

Fault diagnosis and process monitoring through model-based case based reasoning

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Abstract

In this paper, we present a method for the fault detection and isolation based on the residual generation coupled with a case based reasoning approach. The main idea is to reconstruct the outputs of the system from the measurement using the extended Kalman filter. The estimations completed with qualitative information are included in a Case Based Reasoning system in order to discriminate the possible faults and to have a reliable diagnosis. 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, Distance, Case Based Reasoning

1. Introduction

Nowadays, of safety and performance reasons, 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 decision support 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 [1]. They are generally classified as:

- Methods without models such as quantitative process history based methods (for example, neural networks), or qualitative process history based methods (expert systems...),
- And model-based methods which are composed of quantitative model-based methods (such as analytical redundancy) and qualitative model-based methods (such as causal methods).

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 proposed diagnosis approach. This approach is illustrated through the simulation of the monitoring of a didactic example. This example puts in highlight the limit of this approach with a false diagnosis. Then we propose an evolution which encompasses quantitative and qualitative information to make the diagnosis more reliable.

2. Supervision module

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.

2.1. Residual generation

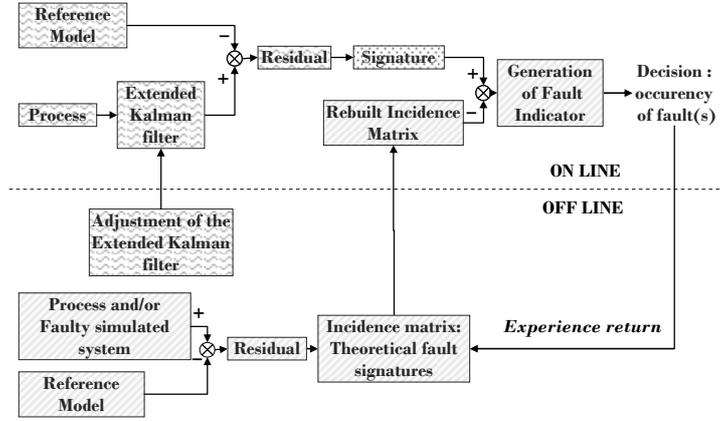


Figure 1. Supervision Architecture

The first part concerns the generation of the residuals (waved pattern in the Figure 1). 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 [2-4]. A description of the extended Kalman filter can be found in [5]. Besides the residual is defined according to the following equation:

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

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 $r_i^r(t)$ is relative. As a matter of fact, this allows the comparison of residuals of different variables, since the residual become independent of the physical size of the variable.

2.2. Signature generation

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

The second part is the generation of the signatures (dotted pattern in the Figure 1). This is the detection stage. It determinates the presence or not of a default. This is made by a detection threshold $\varepsilon_i(t)$. The value of ε_i is chosen according to the model error covariance matrix of the Extended Kalman Filter. The generated structure $S_i^{r,N}(t)$ is denoted by Eqn. 2.

2.3. Fault indicator generation

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 $T_{\cdot,j}$ of a particular default j is obtained by experience or in our case, by simulations of the process with different occurrence dates of this fault. Then, a fault indicator is generated. For this, two distances are defined: the relative Manhattan distance and the improved Manhattan distance. The first distance is denoted by the following expression:

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

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

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

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

3. Application: the adding-evaporation unit operation

3.1. Description

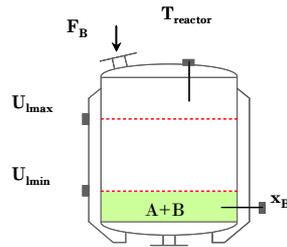


Figure 2. The studied process

Table 1. The operating conditions

	Reactor	Material Feed
T (K)	298.15	263.15
P (atm)	1	1
$x_{A=eau}$	0.6	0.01
$x_{B=methanol}$	0.4	0.99
U_1 (mol)	300	-
Flow rate (mol/min)	-	1.2

The process of adding-evaporation is generally used to change solvents. Its recipe describes a succession of evaporations and adding of the new solvent (methanol). This process is studied here (Figure 2). The operation conditions are listed in the Table 1. The values of the minimum and maximum holdups U_1 are respectively 200 and 800 moles. The steps of this process are the following: a feeding step during 500 seconds, a step of heating and feeding, until the holdup has reached the maximum threshold, and a heating step until the minimum holdup threshold. 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 0.98.

3.2. 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.

3.2.1. Incidence matrix

To perform a monitoring of a process, some off-line adjustments must be made. In one hand, we need to determine the covariance matrices of the model and

measurement disturbances. While the measurement noises are supposed to be well-known by experiments or by the sensor manufacturer, the model disturbances is estimated by an “ensemble method”. Numerous simulations have been performed during which a model parameter has been disturbed. This allowed the estimation of statistic distribution of the model mistakes. Then, if the behavior of the system goes beyond this distribution, its behavior is abnormal. So, the detection thresholds are determined according to the model disturbances. On the other hand, the second adjustment is the learning of the incidence matrix. It is based on the same “ensemble” theory. For this, we perform a set of simulations, during which a fault is introduced at different occurency dates, for each potential state of the hybrid dynamic system. For this study, we consider seven faults:

- Fault 1: The energy system provides no more power;
- **Fault 2: The energy system provides a power lower than the nominal one;**
- Fault 3: The energy system provides a power higher than the nominal one;
- Fault 4: The feeding provides no more material;
- Fault 5: The feeding provides material with a flow rate lower than the nominal one;
- Fault 6: The feeding provides material with a flow rate higher than the nominal one;
- Fault 7: The holdup detector detects a damaged value.

The obtained incidence matrix is the following:

Table 2. Incidence matrix

		Faults						
		1	2	3	4	5	6	7
Signature	Energy Power	0,92828	0,59286	0,50299	0	0	0	0
	Flow Rate	0	0	0	0,84299	0,74166	0,97214	0
	Temperature	0,00667	0	0,00006	0	0	0	0
	Holdup	0,06505	0,40714	0,49695	0,15701	0,25834	0,02786	1
	x_{Water}	0	0	0	0	0	0	0
	$x_{Methanol}$	0	0	0	0	0	0	0

We can notice that all the faults have an affect on the holdup of the mixture. The faults are differentiated thanks to the temperature, energy power or feeding flow rate information.

3.2.2. Detection results

A default of the reactor heating energy feed is introduced at $t = 20000$ seconds. This energy feed provides a heat quantity lower than the nominal one (fault 2). We suggest that we have only a holdup sensor. So, we don't have any information about the temperature, the flow rate and the power. In this case, the extended Kalman filter can not correct the estimated state thanks to the measurements. It only considers the holdup deviation. Figure 3 shows the detection stage. It illustrates the evolution of the residuals linked to the holdup of the mixture. From $t = 80$ seconds, the values of both residuals underline the abnormal behavior of the process. The diagnosis is launched at $t = 21500$ seconds.

Fault detection and isolation based on the model-based approach

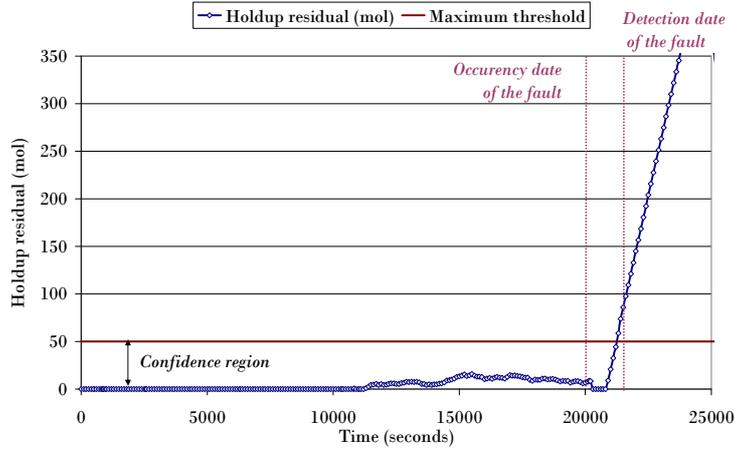


Figure 3. The evolution of the holdup residual

3.2.3. Diagnosis results

Table 3. The instantaneous fault signatures

Signature	Energy Power	0
	Flow Rate	0
	Temperature	0
	Holdup	1
	x_{Water}	0
	x_{Methanol}	0

The residual is then estimated and we obtain the corresponding instantaneous default signature (Table 3). We compare the instantaneous fault signature (Table 3) with the theoretical fault signatures (Table 2), by calculating the relative and improved Manhattan distances (Eqn. 3. and 4.). Then, the fault indicators are generated (Table 4). They correspond to the complement to 1 of these distances.

The Manhattan relative and improved indicators detect the presence of the fault 7 with a probability of 100%. The fault 7 is a false diagnosed. So, with only the holdup measurements, a fault diagnosis is established. We must complete the system information with qualitative information in order to be more precise and relevant during the diagnosis step.

Table 4. The default indicators of the example

	Faults						
	1	2	3	4	5	6	7
Manhattan relative indicator	0,688	0,802	0,832	0,719	0,753	0,676	1
Manhattan improved indicator	0,121	0,611	0,666	0,235	0,387	0,042	1

3.2.4. Improved Approach

To overcome this drawback, the previous approach is coupled with the Case Based Reasoning (CBR) method. This method aims to capitalize and reuse past experiences and knowledge for solving problem. In our case the coupling of both methods allows to have in a same problem description qualitative and quantitative information. In the CBR, illustrated on figure 4 (and detailed in [6]), the problem is described (Represent Step) with the main and most relevant characteristics, no matter the type of information. Then, the problem is compared with other ones stored in a case based and the most similar one and its associated solution are extracted to propose a solution to the initial problem (Reuse). In the previous example, the problem description is composed of the attributes given in Table 3. The model based approach allows the filling of the

quantitative attributes like holdup, and the qualitative attributes like temperature, complete and detail the problem description. The qualitative information comes from detector thresholds for example. With this additional information, the fault 2 is identified, thus the diagnosis refined and more reliable.

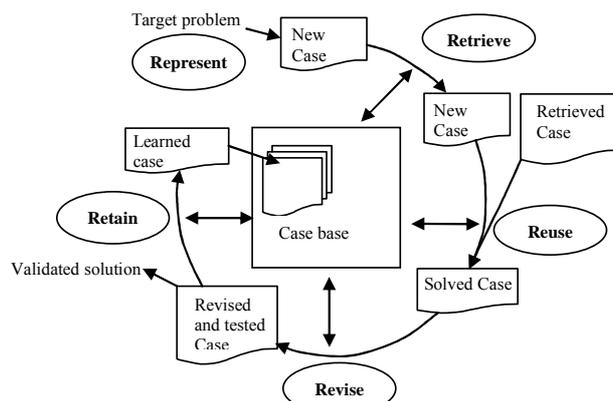


Figure 4. CBR Cycle

4. Conclusion

In this research work, the feasibility of coupling qualitative methods and model based one is demonstrated for fault detection and diagnosis for chemical engineering process monitoring. These two complementary approaches improve the diagnosis phase thanks to simultaneous treatment of both qualitative and quantitative information. Unfortunately, the monitoring task is not limited to the diagnosis, after this step the operator has to take decisions in order to repair the fault under constraints: productivity, economic, security, environmental... Consequently, a relevant decision support tool must help the operator in this difficult task. Currently, in our tool, the solution to the problem encompasses only the diagnosis but it can be extended to the proposition of ways to stop (or stand by) the process until the repair, and after ways to restart it. In these conditions, these proposed ways could be easily tested and then validated by simulation (Revise step of Figure 4) because the model of the process already exists (needed for the generation of the residuals). Only, the new operating conditions must be given.

5. References

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