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Fault detection and isolation based on the model-based approach : Application on chemical processes

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Abstract

In this paper, we present a method for the fault detection and isolation based on the residual generation. The main idea is to reconstruct the outputs of the system from the measurement using the extended Kalman filter. The estimations are compared to the values of the reference model and so, deviations are interpreted as possible faults. The reference model is simulated by the dynamic hybrid simulator, *PrODHyS*. The use of this method is illustrated through an application in the field of chemical process.

Keywords: Fault Detection and Isolation, Extended Kalman Filter, Dynamic Hybrid Simulation, Object Differential Petri nets, Distance.

1. Introduction

In a very competitive economic context, the reliability of the production systems can be a decisive advantage. This is why, the fault detection and diagnosis are the purpose of a particular attention in the scientific and industrial community. The major idea is that the defect must not be undergone but must be controlled. Nowadays, these functions remain a large research field. The literature quotes as many fault detection and diagnosis methods as many domains of application (Venkatasubramanian, et al., 2003). A notable number of works has been devoted to fault detection and isolation, and the techniques are generally classified as:

- Methods without models such as quantitative process history based methods (neural networks (Venkatasubramanian, et al., 2003), statistical classifiers (Anderson, 1984)), or qualitative process history based methods (expert systems (Venkatasubramanian, et al., 2003)),
- And model-based methods which are composed of quantitative model-based methods (such as analytical redundancy (Chow and Willsky, 1984), parity space (Gertler and Singer, 1990), state estimation (Willsky, 1976), or fault detection filter (Franck, 1990)) and qualitative model-based methods (such as causal methods: digraphs (Shih and Lee, 1995), or fault tree (Venkatasubramanian, et al., 2003)).

In this paper, the proposed approach to fault detection and isolation is a model-based approach. The first part of this communication focuses on the main fundamental concepts of the simulation library *PrODHyS*, which allows the simulation of the system reference model of a typical process example. Then, the proposed detection approach is presented. This exploits the extended Kalman Filter, in order to generate a fault indicator. In the last part, this approach is exploited through the simulation of the monitoring of a didactic example.

2. *PrODHyS* environment

The research works performed for several years within the *PSE* research department *(LGC)* on process modelling and simulation have led to the development of *PrODHyS.* This environment provides a library of classes dedicated to the dynamic hybrid simulation of processes. Based on *object concepts, PrODHyS* offers extensible and reusable software components allowing a rigorous and systematic modelling of processes. The primal contribution of these works consisted in determining and designing the foundation buildings classes.
The last important evolution of *PrODHyS* is the integration of a dynamic hybrid simulation kernel (Perret *et al.*, 2004 ; Olivier *et al*., 2006, 2007). Indeed, the nature of the studied phenomena involves a rigorous description of the continuous and discrete dynamic. The use of *Differential and Algebraic Equations* (*DAE*) systems seems obvious for the description of continuous aspects. Moreover the high sequential aspect of the considered systems justifies the use of Petri nets model. This is why the *Object Differential Petri Nets (ODPN)* formalism is used to describe the simulation model associated with each component. It combines in the same structure a set of *DAE* systems and high level Petri nets (defining the legal sequences of commutation between states) and has the ability to detect *state* and *time events*. More details about the formalism *ODPN* can be found in previous papers (Perret *et al.*, 2004).

3. The supervision module

Nowadays, for reasons of safety and performance, monitoring and supervision have an important role in process control. The complexity and the size of industrial systems induce an increasing number of process variables and make difficult the work of operators. In this context, a computer aided decision-making tool seems to be wise. Nevertheless the implementation of fault detection and diagnosis for stochastic system remains a challenging task. Various methods have been proposed in different industrial contexts (Venkatasubramanian *et al.*, 2003).

3.1. Architecture

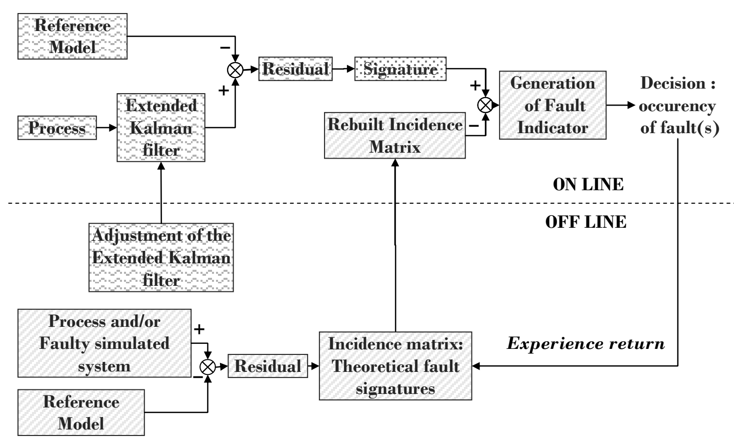

Figure 1. Supervision Architecture

For this purpose, the simulation model of *PrODHyS* is used as a reference model to implement the functions of detection and diagnosis. The supervision module must be able to detect the faults of the physical systems (leak, energy loss, etc.) and the faults of the control/command devices (actuators, sensors, etc.). As defined in (De Kleer *et al.*, 1984), our approach is based on the hypothesis that the reference model is presumed to be correct. The global principle of this system is shown in Figure 1, where the sequence of the different operations is underlined. Moreover, a distinction between the on-line and off-line operations is made. Our approach is composed of three parts: the generation of the residuals, the generation of the signatures and the generation of the fault indicators.

3.2. The generation of the residuals

The first part concerns the generation of the residuals (waved pattern in the Figure 1). In order to obtain an observer of the physical system, a real-time simulation is done in parallel. So, a complete state of the system will be available at any time. Thus, it is based on the comparison between the predicted behavior obtained thanks to the simulation of the reference model (values of state variables) and the real observed behavior (measurements from the process correlated thanks to the Extended Kalman Filter). The main idea is to reconstruct the outputs of the system from the measurement and to use the residuals for fault detection (Mehra and Peschon, 1971, Welch and Bishop, 1995, Simani and Fantuzzi, 2006). A description of the extended Kalman filter can be found in (Olivier-Maget *et al.*, 2007). Besides the residual is defined according to the following equation:

$$r_i^r(\mathrm{t}) = \frac{\hat{X}_i(t) - X_i(t)}{X_i(t)} \quad avec \quad i \in \{1, n\} \qquad \text{(Eqn. 1.)}$$

where X_i is the state variable, $\hat{X}_i$ is the estimated state variable with the extended Kalman Filter and n is the number of state variables. Note that the generated residual $r_i^r(\mathrm{t})$ is relative. As a matter of fact, this allows the comparison of a residual of a variable with a residual of an other one, since the residual become independent of the physical size of the variable.

3.3. The generation of the signatures

The second part is the generation of the signatures (doted pattern in the Figure 1). This is the detection stage. It determinates the presence or not of a default. This is made by a simple threshold, $\varepsilon_i(\mathrm{t})$. The generated structure $S_i^{rN}(\mathrm{t})$ is denoted by the following equation:

$$S_i^{rN}(\mathrm{t}) = \frac{Max\left[\left(\left|r_i^r(t)\right| - \varepsilon'_i(t)\right); 0\right]}{\sum_{k=1}^{n} Max\left[\left(\left|r_k^r(t)\right| - \varepsilon'_k(t)\right); 0\right]} \quad avec \quad i \in \{1, n\} \qquad \text{(Eqn. 2.)}$$

with $\varepsilon'_i(\mathrm{t}) = \frac{\varepsilon_i(\mathrm{t})}{X_i(t)}$, where ε_i is the detection threshold. The value of ε_i is chosen according to the model error covariance matrix of the Extended Kalman Filter.

3.4. The generation of the fault indicators

The last part deals with the diagnosis of the fault (hatched pattern in the Figure 1). The signature obtained in the previous part is compared with the theoretical fault signatures by means of distance. A theoretical signature $T_{\bullet,j}$ of a particular default j is obtained by experience or in our case, by simulations of the process with different occurency dates of this fault. Then, a fault indicator is generated. For this, we define two distances: the relative Manhattan distance and the improved Manhattan distance. The first distance is denoted by the following expression:

$$D_j^{Mr}(\mathrm{t}) = \frac{\sum_{i=1}^{n} \left| S_i^{rN}(t) - T_{ij} \right|}{n} \qquad \text{(Eqn. 3.)}$$

The second distance, which allows the diagnosis of many simultaneous faults, is denoted by the following expression:

$$D_j^{Ma}(\mathrm{t}) = \frac{\sum_{i=1}^{n} \left| S_i^{rN}(t) \times m' - T_{ij} \times n' \right| \cdot T_{ij}}{n'} \qquad \text{(Eqn. 4.)}$$

where n' is the number of non-zero elements of the theoretical default signature $\mathrm{T}_{\bullet,j}$ and m' is the number of non-zero elements of the default signature $\mathrm{S}^{rN}(\mathrm{t})$.

4. Application: the adding-evaporation unit operation

4.1. Description

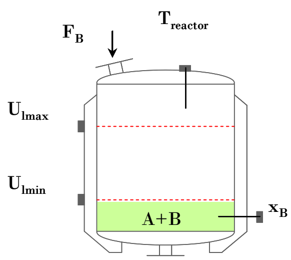

Figure 2. The studied process

	Reactor	Material Feed
T (K)	298,15	298,15
P (atm)	1	1
$x_{A=eau}$	0,6	0,01
$x_{B=méthanol}$	0,4	0,99
U_l (mol)	300	-
Flow rate (mol/min)	-	5

Table 1. The operating conditions

The process of adding-evaporation is generally used to change solvents. Its recipe describes a succession of evaporations and adding of the new solvent. This process is studied here (Figure 2). The operation conditions are listed in the Table 1. The values of the minimum and maximum holdups are respectively 200 and 800 moles. Before each adding of solvent, the reactor is cooled up to the temperature of 300,15K. The pressure is supposed to be constant during this operation. The goal of this process is to have a molar composition of methanol in the reactor at 0,95.

4.2. Results

The behavior of this process is governed by thermal phenomena. A default of the reactor thermal system can damage the success of this operation. That is why, it is important to detect it as soon as possible.

4.2.1. Detection results

We remind that the thresholds for the detection correspond to the model uncertainties obtained by the adjustment of the Extended Kalman filter. A default of the reactor heating energy feed is introduced at t = 20 min. This energy feed provides a heat quantity lower than the nominal one. Figure 3 shows the detection stage. It illustrates the evolution of the residuals linked to the liquid composition of water and methanol. From t = 80 min, the values of the both residuals underline the abnormal behavior of the process. The diagnosis is launched at t = 95 min.

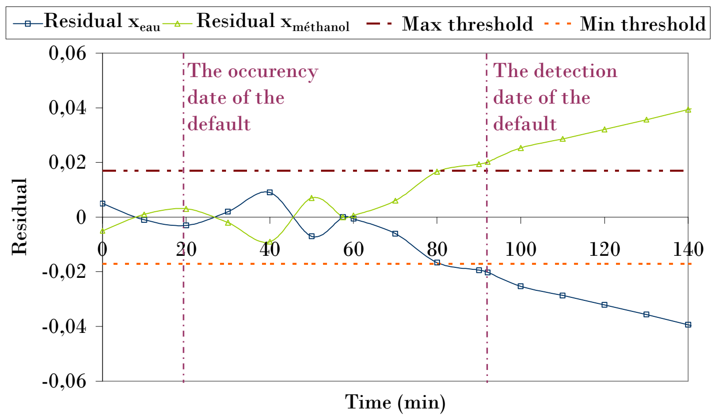

Figure 3. The evolutions of the composition residuals during the evaporation stage

s_1	0,0044098
s_2	0,49367559
s_3	0,50191462
s_4	0
s_5	0
s_6	0
s_7	0

Table 2. The instantaneous fault signature

4.2.2. Diagnosis results

The residual is then estimated and we obtain the corresponding instantaneous default signature (Table 2).

Notice that the exploited signature in this approach is non binary, in order to quantify the deviation due to the default. The construction of the theoretical fault signatures is based on numerous simulations, in which one of the defaults exposed in the Table 3 is generated. We compare the instantaneous fault signature (Table 2) with the theoretical fault signatures, by calculating the relative and improved Manhattan distances (Eqn. 3. and 4.). Then, the fault indicators are generated (Table 3). They correspond to the complement to 1 of these distances.

		Manhattan relative indicator	Manhattan improved indicator
Default 1	The up holdup sensor detects a value higher than the nominal value.	0,71428571	0,605
Default 2	The up holdup sensor detects a value lower than the nominal value.	0,71554566	0,7254961
Default 3	The temperature sensor detects a value higher than the nominal value.	0,71428571	0,64
Default 4	The temperature sensor detects a value lower than the nominal value.	0,71554566	0,7104961
Default 5	The material feed provides material with a degraded flow rate.	0,71714286	0,645
Default 6	The heating energy feed of the reactor has a temperature lower than the nominal one.	0,71428571	0,645
Default 7	The heating energy feed provides a heat quantity lower than the nominal value.	0,99819303	0,75330735
Default 8	The energy feed used for the cooling of the reactor has a temperature higher than the nominal one.	0,71554566	0,7104961
Default 9	The energy feed used to the cooling of the reactor provides a heat quantity lower than the nominal value.	0,71428571	0,585

Table 3. The default indicators of the example

The relative Manhattan indicator detects the presence of the fault 7 with a probability of 99,8%. Nevertheless, any default is discriminated, since their indicators are higher than 0,68. 0,69 is the fixed criterion, which corresponds to the probability at the standard deviation according to the normal distribution. In the opposite, with the improved Manhattan indicator, the defaults 1, 3, 5,6 and 9 are eliminated, since their indicators are lower than 0,68. The four possibilities are these defaults 2, 4, 7 and 8. This example underlines the importance to the use of the both indicators to be able to conclude. So, by combining the results of the both indicators, we can rule on the presence of the default 7, since their indicators are the maximums. For this reason, this default is the most probable. So, the default is located on the energy feed of the reactor. Furthermore, it has been identified: the heating energy feed of the reactor provides a heat quantity lower than the nominal value.

5. Conclusion

In this research work, the feasibility of using the simulation as a tool for fault detection and diagnosis is demonstrated. The method developed in this PhD rests on the hybrid dynamic simulator PrODHyS. This simulator is based on an object oriented approach. The fault detection and diagnosis approach, developed here, is a general method for the detection and isolation of the occurency of a fault. Besides, this approach allows the detection of numerous types of fault and has the ability to underline the simultaneous occurency of many faults. The works in progress aim at integrating this simulation model within a model-based supervision system. The goal is to define a recovery solution following the diagnosis of a default. For this, we exploit the results of signatures in order to generate qualitative information. For example, with these results, we have the ability to distinguish a simple degradation and a failure. Next, we combine our diagnosis approach with an other method, such as classification or case-based reasoning.

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