Chapter 7

Root Cause Analysis of Actuator Fault

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Additional information is available at the end of the chapter

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Abstract

This chapter develops a two-level fault diagnosis (FD) and root cause analysis (RCA) scheme for a class of interconnected invertible dynamic systems and aims at detecting and identifying actuator fault and the causes. By considering actuator as an individual dynamic subsystem connected with process dynamic subsystem in cascade, an interconnected system is then constituted. Invertibility of the interconnected system in faulty model is studied. An interconnected observer is introduced and aims at monitoring the performance of the interconnected system and providing information of actuator fault occurrence. A local fault filter algorithm is then triggered to identify the root causes of the detected actuator faults. According to real plant, outputs of the actuator subsystem are assumed inaccessible and are reconstructed by measurements of the global system, thus providing a means for monitoring and diagnosing the plant at both local and global level.

Keywords: actuator fault, invertibility, interconnected system, input estimation

1. Introduction

Actuators are fundamental components in process industry. However, as they are installed in outdoor environment, continuous exposure to harsh environmental conditions (sun beam, rainfall, etc.) may reduce the optimal performance of system. Among all classes of possible faults, actuator fault has been considered to be one of the most critical challenges to be solved, since an actuator fault may cause significant disturbances on the final product. In addition, with the development of technological advances, actuators are increasingly integrated, intelligent and complex; therefore, each actuator itself is a dynamic system and exhibits complicated dynamics of system. For example, a valve actuator is an assembly of positioner, pneumatic servo-motor and control valve, as given in [1]; mathematical models presented in, like [2, 3], have shown that control valve can be seen as a nonlinear dynamic system. Therefore, modern control system can be viewed as composed of dynamic subsystems connected in series. In all situations, the global plant and/or each subsystem can be analyzed at different levels down to the component level in estimating the reliability of the whole plant. A typical control system, for example, has at least three cascade subsystems: sensor, process and actuator subsystems.

As a result of the increasingly complexities, the probability of occurrence of an actuator fault is also increased. In real industrial system, the actuator faults may related to, for example, pressure drop out in hydraulic components, short circuiting or overheating of electrical components, breakage in bearings due to mechanical stresses, leakages in pipes, sticking of valves, cracks in tanks, and so on. Actuator fault may cause a malfunction of the installation; resulting in a serious impact in equipment, such as production quality, security, economy, levels of contamination, in the worst of cases a fault may even cause severe accidents. According to Zhang [4], about 42% of the potential waste in annual energy consumption is estimated due to leaks of compressed air in a pneumatic system, leaks can degrade machine performance since actuators produce less force, run slower, and less responsive. Faults may even lead to catastrophic incidents. A lesson is from the well-known TMI-II accident in 1979, and it has been proved that this accident was initiated by the valve position failure of feed water pump of the main reactor [5].

Consequently, in order to maintain high-efficiency of the operation and ensure stability of the product quality, real-time actuator fault detection, identification and accurate fault location are quite desired.

2. Status and challenges of current actuator FDD methodologies

The last few decades have witnessed significant improvements in actuator FDD techniques, as illustrated in **Figure 1**. One main approach is system level-based diagnosis approach aims at detecting and identifying actuator fault existence and location from view point of global system. Another common kind of methodologies focuses on the field device level and aims at analyzing internal dynamics of a specific actuator.

2.1. System level-based diagnosis

Traditionally, for most engineers, system level-based methods act as basic tools to design and carry out some monitoring activities where intelligence is at the system level of the process plant, rather than at the field device level. In these methods, dynamics of filed devices (actuator) is ignored, instead, they are treated as a component which is viewed as constants in the input or output coefficient matrix (function) of the process system model. The malfunctions can be treated separately, and they enter the process model as actuator where faults are considered as changes of the input or output coefficient matrix elements. An actuator fault is normally considered as additive effects, as internal dynamics of the field device may be lost.

Many different approaches to system level model-based fault detection and diagnosis have been introduced. Works in [6] reviewed process fault detection and diagnosis based on the principle of analytical redundancy. A key approach is based on residuals generation.

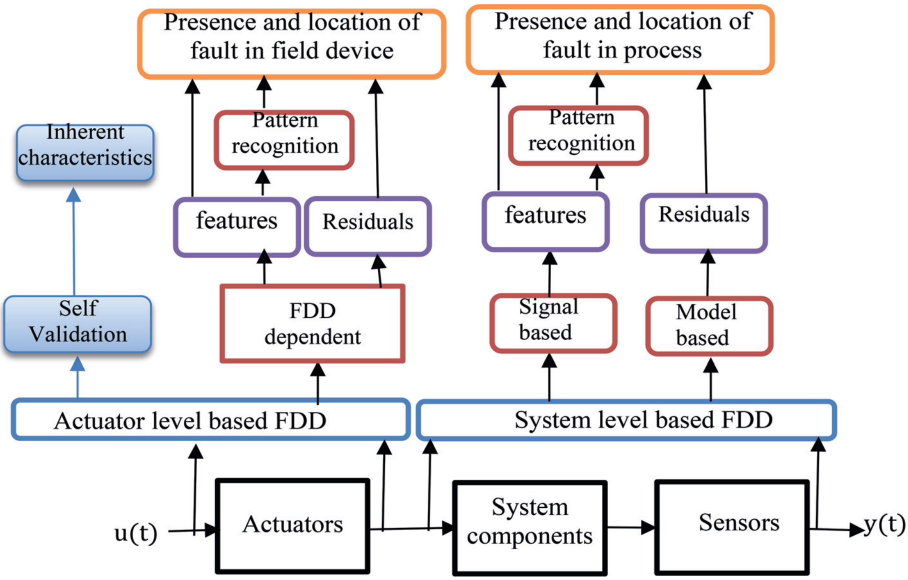

Figure 1. Typical usages of different categories of actuator FDD methods.

In [7], a nonlinear FDI filter is designed to solve a fundamental problem of residual generation using a geometric approach. The objective is to build a dynamic system for the generation of residuals that are affected by a particular actuator fault and not affected by disturbances and the rest of faults. The problem of actuator fault isolation is also studied by exploiting the system structure to generate dedicated residuals (see, e.g. [8]). In addition, adaptive estimation techniques are used to explicitly account for unstructured modeling uncertainties for a class of Lipschitz nonlinear systems (see, e.g. [9]). Another approach different to residual generation is fault estimation or fault reconstruction which can determine the size, location and dynamics behavior of the actuator fault, like in [10, 11]. There are several methods typically used for fault reconstruction: sliding mode observers [12, 13], unknown input observers [14, 15], input reconstruction [16, 17]. For instance, a sliding mode observer is designed to reconstruct or estimate faults by decoupling the input in [18]. Veluvolu et al. [19] develop a high gain observer with multiple sliding modes for simultaneous state and fault estimations for MIMO nonlinear systems.

As a result of incomplete identification of internal variables of the actuator, the applications of system level-based FDD methodologies are mainly limited to the existence and isolation of a fault from view point of the global level, while root causes of this fault cannot be obtained. For example, Di Miceli Raimondi et al. [20] have shown that decrease of output temperature may due to decrease of fluid flowrate, and the causes of this decrease of fluid flowrate may be caused by valve clogging, stop of utility fluid pump or leakage. Nevertheless, with respect to the abovementioned system level-based FDD methodologies, fault symptoms can be detected and isolated without having the capability to pinpoint the real root cause of the fault.

However, root causes of a fault in a component can cause significant process disturbances and influence the quality of the final product. On the one hand, in each component system, there can be fault types specific for that system; therefore it is not capable of analyzing all the actuator faults at the process level. However, recognizing the root cause of a fault correctly is essential in order to be able to allocate resources effectively to repair the problem and perform maintenance actions. Another major problem related to system level-based FDD approaches is the delay of detection. Since lack of internal dynamics of a component, an abnormal deviation of an internal variable inside the field device may not be observable until some internal variable saturates and field device performance are affected [21]. After field device performance is affected by the internal faults, these faults can then be detected through process variables. But the detection may occur too late to keep process performance at an optimal level and to have time to prepare repair work.

2.2. Actuator level-based diagnosis

For the purpose of bettering understanding potential relationship from cause to effect of an actuator fault, component-level diagnosis can be a solution whereby capability of locating subcomponent faults for root cause analysis is available. The development of actuator FDD can be categorized as intelligent self-validation approaches and FDD-dependent methods.

Intelligent self-validation approaches make use of Instrumentation and Control (I&C) technologies, as so called intelligent devices, or smart sensing [22]. It is an instrument that is designed to compensate for its own undesirable inherent characteristics to correct from fault conditions, for example, smart positioner in [1], self-validating actuator in [23, 24]. However, existed intelligent instrument is restricted to self-diagnosis from a low level, and they lack capability of supervising performance of the overall plant.

The most active research area in actuator diagnostics are FDD involved methods, categorized as: signal-based methods and model-based methods. The signal-based methods consider input and output of the device measurement signals and their key characteristics. For example, Sarosi et al. [25] propose an algorithm to detect valve stiction for diagnosis oscillation of control valve by signal processing. Wavelet analysis is a major aspect of signal processing method for fault detection. As in [26], it developed automatic feature extraction of waveform signals for process diagnostic performance improvement. In [27], wavelet transform is applied to detect abrupt changes in the vibration signals obtained from operating bearings being monitored, whereas the model-based methods use first-principle models or system identification techniques to diagnose fault resource. They rely mainly on model-based identification procedures to estimate related parameters. Like in [28, 29], a set of nonlinear differential equations representing the system dynamics based on physics are derived. In [30], derivations of similar nonlinear models have been presented in many recent publications, in which a detailed mathematical model of dual action pneumatic actuators controlled with proportional spool valves and two nonlinear force controllers based on the sliding mode control theory were developed. Puig et al. [2] develop an interval observers-based passive fault detection method and apply to a control valve in the DAMADICS benchmark problem. The authors in [31] introduce a state space sliding-stem control valve

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model in order to utilize an advanced nonlinear model predictive control strategy to compensate for the effects of friction. Other nonlinear modeling approaches involve using neural networks or fuzzy logic, such as in [32, 33].

A major difficulty of actuator level-based diagnosis methodology is lack of dynamics information of global system. Another challenge is getting data from the subsystem since direct access to actuators is often not possible or difficult via physical measurements due to distances or rough environment. Sensors have to be installed to all the primary variables of the field devices to make faults of these field devices observable. However, installing additional sensors into the field devices leads to very complicated and expensive systems. Moreover, even if the output of the field device (e.g., actuator) is available for measurement, considering the noisy output of the sensor of the field device, the numerical differentiation would be too noisy. The noisy control input made from these signals, not only could damage the field device, but also would make less accuracy in tracking and then instability in the control scheme. Furthermore, some parameters are not available for directly measurement, for instance, as a common actuating signal, concentration in chemical process cannot be measured through physical sensors.

Therefore, although many different fault diagnosis methods have been developed from various industries, neither of the aforementioned system level based or actuator level-based FDD methods are however sufficient alone to achieve effective diagnosis to handle all the requirements for an engineering problem. In summary, there is a need for a FDD algorithm which is capable of root cause diagnosing at local actuator level as well as system supervising at global plant level.

3. Problem formulations

Motivated by the above considerations, this chapter is concerned with the challenges of applying system inverse and model-based FDD techniques theory to handle the joint problem of actuator fault diagnosis both locally and globally. We try to develop a hybrid approach that combines different methods, thus, the weaknesses of individual methods can be compensated and more accurate diagnosis results are obtained. For that, the overall system is decomposed into several subsystems and develops the FDD algorithm from the view point of both local and global system, as shown in **Figure 2**.

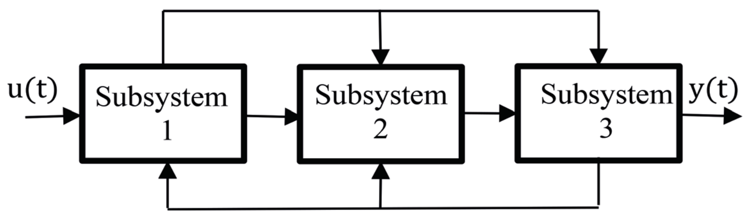

Figure 2. System decomposition and interconnections.

As shown in **Figure 2**, according to real engineering plant, the information that can be obtained from the developed system will include only the performance of critical parameter, such as temperature of continuous chemical reactor, and manipulated variables of the component such as the input of the reactor main control valve. The attempt is to explain how the behavior of overall output can be interpreted to identify subcomponent faults in component subsystem, so as to carry out advanced FDD algorithm for recognizing root causes of detected faults. Like this, this will enable individual actuator to monitor internal dynamics locally to improve plant efficiency and diagnose potential fault resources to locate malfunction when operation performance of global system degrades or has measurement faults. This reduces the complexity of the centralized or distributed monitoring system because the dimensionality problem, the number of sensors, wires, and diagnosis loops connected to the monitoring system is reduced. On the other hand, the obtained information is assumed to be only global output, this can be more realistic and technical availability because field devices are normally remote from the control room and additional sensors may cause reliability and economy problem.

In order to achieve the objectives, there are several tasks the new nonlinear FDD schemes need to study. The first intention is to develop a reasonable system structure for the FDD algorithm, by which local faults can be distinguished globally. The second intention is to establish a complete observer-based FDD framework for local nonlinear subsystems.

4. Invertible interconnected system structure

As mentioned above, a modern control system can be analyzed at different levels down to the component level in estimating the reliability of the whole plant. Therefore, the first consideration is to answer the question of how to decompose the given control problem into manageable subproblems, thus forming a dynamic system structure. We develop an interconnected dynamic system by considering that actuator is viewed as subsystem connected with the process subsystem in series. Through the overall system, the only available measurement is the output of the terminal process subsystem. We then consider the problem that arises when the output from the low-level nonlinear subsystem is not available directly, but instead available via a second nonlinear subsystem. That is, the output from the low-level nonlinear subsystem acts as the input to a high-level subsystem, from which output measurement is in turn available. This situation results in a cascade interconnection that is illustrated in **Figure 3**.

As shown in **Figure 3**, it is considering an interconnected system $\sum$which consists of two subsystems: actuator $\sum_a$ and process $\sum_p$ subsystems. The vector u represents the input vector of the actuators subsystem, which is also the input of the series system, v is the fault vector related to parameter variations of actuator subcomponent or external disturbance, u_a is the actuators output vector, also the input of process subsystem and y is the output vector of the process subsystem, also the output of the overall series system. The basic idea is to identify the fault v at the local level, while monitoring dynamics of the overall plant at the global level.

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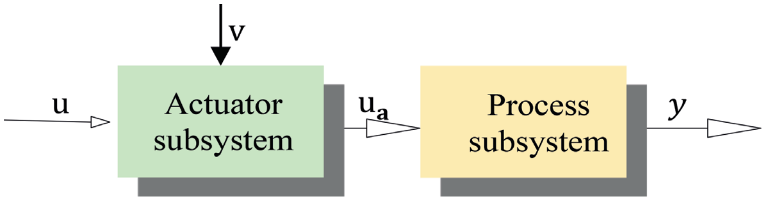

Figure 3. An interconnected system structure.

A key feature, opportunity and technical challenge of the scheme is to obtain the conditions by which the information (useful input u or faults v) issued by actuator subsystem can completely be transmitted to the final terminal and have distinguishable effects on the output of the process system y. In this way, we can realize actuator faults in local subcomponent while utilizing the measurable output y of the process system. With respect to this consideration, if view v as unknown input in the system, this can be seen as problem of input observability. Input or fault observability is equivalent with left invertibility of system. In [35], input can be uniquely recovered from output and the initial state if dynamical system is left invertible.

We then consider a left invertible interconnected nonlinear system structure by which actuator is viewed as a subsystem connected with the process subsystem in cascade manners, thus identifying component faults with advancing FDD algorithm in the subsystem. The left invertibility of the interconnected system is required for ensuring faults occurred in actuator subsystem can be distinguished globally. In this case, the performance of the overall interconnected system and fault occurrence are recognized by a system level-based diagnosis algorithm while several independent local diagnosis subsystems are responsible for potential fault candidates of internal component.

4.1. Process subsystem modeling

Assuming the MIMO process subsystem is input affine nonlinear system which is a common consideration involving system inverse, and is described by Eq. (1):

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

where the state of the process subsystem vector $x \in M$, an n-dimensional real connected smooth manifold, e.g. $\mathfrak{R}^n$, f, g_i are smooth vector field on M, $u_a \in \mathfrak{R}^m$ is the input of process subsystem, which is also the output of the actuator and which we assume to be inaccessible and want to estimate on the basis of measures taken on the evolution of the system, $y \in \mathfrak{R}^p$ is overall system output. If initial conditions are specified, the relevant equation $x(t_0) = x_0$ is added to the system.

4.2. Actuator subsystem modeling

Normally, an actuator subsystem can be described by Eq. (2):

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

where $x_a \in \mathcal{R}^n$ is the state, $u \in \mathcal{R}^l$ is the input, $u_a \in R^p$ is the output of the actuator subsystem, which is also the input of the process subsystem, $\theta_{fa} \in \mathcal{R}^q$ represents the actual 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). If initial conditions are specified, the relevant equation $x_a(t_0) = x_{a0}$ is added to the system.

Thus, an interconnected system $\sum$ is then constructed by these two subsystems $\sum_a$ and $\sum_p$ subsystems whereby the input is vector of u while output vector is y.

Assumption 1: The input vector of both subsystem u_a and u are locally essentially bounded function: $u_a(.) \in [t, \infty) \to \mathfrak{R}^m$, $u(.) \in [t, \infty) \to \mathfrak{R}^l$; if two inputs differ on a set of measure zero, i.e. almost everywhere (a.e), then they are considered to be equal.

If fault v is as integration of either parameters fault θ_{fa}, θ_{fs} or other disturbance signals, a fault mode of Eq. (2) is then obtained:

$$\Gamma_a := \begin{cases} \dot{\hat{x}}_a = f(x_a, u) + \sum_i^m g_{ai}(x_a, u) v_i \\ \\ u_a = h_a(x_a, u) + \sum_i^m l_{ai}(x_a, u) v_i \end{cases} \tag{3}$$

where g, l are analytic functions of the system subject to multiple, possible simultaneously faults. The v (t) is the fault signal $(v_1, \ \ldots, \ v_m)$ whose element $v_i : [0, +\infty) \to \mathcal{R}$ are arbitrary functions of time.

Remark 1: The fault $\sum_i^m g_{ai}(x_a, u) v_i$ represents the parameters fault in θ_{fa} or external disturbance while $\sum_i^m l_{ai}(x_a, u) v_i$ represents the parameters faults in θ_{fs} or external disturbance. Effect of faults on outputs is independent.

The detectability of one fault in nonlinear system Eq. (3) can be defined as:

Definition 1: The fault v_i, $i = 1, \ldots, m$, is said to be non-detectable if for $v_i \neq 0$ the relation

$$u_a(x_{a0}, \ x_a, u, 0) = u_a(x_{a0}, \ x_a, u, 0, \ldots, v_i, \ldots, 0) \tag{4}$$

is satisfied; if not, the fault v_i is detectable.

Definition 2: The fault $v_i, i = 1, \ldots, m,$ is said to be detectable and has independent effect on the system output y if the series system is invertible.

Definition 3: Fix an output set $\mathcal{Y}$ and consider an arbitrary interval $[t_0, T)$, the interconnected system described by Eqs. (1) and (2) is invertible at a point $(x_{a0},\ x_0) := x(t_0) \in \mathcal{X}$ over $\mathcal{Y},\ x_a(t_0) \in \mathcal{X}_a(t_0)$ over $\mathcal{U}_a,$ if for every $y_{[t_0,T)} \in \mathcal{Y},$ the equality $\left(H_a \circ H_p\right)_{\left(x_{a0},\ x_0\right)}\left(u_{1[t_0,T)}\right) = \left(H_a \circ H_p\right)_{\left(x_{a0},\ x_0\right)}\left(u_{2[t_0,T)}\right) = y_{[t_0,T)}$ implies that $\exists \varepsilon > 0,$ such that $u_{1[t_0,t_0+\varepsilon)} = u_{2[t_0,t_0+\varepsilon)}$. The system is strongly invertible at a point $(x_{a0},\ x_0)$ if it is invertible for each $x_a \in \mathcal{N}_a(x_{a0}),\ x \in \mathcal{N}(x_0),$ where $(\mathcal{N}_a, \mathcal{N})$ is some open neighborhood of $(x_{a0},\ x_0)$. The system is strongly invertible if there exists an open and dense sub-manifold $\mathcal{M}_a$of $\mathcal{X}_a$, $\mathcal{M}$of $\mathcal{X},$ such that $\forall (x_{a0}, x_0) \in (\mathcal{M}_a, \mathcal{M}),$ the system is strongly invertible at $(x_{a0},\ x_0)$.

Theorem 1: Consider the interconnected system $\sum$ which consists of two subsystems: actuator $\sum_a$ and process$\sum_p$ subsystems depicted by Eqs. (1) and (2), and an output set $\mathcal{Y}$. The interconnected system is invertible at (x_0, x_{a0}) over $\mathcal{Y}$, if and only if each subsystem actuator $\sum_a$ and process$\sum_p$ is invertible at x_{a0} over $\mathcal{U}_a,$ and x_0 over $\mathcal{Y}$, respectively.

Proof: Considered H_a as the input output mapping of actuator $\sum_a$subsystem, while H_p is the input output mapping of process$\sum_p$ subsystem. Then, the input output mapping of the interconnected system is the composition $H_a \circ H_p$.

a. (Sufficiency): invertibility of a dynamic system refers to bijective of the input output mapping. Since both subsystems are invertible, the corresponding mapping H_a and mapping H_p are bijective mapping. Moreover, composition of two bijective mappings is a bijective mapping, so input output mapping $H_a \circ H_p$of the cascade system is bijective. Thus, the cascade interconnected system is invertible.

b. (Necessity): We now show that if any of the subsystems is not invertible at (x_0, x_{a0}), then the interconnected system $\sum$ is not invertible.

On the one hand, supposed that the process subsystem $\sum_p$ is not invertible, while the actuator subsystem $\sum_a$ is invertible. Then for the actuator subsystem, fix an output set $\mathcal{U}_a$ and consider an arbitrary interval $[t_0, T)$, there exist two distinct inputs for $\exists \varepsilon > 0\ u_1 \neq u_2$ on $[t_0, t_0 + \varepsilon),$ that may yield two distinct outputs $H_{a(x_{a0})}\left(u_{1[t_0,T)}\right) = u_{a1[t_0,T)}, H_{a(x_{a0})}\left(u_{2[t_0,T)}\right) = u_{a2[t_0,T)},\ u_{a1[t_0,T)} \neq u_{a2[t_0,T)}$. However, for the process subsystem, fix an output set $\mathcal{Y}$, these two distinct inputs $u_{a1} \neq u_{a2}$ on $[t_0, t_0 + \varepsilon)$ may produce two equal outputs $H_{p(x_0)}\left(u_{a1[t_0,T)}\right) = H_{p(x_0)}\left(u_{a2[t_0,T)}\right) = y_{[t_0,T)}$. Therefore, for the series system, these two distinct inputs $u_1 \neq u_2$ on $[t_0, t_0 + \varepsilon)$ may result in two equal outputs:

$$\left(H_a \circ H_p\right)_{\left(x_{a0},\ x_0\right)}\left(u_{1[t_0,T)}\right) = \left(H_a \circ H_p\right)_{\left(x_{a0},\ x_0\right)}\left(u_{2[t_0,T)}\right) = y_{[t_0,T)} \tag{5}$$

Thus, it implies that the interconnected system $\sum$ is not invertible at (x_0, x_{a0}) over $(\mathcal{U}_a, \mathcal{Y})$.

On the other hand, supposed that the process subsystem $\sum_p$ is invertible, while the actuator subsystem $\sum_a$ is not invertible. Then for the actuator subsystem $\sum_a$ in (4.2), fix an output set $\mathcal{U}_a$ and consider an arbitrary interval $[t_0, T)$, there exist two distinct inputs for $\exists\varepsilon > 0$ $u_1 \neq u_2$ on $[t_0, t_0 + \varepsilon)$, that may yield two equal outputs $H_{a(x_{a0})}\left(u_{1[t_0,T)}\right) = u_{a1[t_0,T)}$, $H_{a(x_{a0})}\left(u_{2[t_0,T)}\right) = u_{a2[t_0,T)}$, $u_{a1[t_0,T)} = u_{a2[t_0,T)}$. Even if, the process subsystem $\sum_a$ in (4.1) is invertible, these two distinct inputs $u_{a1} = u_{a2}$ on $[t_0, t_0 + \varepsilon)$ can only precede one output $H_{p(x_0)}\left(u_{a1[t_0,T)}\right)$ $= H_{p(x_0)}\left(u_{a2[t_0,T)}\right) = y_{[t_0,T)}$. However, for the series interconnected system, these two distinct inputs $u_1 \neq u_2$ on $[t_0, t_0 + \varepsilon)$ result in two equal outputs:

$$\left(H_a \circ H_p\right)_{\left(x_{a0},\quad x_0\right)}\left(u_{1[t_0,T)}\right) = \left(H_a \circ H_p\right)_{\left(x_{a0},\quad x_0\right)}\left(u_{2[t_0,T)}\right) = y_{[t_0,T)} \tag{6}$$

Thus, it implies that the interconnected system $\sum$ is not invertible at (x_0, x_{a0}) over $(\mathcal{U}_a, \mathcal{Y})$. ∎

5. Multilevel fault diagnosis and root cause analysis

The major objective of the chapter focuses on the problem of model-based FDD and root cause analysis (RCA) for multivariable interconnected dynamic system. The attempt is to explain how the behavior of overall output can be interpreted to identify subcomponent faults in actuator subsystem, so as to carry out advanced FDD algorithm for recognizing root causes analysis of faults. As shown in **Figure 4**, the overall objective is to identify the occurrence of the fault v_i in Eq. (3) independently from each other while monitoring the overall plant at both local and global level, as required for reliable operation of complex and high interconnected process system. Fault v_i refers to the parameter variations which are related with special physical meaning, for example, v_i represents fault caused by leakage or valve clogging of an actuator. To realize these causes of an actuator fault is defined as root cause analysis (RCA) in

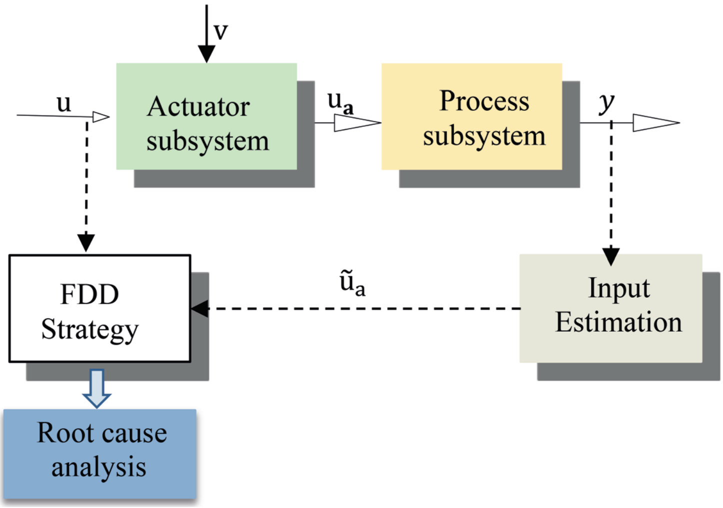

Figure 4. FDD algorithm for component FDD and RCA.

this work. We assume to feed the FDD strategy with input u and output u_a of actuator subsystem at local level, so as to achieve root cause analysis. However, online diagnosis of actuator component is often achieved by a remote supervisory diagnostic system; therefore, to a large extent, it is impractical to measure u_a in realistic industrial condition, so u_a is supposed to be inaccessible in this work. Besides, in order to monitor the plant at a global level, information of global level should be included when FDD function is performed at local subsystem. It became apparent that the FDD algorithm design of an interconnected system with multilevel-based consideration requires that the interconnection be treated as special signals. If u_a can be estimated from the global level measurement y uniquely, then the abovementioned two problems can be solved. In that way, the residual generator of advanced FDD strategy performs some kind of validation of the nominal relationships of the system, using the actual input u, and output $\tilde{u}_a$ reconstructed from measured output y. Hence, a means of monitoring and diagnosis of the overall plant at both local and global level is provided, which result in improved fault localization and provide better predictive maintenance aids.

As mentioned above, invertibility of the interconnected system can be a solution for guaranteeing that the information of actuators subsystem has distinguishable effects on system output. Moreover, an essential requirement of the combination of individual actuator with an advanced diagnostic capability to perform FDD 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 can also be viewed as problem of system inversion, as shown in **Figure 4**. Some issues of inversion concepts for input reconstruction were discussed, e.g. [34–36].

In summary, if the overall cascade system is invertible, fault vector v has distinguishable effect on system output vector y. While if process subsystem is invertible, u_a can be uniquely reconstructed by output vector y, in that case, reconstructed $\tilde{u}_a$ and fault vector v also has one-to-one relationship. Then, one can utilize advanced FDD strategy in actuator subsystem while use the output vector y of the interconnected system to identify v, thus achieving FDD at local level while monitoring the whole system at the global level. Above all, the key problem is to provide condition for guaranteeing invertibility of the overall cascade system and individual subsystems.

5.1. Input estimation

According to the input estimation procedure introduced [37], if the process subsystem Eq. (1) is differentially left invertible, the input can be recovered from the output by means of a finite number of ordinary differential equations. Indeed, to derive an expression for $u_a(t)$ as a function of states and output in Eq. (1), following the inversion algorithm given by [37], we have:

$$\begin{bmatrix} y_1^{(r_1)} \\ \vdots \\ y_m^{(r_m)} \end{bmatrix} = \begin{bmatrix} L_f^{r_1} h_1(x) \\ \vdots \\ L_f^{r_m} h_m(x) \end{bmatrix} \begin{bmatrix} L_{g_1} L_f^{r_1-1} h_1(x) & \dots & L_{g_m} L_f^{r_1-1} h_1(x) \\ \dots & \dots & \dots \\ L_{g_1} L_f^{r_m-1} h_m(x) & \dots & L_{g_m} L_f^{r_m-1} h_m(x) \end{bmatrix} u_a \tag{7}$$

the Eq. (7) can be solved for u to obtain:

$$\tilde{u}_a = A(x)^{-1}.\left(\begin{bmatrix} y_1^{(r_1)} \\ \vdots \\ y_m^{(r_m)} \end{bmatrix} - \begin{bmatrix} L_f^{r_1} h_1(x) \\ \vdots \\ L_f^{r_m} h_m(x) \end{bmatrix}\right) \tag{8}$$

5.2. Local fault filter design for RCA

Considering the actuator subsystem model Eq. (3), by utilizing the reconstructed $\tilde{u}_a$, as well as analyzing the fault resources $v_i, i = 1, .., k$, we can recognize the root cause of the detected fault. To achieve this purpose, through adaptive diagnostic techniques proposed in [8], m banks of k observers corresponding for all possible faulty models are constructed and extended as below:

$$1 \le j \le m, 1 \le i \le k, t \ge t_f$$

$$\begin{cases} \dot{\hat{x}}_a^{i_j} = f_a^j\left(\hat{x}_a^{i_j}, u_j\right) + \sum\limits_{l \ne i} g_{al}^j\left(\hat{x}_a^{i_j}, u_j\right)\theta_l^j + g_{ai}^j\left(\hat{x}_a^{i_j}, u_j\right)\hat{v}_i^j + H_{i_j}\left(\tilde{u}_a^j - \hat{u}_a^{i_j}\right) \\ \hat{v}_i^j = 2\gamma_{i_j}\left(\tilde{u}_a^j - \hat{u}_a^{i_j}\right)^T P_{i_j} g_{ai}^j \\ \hat{u}_a^{i_j} = h_a^j\left(\hat{x}_a^{i_j}, u_j\right) \end{cases} \tag{9}$$

where j denotes jth actuator, i is ith observer corresponding to the ith fault resource candidate v_i. $\hat{x}_a^{i_j} \in \mathcal{R}^n$ 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 $\hat{u}_a^{i_j}$ 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, h_a^j, g_a^j are analytic functions of jth actuator. H_{i_j} is a Hurwitz matrix that can be chosen freely with a goal to increase as much as possible the dynamic of the observer, γ_{i_j} is a design constant and P_{i_j} is a positive definite matrix.

6. Application to a heat exchanger-control valve interconnected system

6.1. System modeling

Consider a counter heat exchanger subsystem can be written in a state-space form:

$$\begin{cases} \dot{x}_1 = G_1(x_1)x_2 + g_1(x_1, u) \\ \dot{x}_2 = \varepsilon(u, \dot{u}, x_a) \\ y = x_1 \end{cases} \tag{10}$$

$$\text{where, } G_1(x_1) = \begin{pmatrix} \dfrac{(T_{pi} - x_{11})}{V_p} & 0 \\ 0 & \dfrac{(T_{ui} - x_{12})}{V_u} \end{pmatrix}, \text{ and } f_1(x) = \begin{pmatrix} \dfrac{h_p A}{\rho_p C_{p_p} V_p}(x_{11} - x_{12}) \\ \dfrac{h_u A}{\rho_u C_{p_u} V_u}(x_{12} - x_{11}) \end{pmatrix}.$$

where the state vector as $x_1^T = [x_{11}, x_{12}]^T = [T_p, T_u]^T$, the control input $x_2^T = u_a^T = [u_{a1}, u_{a2}]^T = [F_p, F_u]^T$, the output vector of measurable variables $y^T = [x_{11}, x_{12}]^T = [T_p, T_u]^T$, 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_{p_p}, C_{p_u} 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 is the process fluid temperature of previous, the inlet temperature is T_{pi}. T_u is the utility fluid temperature, the inlet temperature of utility fluid T_{ui}.

Consider actuator subsystem is described by four states, two inputs and two outputs, as:

$$\begin{cases} \dot{x}_a = \begin{bmatrix} 0 & 1 & 0 & 0 \\ -\dfrac{k_1}{m} & -\dfrac{\mu_1}{m} & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & -\dfrac{k_2}{m} & -\dfrac{\mu_2}{m} \end{bmatrix} x_a + \begin{bmatrix} \dfrac{A_a}{m} & 0 \\ 0 & 0 \\ 0 & \dfrac{A_a}{m} \\ 0 & 0 \end{bmatrix} u \\ u_a = \begin{bmatrix} C_v\sqrt{\dfrac{\Delta P_1}{sg}} & 0 & C_v\sqrt{\dfrac{\Delta P_2}{sg}} & 0 \end{bmatrix} x_a \end{cases} \tag{11}$$

where $x_a^T = [x_{a1} \quad x_{a2} \quad x_{a3} \quad x_{a4}] = \begin{bmatrix} X_1 & \dfrac{dX_1}{dt} & X_2 & \dfrac{dX_2}{dt} \end{bmatrix}$, $u^T = [u_1 \quad u_2] = [p_{c1} \quad p_{c2}]$, $u_a^T = [F_1 \quad F_2] = \begin{bmatrix} C_v\sqrt{\dfrac{\Delta P_1}{sg}}X_1 & C_v\sqrt{\dfrac{\Delta P_2}{sg}}X_2 \end{bmatrix}$, $C = [c_1 \quad c_2 \quad c_3 \quad c_4] = \begin{bmatrix} C_v\sqrt{\dfrac{\Delta P_1}{sg}} & 0 & C_v\sqrt{\dfrac{\Delta P_2}{sg}} & 0 \end{bmatrix}$,
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 manufacturer), 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, 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, k is the spring compliance, and X is the stem displacement or percentage opening of the valve.

Thus, $\varepsilon(\mathrm{u}, \dot{\mathrm{u}}, \mathrm{x_a})$ can be obtained by a function for the derivatives for $\mathrm{u_a}$:

$$\dot{\mathrm{u}}_\mathrm{a} = \varepsilon(\mathrm{u}, \dot{\mathrm{u}}, \mathrm{x_a}) = \frac{\partial \mathrm{h_a}}{\partial u}(\mathrm{u}, \mathrm{x_a})\dot{\mathrm{u}} + \frac{\partial \mathrm{h_a}}{\partial \mathrm{x_a}}(\mathrm{u}, \mathrm{x_a})\mathrm{f_a}(\mathrm{u}, \mathrm{x_a}) \tag{12}$$

$$= \left(\mathrm{C_v}\sqrt{\frac{\Delta \mathrm{P_1}}{\mathrm{sg}}} \quad 0 \quad \mathrm{C_v}\sqrt{\frac{\Delta \mathrm{P_2}}{\mathrm{sg}}} \quad 0 \right)\mathrm{x_a} + \left(\frac{\mathrm{A_a}}{\mathrm{m}}\mathrm{C_v}\sqrt{\frac{\Delta \mathrm{P_1}}{\mathrm{sg}}} \quad \frac{\mathrm{A_a}}{\mathrm{m}}\mathrm{C_v}\sqrt{\frac{\Delta \mathrm{P_2}}{\mathrm{sg}}} \right)\mathrm{u}$$

Four kinds of fault influencing dynamics of the valve are considered in this work: (1) fault f1: valve clogging, occurs when the servomotor stem is blocked by an external event of a mechanical nature. It results in limitation of the piston movement in both direction, and therefore the flow cannot drop below a certain value; (2) fault f2: change of pressure drop across valve, results in $\Delta P + \Delta \mathrm{P}'$; (3) fault f3: bellow-seal leakage due to leak, resulting in $\mathrm{p_c A_a} + \mathrm{P}$ changed; valve internal leakage is a common malfunction with industrial control valves. The causes of such leakage are numerous, including damaged plug or seat, insufficient seat load or reduced spring rate; (4) fault f4: control valve diaphragm perforation due to pinhole cracks in the periphery, resulting in k changed.

As above description shown, actuator fault may be caused by parameters μ, k, u, Δp, then there are eight related parameters in two actuators: $\left[\mathrm{k_1} \quad \mu_1 \quad \mathrm{k_2} \quad \mu_2 \quad \mathrm{p_{c1}} \quad \mathrm{p_{c2}} \quad \Delta \mathrm{P_1} \quad \Delta \mathrm{P_2}\right]$. The process of RCA is to identify abnormal variations of these eight parameters. Two banks of RCA observers are generated, aim at generating two banks of four residuals for those abovementioned fault causes. One bank of residuals are $s_{11}, s_{12}, s_{13}, s_{14}$, aim at identifying fault causes f1, f2, f3, and f4 in actuator of process fluid, the other bank are $s_{21}, s_{22}, s_{23}, s_{24}$, aim at identifying fault causes f1, f2, f3, and f4 in actuator of utility fluid respectively. If any of these residuals exceeds its threshold, the fault is caused by the corresponding fault causes.

6.2. Numerical simulation results

The simulation results validate the proposed strategy. We first give the operating conditions of the simulation. The input of the inlet flow rate of the utility fluid $\mathrm{F_u}$ is $4.22\mathrm{e}^{-5}\mathrm{m}^3\mathrm{s}^{-1}$, and inlet flow rate of the process fluid $\mathrm{F_p}$ is $4.17\mathrm{e}^{-6}\mathrm{m}^3\mathrm{s}^{-1}$. Initial condition for observers supposed to be 0. Parameters in actuator subsystem are: $\mathrm{m} = 2\,\mathrm{kg}$, $\mathrm{A}_a = 0.029\,\mathrm{m}^2$, $\mu = 1500\,\mathrm{Nsm}^{-1}$ and $\mathrm{k} = 6089\,\mathrm{Nm}^{-1}$, $\mathrm{P_c}$ for utility fluid is $1\,\mathrm{MP_a}$, 1.2 Mpa for process fluid, pressure drop ΔP in utility fluid is $0.6\,\mathrm{MP_a}$ and $60\,\mathrm{KP_a}$ in process fluid.

As above mentioned, for most part in practical situation, single fault is observed while multiple faults rarely occur on each actuator. Therefore, we consider each actuator is subject to only one fault, and then two faults may occur simultaneously in the actuator subsystem. Suppose the output measurement y 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 standard deviation of the colored noise is about 3.5.

For actuator of process fluid, it is supposed to suffer leakage fault, and reasons that can lead to the leakage are as follows: valve tightness, leaky bushing, and terminals. Valve clogging fault

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is supposed in actuator of utility fluid, it is a commonly encountered fault. If not properly repaired, this kind of fault may cause severe impacts on system performance. Simulation results are demonstrated in **Figures 5–8**.

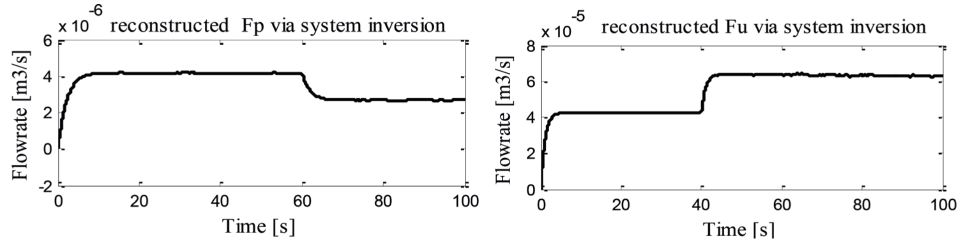

Figure 5. Reconstructed input $\tilde{F}_u$, $\tilde{F}_p$ from output Tp, Tu.

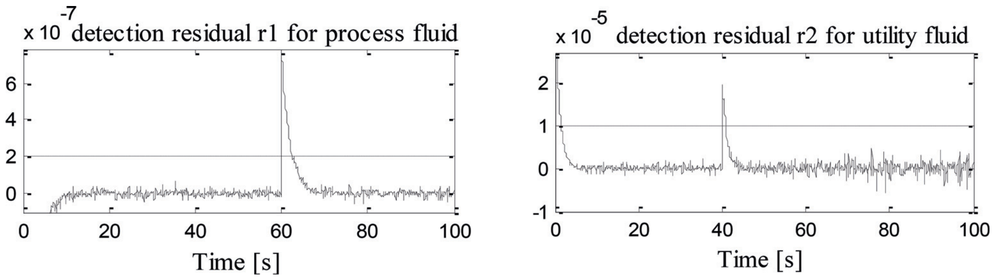

Figure 6. Detection residual.

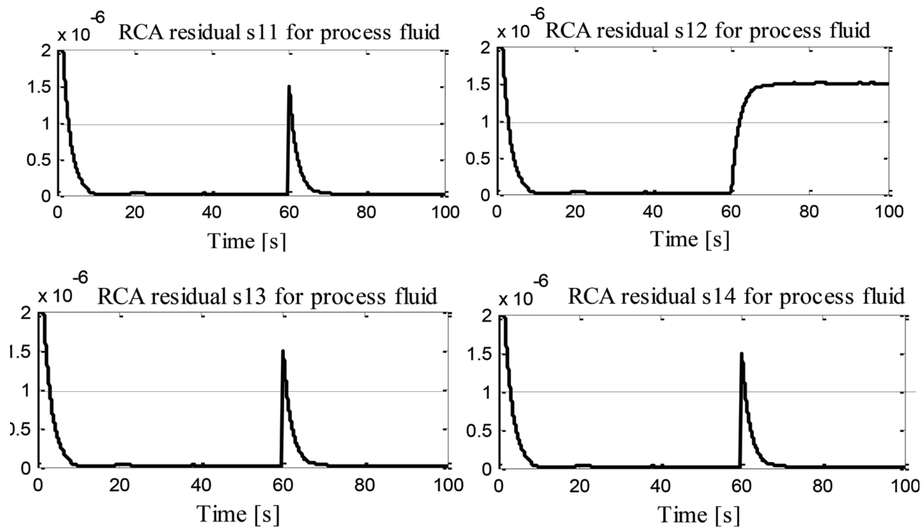

Figure 7. Residuals for identifying fault cause in process fluid.

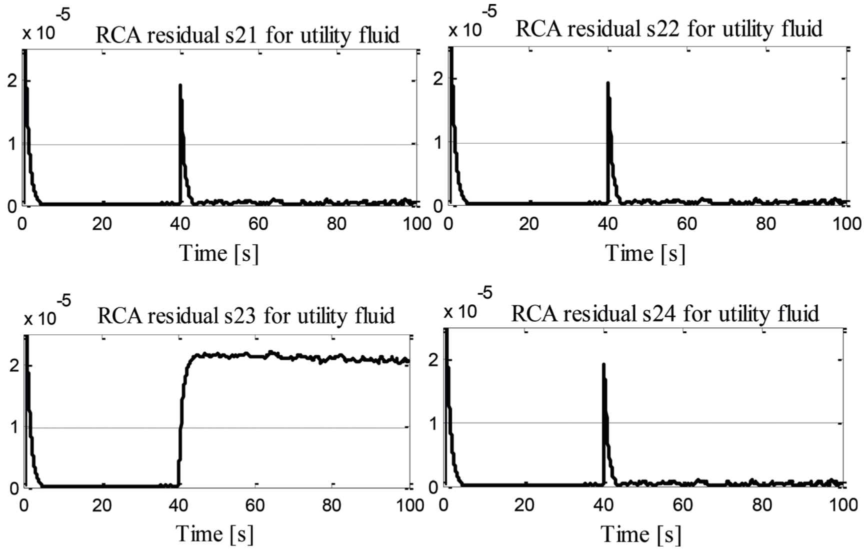

Figure 8. Residuals for identifying fault cause in utility fluid.

It can be seen from **Figure 5** that although noise exists, the developed input reconstruction techniques can provide reconstructed inputs with a good accuracy. At actuator of process fluid, sudden decrease occurs at 60 s which indicates occurrence of a fault, and it takes 4 s to steady at new value. For actuator of utility fluid, the reconstructed value increases from 40 s, and is stable after about 3 s. A fault is detected due to the unexpected increase.

As illustrated in **Figure 6**, detection residual r_1 indicates a fault in actuator of process fluid at 60 s, it takes 1.2 s to determine the occurrence of the fault. Detection residual r_2 refers to a fault in actuator of utility fluid at 40 s, and it takes 1.5 s to detect it. We can shorten the detection time and detect smaller fault by employing larger gain for the detection observers or adopt a smaller threshold. However, larger gain or larger threshold may fail to detect the fault correctly, since observer with larger gain is too sensitive to noise and smaller threshold may lead to be undistinguished from noise. Therefore, a trade between detectability and sensitivity should be made in order to detect the fault correctly. In summary, a small magnitude fault may not be detected within the existence of the noise. Again, after detection of the faults, we have to identify their root causes.

We can see from **Figure 7** that only RCA residual s_{12} breaks through its threshold and remains beyond it; the rest three RCA residuals are below their thresholds, and then the fault resource f2 of actuator of process fluid is identified. When comes to RCA residuals for actuator of utility fluid in **Figure 8**, only s_{23} is beyond its threshold which verifies the occurrence of fault cause f3.

From the above simulation results, we can see that the proposed strategy is available to detect and locate a fault correctly, and root cause analysis for each detected fault is achieved with a good accuracy. Encouraging simulation results are obtained thanks to the robustness.

7. Conclusions

We propose a left invertible interconnected nonlinear system structure with a dynamic inversion-based input estimation laws, forming a novel model-based multilevel-based actuator FDD algorithm. This algorithm provides a systematic solution to performance monitoring and actuator fault diagnosis for nonlinear dynamic system. The new system structure, together with the fault diagnosis algorithm design, is the first to emphasize the importance of root cause analysis of field devices fault, as well as the influences of local internal dynamic on the global dynamics. The developed multilevel model-based fault diagnosis algorithm is then a first effort to combine the strength of the system level and the component level model-based fault diagnosis.

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Conflict of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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