ/h	Q_3	2900 MJ/h
V_1	1 m^3	V_2	0.5 m^3
V_3	1 m^3		

Table 3. Decompositions for the CSTR process

Subsystem	state variable	measurement	Inputs
1	x_{A1}, x_{B1}, T_1	T_1	Q_1
2	x_{A2}, x_{B2}, T_1	T_2	Q_2
3	x_{A3}, x_{B3}, T_3	T_3	Q_3

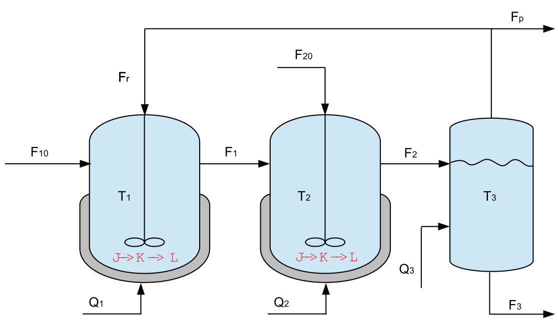

Fig. 3. Reactor-separator process

The composition of the overhead stream relative to the composition of the liquid holdup in the flash tank is formulated with:

$$x_{Ar} = \frac{\alpha_A x_{A3}}{\alpha_A x_{A3} + \alpha_B x_{B3} + \alpha_C x_{C3}} \quad (12a)$$

$$x_{Br} = \frac{\alpha_B x_{B3}}{\alpha_A x_{A3} + \alpha_B x_{B3} + \alpha_C x_{C3}} \quad (12b)$$

$$x_{Cr} = \frac{\alpha_C x_{C3}}{\alpha_A x_{A3} + \alpha_B x_{B3} + \alpha_C x_{C3}} \quad (12c)$$

Process noise was added to the process of Eq. (11) to test the disturbances/noises. As shown in Table (3), the global plant is divided into three subsystems according to the relations of the three vessels. Then, distributed EKFs are designed to estimate the system states x_{Ai}, x_{Bi}, T_i with the measurements T_1, T_2, T_3.

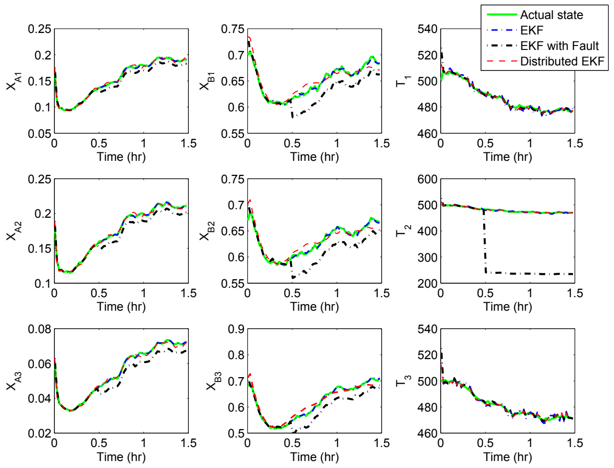

Fig. 4. The estimation performance for both fault-free and sensor fault reactor-separator process under centralized EKF and distributed EKF

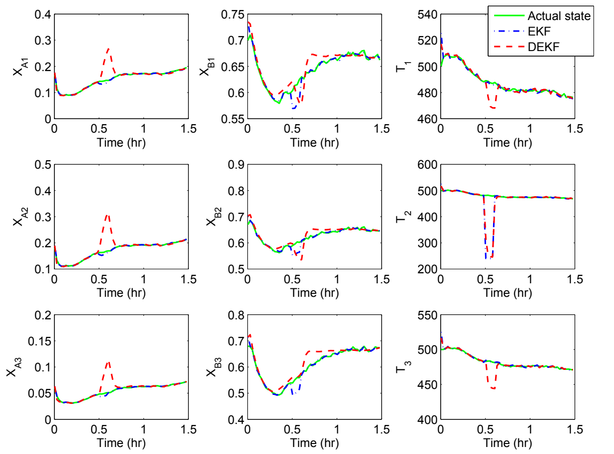

Fig. 5. The estimation performance for both fault-free and sensor fault reactor-separator process with fault detection scheme

As shown in Figure 4, the fault-free case and sensor fault case are respectively considered under centralized Kalman filter and distributed Kalman filter. It is shown that, without sensor faults, the EKF and distributed EKF both can achieve good estimation performance for the CSTR process. However, when there is a sensor fault for T_2 after $t > 0.5$ hour, the performance of estimation becomes unacceptable (see green dash-dot line in Figure 4). Thus, it is crucial to derive the fault detection for the process. As shown in Figure 5, the fault is detected at time and the measurement is switched to the backup sensor. Then, the distributed EKF can achieve a good estimation performance.

5. CONCLUSION

To deal with the senor failures in a nonlinear process system, a distributed fault detection structure is presented in this work. A distributed fault detection and diagnosis module is derived by proposing residual generator; Then, the fault compensating strategy is developed by proposing a distributed EKF to estimate the unmeasurable system states; Finally, the proposed DEKF is presented for fault detection and isolation in a distributed framework.

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