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Mei ZHANG, Ze-tao LI*, Boutaïeb. DAHHOU, Michel. CABASSUD

Abstract—**A fault diagnosis approach is developed for pneumatic valve used in intensified HEX/reactor system. The pneumatic valve is viewed as an actuator subsystem interconnected with process subsystem in series. A condition of invertibility of the cascade system has been derived in [18], characterizing that effects of faults occurred in actuator subsystem are distinguishable by the global output uniquely. Using this idea, the fault diagnosis scheme proposed in this paper is based on local fault filtering, each subsystem is assigned to monitor one subsystem and provided a decision regarding its health. In particular, the connection point between the two subsystems is not accessible to measurements. An input estimator is then developed to estimate this unknown connection point only rely on the global system output. Different from [18], any information of the derivatives of the output vectors is not involved in the input estimation stage. For that, a high-gain second-order sliding mode observer is considered to exactly estimate the derivatives of the output vectors in a finite time. Numerical simulation examples are given to illustrate the effectiveness of the proposed methods.**

Key words: **Cascade nonlinear system; Invertibility; Input estimator; Sliding mode observer; Local fault diagnosis;**

I. INTRODUCTION

The fault detection and diagnosis (FDD) of actuator in intensified process industry is strategically important because of its various implications (see in [1], e.g., avoiding major plant breakdowns, safety problems, fast and appropriate response to emergency situations and plant maintenance).

Over the past decades, the topic of FDD for nonlinear system has been extensively studied in the literature, see for instance survey [2] and book [3]. The literature on actuator safety related issues in process industries is mainly classified into two categories: a) actuator is treated as a component and b) actuator is treated as a nonlinear system.

Actuator is generally viewed as constants in the input matrix function of the model in the process system. Varying failure signatures are denoted by the changes of elements of the input matrix function. One major aspect is to check whether the outputs of the system monitored are consistent with the inputs given the model, using state estimation or parameter estimation techniques. Such as extended high gain approaches in [4], adaptive observers in [5,6,7] and interval parameter filters in [8]. Another main aspect is inversion-based FDI, which uses the system inverse to check whether the expected inputs are consistent with the measured outputs, such as [9]. System inversion is also used to estimate fault dynamics, popular techniques include sliding mode observer [10], differential-geometric [11] , unknown input observer in [12]. Since internal dynamics of actuator is not accessible, the applications of these FDD methodologies mainly limit to the existence and the isolation of an actuator fault at a global level.

In order to examine potential relationship from causes to effect of an actuator fault, actuator is treated as an individual nonlinear system by different scientific communities. Like passive fault detection method in [13], literatures also focus on development of fuzzy logic and neural network based approaches for fault diagnosis of pneumatic valve, like in [14]. With the help of above FDD algorithms, we can realize the root cause of an actuator fault, however, without having the capability to recognize effects of the fault on the global system.

Recent literatures focus on the problem of monitoring and FDD of interconnected complex system. Like distributed fault detection schemes developed in[15][16], a local fault detection scheme is designed for each subsystem by utilizing local measurements. However, one major difficulty lies in the availability of the local measurement. Papers consider the issues of state and unknown information reconstruction by means of sliding modes observer like in [17].

This paper focuses on developing intelligent fault diagnosis system for pneumatic valve used in intensified Hex/reactor. We consider the actuator as an individual subsystem connected with process subsystem in series. The objective is to explain how the behavior of global output can be interpreted to identify root cause of actuator faults in actuator subsystem. A condition of invertibility of the cascade system has been developed in [18], it guarantees that faults occurred in the actuator subsystem affect the measured output of the global system distinguishably. Using this characteristic, a local fault diagnosis method is developed, aimed at filtering the root cause of an actuator fault. An input estimator is developed to estimate the inaccessible output of the actuator subsystem. Different from [18], system inverse is not directly used for unknown input reconstruction. Instead, a high-gain second-order sliding mode observer is considered to exactly estimate the derivatives of the output. Based on this, a kind of algebraic unknown input estimation method is proposed.

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II. PROBLEM FORMULATION

Fault diagnosis will be applied on a pilot HEX/reactor system depicted in [1]. It is considered as a cascade system Σ modeled by two nonlinear subsystems connected in series: actuator Σ_a and process Σ_p subsystems, as shown in Fig 1.

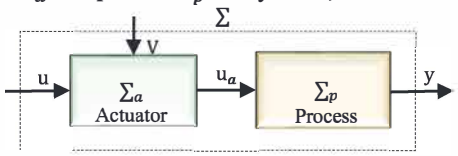

Fig.1 the cascade system structure

A. *System modelling*

1. Process subsystem modelling

The heat exchanger can be modeled as N ideally mixed interconnected tanks, the modelling of a given cell k is based on the mass and energy balances which describe the evolution of the characteristic values: temperature, mass, composition, pressure, etc.

Heat balance of the process fluid:

$$\dot{T}_p^k = \frac{UA}{\rho_p c_{pp} V_p}\left(T_u^k - T_p^k\right) + \frac{1}{V_p}\left(T_p^{k-1} - T_p^k\right)F_p$$

Heat balance of the utility fluid:

$$\dot{T}_u^k = \frac{UA}{\rho_u c_{pu} V_u}\left(T_p^k - T_u^k\right) + \frac{1}{V_u}\left(T_u^{k+1} - T_u^k\right)F_u$$

where ρ_p, ρ_u are density of the process fluid and utility fluid (in $kg.m^{-3}$), V_p, V_u are volume of the process fluid and utility fluid (in m^3), c_{pp}, c_{pu} are specific heat of the process fluid and utility fluid (in $J.kg^{-1}.K^{-1}$) , U is the overall heat transfer coefficient (in $J.m^{-2}.K^{-1}.s^{-1}$). A is the reaction area (in m^2). F_p, F_u are mass flowrate of process fluid and utility fluid (in $kg.s^{-1}$). T_p^{k-1} is the process fluid temperature of previous cell, for the cell 1, it is the inlet temperature of process fluid T_p^{in}. T_u^{k+1} is the utility fluid temperature of previous cell, for the cell N, it is the inlet temperature of utility fluid T_u^{in}.

For simplicity, we consider one cell model. Define the state vector as $x^T = [x_1, x_2]^T = [T_p, T_u]^T$, the control input $u_a{}^T = [u_{a1}, u_{a2}]^T = [F_p, F_u]^T$, the output vector of measurable variables $y^T = [y_1, y_2]^T = [T_p, T_u]^T$, then above two the equations can be rewritten in the following state-space form:

$$\begin{cases} \dot{x} = f(x) + \sum_{i=1}^{2} g_i(x)u_a \\ y = h(x, u_a) \end{cases} \quad (1)$$

where $f(x) = \begin{pmatrix} f_1(x) \\ f_2(x) \end{pmatrix} = \begin{pmatrix} \frac{h_p A}{\rho_p c_{p_p} V_p}(T_p - T_u) \\ \frac{h_u A}{\rho_u c_{p_u} V_u}(T_u - T_p) \end{pmatrix}$, and $g(x) = (g_1, g_2) = \begin{pmatrix} \frac{(T_{pi} - T_p)}{V_p} & 0 \\ 0 & \frac{(T_{ui} - T_u)}{V_u} \end{pmatrix}$, $y_1 = x_1, y_2 = x_2$.

2. Actuator subsystem modelling

Actuator used in the studied intensified HEX/reactor system is pneumatic valve. By application of Bernoulli's continuous flow law of incompressible fluids, we have:

$$F = C_v f(X)\sqrt{\frac{\Delta P}{sg}}$$

where F is flow rate ($m^3 s^{-1}$), ΔP is the fluid pressure drop across the valve (Pa), sg is specific gravity of fluid and equals 1 for pure water, X is the valve opening or valve "lift" (X=1 for max flow), C_v is valve coefficient (given by manufacture), f(X) is flow characteristic which is defined as the relationship between valve capacity and fluid travel through the valve. There are three flow characteristics to choose from: linear valve control; quick opening valve control; equal percentage valve control. For linear valve, $f(X) = X$, the valve opening is related to stem displacement. In [13] , a pneumatic control valve has a dynamic model of the type:

$$p_c A_a = m\frac{d^2X}{dt} + \mu\frac{dX}{dt} + kX$$

where Aa is the diaphragm area on which the pneumatic pressure acts, p_c is the pneumatic pressure, m is the mass of the control valve stem, μ is the friction of the valve stem, k is the spring compliance, and X is the stem displacement or percentage opening of the valve.

Define subscript 1, 2 to denote the actuator of process fluid and utility fluid, then we have twelve parameters X_1, p_{c1}, ΔP_1, k_1, μ_1, F_1, X_2, p_{c2}, ΔP_2, k_2, μ_2, F_2 for both fluid, they represent the percentage opening of the valve, the pneumatic pressure, and the fluid pressure drop across the valve, the spring compliance, the friction of the valve stem and flowrate of the fluid. Linear valve is used, so $f(X_1) = X_1, f(X_2) = X_2$.

The candidate root causes of an actuator fault could be valve clogging, stop of utility fluid pump or leakage, which may influenced $p_c, \mu, k, \Delta P$ respectively. In order to obtain a model for the sake of diagnosis requirements, define the vector state x_a, input u, and output u_a as:

$$x_a{}^T = [x_{a1} \quad x_{a2} \quad x_{a3} \quad x_{a4} \quad x_{a5} \quad x_{a6}] = \left[X_1 \quad \frac{dX_1}{dt} \quad X_2 \quad \frac{dX_2}{dt} \quad C_v\sqrt{\frac{\Delta P_1}{sg}}X_1 \quad C_v\sqrt{\frac{\Delta P_2}{sg}}X_2\right]$$

$$V = [v_1 \quad v_2 \quad v_3 \quad v_4 \quad v_5 \quad v_6 \quad v_7 \quad v_8]^T = [k_1 \quad \mu_1 \quad k_2 \quad \mu_2 \quad p_{c1} \quad p_{c2} \quad \Delta P_1 \quad \Delta P_2]^T$$

$$u_a{}^T = [u_{a1} \quad u_{a2}] = [F_1 \quad F_2] = [x_{a5} \quad x_{a6}] = \left[C_v\sqrt{\frac{\Delta P_1}{sg}}X_1 \quad C_v\sqrt{\frac{\Delta P_2}{sg}}X_2\right]$$

$$\tilde{C} = [0 \quad 0 \quad 0 \quad 0 \quad 1 \quad 1]$$

Then, the actuator subsystem is with six states, eight unknown inputs and two outputs. These two outputs are unmeasured which need to be constructed by the global measured outputs. The actuator subsystem is :

$$\begin{cases} \dot{x}_a = f_a(x_a) + \sum_{i}^{8} g_a(x_a)V \\ u_{a=}\tilde{C}x_a \end{cases} \quad (2)$$

Where $f_a(x_a) = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$

$$g_a(x_a) = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -\frac{x_{a1}}{m} & -\frac{x_{a2}}{m} & 0 & 0 & \frac{A_a}{m} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & -\frac{x_{a3}}{m} & -\frac{x_{a4}}{m} & 0 & \frac{A_a}{m} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & C_v\frac{1}{sg}x_{a1} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & C_v\frac{1}{sg}x_{a2} \end{bmatrix}$$

B architecture of the proposed FDD

As shown in Fig.2, the objective is to identify the occurrence of the fault $V = (v_i, \dots)$ in (2) independently from each other using global outputs y in (1). The fault diagnosis is based on local fault filtering schemes carried out in actuator subsystem, each subsystem is assigned to monitor its own dynamics and provide a decision regarding its health.

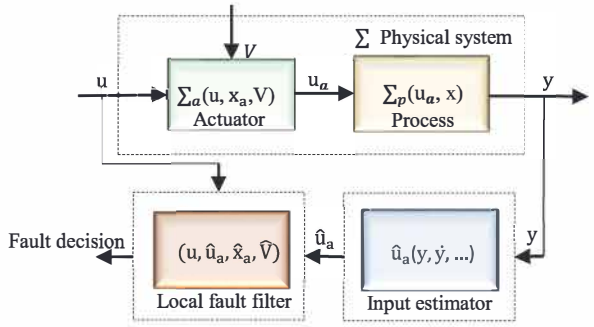

Fig. 2 architecture of proposed algorithm

In order to accomplish the aims, there are three steps:

a-) provide condition for guaranteeing that effects of faults $V = (v_i, \dots)$ occurred in actuator subsystems are distinguishable by the global output y uniquely.

b-) estimate the unknown outputs u_a of actuator subsystem through measured outputs y of process subsystem

c-) propose local fault filter for recognizing faults $V = (v_i, \dots)$ occurred in actuator subsystems.

III. SYSTEM FAULT DIAGNOSIS METHOD

A Invertibility analysis

In previous paper [18], it has proved that faults occurred in actuator subsystem will affect the measured output of the global system distinguishably if the interconnected system is invertible. While invertibility of individual subsystem is a necessity and sufficient condition for guaranteeing invertibility of the interconnected system.

In this section, invertibility of individual and the cascade system is derived. Define the input-output map of process subsystem $H_p: U_a \to Y$ for input function space U_a and the corresponding output function space generated by Y. H_p maps an input $u_a(.)$ to the output $y(.)$ generated by the system driven by $u_a(.)$ with an initial condition x_0.

Theorem 1: Fix an output set Y, the system (1) is invertible at a point $x_0 := x(t_0)$, if for every $y \in Y$, the equality $H_p(u_{a1}) = H_p(u_{a2}) = y$ implies that $u_{a1} = u_{a2}$.

Theorem 2: Consider the interconnected system $\sum$ which consists of two subsystems: actuator $\sum_a$ and process $\sum_p$ subsytems, and an output set(U_a, Y). The interconnected system is invertible at (x_0, x_{a0}) over (U_a, Y). If and only if each subsystem actuator $\sum_a$ and process $\sum_p$ is invertible at x_{a0} over U_a, and x_0 over Y respectively.

Proof: For the sake of space limitation, the proof of the above theorems is omitted. Interested readers can contact the corresponding author for details [18].

Unlike [18], in this paper, system inverse is only used for guaranteeing effectiveness of local fault filter. While in order to avoid using any information of the derivatives of the output, a high-gain second-order sliding mode observer is considered to exactly estimate the derivatives of the output. A kind of algebraic unknown input estimation method is then proposed.

B Input Estimator

If a system is differentially left-invertible, the input can be recovered from the output by means of a finite number of ordinary differential equations.

Step 1: Obtain a differential algebraic polynomial of the input vector u_a by means of the output vector y through system inverse.

For invertible nonlinear system described by (1), the relative order r_i of the output y_i , is the smallest integer for which:

$$L_g L_f^{r_i-1} h_i(x) = \left[L_{g1} L_f^{r_i-1} h_i(x) L_{g2} L_f^{r_i-1} h_i(x) \ \dots L_{gm} L_f^{r_i-1} h_i(x)\right] \neq [0, 0, \dots, 0]$$

Given finite relative order $r_1, \dots, r_m$ for (1) with respect to the output y, calculating expressions for their derivatives, we get:

$$\begin{bmatrix} y_1^{(r_1)} \\ \vdots \\ y_m^{(r_m)} \end{bmatrix} = \begin{bmatrix} L_f^{r_1} h_1(x) \\ \vdots \\ L_f^{r_m} h_m(x) \end{bmatrix} + \begin{bmatrix} L_{g_1} L_f^{r_1-1} h_1(x) & \dots & L_{g_m} L_f^{r_1-1} h_1(x) \\ \dots & \dots & \dots \\ L_{g_1} L_f^{r_m-1} h_m(x) & \dots & L_{g_m} L_f^{r_m-1} h_m(x) \end{bmatrix} u_a$$

Let the matrix:

$$A(x) = \begin{bmatrix} L_{g_1} L_f^{r_1-1} h_1(x) & \dots & L_{g_m} L_f^{r_1-1} h_1(x) \\ \dots & \dots & \dots \\ L_{g_1} L_f^{r_m-1} h_m(x) & \dots & L_{g_m} L_f^{r_m-1} h_m(x) \end{bmatrix}$$

Define the following change of the coordinates:

$$\xi_i = \left[\xi_i^1, \xi_i^2, \dots, \xi_i^{r_i}\right] = \left[\phi_i^1(x), \phi_i^2(x), \dots, \phi_i^{r_i}(x)\right] = \left[h_i(x), L_f h_i(x), \dots, L_f^{r_i-1} h_i(x)\right] \ i = 1, \dots, m$$

$$\xi = [\xi_1, \xi_2, \dots, \xi_m] = [\phi_1(x), \phi_2(x), \dots, \phi_m(x)]$$

$$\eta = [\phi_{r+1}(x), \phi_{r+2}(x), \dots, \phi_n(x)]$$

$$y = [\xi_1^1, \xi_2^1, \dots, \xi_m^1]$$

By application new local coordinates transformation proposed in [19], it is always possible to find the function $\phi_{r+1}(x), \phi_{r+2}(x), \dots, \phi_n(x)$, thus

$$\Phi(x) = [\phi_1(x), \phi_2(x), \dots, \phi_m(x), \phi_{r+1}(x), \dots, \phi_n(x)]$$

$$x = \Phi^{-1}(\xi, \eta)$$

Then input vector u_a can be obtained by means of the output vector y and its derivatives.

$$u_a = A\left(\Phi^{-1}(\xi,\eta)\right)^{-1}\left(\begin{bmatrix}\xi_1^{(r_1)}\\ \vdots \\ \xi_m^{(r_m)}\end{bmatrix} - \begin{bmatrix}L_f^{r_1}h_1(\Phi^{-1}(\xi,\eta)\\ \vdots \\ L_f^{r_m}h_m(\Phi^{-1}(\xi,\eta)\end{bmatrix}\right) \quad (3)$$

The inversion based algebraic polynomial (3), however, requires the computation of successive derivatives of outputs, which might be unrealistic in practical applications where measurements suffer noise and disturbances.

Step 2: estimate the derivatives of the output vectors

To avoid use any derivative information $\xi_i^j, 1 \le i \le m, 1 \le j \le r_i$ of measurement output directly, a high-gain second-order sliding mode observer is considered to exactly estimate them in a finite time.

By construction:

$$y_i = \xi_i^1$$

$$\dot{\xi}_i^j = \xi_i^{j+1}; 1 \le j \le r_i - 1$$

$$\dot{\xi}_i^{r_i} = L_f^{r_i}h_i(\Phi^{-1}(\xi,\eta) + \sum_{j=1}^{m} L_{g_i}L_f^{r_i-1}h_i(\Phi^{-1}(\xi,\eta))\, u_{aj}; j = r_i$$

Following is structure of the observer:

$$\hat{y}_i = \hat{\xi}_i^1$$

$$\dot{\hat{\xi}}_i^j = \hat{\xi}_i^{j+1} + \lambda_i^j|\hat{y}_i - y_i|^{1/2}\mathrm{sgn}(\hat{y}_i - y_i); 1 \le j \le r_i - 1$$

$$\dot{\hat{\xi}}_i^{r_i} = \lambda_i^{r_i}|\hat{y}_i - y_i|^{1/2}\mathrm{sgn}(\hat{y}_i - y_i); j = r_i$$

Step 3: by using the estimates of output derivatives, a kind of algebraic unknown input reconstruction method is proposed.

$$\hat{u}_a = A\left(\Phi^{-1}(\hat{\xi},\hat{\eta})\right)^{-1}\left(\begin{bmatrix}\hat{\xi}_1^{(r_1)}\\ \vdots \\ \hat{\xi}_m^{(r_m)}\end{bmatrix} - \begin{bmatrix}L_f^{r_1}h_1(\Phi^{-1}(\hat{\xi},\hat{\eta})\\ \vdots \\ L_f^{r_m}h_m(\Phi^{-1}(\hat{\xi},\hat{\eta})\end{bmatrix}\right) (4)$$

C Local fault filter design

In order to recognize $V(v_1, .. v_i, ...)$, four possible candidates in each actuator, we construct two banks of four observers as follows (5):

$$1 \le j \le 2, 1 \le i \le 4$$

$$\begin{cases} \dot{\hat{x}}_a^{ij} = f_a^j\left(\hat{x}_a^{ij}, u_j\right) + \sum_{l \ne i} g_{al}^j\left(\hat{x}_a^{ij}, u_j\right)\theta_l^j + g_{ai}^j\left(\hat{x}_a^{ij}, u_j\right)\hat{v}_i^j + H_{ij}\left(\tilde{u}_a^j - \hat{u}_a^{ij}\right) \\ \hat{v}_i^j = 2\gamma_{ij}\left(\tilde{u}_a^j - \hat{u}_a^{ij}\right)^T P_{ij} g_{ai}^j \\ \hat{u}_a^{ij} = c\,\hat{x}_a^{ij} \end{cases} \quad (5)$$

where j denotes jth actuator, i is ith observer corresponding to the ith fault resources candidates. $\hat{x}_a^{ij}$ is the estimated state vector of ith observer for jth actuator, $\hat{v}_i^j$ is the fault estimation of v_i of jth actuator, and $\hat{u}_a^{ij}$ is the estimated output vector of the ith observer for jth actuator. $\tilde{u}_a^j$ is reconstructed output of jth actuator from y, u_j is the input of jth actuator. θ_l^j is the nominal value of parameters in jth actuator, subscript $l \ne i$. f_a^j, g_a^j are analytic functions of jth actuator. H_{ij} is a Hurwitz matrix that can be chosen freely with a goal to increase as much as possible the dynamic of the observer, γ_{ij} is a design constant and P_{ij} is a positive definite matrix. We can calculate the matrix P_{ij} with the help of (6); where Q_{ij} is a positive definite matrix that can be chosen freely.

$$H_{ij}^T P_{ij} + P_{ij} H_{ij} = -Q_{ij} \quad (6)$$

Denote $e_y^{ij}(t)$ as the tracking error of the ith observer for jth actuator that: $e_y^{ij}(t) = \tilde{u}_a^j - \hat{u}_a^{ij}$

We define the root cause analysis (RCA) residuals as:

$$s_{ij}(t) = \left\| e_y^{ij}(t) \right\|, \; 1 \le j \le 2, 1 \le i \le 4$$

The above observers aim at generating two banks of four residuals for those above mentioned fault causes. One bank of residuals are $s_{11}, s_{12}, s_{13}, s_{14}$, aimed at identifying fault causes ($p_{c1}, \mu_1, \Delta P_1, k_1$) in actuator of process fluid, the other bank are $s_{21}, s_{22}, s_{23}, s_{24}$ for fault causes ($p_{c2}, \mu_2, \Delta P_2, k_2$) in actuator of utility fluid respectively. If any of those residuals exceeds its threshold, the fault is caused by the corresponding fault causes.

IV. SIMULATION RESULTS AND DISCUSSION

In this section, we consider a numerical example to illustrate the effectiveness of the proposed fault diagnosis method. The constants and physical data used in the pilot are given in TABLE I. More detail information about the studied system could find in [1].

TABLE I PHYSICAL DATA USED IN THE PILOT

Constant	description	Value	units
hA	overall heat transfer coefficient*reaction area	214.8	$W.K^{-1}$
A	Reaction area	$4e^{-6}$	m^3
V_p	process fluid volume	$2.685e^{-5}$	m^3
V_u	utility fluid volume	$1.141e^{-4}$	m^3
ρ_p, ρ_u	fluid density	1000	$kg.m^{-3}$
c_{p_p}, c_{p_u}	specific heat of the fluid	4180	$J.kg^{-1}.k^{-1}$
T_{ui}	utility fluid input	15.6	°C
T_{pi}	process fluid input	76	°C

The input of the inlet flow rate of the utility fluid F_u is $4.22e^{-5}m^3s^{-1}$, and inlet flow rate of the process fluid F_p is constant $4.17e^{-6}m^3s^{-1}$. Parameters in actuator subsystem

are: m=2kg, A_a =0.029m2, μ =1500Ns/m and k=6089 Ns/m, Pc for utility fluid is 1MPa, 1.2Mpa for process fluid, pressure drop ΔP in utility fluid is 0.6Mpa and 60KPa in process fluid.

A System output and estimated input in fault free case

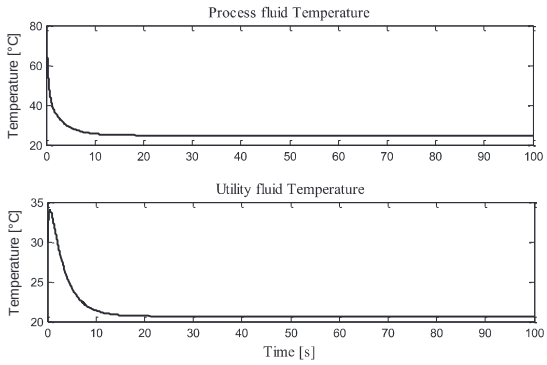

Fig.3 Output temperature of both fluid in fault free case

Fig. 3 shows the output temperature of both fluid under normal condition, obvious difference from the curve may indicate existence of faults.

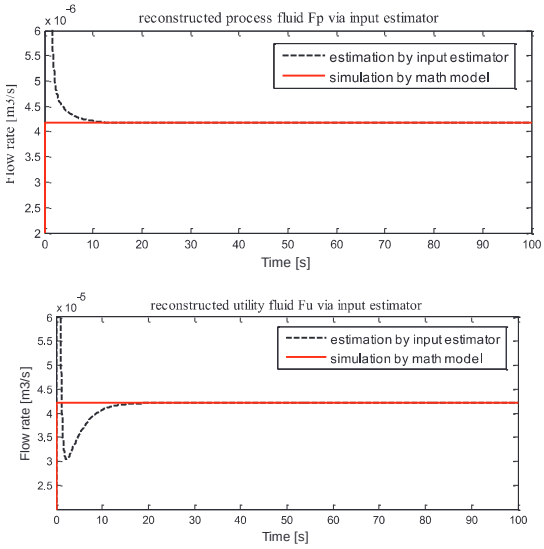

Fig 4. Estimated inputs of both fluid

Fig. 4 confirms the effectiveness of the proposed input estimator. It can be seen from Fig. 4 that the estimated inputs in dash line can track the simulation values in solid line correctly after a short transient period. Then the fault case is carried out to test the effectiveness of the proposed fault diagnosis scheme.

B fault filter illustration

Single fault for each actuator is observed, two simultaneous faults are considered. For process fluid, because of erosion, the gland packing of the valve may loosen, which leads to stem vibration, a failure value 1000 adds to the spring compliance k. And for utility fluid, due to unexpected pressure drop across the valve, we supposed that an expected 50KPa pressure drop adds to the nominal pressure drop ΔP at time 40s Simulation results are listed in Fig.5-Fig.9.

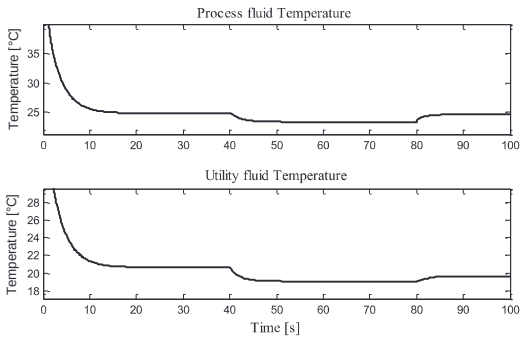

Fig.5 Output temperature of both fluid in fault case

We already know, from Fig. 3, the output temperatures of both fluid stabilize at a specific value in the steady state in fault free case. However, as we can observed from Fig. 5, the output temperatures of both fluid vary according to time, which indicate the occurrence of faults. In the following stage, we use the measured temperature outputs to estimate the inputs of fluid flowrate in order to identify cause of these changes.

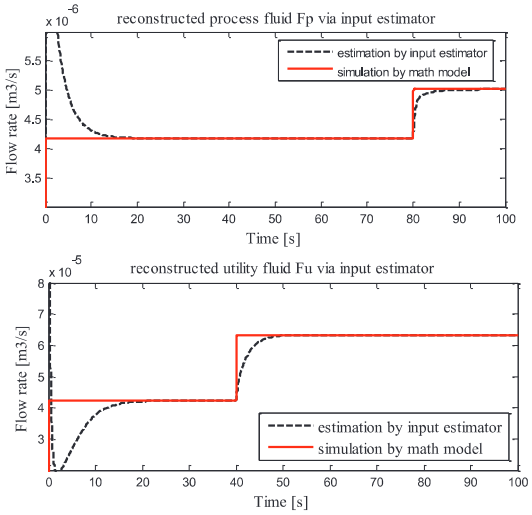

Fig. 6 estimated inputs of process fluid in fault case

As shown in Fig.6, after a short transient time, both the estimation (dash line) and simulation (solid line) flowrates give an accurate estimation value to the real inputs $u_{a1} = F_p, u_{a2} = F_u$. At 80s, the simulation F_p unexpectedly increases, and finally stabilizes at a new level. As observed from Fig. 6, the estimation F_p also follows this increase and tracks the stable value after another transient period. The similar result is obtained in the process of estimating F_u of utility fluid. This time, the sudden change happens at t=40s. For one hand, the simulation results indicate that the proposed input estimator in this paper is proper for recovering time varying unknown inputs. For the other, compared with the nominal values, the increases in both curves imply fault occurrences and no further variations illustrate no additional fault. However, we can only detect and isolation the existence of the actuator fault only by the recovering inputs, the causes of the fault are not available. Therefore it is useful and necessary to identify causes of the faults, thus providing better maintenance aides.

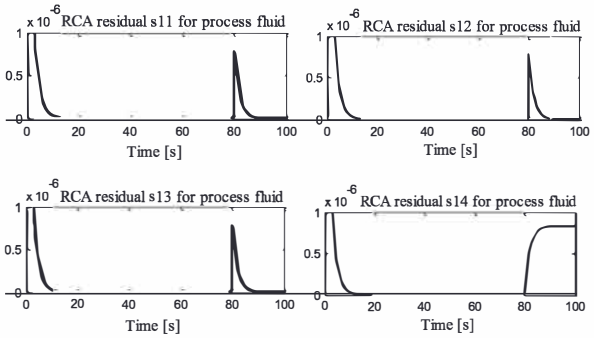

Fig.7 diagnosis residual for fault in process fluid

Fig.7 aims at recognizing root causes of the unexpected increase at actuator of process fluid as shown in Fig. 6. Diagnosis residuals $s_{11}, s_{12}, s_{13}, s_{14}$ are designed to recognize four possible parameters: $p_{c1}, \mu_1, \Delta P_1, k_1$ It is obviously in Fig.7 that only s_{14} breaks through and remains above the threshold, which means that fault in actuator of process fluid is caused by fault k_1. Simulation result is consistent with the assumption, which confirms the effectiveness of the developed scheme.

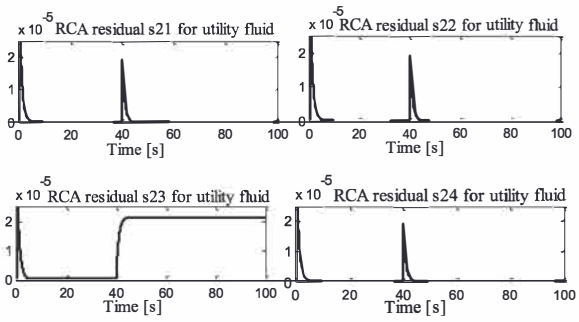

Fig.8 diagnosis residual for fault in utility fluid

Fig.8 aims at recognizing root cause of the fault at actuator of process fluid in Fig. 6. Diagnosis residuals $s_{21}, s_{22}, s_{23}, s_{24}$ are designed to recognize four possible parameters in the model of process fluid: $p_{c2}, \mu_2, \Delta P_2, k_2$. Thanks to the diagnosis residuals, we can determine the cause of the sudden change in the utility fluid flowrate in Fig. 6. It can be seen from Fig.5 that only s_{23} exceeds and remains above the threshold, this illustrates that fault in actuator of process fluid is caused by parameter ΔP_2. Encouraging results are obtained through the robustness performance of the proposed scheme. All the simulated faults have been correctly detected and diagnosed, leading to a desired fault diagnosis results.

V. CONCLUSION

In this paper, a fault diagnosis approach for an invertible cascade nonlinear systems is presented. The main contribution of this paper is the combination of local fault filtering capability with global system monitoring capability. It is accomplished since output of the local subsystem is estimated by the output of global outputs and its derivatives. A high gain sliding mode observer is proposed for the purpose exactly estimate derivatives of outputs which is used to substitute the successive outputs derivatives in the differential algebraic polynomial obtained via system inverse. Results show that the approach achieves satisfactory performances in terms of detection and diagnosis capabilities.

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