Observer-based actuator fault detection for chemical batch reactors: a comparison between nonlinear adaptive and $\mathcal{H}_\infty$ - based approaches

F. Pierri*, G. Paviglianiti†

* Dipartimento di Ingegneria e Fisica dell’Ambiente,
Università degli Studi della Basilicata, Potenza, Italy (email: francesco.pierri@unibas.it)
†Dipartimento di Informatica, Matematica, Elettronica e Trasporti,
Università degli Studi "Mediterranea", Reggio Calabria, Italy

Abstract—This paper deals with actuator fault diagnosis for chemical batch reactors. Two different nonlinear model-based approaches have been developed in order to detect incipient and abrupt faults. Two residual generators were built by using an adaptive observer and a $\mathcal{H}_\infty$ approach. Both approaches are well used for sensor fault detection due to their capability to estimate uncertain parameters and to guarantee robustness against modeling errors and disturbances. Here, the approaches have been extended to achieve actuator fault detection and a comparison of both techniques has been done by simulating the whole system in-design and off-design operating conditions.

I. INTRODUCTION

In the chemical industry, faults can occur due to sensors failures, equipment failures or changes in process parameters. The occurrence of a fault may cause a process performance degradation (e.g., lower product quality) or, in the worst cases, fatal accidents, such as run-away. Faults can be divided into actuator faults (e.g., electric-power failure, pump failure, valve failure), process faults (e.g., abrupt variation of the heat transfer coefficient, side reaction due to impurity in the raw material) and sensor faults. Several fault detection (FD) approaches have been proposed for processes operating mainly in steady-state conditions (e.g., CSTR reactors). Application of these techniques to batch chemical processes are usually challenging, because of their nonlinear dynamics and intrinsically unsteady operating conditions. Also, complete state and parameters measurements (i.e., products composition) are usually not available.

Existing fault diagnosis approaches for chemical processes can be roughly classified in model-free approaches and model-based approaches.

Model-based analytical redundancy approaches to FD (see [1], [2] for wide overview) are based on the comparison between the measurements of a set of variables characterizing the behavior of the monitored system and the corresponding estimates, predicted via a mathematical model of the system. The inconsistencies between measured and estimated variables provide a set of residuals sensitive to the occurrence of faults; then, by processing the information carried by the residuals, the faults can be detected (i.e., the presence of one or more faults can be recognized) and isolated (i.e., the faulty components are determined). Among model-based analytical redundancy approaches, observer-based schemes have been successfully adopted in a variety of application fields. Namely, a model of the system (often called diagnostic observer) is operated in parallel to the process to produce estimates of some system variables to be used for the residual generation. Since perfect knowledge of the model is rarely a reasonable assumption, soft computing methods, integrating quantitative and qualitative modeling information, have been developed to improve the performance of FD observer-based schemes for uncertain systems [3]. Major contributions to the observer-based approaches can be found in [4], where the failures are identified by using the so-called on-line interpolators (e.g., ANNs whose weights are updated on line).

The literature about FD for chemical plants do not present a significant number of applications of observers: in [5] an unknown input observer is adopted for a CSTR, in [6] and in [7] an extended Kalman filter (EKF) is used, but in these works the FD is performed in open loop, while most chemical processes operate in closed-loop and the control action may affect the fault diagnosis system performance. Regarding the FD in the presence of closed-loop, an EKF, [8], a generalized Lukenbergen observer, [9] and an unknown input observer, [10], have been adopted.

Many works deal with the diagnostics of actuators. Following approaches were applied: spectral analysis [11], pattern recognition [12], neural network approaches [13], fuzzy and fuzzy-neural approaches [15], observers [16].

This work deals with actuator fault detection for a jacketed batch reactor. Recently, two observers for state estimation have been proposed: in [17] a robust $\mathcal{H}_\infty$ - based observer in conjunction with an on-line universal interpolator has been adopted for sensor fault detection, while in [18] an adaptive nonlinear observer has been used for control purposes. Here a fault detection scheme is proposed extending these observers in such a way to achieve actuator fault detection. A simulation case study is developed to test and compare the effectiveness of the proposed approaches in the presence of different faulty and healthy operating conditions. Both schemes were tested in off-design conditions and a comparison of the performance is provided.
II. MODELING

Let us consider a jacketed ideal batch reactor, in which the exothermic reaction \( A \rightarrow B \rightarrow C \) takes place. Assuming first-order kinetics and perfect mixing, the mass balances give

\[
\dot{C}_A = -k_1(T_r)C_A, \quad \dot{C}_B = k_1(T_r)C_A - k_2(T_r)C_B,
\]

where \( T_r \) is the reactor temperature (\(^\circ\)C), \( C_A \) and \( C_B \) are the concentrations (mol \( \cdot \) m\(^{-3}\)) of the reactant A and of the desired product B, respectively, \( k_i(T_r) \) (\( i = 1, 2 \)) are the reaction rate constants.

The energy balance in the jacket gives

\[
\dot{T}_j = \frac{Q}{V_r \rho_r C_{pr}} = \frac{US(T_r - T_j)}{V_r \rho_r C_{pr}},
\]

where \( T_j \) is the temperature (\(^\circ\)C) of the fluid in the jacket, \( V_r \) is the reactor volume (m\(^3\)), \( \rho_r \) is the density of the reacting mixture (kg \( \cdot \) m\(^{-3}\)), \( C_{pr} \) is the mass heat capacity of the reactor contents (J \( \cdot \) kg\(^{-1}\) \( \cdot \) K\(^{-1}\)), \( U \) is the heat transfer coefficient (J \( \cdot \) m\(^2\) \( \cdot \) K \( \cdot \) s\(^{-1}\)) and \( S \) is the heat transfer area (m\(^2\)).

The energy balance in the reactor gives

\[
\dot{T}_r = \frac{Q(C_A, C_B, T_r) - US(T_r - T_j)}{V_r \rho_r C_{pr}},
\]

where \( q(C_A, C_B, T_r) = \frac{Q(C_A, C_B, T_r)}{V_r \rho_r C_{pr}} = \frac{(-\Delta H_1)k_1(T_r)C_AV_r + (-\Delta H_2)k_2(T_r)C_BV_r}{V_r \rho_r C_{pr}} \),

where \( Q \) (J \( \cdot \) s\(^{-1}\)) is the heat released by the reaction and \( \Delta H_1, \Delta H_2 \) are the molar enthalpy changes of the two reactions (J \( \cdot \) mol\(^{-1}\)).

Under the assumption of perfect mixing in the jacket, the energy balance in the jacket yields

\[
\dot{T}_j = \frac{US(T_r - T_j)}{V_r \rho_r C_{pr}} = \frac{(T_m - T_j)}{V_j} F,
\]

where \( V_j \) is the jacket volume, \( \rho_j \) is the density of the fluid in the jacket, \( C_{pj} \) is the mass heat capacity of the fluid in the jacket, \( T_m \) is the temperature of the fluid entering the jacket and \( F \) is the flow rate (m\(^3\) \( \cdot \) s\(^{-1}\)) of the fluid entering the jacket.

In order to rewrite the whole model in the form of state equations, let define the state vector

\[
\mathbf{x} = \begin{bmatrix} x_M \\ x_E \end{bmatrix}, \quad \mathbf{x}_M = \begin{bmatrix} C_A \\ C_B \end{bmatrix}, \quad \mathbf{x}_E = \begin{bmatrix} T_r \\ T_j \end{bmatrix},
\]

the control input

\[
u = T_m,
\]

and the output vector of measurable variables:

\[
y = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \mathbf{x}_E,
\]

and the vector of parameters

\[
\mathbf{\theta} = [\theta_r, \theta_j]^T = \begin{bmatrix} US \\ US/V_r/p_r/C_{pr} \end{bmatrix}^T.
\]

Then, Equations (1), (3) and (4) can be rewritten in the following state-space form:

\[
\begin{align*}
\dot{x}_M &= -k_1(y_1)x_M, \\
\dot{x}_E &= \alpha_1k_1(y_1)x_M + \alpha_2k_2(y_2)x_M - \theta_r(x_E_1 - x_E_2),
\end{align*}
\]

where \( (i = 1, 2) \)

\[
\alpha_i = \frac{(-\Delta H_i)}{\rho_r C_{pr}}, \quad \beta_j = \frac{F}{V_j}.
\]

Equation (5) can be rearranged to take into account the effects of the uncertain parameters and of actuator faults. Since in chemical batch reactors the vectors of parameters \( \theta \) is often uncertain, it can be expressed as

\[
\dot{\theta} = \theta_0(1 + \Delta \theta),
\]

where \( \theta_0 = [\theta_r, \theta_j] \) is the available nominal value and \( \Delta \theta = [\Delta \theta_r, \Delta \theta_j]^T \) is the vector of the percentage variations of the parameters with respect to theirs nominal value. Hence, equation (5) can be rewritten as follows

\[
\begin{align*}
\dot{x}_M &= A_M(y)\mathbf{x}_M, \\
\dot{x}_E &= [A_0 + \Delta A]x_E + \zeta(x) + b_E(u + f_a),
\end{align*}
\]

where \( f_a, w_m \) are the actuator fault and the sensor noise vector, and

\[
A_M = \begin{bmatrix} -k_1(y_1) & 0 \\ k_1(y_1) & -k_2(y_1) \end{bmatrix},
\]

\[
A_0 = \begin{bmatrix} -\theta_r & 0 \\ \theta_r & -\theta_j - \beta_j \end{bmatrix}, \quad \zeta(x) = \begin{bmatrix} q(x) \\ 0 \end{bmatrix},
\]

\[
A = \begin{bmatrix} -\theta_r \Delta \theta_r & 0 \\ 0 & -\theta_j \Delta \theta_j \end{bmatrix}, \quad b_E = \begin{bmatrix} 0 \\ \beta_j \end{bmatrix}.
\]

III. DIAGNOSTIC OBSERVERS

In this section two different diagnostic observers for residuals generation, based on the observers proposed in [17] and in [18], are presented. The first observer is a full-order observer, that, on the basis of the knowledge of the reaction kinetics, estimates the whole state, and, using a suitable adaptive law, the uncertain parameters. The latter observer estimates the measurable state (i.e. the state variables \( x_E \)) while the kinetics is taken into account with the use of an online universal interpolator; moreover, the matrix gain is designed via a \( \mathcal{H}_{\infty} \) approach, that guarantees robustness against the interpolation error and parameter uncertainties and emphasizes fault signature on the residuals.
A. Nonlinear adaptive observer

The following nonlinear adaptive observer can be adopted as residual generator
\[
\begin{align*}
\dot{x} &= A(y) \dot{x} + b(y, u) + L \tilde{y} + C^T \psi(y) \hat{\theta}, \\
\hat{y} &= C \hat{x},
\end{align*}
\]
where
\[
A(y) = \begin{bmatrix}
-k_1(y_1) & 0 & 0 & 0 \\
k_1(y_1) & -k_2(y_1) & 0 & 0 \\
\alpha_k_1(y_1) & \alpha_k_2(y_1) & 0 & 0 \\
0 & 0 & 0 & 0
\end{bmatrix},
\]
\[
b(y, u) = \begin{bmatrix}
0 \\
0 \\
0 \\
\beta_j(y - y_q)
\end{bmatrix}, \\
C = \begin{bmatrix}
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1
\end{bmatrix},
\]
\[
\psi(y) = \begin{bmatrix}
-y_1 - y_2 \\
0 \\
0 \\
(y_1 - y_2)
\end{bmatrix},
\]
\[
\hat{x} \text{ denotes the vector of the state estimates; } \tilde{y} \text{ and } \hat{y} = y - \hat{y} \text{ denote the vectors of output estimates and output estimation errors, respectively; } L \text{ is a } (4 \times 2) \text{ matrix of positive gains } (l_i, i = 1, \ldots, 4).
\]
\[
L = \begin{bmatrix}
L_M \\
L_E
\end{bmatrix}, \\
L_M = \begin{bmatrix}
l_1 & 0 \\
l_2 & 0
\end{bmatrix}, \\
L_E = \begin{bmatrix}
l_3 & 0 \\
0 & l_4
\end{bmatrix},
\]
\]
and the estimate \( \hat{\theta} \) of the parameters is given by the update law:
\[
\dot{\hat{\theta}} = \Gamma^{-1} \psi^T(y) \tilde{y},
\]
where \( \Gamma \) is a (2 \times 2) matrix of positive gains.

For fault detection purposes, it may be defined \( r = \tilde{y} \) as residual vector. By comparing equations (6) and (7) it can be recognized that fault function affects residual dynamics:
\[
\dot{r} = \tilde{y} = F(y) \dot{x} + \psi(y) \hat{\theta} + D \dot{w}_m + b_E f_a.
\]
where \( F(y) = C(A(y) - LC) \).

In [18] it is shown that a suitable choice of \( L \) and \( \Gamma \) exists, which ensures asymptotic convergence of the state estimation error \( \hat{x} = x - \hat{x} \). As usual in direct adaptive estimation and/or control schemes, the convergence to 0 of the parameter estimation error \( \dot{\theta} \) is not guaranteed, unless the persistence of excitation condition is fulfilled [19]. Remarkably, when an accurate estimate of the heat-transfer coefficient is available (and thus, the adaptive update law is not used), the convergence can be proven to be exponential [18]; this ensures robustness of the observer in the face of unmodeled uncertainties and/or perturbations.

B. Nonlinear \( H_\infty \) observer

Differently from previous approach, knowledge about reaction kinetics is not required and the term \( q(x) \) is estimated via an on-line universal approximator [4]. Moreover, the design of the observer is based on \( H_\infty \) techniques, which allow to effectively take into account external disturbances and modeling errors (e.g., due to inaccuracies of the on-line interpolator).

The proposed diagnostic observer has the form
\[
\begin{align*}
\dot{\hat{x}}_E &= A_0 \hat{x}_E + \hat{\zeta}(y, \eta) + b_E u + G \tilde{y}, \\
\dot{\tilde{y}} &= \hat{x}_E
\end{align*}
\]
where \( \hat{x}_E \) and \( \hat{\zeta} \) are the estimates of \( x_E \) and \( \zeta \), respectively. As usual in direct interpolation error of the neural network is modeled as
\[
\zeta(x, x_E) = \phi(x, y) = [\varphi_1(x), \cdots, \varphi_p(y)]^T.
\]
The weights are adapted on-line by using the following update law
\[
\dot{\eta} = \frac{1}{\lambda} \varphi(y) \tilde{y},
\]
where \( \lambda \) is a positive gain.

The state estimation error dynamics is then given by
\[
\dot{\tilde{x}}_E = A_0 \tilde{x}_E + \Delta A x_E + \zeta(x) - \hat{\zeta}(y, \eta) + b_E f_a - G \tilde{y}.
\]
The interpolation error of the neural network is modeled as
\[
\tilde{\zeta}(x, x_E) = \zeta(x, x_E) - \hat{\zeta}(y, \eta) = B_w w_p.
\]
where \( w_p \) is an unknown input collecting the network interpolation errors and
\[
B_w = \begin{bmatrix}
1 \\
0
\end{bmatrix}.
\]
Therefore, the estimation error system can be rewritten as
\[
\begin{align*}
\dot{\tilde{x}}_E &= A_0 \tilde{x}_E + \Delta A x_E \Delta \theta + B_w w_p + b_E f_a - G \tilde{y}, \\
\tilde{z}_E &= y - \tilde{y} - b_E f_a
\end{align*}
\]
where matrix \( \Delta A(x_E) \) has the Linear Parameter Varying (LPV) form [20]:
\[
\Delta A(x_E) = \begin{bmatrix}
-\theta_{r,0} (x_{E_1} - x_{E_2}) & 0 \\
0 & \theta_{b,0} (x_{E_1} - x_{E_2})
\end{bmatrix}.
\]
The matrix gain \( G \) is designed on the basis of \( H_\infty \) criteria, in order to minimize the effects of disturbances and parameters uncertainties, and, at the same time, to emphasize the effect of the actuator faults on the residuals.

Let define the vector of the disturbances affecting the estimation error dynamics (14) as \( w = [\Delta \theta^T, w_p^T, w_m^T, f_a]^T \). For design purposes, let consider \( x_E \) as a vector of time-varying parameters \( \pi = x_E \).

Then, the following problem can be stated.

Problem 1. Given a positive number \( \gamma \), find a matrix gain \( G \) for the observer (10) guaranteeing:
- Uniform exponential stability of the error dynamics for all the time-varying realizations of the parameter 
  \( \pi \in \Pi = \left[ T_{\min}, T_{\max} \right] \times \left[ T_{\min}, T_{\max} \right] \).
- An \( \mathcal{H}_\infty \) norm bound \( \gamma \) on the \( w - \tilde{z} \) input-output channel, i.e., the following inequality has to be satisfied [21]
  \[
  \sup_{\pi \in \Pi, w \in \mathcal{L}_2} \frac{||\tilde{z}||_2}{||w||_2} < \gamma,
  \]
  where \( \mathcal{L}_2 \) denotes the space of square integrable vector-valued functions, and, for a given vector-valued signal \( v(\cdot) \), \( ||v||_2 \) denotes the usual \( \mathcal{L}_2 \) norm of \( v(\cdot) \).
- Poles of the error dynamics (14) belonging to a specified sub-region of the complex plane \( \mathcal{D}(\alpha_{\min}, \zeta_{\min}, \omega_{n,\max}) \), determined by a maximum natural frequency \( \omega_{n,\max} \), a minimum damping coefficient \( \zeta_{\min} \) and a minimum real part \( \alpha_{\min} \).

Due to the duality of the control and observation problem, in order to obtain the observer matrix gain \( G \), we can reformulate the FDI design problem in the \( \mathcal{H}_\infty \) framework. Namely, the problem is that of finding an optimal closed loop control law \( \nu \) for the following LPV system [22]:

\[
\dot{x}_E = A_0 x_E + [\Delta A(\pi) B_w 0 b_E] w - I \nu = A \tilde{x}_E + B_1(\pi) w - I \nu
\]

\[
\tilde{z}_E = y - \tilde{y}_E - b_E f_a = \tilde{x}_E + [O O D_w - b_E] w = C_1 \tilde{x}_E + D_{11} w
\]

\[
\tilde{y}_E = y - \tilde{y}_E = \tilde{x}_E + [O O D_w O] w = C_2 \tilde{x}_E + D_{21} w
\]

where \( \tilde{y}_E \) is the vector of the so-called measured outputs, \( \tilde{z}_E \) is the vector of the so-called controlled outputs, and \( \nu = G \tilde{y}_E \) is the input to be determined.

Defining the residual vector

\[
r \triangleq \tilde{y}_E = \tilde{z}_E + b_E f_a
\]

it follows that

\[
||r - b_E f_a||_2/||w||_2 < \gamma
\]

as \( ||\tilde{z}_E||_2/||w||_2 < \gamma \). In other words, if \( ||\tilde{z}_E||_2 \) is small and \( w \) is norm-bounded in the \( \mathcal{L}_2 \) sense, \( ||r - b_E f_a||_2 \) tends to be small in the \( \mathcal{L}_2 \) norm sense. Hence, the residual \( r \) is forced to be sensitive to \( f_a \) but not to \( \Delta \theta, w_p, w_m \). As standard in \( \mathcal{H}_\infty \) practice \( ||\tilde{z}_E||_2/||w||_2 < \gamma \) can be achieved in correspondence of a prespecified range of frequencies if weighting filters are used.

For the design of the observer gain matrix \( G \) the procedure in [17] has been adopted.

IV. NUMERICAL RESULTS

A case study is developed to test the effectiveness of the proposed scheme on a simulation model built in the Matlab/Simulink environment. In order to simulate a realistic industrial context the simulation model has been built according to the following assumptions.

- A wrong nominal estimate of the parameters vector has been considered, \( \theta_0 = 0.65 \theta \) (i.e. a 35% error).
- Gaussian white noise, with zero mean and variance equal to \( 5 \cdot 10^{-3} \), is added to the temperature measurements.
- A first-order linear dynamics (with a time constant equal to \( \tau = 0.03 \) [min]) between the commanded control input (computed by the controller) and the real temperature of the water entering the jacket is introduced, but not modeled both in the design of the controller and in the design of the FD system.

The relevant parameters of the reactor and jacket models are summarized in Table I.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( k_{01}, k_{02}, k_{03} )</td>
<td>( 5.35 \cdot 10^4, 4.00 \cdot 10^4, 10^5 ) [mm (^{-1} )]</td>
</tr>
<tr>
<td>( \varepsilon_{\text{min}}, \varepsilon_{\text{max}} )</td>
<td>( 7 \cdot 10^{-3}, 5 \cdot 10^{-3} ) [kJ/mol]</td>
</tr>
<tr>
<td>( \Delta H_1, \Delta H_2, \Delta H_3 )</td>
<td>(-35, -120, -150 ) [kJ/mol]</td>
</tr>
<tr>
<td>( \alpha_{\text{min}} )</td>
<td>2052 [kJ/min K]</td>
</tr>
<tr>
<td>( F )</td>
<td>4 [m(^2)/min]</td>
</tr>
<tr>
<td>( V_r, V_j )</td>
<td>6.15 [m(^3)]</td>
</tr>
<tr>
<td>( p_r, C_{pr} )</td>
<td>1.9 \cdot 10^{-3} [kJ/m(^3) K]</td>
</tr>
<tr>
<td>( p_f, C_{pf} )</td>
<td>4.19 \cdot 10^{-3} [kJ/m(^3) K]</td>
</tr>
<tr>
<td>( C_{q}(0), C_{q}(0) )</td>
<td>2400, 100 [mol/min]</td>
</tr>
<tr>
<td>( T_r(0), T_j(0) )</td>
<td>293, 310 [K]</td>
</tr>
</tbody>
</table>

- \( u^* (t) = u(t) + f_a(t) \), where \( u(t) \) is the commanded input.
- The time profile adopted for the fault function \( f_a(t) \) is
  \[
f_a(t) = u_0 \left(1 - e^{-\mu(t-t_0)} \right), \quad \text{for} \ t \geq t_0
  \]
  where \( u_0 \) is the maximum amplitude, \( t_0 \) is the fault occurrence time, and \( \mu \) is the fault evolution rate. Parameter \( \mu \) is used to simulate a desired time evolution: small value characterize slowly developing faults (incipient faults);
large values are used to model step-like behaviors of the fault (abrupt faults).

Both the observers have been tested in-design operating condition, i.e., known kinetic structure and reactor and jacket temperatures in the range \( T_r, T_j \in [293, 330] \text{K} \).

Fig. 1 shows satisfactory performance for the behavior of the residuals signals of both observers in the presence of an abrupt and of an incipient fault. Residuals have been normalized with respect to suitable thresholds \( \nu_A = 0.09 \) and \( \nu_H = 0.15 \), in such a way that a fault can be declared when \( (\star = A, H) \):

\[
\frac{\|r\|}{\nu_\star} \geq 1.
\]

A. Case study 1

In order to test the robustness of the adaptive approach the setup is modified so as to introduce unmodeled dynamics. Namely an unmodeled side reaction, characterized by first-order kinetics, is added to the simulation model; in detail the reaction scheme becomes:

\[
A \rightarrow B \rightarrow C
\]

and consequently the mass balance (1) is modified as follows

\[
\dot{C}_A = - (k_1(T_r) + k_3(T_r)) \cdot C_A, \\
\dot{C}_B = k_1(T_r) \cdot C_A - k_2(T_r) \cdot C_B. \tag{18}
\]

The parameter of the side reaction can be found on Table I.

Fig. 2 shows the comparison of the residuals of the adaptive observer in-design and off-design conditions in a faulty free situation. It is worth noticing that in the presence of unmodeled reaction while the residual of the \( \mathcal{H}_\infty \) observer is robust, the threshold of the adaptive observer, \( \nu_A \), must be increased \( (\nu_A = 0.15) \), so as to avoid false alarms.

Due to new threshold, fault detection time of the adaptive scheme grows up as shown in Fig. 3. While for the abrupt case the increase in detection time may be neglected, for the incipient fault the detection delay becomes considerable (about 10 minutes).

B. Case study 2

The robustness of the \( \mathcal{H}_\infty \) approach has been tested modifying the operating temperature range. Namely, \( \mathcal{H}_\infty \) observer gain is designed so as to assure certain desired performance in a prespecified variable range (see Problem 1). It is possible that the desired reactor temperature profile overcomes the upper and/or lower bounds during the batch time. This may lead to worse performance of the FD scheme. In particular, the upper bound of the temperature profile has been increased of about 30 degrees.

Fig. 4 shows the comparison of the residuals of the \( \mathcal{H}_\infty \) observer in-design and off-design conditions in a faulty free situation. As expected, the threshold of the \( \mathcal{H}_\infty \) residual must to be increased so as to avoid false alarms \( (\nu_H = 0.21) \).

As for case study 1, the new threshold implies the growing of detection time that becomes more evident in the presence of an incipient fault as depicted in Fig. 5.

V. Conclusions

In this paper two different nonlinear model-based approaches has been developed for actuator Fault Diagnosis of a chemical batch reactor. An adaptive observer and a \( \mathcal{H}_\infty \) approach has been used to build a residual generator able to perform detection of incipient and abrupt faults. The former is designed so as to estimate the whole state.
and the uncertain parameter thanks to the knowledge of the kinetics scheme of the reaction. The latter was built so as to estimate the measurable state while parameter uncertainties are taken into account with the use of an online universal interpolator; moreover, the $\mathcal{H}_\infty$ design guarantees robustness against the interpolation error and parameter uncertainties emphasizing fault signature on the residuals. A comparison of the two approaches has been done via simulation model in order to test their effectiveness in-design and off-design conditions.

From numerical results, it can be recognize that in-design conditions both the observers achieve good and similar performance. In off-design conditions, the adaptive scheme suffers, as expected, from unknown dynamics, while the $\mathcal{H}_\infty$ observer keeps its performance level. Otherwise, for desired temperature out of designed range, the $\mathcal{H}_\infty$ scheme performance decrease in terms of detection time. Remarkably, it is worth noticing that both approaches show a certain robustness level providing good estimate and detection capability (with low delays in case of incipient faults) also in off-design conditions.

REFERENCES