Faults isolation and identification of Heat-exchanger/ Reactor with parameter uncertainties

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Abstract

This paper deals with sensor and process fault detection, isolation (FDI) and identification of an intensified heat-exchanger/reactor. Extended high gain observers are adopted for identifying sensor faults and guaranteeing accurate dynamics since they can simultaneously estimate both states and uncertain parameters. Uncertain parameters involve overall heat transfer coefficient in this paper. Meanwhile, in the proposed algorithm, an extended high gain observer is fed by only one measurement. In this way, observers are allowed to act as soft sensors to yield healthy virtual measures for faulty physical sensors. Then, healthy measurements, together with a bank of parameter interval filters are processed, aimed at isolating process faults and identifying faulty values. Effectiveness of the proposed approach is demonstrated on an intensified heat-exchanger/ reactor developed by the Laboratoire de Génie Chimique, Toulouse, France.

1 Introduction

Nowadays, safety is a priority in the design and development of chemical processes. Large research efforts contributed to the improvement of new safety tools and methodology. Process intensification can be considered as an inherently safer design such as intensified heat exchangers (HEX) reactors in [1], the prospects are a drastic reduction of unit size and solvent consumption while safety is increased due to their remarkable heat transfer capabilities.
However, risk assessment presented in [2] shows that potential risk of thermal runaway exists in such intensified process. Further, several kinds of failures may compromise safety and productivity: actuator failures (e.g., pump failures, valves failures), process failures (e.g., abrupt variations of some process parameters) and sensor failures. Therefore, supervision like FDI is required prior to the implementation of an intensified process.
For complex systems (e.g. heat-exchanger/reactors), fault detection and isolation are more complicated for the reason that some sensors cannot be placed in a desirable place, and for some variables (concentrations), no sensor exists. In addition, complete state and parameters measurements (i.e. overall heat transfer coefficient) are usually not available.
Supervision studies in chemical reactors have been reported in the literature concerning process monitoring, fouling detection, fault detection and isolation. Existing approaches can be roughly divided into data based method as in [3], neural networks as in [4] and model based method as in [5,6,7,8,9]. Among the model based approach, observer based methods are said to be the most capable [10,11,12,13,14] if analytical models are available.
Most of previous approaches focus on a particular class of failures. This paper deals with integrated fault diagnosis for both sensor and process failures. Using temperature measurements, together with state observers, an integrated diagnosis scheme is proposed to detect, isolate and identify faults. As for sensor faults, a FDI framework is proposed based on the extended observer developed in [15]. Extended high gain observers are adopted in this paper due to its capability of simultaneous estimation of both states and parameters, resulting in more accurate system dynamics. The estimates information provided by the observers and the sensors measurements are processed so as to recognize the faulty physical sensors, thus achieving sensor FDI. Moreover, the extended high gain observers will work as soft sensors to output healthy virtual measurements once there are sensor faults occurred. Then, the healthy measures are utilized to feed a bank of parameter intervals filters developed in [11] to generate a bank of residuals. These residuals are processed for isolating and identifying process faults which involves jumps in overall heat transfer coefficient in this work.
It should be pointed out that the contribution of this work does not lie with the soft sensor design or the parameter interval filter design as either part has individually already been addressed in the existing literature. However, the authors are not aware of any studies where both tasks are combined for integrated FDI, besides, there is no report whereby parameter estimation capacity of the extended high gain observer is used to adapt the coefficient, rather than parameter FDI, thus together with sensor FDI framework forms the contribution of this work.

2 System modelling

2.1 Process description

The key feature of the studied intensified continuous heat-exchanger/reactor is an integrated plate heat-exchanger technology which allows for the thermal integration of several functions in a single device. Indeed, by combining a reactor and a heat exchanger in only one unit, the heat generated (or absorbed) by the reaction is removed (or supplied) much more rapidly than in a classical batch reactor. As a consequence, heat exchanger/reactors may offer better safety (by a better thermal control of the reaction), better selectivity (by a more controlled operating temperature).

2.2 Dynamic model

Supervision like FDI study can be much more efficient if a dynamic model of the system under consideration is available to evaluate the consequences of variables deviations and the efficiency of the proposed FDI scheme.

Generally speaking, intensified continuous heat-exchanger/reactor is treated as similar to a continuous reactor [16,17], 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). According to [18] , the number of cells N should be greater than the number of heat transfer units, and the heat transfer units is related with heat capacity flowrate. The modelling of a cell is based on the expression of balances (mass and energy) which describes the evolution of the characteristic values: temperature, mass, composition, pressure, etc. Given the specific geometry of the heat-exchanger/reactor, two main parts are distinguished. The first part is associated with the reaction and the second part encompasses heat transfer aspect. Without reaction, the basic mass balance expression for a cell is written as:

{Rate of mass flow in – Rate of mass flow out = Rate of change of mass within system}

The state and evolutions of the homogeneous medium circulating inside cell k are described by the following balance:

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

$$\rho_p^k V_p^k {C_{p_p}}^k \frac{dT_p^k}{dt} = h_p^k A^k (T_p^k - T_u^k) + \rho_p^k F_p^k {C_{p_p}}^k (T_p^{k-1} - T_p^k) \quad (1)$$

where ρ_p^k is density of the process fluid in cell k (in $kg.m^{-3}$), V_p^k is volume of the process fluid in cell k (in m^3), ${C_{p_p}}^k$ specific heat of the process fluid in cell k (in $J.kg^{-1}.K^{-1}$) , h_p^k is the overall heat transfer coefficient (in $J.m^{-2}.K^{-1}.s^{-1}$).

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

$$\rho_u^k V_u^k {C_{p_u}}^k \frac{dT_u^k}{dt} = h_u^k A^k (T_u^k - T_h^k) + \rho_u^k F_u^k {C_{p_u}}^k (T_u^{k-1} - T_u^k) \quad (2)$$

where ρ_u^k is density of the utility fluid in cell k (in $kg.m^{-3}$), V_u^k is volume of the utility fluid in cell k (in m^3), ${C_{p_u}}^k$ specific heat of the utility fluid in cell k (in $J.kg^{-1}.K^{-1}$) , h_u^k is overall heat transfer coefficient (in $J.m^{-2}.K^{-1}.s^{-1}$).

The eq. (1) (2) represent the dynamic reactor comportment. The two equations represent the evolution of two states (T_p: reactor temperature and T_u: utility fluid temperature).The heat transfer coefficient (h) is considered as a variable which undergoes either an abrupt jumps (by an expected fault in the process) or a gradual variation (essentially due to degradation). The degradation can be attributed to fouling. Fouling in intensified process is tiny due to the micro channel volume and cannot be a failure leads to fatal accident normally, but it may influence the dynamic of the process and it is rather difficult to calculate the changes online. In this paper, we treat the parameter uncertainty as an unmeasured state, and employ an observer as soft sensor to estimate it, unlike other literature, the estimation here is not for fouling detection but for more accurate model dynamics, and to ensure the value of the variable is within acceptable parameter, (e.g., upper and lower bounds of the process variable value).

To rewrite the whole model in the form of state equations, due to the assumption that every element behaves like a perfectly stirred tank, we suppose that one cell can keep the main feature of the qualitative behavior of the reactor. For the sake of simplicity, only one cell has been considered. Let us delete the subscript k for a given cell.

Define the state vector as ${x_1}^T = [x_{11}, x_{12}]^T = [T_p, T_u]^T$, unmeasured state ${x_2}^T = [x_{21}, x_{22}]^T = [h_u, h_p]^T$, $\frac{dh_p}{dt} = \frac{dh_u}{dt} = \varepsilon(t)$, $\varepsilon(t)$ is an unknown but bounded function refers to variation of h, the control input $u = T_{ui}$, the output vector of measurable variables $y^T = [y_1, y_2]^T = [T_p, T_u]^T$, then the equation (1) and (2) can be rewritten in the following state-space form:

$$\begin{cases} \dot{x}_1 = F_1(x_1)x_2 + g_1(x_1, u) \\ \dot{x}_2 = \varepsilon(t) \\ y = x_1 \end{cases} \quad (3)$$

Where, $F_1(x_1) = \begin{pmatrix} \frac{A}{\rho_p C_{p_p} V_p}(T_p - T_u) & 0 \\ 0 & \frac{A}{\rho_u C_{p_u} V_u}(T_u - T_p) \end{pmatrix}$,

and $g_1(x) = \begin{pmatrix} \frac{(T_{pi} - T_p)F_p}{V_p} \\ \frac{(T_{ui} - T_u)F_u}{V_u} \end{pmatrix}$, T_{pi}, T_{ui} is the output of previous cell, for the first cell, it is the inlet temperature of process fluid and utility fluid.

In this case, the full state of the studied system is given as:

$$\begin{cases} \dot{x} = F(x_1)x + G(x_1, u) + \bar{\varepsilon}(t) \\ y = Cx \end{cases} \quad (4)$$

Where $x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$, $F(x_1) = \begin{pmatrix} 0 & F_1(x_1) \\ 0 & 0 \end{pmatrix}$, $G(x_1, u) = \begin{pmatrix} g_1(x, u) \\ 0 \end{pmatrix}$, $C = (I \quad 0)$, $\bar{\varepsilon}(t) = \begin{pmatrix} 0 \\ \varepsilon(t) \end{pmatrix}$

3 Fault detection and diagnose scheme

3.1 Observer design for sensor FDI

The extended high gain observer proposed by [15] can be used like an adaptive observer for estimation both states and parameters simultaneously, in this paper, the latter capability is utilized to estimate incipient degradation of overall heat transfer coefficient (due to fouling), thus guaranteeing a more accurate approximation of the temperature. It is quite useful in chemical processes since parameters are usually with uncertainties and unable to be measured.

Consider a nonlinear system as the form:

$$\begin{cases}\dot{x} = F(x_1)x + G(x_1, u) \\ y = Cx\end{cases} \quad (5)$$

where $x = (x_1, x_2)^T \in \mathcal{R}^{2n}$, $x_1 \in \mathcal{R}^n$ is the state, $x_2 \in \mathcal{R}^n$ is the unmeasured state, $x_2 = \epsilon(t)$, $u \in \mathcal{R}^m$, $y \in \mathcal{R}^p$ are input and output, $\epsilon(t)$ is an unknown bounded function which may depend on $u(t), y(t)$, noise, etc., and

$$F(x_1) = \begin{pmatrix} 0 & F_1(x_1) \\ 0 & 0 \end{pmatrix}, G(x_1, u) = \begin{pmatrix} g_1(x, u) \\ 0 \end{pmatrix}, C(I \quad 0),$$

$F_1(x_1)$ is a nonlinear vector function, $g_1(x, u)$ is a matrix function whose elements are nonlinear functions.
Supposed that assumptions related boundedness of the states, signals, functions etc. in [15] are satisfied, the extended high gain observer for the system can be given by:

$$\begin{cases}\dot{\hat{x}} = F(\hat{x}_1)x + G(\hat{x}_1, u) - \Lambda^{-1}(\hat{x}_1)S_\theta^{-1}C^T(\hat{y} - y) \\ \hat{y} = C\hat{x}\end{cases} \quad (6)$$

Where: $\Lambda(\hat{x}_1) = \begin{bmatrix} I & 0 \\ 0 & F_1(\hat{x}_1) \end{bmatrix}$

S_θ is the unique symmetric positive definite matrix satisfying the following algebraic Lyapunov equation:

$$\theta S_\theta + A^T S_\theta + S_\theta A - C^T C = 0 \quad (7)$$

Where $A = \begin{bmatrix} 0 & I \\ 0 & 0 \end{bmatrix}$, $\theta > 0$ is a parameter define by [15] and the solution of eq. (7) is:

$$S_\theta = \begin{bmatrix} \frac{1}{\theta} I & -\frac{1}{\theta^2} I \\ -\frac{1}{\theta^2} I & \frac{2}{\theta^3} I \end{bmatrix} \quad (8)$$

Then, the gain of estimator can be given by:

$$H = \Lambda^{-1}(\hat{x}_1)S_\theta^{-1}C^T = \Lambda(\hat{x}_1)\begin{bmatrix} 2\theta I \\ \theta^2 F_1^{-1}(\hat{x}_1) \end{bmatrix} \quad (9)$$

Notice that larger θ ensures small estimation error. However, very large values of θ are to be avoided in practice due to noise sensitiveness. Thus, the choice of θ is a compromise between fast convergence and sensitivity to noise.

3.2 Sensor fault detection and isolation scheme

The above observer could guarantee the heat-exchanger/reactor dynamics ideally. Then, a bank of the proposed observers, together with sensor measurements, are used to generate robust residuals for recognizing faulty sensor. Thus, we propose a FDI scheme to detect, meanwhile, isolate and recovery the sensor fault.

3.2.1 Sensor faulty model

A sensor fault can be modeled as an unknown additive term in the output equation. Supposed θ_{sj} is the actual measured output from jth sensor, if jth sensor is healthy, $\theta_{sj} = y_j$, while if jth sensor is faulty, $\theta_{sj} = y_j^f = y_j + f_{sj}$, ($f_{sj}$ is the fault), for $t \geq t_f$ and $\lim_{t\to\infty}|y_j - \theta_{sj}| \neq 0$.That means y_j^f is the actual output of the jth sensor when it is faulty, while y_j is the expected output when it is healthy, that is:

$$\theta_{si} = \begin{cases} y_i; & \text{jth sensor when it is faulty} \\ y_i^f = y_i + f_{si}; & \text{jth sensor when it is faulty} \end{cases} \quad (10)$$

With this formulation, the faulty model becomes:

$$\begin{cases}\dot{x} = F(x_1)x + G(x_1, u) + \bar{\varepsilon}(t) \\ y = Cx + F_s f_s\end{cases} \quad (11)$$

F_s is the fault distribution matrix and we consider that fault vector $f_s \in \mathcal{R}^p$ (f_{sj} is the jth element of the vector) is also a bounded signal. Notice that, a faulty sensor may lead to incorrect estimation of parameter. That is why we emphasized healthy measurement for parameter fault isolation as mentioned above.

3.2.2 Fault detection and isolation scheme

The proposed sensor FDI framework is based on a bank of observers, the number of observers is equal to the number of sensors. Each observer use only one sensor output to estimate all the states and parameters. First, assumed the sensor used by ith observer is healthy, let y_i denotes the ith system output used by the ith observer. Then we form the observer as:

$$1 \leq i \leq p \begin{cases}\dot{\hat{x}}^i = F(\hat{x}_1^i)x + G(\hat{x}_1^i, u) + H_i(y_i - \hat{y}_i^i) \\ \hat{y}^i = C\hat{x}^i\end{cases} \quad (12)$$

Define $e_x^i = \hat{x}^i - x$, $e_y^i = Ce_x^i$, $e_{yj}^i = \hat{y}_j^i - y_j$, $r_j^i(t) = \|\hat{y}_j^i - y_j\|$, $\mu_i = \|r_j^i(t)\| := \sup\|r_j^i(t)\|$, for $t \geq 0$.
Where i denotes the ith observer, $\hat{y}_i^i, \hat{y}_j^i$ denotes the ith, jth estimated system output generated by the ith observer, H_i is the gain of ith observer determined by the following equation :

$$H_i = \Lambda^{-1}(\hat{x}_1)S_{\theta_i}^{-1}C^T = \Lambda(\hat{x}_1)\begin{bmatrix} 2\theta_i I \\ \theta_i^2 F_1^{-1}(\hat{x}_1) \end{bmatrix}$$

Then we get:
Theorem 1:
If the lth sensor is faulty, then for system of form (4), the observer (12) has the following properties:
For $i \neq l$, $\hat{y}^i = y$ asymptotically
For $i = l$, $\hat{y}^i \neq y$
Proof: If the lth sensor is faulty, then:
For $i \neq l$, means that $f_{si} = 0, y_i = \theta_{si}$, we have:

$$\lim_{t\to\infty} e_x^i = \lim_{t\to\infty}(\hat{x}^i - x) = 0 \quad (13)$$

Then the vector of the estimated output $\hat{y}^i$ generated by ith observer guarantee $\hat{y}^i = y$ after a finite time.
For $i = l$, means that $\theta_{sl} = y_l^f = y_l + f_{sl}$, $f_{sl} \neq 0$, the observer is designed on the assumption that there is no fault occurs, because there is fault f_{sl} exit, so the estimation error $e_x^l = 0$ asymptotically cannot be satisfied, then :

$$\lim_{t\to\infty}(\hat{x}^i - x) = \lim_{t\to\infty}(\hat{x}^l - x) \neq 0 \quad (14)$$

we have:

$$\dot{e}_x^l = F(\hat{x}_1^i, u)\ e_x^l - H_i G(\hat{x}_1^i, u, f_{sl})\ e_x^l \quad (15)$$

Then the vector of the estimated output $\hat{y}^i$ generated by the ith observer is different from y, that is $\hat{y}^i \neq y$.⊡
As mentioned above, the observers are deigned under the assumption that no fault occurs, furthermore, each observer just subject to one sensor output. Residual r_i^i is the difference between the ith output estimation $\hat{y}_i^i$ determined by the ith observer and the ith system output y_i, then Theorem 2 formulates the fault detection and isolation scheme.

Theorem 2:
If the lth sensor is faulty, then:
For $i \neq l$, we have:

$$f_{si} = 0, y_i = \theta_{si} \quad (16)$$

thus $\hat{y}_i^i$ converges to y_i asymptotically, we get:

$$r_i^i = \|\hat{y}_i^i - y_i\| \leq \mu_i \quad (17)$$

For $i = l$, we have:
$f_{sl} \neq 0, \theta_{sl} = y_l^f = y_l + f_{sl} \neq y_l$, then $\hat{y}_l^l$ could not track y_l correctly:

$$r_l^l = \|\hat{y}_l^l - y_l\| \geq \mu_l \quad (18)$$

Therefore, in practice, we can check all the residuals r_i^i, for $1 \leq i \leq p$, if $r_i^i \geq \mu_i$ denotes that ith sensor is faulty, then the sensor fault detection and isolation is achieved.
The residuals are designed to be sensitive to a fault that comes from a specific sensor and as insensitive as possible to all the others sensor faults. This residual will permit us to treat not only with single faults but also with multiple and simultaneous faults.
Let r_{si} denotes the fault signature of the ith sensor, define:

$$r_{si}(t) = \begin{cases} 1 & \text{if } r_i^i \geq \mu_i; \text{ith sensor is faulty} \\ 0 & \text{if } r_i^i \leq \mu_i; \text{ith sensor is health} \end{cases} \quad (19)$$

3.2.3 Fault identification and handling mechanism

1) Fault identification

Supposed there are m healthy sensors and $p - m$ faulty ones, then to identify the faulty size of ith sensor, use m estimated output $\hat{y}_i^m$ generated by m observers which use healthy measures, $1 \leq m \leq p-1, m \neq i$, define $\hat{f}_{si}$ as the estimated faulty value of the ith sensor, then:

$$\hat{f}_{si} = \frac{1}{m}\sum_{i=1}^{m}|\hat{y}_i^m - \theta_{si}| \xrightarrow{\Delta} f_{si} \quad (20)$$

2) Fault recovery
As mentioned above, the extended high gain observer is also worked as a software sensor to provide an adequate estimation of the process output, thus replacing the measurement given by faulty physical sensor.
θ_{si} is the actual measured output from ith sensor:

$$\theta_{si} = \begin{cases} y_i \\ y_i^f = y_i + f_{si} \end{cases} \quad (21)$$

Let m observers use healthy measurements as the soft sensor for ith sensor, define:

$$\bar{y}_i = \frac{1}{m}\sum_{i=1}^{m}\hat{y}_i^m \quad (22)$$

If ith sensor is healthy, let the sensor actual output as θ_{si} its output, while if it is faulty, let $\bar{y}_i$ to replace θ_{si}, that is:

$$y_i = \begin{cases} \theta_{si}, \text{if ith sensor healthy} \\ \bar{y}_i, \text{if ith sensor faulty} \end{cases} \quad (23)$$

3.3 process fault diagnose

In order to achieve process FDD, healthy measurements are fed to a bank of parameter intervals filters developed in [11] to generate a bank of residuals. These residuals are processed for identifying parameter changes, which involves variation of overall heat transfer coefficient in this paper. The main idea of the method is as follows.
The practical domain of the value of each system parameter is divided into a certain number of intervals. After verifying all the intervals whether or not one of them contains the faulty parameter value of the system, the faulty parameter value is found, the fault is therefore isolated and estimated.
The practical domain of each parameter is partitioned into a certain number of intervals. For example, parameter h_p is partitioned into q intervals, their bounds are denoted by $h_p^{(0)}, h_p^{(1)}, \ldots, h_p^{(i)}, \ldots, h_p^{(q)}$. The bounds of ith interval are $h_p^{(i-1)}$ and $h_p^{(i)}$, are also noted as h_p^{bi} and h_p^{ai}, and the nominal value for h_p denotes by h_{p0}.
To verify if an interval contains the faulty parameter value of the post-fault system, a parameter filter is built for this interval. A parameter filter consists of two isolation observers which correspond to two interval bounds, and each isolation observer serves two neighboring intervals. An interval which contains a parameter nominal value is unable to contain the faulty parameter value, so a parameter filter will not be built for it.
Define Eq. (3) into a simple form as:

$$\begin{cases} \dot{x}_1 = F_1(x_1)x_2 + g_1(x_1, u) \\ y = x_1 \end{cases} = \begin{cases} \dot{x}_1 = f(x_1, h_p, u) \\ y = x_1 \end{cases} \quad (24)$$

The parameter filter for ith interval of h_p is given below. The isolation observers are:

$$\begin{cases} \dot{\hat{x}}^{ai} = f(\hat{x}_1, h_{p0}^{ai}, u) + H(y - \hat{y}^{ai}) \\ \dot{\hat{y}}^{ai} = c\dot{\hat{x}}^{ai} \\ \varepsilon^{ai} = y - c\dot{\hat{x}}^{ai} \end{cases} \quad (25)$$

$$\begin{cases} \dot{\hat{x}}^{bi} = f(\hat{x}_1, h_{p0}^{bi}, u) + H(y - \hat{y}^{bi}) \\ \dot{\hat{y}}^{bi} = c\dot{\hat{x}}^{bi} \\ \varepsilon^{bi} = y - h\hat{x}^{bi} \end{cases} \quad (26)$$

Where:

$$h_{p0}^{ai}(t) = \begin{cases} h_{p0}, & t < t_f \\ h_p^{(i)}, & t \geq t_f \end{cases}, h_{p0}^{bi}(t) = \begin{cases} h_{p0}, & t < t_f \\ h_p^{(i-1)}, & t \geq t_f \end{cases}, (27)$$

The isolation index of this parameter filter is calculated by:

$$\nu^i(t) = \mathrm{sgn}(\varepsilon^{ai})\mathrm{sgn}(\varepsilon^{bi}) \quad (28)$$

As soon as $\nu^i(t) = 1$, the parameter filter sends the 'non-containing' signal to indicate that this interval does not contain the faulty parameter value. And if the fault is in the ith interval. Let:

$$\hat{h}A = \frac{1}{2}(h^{ai}A + h^{bi}A) \quad (29)$$

to represent the faulty value, fault isolation and identification is then achieved.

4 Numerical simulation

A case study is developed to test the effectiveness of the proposed scheme. The real data is from a laboratory pilot of a continuous intensified heat-exchanger/reactor. The pilot is made of three process plates sandwiched between five utility plates, shown in Fig.1. More Relative information could be found in [2]. As previously said, the simulation model is considered just for one cell which may lead to moderate inaccuracy of the dynamic behavior of the realistic reactor. However, this point may not affect the application and demonstration of the proposed FDD algorithm encouraging results are got.

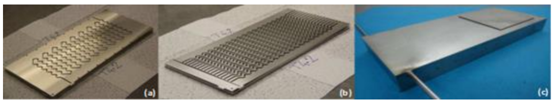


Figure 1 (a) Reactive channel design; (b) utility channel design; (c) the heat exchanger/reactor after assembly.

The constants and physical data used in the pilot are given in table1.

Table 1. Physical data used in the pilot

Constant	Value	units
hA	214.8	$W.K^{-1}$
A	$4e^{-6}$	m^3
V_p	$2.685e^{-5}$	m^3
V_u	$1.141e^{-4}$	m^3
ρ_p, ρ_u	1000	$kg.m^{-3}$
c_{p_p}, c_{p_u}	4180	$J.kg^{-1}.k^{-1}$

4.1 operation conditions

The inlet fluid flow rate in utility fluid and process fluid are $F_u = 4.17e^{-6}m^3, F_p = 4.22e^{-5}m^3s^{-1}$.The inlet temperature in utility fluid is time-varying between 15.6℃ and 12.6℃, which is a classical disturbance in the studied system, as shown in Fig.2. The inlet temperature in process fluid is 76℃. Initial condition for all observers and models are supposed to be $\widehat{T}_p^0 = \widehat{T}_u^0 = 30$℃, $hA = 214.8\ W.K^{-1}$.

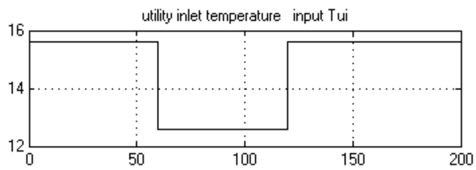


Fig.2 utility inlet temperature T_{ui}

4.2 High gain observer performance

To prove the convergence of the observers and show their tracking capabilities, suppose the heat transfer coefficient subjects to a decreasing of $h = (1 - 0.01t)h$ and followes by a sudden jumps of 15 at $t = 100s$. These variations and observer estimation results are reported in Fig.3.

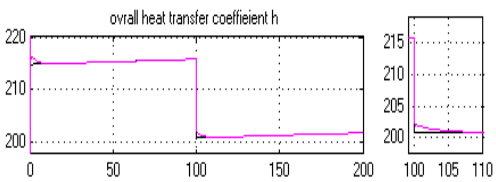


Fig.3. simulation and estimation of heat transfer coefficient variation.

Black curve simulates the actual changes of the parameter while the red one illustrates the estimation generated by the proposed observer, it can be seen from Fig. 3 that the estimation value tracks behavior of the real value with a good accuracy, thus ensuring a good dynamics.

4.3 Sensor FDI and recovery demonstration

In order to show effectiveness of the proposed method on sensor FDI, multi faults and simultaneous faults in the temperature sensors are considered in case 1 and case 2 respectively. Besides, the pilot is suffered to parameter uncertainties caused by heat transfer coefficient decreases with $h = (1 - 0.01t)h$. Two extended high gain observers are designed to generate a set of residuals achieving fault detection and isolation in individual sensors. Observer 1 is fed by output of sensor T_p to estimate the whole states and parameter while observer 2 uses output of sensor T_u. Advantages of the proposed FDI methodology drop on that if one sensor is faulty, we can use the estimated value generated by the healthy one to replace the faulty physical value, thus providing a healthy virtual measure.

Case 1: abrupt faults occur at output of sensor T_p at t=80s, 100s, with an amplitude of 0.3℃, 0.5℃ respectively.the results are reported in Fig.5-8.

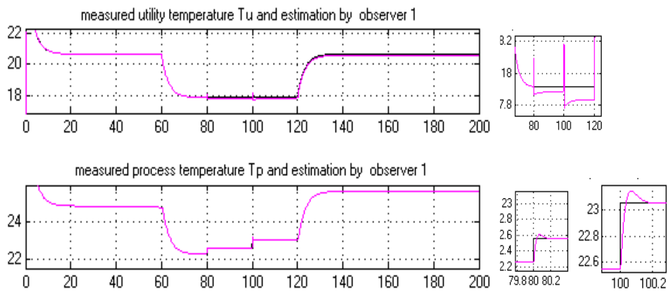


Fig. 5 output temperature of both fluid in case 1 by observer 1, red curve demonstrates the estimated value while black one is the measured value.

It is obviously that since t=80s, $\hat{T}_u$ (red curve) cannot track T_u (black curve) correctly, while it needs about 0.2s for $\hat{T}_p$ to track T_p at t=80s and t=100s. It suggests that faults occur, then the following task is to identify size and location of faulty sensors. Fig.6 and Fig.7 achieves the goal. It takes 0.1s and 0.3s for isolating the faults at 80s, 100s respectively.

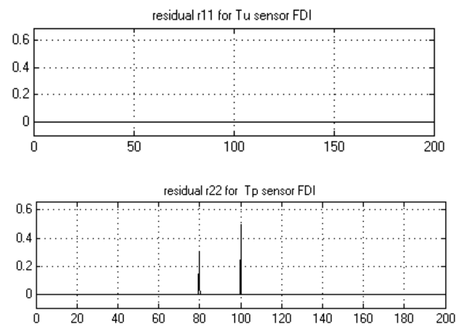
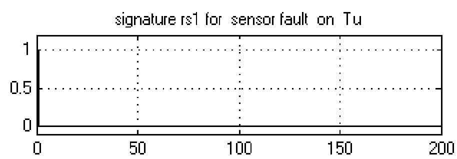


Fig.6 isolation residual in case 1.



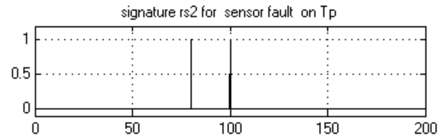


Fig.7b fault signature in case 1, obviously, faults only occur at output of sensor T_p.

For fault recovery, we can employ observer 2 as soft sensor to generate a health value for faulty sensor T_p . Observer 2 uses only measured T_u to estimate all states and parameters. Therefore, $\hat{T}_u, \hat{T}_p$ generated by observer 2 are only decided by T_u. In case 1, faults occur only on sensor T_p, sensor T_u is healthy, that is to say $\hat{T}_u, \hat{T}_p$ generated by observer 2 will be satisfied their expected values. As shown in Fig.8, we can see that since T_u is healthy, estimated value $\hat{T}_u$ tracks measured T_u perfectly, while estimated value $\hat{T}_p$ (red curve) does not track the faulty measured value T_p (black curve), $\hat{T}_p$ (red curve) illustrates the expected value for sensor T_p, we can use estimate $\hat{T}_p$ (red curve) to replace measured faulty value T_p (black curve) for fault recovery.

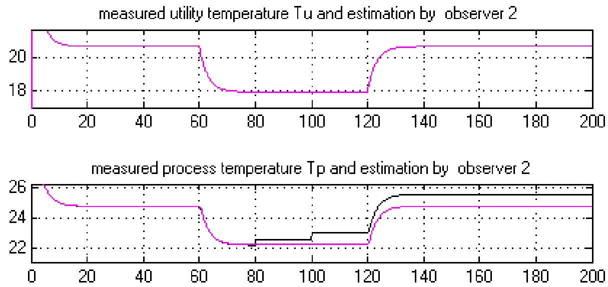
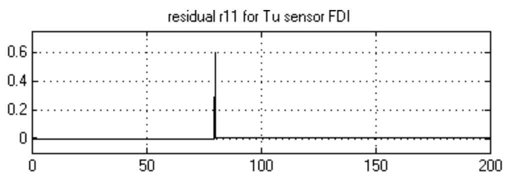


Fig.8 fault recovery in case 1, red curve demonstrates the estimated value while black one is the measured value.

If there are faults occurred only on output of sensor T_u, the same results can be yield easily. For multi and simultaneous faults on both sensors, we can still isolate the faults correctly. Case 2 will verify this point.

Case 2: simultaneous faults imposed to the outputs of sensors T_p as in case 1 and T_u at t=80s with amplitude of 0.6℃. Results are reported in Fig.9-10. Residuals are beyond their threshold obviously at time 80s, 100s.

It can be seen from Fig.9, Fig .10 that the proposed FDI scheme can isolate faults correctly, and it takes 0.25s, 0.4s for isolating the faults in sensor T_p at 80s, 100s and 0.2s for isolating that in sensor T_u at t=80s respectively. Compared with Case 1, more times is needed in this Case 2.



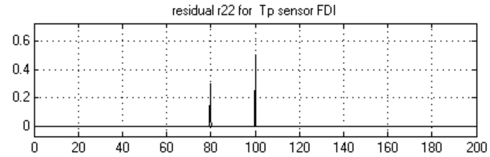


Fig. 9 isolation residual in case 2

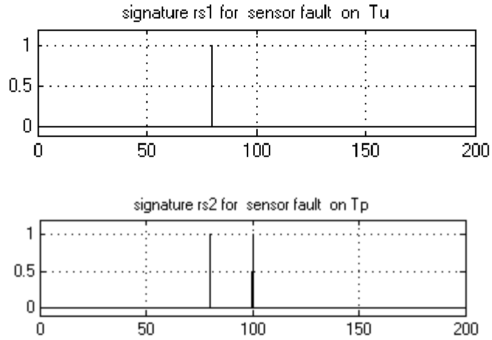


Fig 10. Fault signature in case 2

4.4 Fast process fault isolation and identification

Process fault is related to variation of overall heat transfer coefficient (h). The heat transfer coefficient is considered as variable which undergoes either an abrupt jumps (by an expected fault in the flow rate) or a gradual variation (essentially due to fouling). For incipient variation, since fouling in intensified heat-exchanger/reactor is tiny and only influence dynamics, we have employed extended high observers to ensure the dynamic influenced by this slowly variation. Therefore, the abrupt changes in heat transfer coefficient h can only be because of sudden changes in mass flow rate. It implies that the root cause of process fault is due to actuator fault in this system.

Supposed an abrupt jumps in h at t=40 from 214.8 to 167.

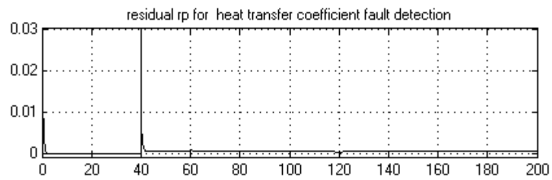


Fig.11 detection residual in process faulty case

From Fig.11, at t=40s, unlike sensor fault cases, the residual leaves zero and never goes back, this indicates that process fault occurs. For fast fault isolation and identification, we use the methodology of parameter interval filters developed in [11]. In [2], heat transfer coefficient h changes between 130.96 and 214.8, then h is divided into 4 intervals as shown in table 2 and simulation results are shown in Fig.12. It can be seen at t=40s, only index for interval 150-170 goes to zero rapidly, then there is a fault in this interval. The faulty value is estimated by $\hat{h}A = \frac{1}{2}(h^a A + h^b A) = \frac{1}{2}(150 + 170) = 160$. We can see it is closely to actual faulty value 167, and if more intervals are divided, the estimated value may be closer to the actual faulty value.

Table 2 parameter filter intervals

Interval NO.	1	2	3	3
$h^a A$	130	150	170	190
$h^b A$	150	170	190	214

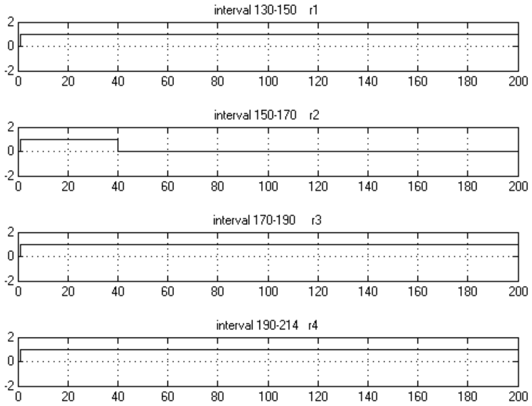


Fig.12 "non_containing fault" index sent by parameter filter

5 Conclusion

An integrated approach for fault diagnose in intensified heat-exchange/reactor has been developed in this paper. The approach is capable of detecting, isolating and identifying failures due to both sensors and parameters. Robustness of the proposed FDI for sensors is ensured by adopting a soft sensor with respect to parameter uncertainties. Ideal isolation speed for process fault is guaranteed due to adoption of parameter interval filter. It should be notice that the proposed method is suitable for a large kind of nonlinear systems with dynamics models as the studied system. Application on the pilot heat-exchange/reactor confirms the effectiveness and robustness of the proposed approach.

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