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Actuator Fault Detection and Isolation via Input Reconstruction: Application to Intensified Heat Exchanger Reactor

Mei ZHANG [1], Boutaïeb. DAHHOU [2], Michel. CABASSUD [3], Ze-tao.LI [4]

*Abstract***— This paper proposes a left invertible cascade non-linear system structure with a dynamic inversion based input reconstruction laws, forming a novel model-based actuator fault detection and isolation (FDI) algorithm. Actuator is viewed as subsystem connected with the process subsystem in series, thus identifying actuator faults with advancing FDI algorithm in the subsystem whose outputs are assumed unmeasured. The left invertibility of individual subsystem is required for ensuring faults occurred in actuator subsystem can be transmitted to the process subsystem uniquely, and for reconstructing process inputs, also actuator outputs, from measured process outputs. Effectiveness of the proposed approach is demonstrated on an intensified HEX reactor developed by the Laboratoire de Génie Chimique (LGC -Toulouse, France).**

Key words: **cascade inversion system; actuator subsystem; input reconstruction; fault detection and isolation.**

I. Introduction

Due to complexity, integrated operations, multivariable scenarios, and non-linear relationships, fault tolerance is a rapidly evolving, interdisciplinary field of research, which can be achieved not only by improving the individual reliabilities of the functional units but also by an efficient fault detection, isolation (FDI) and accommodation concept.

Actuator malfunctions are very common in industrial systems. During the past several decades, the so-called robust methods of FDI for actuator have been developed to enhance significantly the reliability of the monitored process. Model based methods play an important role in actuator FDI. Various types of observer-based FDI design approaches have been reported in the literature using several approaches, e.g., sliding mode observers in [1], unknown input observers in [2], adaptive observers in [3], interval observers in [4]. The use of system inversion for sensor and actuator FDI was first proposed in [5] for linear system, then extended for nonlinear control affine system in [6]. Recently, strategies based on deferential geometry or system inversion have been proposed to deal with FDI for nonlinear systems, see some important representations in the literature of [7][8][9].

Most of the FDI algorithms proposed to date have been essentially limited to the detection and identification of global faults in a system, although some efforts have been made to locate subcomponent faults [10][11] for root cause analysis, but they are normally FDI method independent, as in [12], fewer further attempts have been made to provide a means of monitoring and diagnosis of subcomponent via advanced FDI algorithm at both local and global level. To authors knowledge, only work [13] proposed a methodology based on this consideration for a linear model of nuclear reactor.

The attempt in this work is to explain how the behavior of the measured outputs and/or states of the overall plant can be interpreted to identify subcomponent (actuator) faults. Existing results mainly consider the actuators as constants in the input coefficient matrix/function of the process system and consider actuator faults as changes of the input coefficient matrix elements. However, usually these assumptions are impractical, for one hand, an actuator is a device with its interior structure and dynamic characteristic in a practical engineering control system, in most cases, it cannot be simply approximated as constant coefficients. For the other, it is more likely impracticable to measure the value of the actuator in realistic industrial conditions (e.g. the initial concentration in chemical reactor as input is not accessible, or actuator is far from the controller), hence, despite the significant amount of research in this field, their capability is severely limited.

Different from the traditional idea, we propose a left inversion cascade nonlinear system structure by considering actuator as a subsystem connected to process subsystem in series, meanwhile, we suppose outputs of the actuator subsystem (also input of the process subsystem) are inaccessible. Our primary objective is to find conditions to guarantee given fault in actuator subsystem can yield unique output of process subsystem, thus implementing actuator FDI in the local subsystem while using the outputs of the global system. The involving conditions are left invertibility of the cascade system which requires individual subsystems are left invertible. Furthermore, availability of the unmeasured output of actuator subsystem is solved by reconstructing the process input which is viewed as a dynamic inversion problem. The simulation results confirm the effectiveness of the proposed scheme.

II. PROBLEM FORMULATION

As shown in Fig.1, it is considering the cascade system consists two subsystems: actuator and process subsystems. The basic idea is to identify the fault v at local level, while monitoring the overall plant at global level. The residual generator performs some kind of validation of the nominal relationships of the system, using the actual input u, and output u_a reconstructed from measured output y.

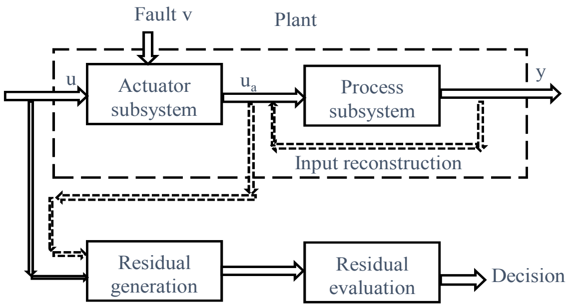

Fig.1 System structure and FDI algorithm

Assuming the MIMO process subsystem is an input affine nonlinear system, and is described by eq.1:

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

where $x \in \Re^n$ is the state of the process subsystem vector, $u_a \in \Re^m$ is the input of process subsystem , $y \in \Re^p$ is overall system output. $f(x)$, $h(x)$ and $g(x)$ are assumed to be smooth on their domains of definition.

And actuator subsystem described by eq.2:

$$\Gamma_a \begin{cases} \dot{x_a} = f_a(x_a, u, \theta_{fa}) \\ u_a = h_a(x_a, u, \theta_{fs}) \end{cases} \tag{2}$$

where $x_a \in \mathcal{R}^n$ is the state, $u \in \mathcal{R}^l$ is the input, $u_a \in R^m$ is the output of the actuator subsystem, which is also the input of the process subsystem, the fault vector v is represented by θ_{fa} and θ_{fs}. $\theta_{fa} \in \mathcal{R}^q$ represents the actual subsystem parameters (i.e., when no faults are present in the system), $\theta_{fa} = \theta_{fa0}$ where θ_{fa0} is the nominal parameter vector (understanding "fault" as an unpermitted parameter deviation in the system), $\theta_{fs} \in \mathcal{R}^q$, represents the parameters in the output equation (if a sensor fault occurs $\theta_{fs} \neq \theta_{fs0}$, where θ_{fs0} represent the nominal parameters in the output equation).

A key feature, opportunity and technical challenge of the system is to obtain the conditions by which the information (useful input u or faults v) provided by actuators can completely arrive the output of the process system y, thus realizing actuator faults by using the measurable output y of the process system. The idea was first demonstrated by [13] for LTI and SISO system. It is illustrated in this paper that, if all the subsystems are invertible, the cascade system is invertible, whereby actuator faults can be detected using y. In this paper, we extend this concept to nonlinear MIMO system.

Moreover, an essential requirement of the combination of individual actuator with an advanced diagnostic capability to perform FDI functions is the availability and reliability of the output of the actuator subsystem u_a, which is also the input of the process system. This problem is considered as input reconstruction problem, which is viewed as problem of system inversion, as shown in Fig.2. Some issues of inversion concepts for input reconstruction were discussed, e.g.[14][15].

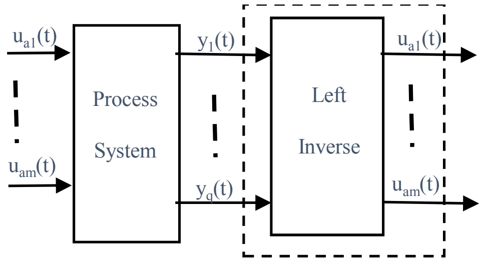

Fig 2. Input reconstruction

III. SYSTEM INVERSION AND FDI

A. Inversion of dynamic nonlinear system

As mentioned before, key for the proposed methodology lies on dynamic invertibility. System inversion refers to a one to one relation between the output and input. With respect to system inversion, some results are obtained [9]. For simplicity, supposed both process subsystem and actuator subsystem are described by Eq.1.

Definition 1: An input-output system Σ from input U_Σ into output Y_Σ is left invertible if there exits an input-output system Σ^{-1} from input Y_Σ to output U_Σ, and a differential polynomial $P(u_a, \dot{u}_a, \dots, y, \dot{y}, \dots)$, such that if $y = \sum(u_a)$, then $\Sigma^{-1}(y) = u_a$, for all pairs $(u_a, y) \in U_\Sigma \times Y_\Sigma$, if:

$$P(u_a, \dot{u}_a, \dots, y, \dot{y}, \dots) \neq 0 \tag{3}$$

Definition 2: For the MIMO nonlinear system described by Eq.1, the relative order r_i of the output y_i or with respect to the manipulated input vector u_a, is the smallest integer for which:

$$L_g L_f^{ri-1} h_i(x) = \left[L_{g1} L_f^{ri-1} h_i(x) L_{g2} L_f^{ri-1} h_i(x) \dots L_{gm} L_f^{ri-1} h_i(x) \right] \neq [0, 0, \dots, 0] \tag{4}$$

Definition 3: For the MIMO nonlinear system described by Eq.1, with finite relative order $r_1, \dots, r_m$, let the matrix:

$$A(x) = \begin{bmatrix} L_{g_1} L_f^{r_1-1} h_1(x) & \dots & L_{g_m} L_f^{r_1-1} h_1(x) \\ \dots & \dots & \dots \\ L_{g_1} L_f^{r_m-1} h_m(x) & \dots & L_{g_m} L_f^{r_m-1} h_m(x) \end{bmatrix} \tag{5}$$

named A(x) as characteristic matrix of the system.

Definition 4: MIMO nonlinear system described by Eq.1, the system is said to be left-invertible, if the characteristic matrix A(x) is nonsingular, or equivalently:

$$\text{rank}\, A(x) = m \tag{6}$$

Corollary 1: consider A, B are characteristic matrixes for process subsystem and actuator subsystem respectively, then characteristic matrix AB of cascade system is invertible, if and only if, both A and B are invertible.

Proof: Let $C = AB$,

Then $B = A^{-1}AB = A^{-1}C$ and $A = ABB^{-1} = CB^{-1}$

Therefore $C = AB = (CB^{-1})(A^{-1}C) = C B^{-1} A^{-1} C$

Then $C\,B^{-1}A^{-1} = I$ So $B^{-1}A^{-1} = C^{-1} = (AB)^{-1}$.

Theorem 1: consider a cascade system consists by several subsystems, the cascade system is invertible if and only if individual subsystems are invertible.

B. Checking Invertibility

Our objective is to give a simple way for the inversion computation algorithm for the diagnostic system. We employ the differential rank to check system invertibility and explore simple way to compute it. Details of differential output rank definitions can be found in [8]. It is defined that differential output rank is the maximum number of outputs that are related by a differential polynomial equation with coefficients over K (independent of x and u).

A simple way to determine the differential output rank:

Step 1: differential all p system outputs

Step 2: find r independent relation of all possible differential polynomials in the following form:

$$H(y_1, y_2, \dots, \dot{y}_1, \dot{y}_2, \dots) = 0 \qquad (7)$$

Step 3: p is the number of outputs, r is number of the independent relations, then differential output rank ρ is the number of least independent outputs, which equals:

$$\rho = p - r \qquad (8)$$

Theorem 2: A system is left-invertible if, and only if the differential output rank ρ is equal to the total number of inputs, e.g. $\rho = m$ in Eq.1.

Remark 1: If a subsystem has more inputs than outputs, then it cannot be left invertible. On the other hand, if it has more outputs than inputs, then some outputs are redundant (as far as the task of recovering the input is concerned). Thus, the case of input and output dimensions being equal is, perhaps, the most interesting case.

C. Input reconstruction by inversion

When a system is invertible, the structure algorithm allows us to express the input as a function of the output, its derivatives and possibly some states. More details in [16].

Theorem 3: If system Eq.1 is left invertible, then the input vector u_a can be obtained by means of the output vector y.

$$\dot{\xi} = f(\xi) + g(\xi)A(\xi)^{-1}\left(\begin{bmatrix} \frac{d^{r_1}y_1}{dt^{r_1}} \\ \vdots \\ \frac{d^{r_m}y_m}{dt^{r_m}} \end{bmatrix} - \begin{bmatrix} L_f^{r_1}h_1(\xi) \\ \vdots \\ L_f^{r_m}h_m(\xi) \end{bmatrix}\right) \qquad (9a)$$

$$u = A(\xi)^{-1}\left(\begin{bmatrix} \frac{d^{r_1}y_1}{dt^{r_1}} \\ \vdots \\ \frac{d^{r_m}y_m}{dt^{r_m}} \end{bmatrix} - \begin{bmatrix} L_f^{r_1}h_1(\xi) \\ \vdots \\ L_f^{r_m}h_m(\xi) \end{bmatrix}\right) \qquad (9b)$$

Although inputs of both subsystems can be reconstructed since it is required individual subsystems are invertible, only process subsystem needs to reconstruct the inputs in the proposed methodology.

D. Actuator FDI algorithm

Consider dynamic system as Eq.2, since the unmeasured outputs u_a have been reconstructed from overall output y, now, one can consider the actuator subsystem as a normal nonlinear system to adopt advanced diagnosis method for fault detection and isolation. Since input nonlinear affine system is considered in this paper, each input represents an actuator which can be described by a nonlinear system of the form of Eq.2. Faults may be caused by the parameters, sensors, inputs in the local subsystem. However, we do not focus on the root cause analysis in this work, our objective is to identify whether or not there are faults existed in each actuator. Since the strong motivation of the work lies on the inaccessible of the outputs of the actuator subsystems, therefore, we suppose all the conditions in each observer are in their nominal values, then if there are faults occurred, actuator subsystem output u_a reconstructed from measured y may be different from the estimated value by observers. Therefore, just through a simple high gain Lunberger observer, fault detection and isolation can be achieved simultaneously.

Considering a bank of observers in [17] for a bank of actuators:

$$1 < i < m \begin{cases} \dot{\hat{x}}_a^i = f_a^i(\hat{x}_a^i, u_i, \theta_{fa0}^i) + H^i(u_a^i - \hat{u}_a^i) \\ \hat{u}_a^i = h_a^i(\hat{x}_a^i, u^i, \theta_{fs0}^i) \end{cases} \qquad (10)$$

where $\hat{x}_a^i \in \mathcal{R}^n$ is the state vector of the ith observer and $\hat{u}_a^i \in \mathcal{R}^p$ is the output vector. H^i is gain matrix, θ_{fa0}^i is the nominal value of actual system parameters of ith actuator, while θ_{fs0}^i is the nominal parameters in the output equation.

Define $\quad e_i(t) = x_a^i - \hat{x}_a^i \qquad (11)$

Through proper designing the matrix *H*, the equilibrium $e_i(t)$ of equation (11) is asymptotically stable.

Let $r_i(t)$ as residual for ith actuator fault detection as:

$$r_i(t) = \|u_a^i - \hat{u}_a^i\| = \|e_i(t)\| \qquad (12)$$

Define threshold as $\mu_i = \|r_i(t)\| := \sup\|r_i(t)\| \;\; t \geq 0$.

Then, we get:

$$r_i = \begin{cases} \|e_i(t)\| < \mu_i; & \text{fault free} \\ \|e_i(t_f)\| \geq \mu_i; & \text{exist fault} \end{cases} \qquad (13)$$

where μ_i is a prespecified threshold. Then through checking the bank of $r_i(t)$, actuators fault detection and isolation is achieved.

IV. APPLICATION TO INTENSIFIED HEX REACTOR

A case study is developed to test the effectiveness of the proposed scheme on an intensified HEX reactor developed by the Laboratoire de Génie Chimique (LGC – Toulouse, France). The pilot is made of three process plates sandwiched between five utility plates, shown in Fig.1. More Relative information could find in [18].

A. System modelling

1. Process subsystem modelling

Generally speaking, intensified continuous heat exchanger reactor is treated as similar to a continuous reactor, then flow modelling is therefore based on the same hypothesis as the one used for the modelling of real continuous reactors, represented by a series of N perfectly stirred tank reactors (cells).The constants and physical data used in the pilot are given in TABLE I.

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	℃
T_{pi}	process fluid input	76	℃

The state and evolutions of the homogeneous medium circulating inside a given cell are described by the following balance. T_P, T_u represents process fluid and utility fluid temperature respectively:

Heat balance of the process fluid ($J.s^{-1}$)

$$\rho_p V_p c_{pp} \frac{dT_P}{dt} = h_p A(T_P - T_u) + \rho_p F_p c_{pp}(T_{Pi} - T_P) \quad (14)$$

Heat balance of the utility fluid ($J.s^{-1}$)

$$\rho_u V_u c_{pu} \frac{dT_u}{dt} = h_u A(T_u - T_P) + \rho_u F_u c_{pu}(T_{ui} - T_u) \quad (15)$$

Define the state vector as $x^T = [x_1, x_2]^T = [T_p, T_u]^T$, the control input $u^T = [u_1, u_2]^T = [F_p, F_u]^T$, the output vector of measurable variables $y^T = [y_1, y_2]^T = [T_p, T_u]^T$, then the equation (14) and (15) can be rewritten in the following state-space form:

$$\begin{cases} \dot{x_1} = \frac{u_1}{V_p}(T_{pi} - x_1) + a(x_2 - x_1) \\ \dot{x_2} = \frac{u_2}{V_u}(T_{ci} - x_2) + b(x_1 - x_2) \end{cases} \quad (16)$$

where $a = \frac{h_p A}{\rho_p c_{p_p} V_p}$, $b = \frac{h_u A}{\rho_u c_{p_u} V_u}$, $y_1 = x_1, y_2 = x_2$

The above model is just for one cell which may lead to moderate differences for the dynamic behavior of the realistic reactor. However, this will not affect the application and demonstration of the proposed FDI algorithm on the reactor, encouraging results are got.

2. Actuator subsystem modelling

Actuators in this system is the most common industrial pneumatic control valve. Bernoulli's continuous flow law of incompressible fluids:

$$F = C_v f(X)\sqrt{\frac{\Delta P}{sg}} \quad (17)$$

where F is flow rate ($m^3 s^{-1}$) , ΔP the fluid pressure drop across the valve (Pa), sg specific gravity of fluid and 1 for pure water, x fraction of valve opening or valve "lift" (X=1 for max flow), f(X) flow characteristic, C_v valve coefficient (given by manufacture). Flow characteristic f(X) 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 [10][11], a pneumatic control valve has a normal model of the type:

$$p_c A_a = m\frac{d^2X}{dt} + \mu\frac{dX}{dt} + kX \quad (18)$$

where A_a 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, is k is the spring compliance, and X is the stem displacement or percentage opening of the valve.

Define:

$$x_{a1} = X, x_{a2} = \frac{dX}{dt}, u = p_c, c = C_v\sqrt{\frac{\Delta P}{sg}}, f(X) = X, u_a = F$$

Then actuator model is:

$$\begin{cases} \dot{x}_{a1} = x_{a2} \\ \dot{x}_{a2} = -\frac{\mu}{m}x_{a2} - \frac{k}{m}x_{a1} + \frac{A_a}{m}u \\ u_a = cx_{a1} \end{cases} \quad (19)$$

In [11] faults in pneumatic control valve may be caused by several reasons: (1) control valve diaphragm failure due to pinhole leaks or cracks in the periphery, resulting in total mass flow change; (2) increased friction in valve stem due to stem misalignment, resulting in μ changed; (3) bellow-seal leakage due to leak, resulting in $p_c A_a + P$ changed; (4) stem vibration owing to loosening of the gland packing of the valve, resulting in k changed totally, there are about 19 kinds of fault may occur, however, according to [10], for most parts, single actuator faults are observed in industrial practice whilst multiple faults rarely occur.

B. *Invertibility Checking*

1 .Process Subsystem Invertibility Checking:

Step 1: differential all two outputs:

$$\begin{cases} \dot{y}_1 = a(y_2 - y_1) + \frac{u_1}{V_p}(T_{pi} - y_1) \\ \dot{y}_2 = b(y_1 - y_2) + \frac{u_2}{V_u}(T_{ui} - y_2) \end{cases} \quad (20)$$

Step2: find all possible relations as for Eq.7.

There exists no any differential equation that output is independent of x and u, therefore, both outputs are differential dependent, r=0.

Step 3: there are 2 outputs, therefore:

$$\rho = p - r = 2 \quad (21)$$

Output differential rank is equal to the total number of inputs, then the process subsystem is invertible.

2 .Actuator subsystem Invertibility Checking:

The same results could easily be got in actuator subsystem. Actuator system is invertible.

Therefore, the total cascade system is invertible.

C. *Input reconstruction via inversion*

Represents the input of the process subsystem as a function of the output and its derivatives.

$$\begin{cases} u_1 = \dfrac{V_p}{T_{pi} - y_1}(\dot{y}_1 - ay_2 + ay_1) \\ u_2 = \dfrac{V_u}{T_{ci} - y_2}(\dot{y}_1 - by_2 + by_1) \end{cases} \quad (22)$$

D. Observer design

There are two actuators, there are then two observers, since both actuators are pneumatic control valve, they have the same form of observers as Eq.10. E.g. observer for control valve of process fluid is as follows:

$$\begin{cases} \dot{\hat{x}}_{a1}{}^1 = \hat{x}_{a2}{}^1 - H^1\left(u_{a1} - \hat{u}_{a1}{}^1\right) \\ \dot{\hat{x}}_{a2}{}^1 = -\frac{\mu 1}{m1}\hat{x}_{a2}{}^1 - \frac{k1}{m1}\hat{x}_{a1}{}^1 + \frac{A1}{m1}u_1 - H^1(u_{a1} - \hat{u}_{a1}{}^1) \end{cases} \quad (23)$$

$$\hat{u}_{a1}{}^1 = c\hat{x}_{a1}{}^1 \quad (24)$$

As mentioned before, faults may influence $\mu, k, \Delta P$. However, as mentioned before, we do not focus on the root cause analysis, our objective is to identify whether or not actuators are faulty. Since the strong motivation of the work here is because of the inaccessible of the output of the actuator subsystem, therefore, we suppose all the conditions in the observers are in their nominal values, then if there are faults occur, u_a reconstructed from measured T_P, T_u may be different from $\hat{u}_{a1}{}^1$ estimated by observers.
Define:

$$r_1(t) = \left\|\hat{u}_{a1}{}^1\text{-}u_{a1}\right\| = \|e_1(t)\| \quad (25)$$

Then, we get:

$$r_1(t) = \begin{cases} \|e_1(t)\| < \ \mu_1; \text{ fault free} \\ \|e_1(t)\| \geq \ \mu_1; \text{ exist fault} \end{cases} \quad (26)$$

Though checking r_1 for process fluid actuator, faults in control valve of process fluid can be detected and isolated simultaneously, and similar regulation can form r_2 for achieving utility fluid FDI.

V. SIMULATION RESULTS AND DISCUSSION

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 $4.17e^{-6}m^3s^{-1}$, initial condition for both observers supposed to be 0. 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. Two kinds of faults have been considered, case A cares about abrupt faults. This kind of fault may be caused by unexpected pressure change across the valve or sudden valve clogging. Incipient faults (due to leakage or valve erosion, et.) are considered in case B.

A. Abrupt fault case

Two abrupt faults in process fluid F_p are introduced at time 60s and 80s respectively, and two abrupt faults in utility fluid F_u are introduced at time 50s and 80s. Besides, to illustrate the robustness of the proposed scheme, measurement noise are considered, the measurement is corrupted by a colored noise. The colored noise is generated with a second order AR filter excited by a Gaussian white noise with zero mean and unitary variance. The summary information is presented in Table Π and simulation results are described in Fig.3-4. Variation in table 2 means the changes in both fluid, e.g. variation of $2e^{-6}m^3s^{-1}$ in process fluid means the flow rate changes from $4.17e^{-6}m^3s^{-1}$ to $(4.17e^{-6} + 2e^{-6})m^3s^{-1}$. Isolation time is the time needs to isolate faults.

TABLE Π REPORT RESULTS FOR ABRUPT FAULTS

Fault			Isolation & identification	
actuator	faulty time	variation	Detection time	Isolation time
F_p	60 s	$2e^{-6}\,m^3s^{-1}$	60.8 s	0.8 s
	80 s	$-3e^{-6}\,m^3s^{-1}$	81.2 s	1.2 s
F_u	50 s	$-1e^{-5}\,m^3s^{-1}$	51s	1 s
	80 s	$2e^{-5}\,m^3s^{-1}$	81.2 s	1.2 s

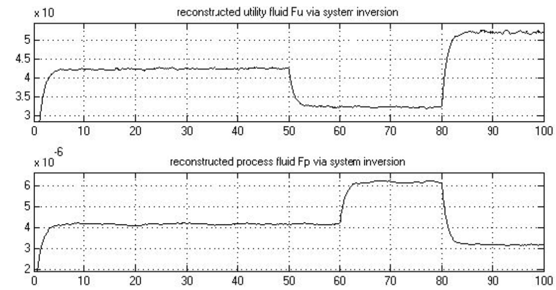

Fig.3 reconstructed inputs F_u, F_p from outputs T_u, T_p in CASE A

In Fig.3, after a short transient time, reconstructed utility fluid flow rate is the same as the expected value, it decreased at 50s and increased at 80s, and both changes took 3s. For process fluid, the reconstructed fluid value took 3.5s to track its sudden changes at time 60s and 80s.

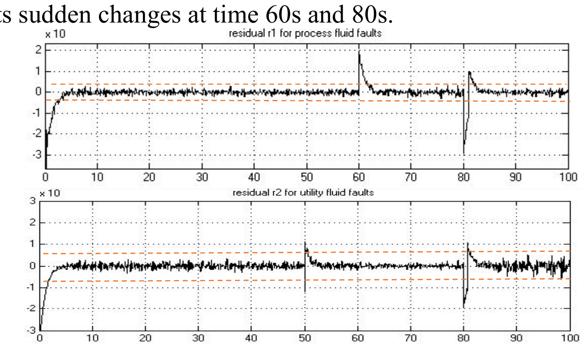

Fig.4 detection and isolation residual in CASE A

In Fig.4, by appropriate threshold chosen to avoid false alarm, the faults can be detected and isolated with satisfactory accuracy despite the disturbance in the system. Residual r_1 is for process fluid FDI, it is obvious there are faults occur at time 60s and 80s since residual r_1 is beyond its threshold. Residual r_2 is for utility fluid FDI, it took 1s and 1.2s to detect and isolate the faults occurred at 50s and 80s. We can see that the proposed methodology could tackle multi and simultaneously faults with satisfactory accuracy despite the disturbance in the system.

B. Incipient fault occur

In this case, incipient faults are introduced in both fluid. It is assumed that the incipient fault in actuator is given by:

$$\text{For } F_p\ (m^3s^{-1}) = \begin{cases} 4.17e^{-6};\ t < 30s \\ (3 + 0.5t) \times 4.17e^{-6};\ t \geq 30s \\ (2 - 0.2(t - 10)) \times 4.17e^{-6};\ t > 60s \end{cases}$$

$$\text{For } F_u\ (m^3s^{-1}) = \begin{cases} 4.22e^{-5};\ t < 60s \\ (1 + 0.2t) \times 4.22e^{-5};\ t \geq 60s \end{cases}$$

Simulation results are shown in the following Fig.5-6 and the summary information is presented in Table III.

TABLE III REPORT RESULTS FOR INCIPIENT FAULTS

fault		isolation & diagnosis	
actuator	faulty time	detection time	isolation time
F_p	30 s	30.4 s	0.4 s
	60 s	61.2 s	1.2 s
F_u	60 s	61.2 s	1.2 s

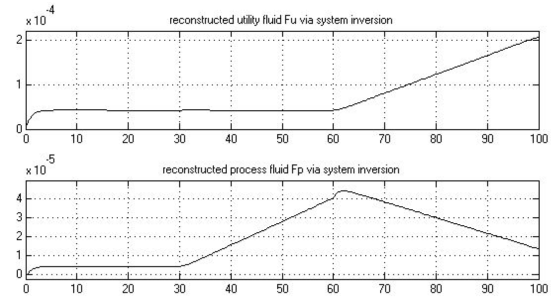

Fig.5 reconstructed inputs F_u, F_p from outputs T_u, T_p in CASE B

From Fig.5, the reconstructed flow rate of utility fluid F_u illustrated that the reconstructed value reaches its nominal value after 3s transient time, and it increases from 60s. And the reconstructed flow rate of process fluid F_p changes incipiently at 30s and 60s.

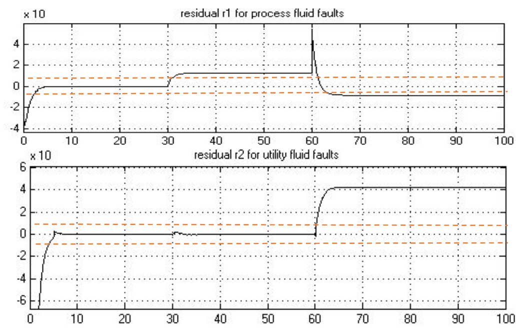

Fig.6 detection and isolation residual in CASE B

In Fig.6, residual r_1 leaves the stable value at 30s, and increases again at 60s, and residual r_2 increases from 60s. In this case, to get a better performance, a trade between threshold magnitude and sensitivity is necessary. Therefore, it takes 0.4s and 1.2s for isolating faults in process fluid F_p at 30s, 60s respectively. And it needs 1.2s to isolate utility fluid F_u fault at time 60s. Incipient faults are thought be extremely difficult to detect immediately from a simple visual inspection of the output signals, the proposed scheme could handle this kind of fault ideally.

VI. CONCLUSION

The main contribution of this paper lies on the integration of system inversion and model-based FDI approaches to facilitate both local and global diagnosis of plant operation, including diagnosis of all subcomponents. By considering actuator and process as individual subsystem connected in cascade manner, it allows advanced FDI methods to be utilized at the local level while monitoring the overall process at global level. Although isolated time is a bit larger than traditional observer based method, it is more practical for an industrial application. Simulated results are included to demonstrate the applicability and robustness of the proposed method and encouraging results are obtained.

REFERENCES

[1] Y. Zhou, J. Liu, and A. L. Dexter, “Estimation of an incipient fault using an adaptive neurofuzzy sliding-mode observer,” Energy Build., vol. 77, pp. 256–269, 2014.

[2] Y. Pang and H. Xia, “Fault detection of nuclear reactors by estimation of unknown input for systems with disturbances,” Nucl. Eng. Des., vol. 275, pp. 91–95, 2014.

[3] F. Grouz, L. Sbita, M. Boussak, and A. Khlaief, “FDI based on an adaptive observer for current and speed sensors of PMSM drives,” Simul. Model. Pract. Theory, vol. 35, pp. 34–49, 2013.

[4] F. Xu, V. Puig, C. Ocampo-Martinez, F. Stoican, and S. Olaru, “Actuator-fault detection and isolation based on set-theoretic approaches,” J. Process Control, vol. 24, pp. 947–956, 2014.

[5] F. Szigeti, C. E. Vera, J. Bokor, and a. Edelmayer, “Inversion based fault detection and isolation,” Proc. 40th IEEE Conf. Decis. Control (Cat. No.01CH37228), vol. 2, no. December, pp. 1005–1010, 2001.

[6] F. Szigeti, J. Bokor, and a Edelmayer, “Input Reconstruction by Means Of System Inversion: Application to Fault Detection and Isolation,” 15th Trienn. World Congr., 2002.

[7] A. Tanwani, A. D. Dominguez-Garcia, and D. Liberzon, “An Inversion-Based Approach to Fault Detection and Isolation in Switching Electrical Networks,” IEEE Trans. Control Syst. Technol., vol. 19, no. 5, pp. 1059–1074, 2011.

[8] R. Martínez-Guerra, J. L. Mata-Machuca, and J. J. Rincón-Pasaye, “Fault diagnosis viewed as a left invertibility problem,” ISA Trans., vol. 52, no. 5, pp. 652–661, 2013.

[9] F. Szigeti, “System Inversion and Fault Detection : the Failure Affine Nonlinear Case,” Automatica, 2002.

[10] M. Bartyś, R. Patton, M. Syfert, S. de las Heras, and J. Quevedo, “Introduction to the DAMADICS actuator FDI benchmark study,” Control Eng. Pract., vol. 14, pp. 577–596, 2006.

[11] K. Roy, R. N. Banavar, and S. Thangasamy, “Application of fault detection and identification (FDI) techniques in power regulating systems of nuclear reactors,” IEEE Trans. Nucl. Sci., vol. 45, no. 6, pp. 3184–3201, 1998.

[12] K. Zhang, “Fault Detection and Diagnosis for A Multi-Actuator Pneumatic System,” Sensors (Peterborough, NH), no. May, p. 134, 2011.

[13] F. Sallem, B. Dahhou, and A. Kamoun, “On the Representation of Actuator Faults Diagnosis and Systems Invertibility,” vol. 8, no. 2, pp. 377–388, 2014.

[14] J. Yang, F. Zhu, K. Yu, and X. Bu, “Observer-based state estimation and unknown input reconstruction for nonlinear complex dynamical systems,” Commun. Nonlinear Sci. Numer. Simul., vol. 20, no. 3, pp. 927–939, 2015.

[15] M. Hou and R. J. Patton, “Input Observability and Input Reconstruction,” Automatica, vol. 34, no. 6, pp. 789–794, 1998.

[16] a. Edelmayer, J. Bokor, Z. Szabo, and F. Szigeti, “Input reconstruction by means of system inversion: A geometric approach to fault detection and isolation in nonlinear systems,” Int. J. Appl. Math. Comput. Sci., vol. Vol. 14, n, no. 2, pp. 189–199, 2004.

[17] E. A. García and P. M. Frank, “Deterministic nonlinear observer-based approaches to fault diagnosis: A survey,” Control Eng. Pract., vol. 5, no. 5, pp. 663–670, 1997.

[18] F. Théron, Z. Anxionnaz-Minvielle, M. Cabassud, C. Gourdon, and P. Tochon, “Characterization of the performances of an innovative heat-exchanger/reactor,” Chem. Eng. Process. Process Intensif., vol. 82, pp. 30–41, 2014.