8th IFAC Symposium on Fault Detection,
Supervision and Safety of Technical Processes (SAFEPROCESS)
August 29-31, 2012. Mexico City, Mexico

Single and multiple faults in system actuators and sensors for ethanol production

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Abstract: This paper focuses on the study of a fault detection and isolation system strategy applied to an ethanol production bioprocess that involves a two-stage bioreactor with a cell recycling loop to reach high biomass concentrations. The various actuators and sensors of this type of bioprocess, impose to develop a fault detection and isolation strategy. In this work, we study the case where multiple faults (with a small delay between them) or simultaneous faults can occur. We assume that only one type of faults can occur at a time and we will focus on the actuators and sensors faults. The sensor fault problem will be reformulated to an actuator fault one by introducing a state variable transformation, so that an augmented system is constructed. Thus we will design a nonlinear model based on an adaptive observer method, for detection, isolation and identification of actuator and sensor single and multiple faults. These approaches use the system model and the outputs of the adaptive observers to generate residuals. Residuals are defined in such way to isolate the faulty instrument after detecting the fault. The validity of the method will be tested in simulation in a nonlinear model of a two-stage ethanol bioprocess with a cell recycling loop.
Keywords: Bioprocess, Fault Detection, Fault Isolation, Fault Identification, Observers, Ethanol Production.

1 INTRODUCTION

The new century impose environmental challenges such as water supply, global warming and new energy sources for substitution of fossil fuels. These two last are closely dependent. In our days ethanol is the main biofuel used in Europe whose production is now based on old technology with performance that requires innovative culture strategies to optimize productivity. In order to overcome this challenge, an innovative bioprocess has been studied by Aldiguier (2006) and Ben Chaabane *et al.* (2006). A two-stage continuous bioreactor with a cell recycling loop allowed a productivity of 41 $kg.m^{-3}.h^{-1}$ to be reached with an ethanol titer of 8.3°GL in the second bioreactor (Ben Chaabane *et al.* 2006).
The two previous works propose a static and a dynamic optimizations of this two-stage continuous bioreactor. In the first time, a steady-state optimization for ethanol production was carried out using a mathematical model based on the mass balance for a two-stage bioreactor. The volume ratio (V_1/V_2) and substrate feed concentrations (S_{f1} and S_{f2}) were varied during optimization in order to optimize process design (Aceves-Lara *et al.* 2010a). In addition, an approach of dynamic optimization of ethanol production by using an optimal closed loop control was studied (Aceves-Lara *et al.* 2010b). Two algorithms were proposed for applied a model predictive control (MPC); a Pattern Search algorithm (PS) and an Interactive Ant Colony Algorithm (IACA).
The final objective of this work is to validate online the method proposed in an experimental pilot. The various actuators and sensors of this kind of bioprocess impose to develop a fault detection and isolation system strategy.
Fault detection and isolation (FDI) techniques could prevent from all the undesirable consequences of the faults and so it is becoming an attractive topic. Stimulated by this growing demand for improving the reliability many methods of FDI have been developed during the last decades with the aim to reduce the isolation time of the procedure. The various research groups propose approaches of FDI based on the expertise of their own field and/or experiment on a specific class of systems. The diversity of the solutions was also enriched by the growing interest of the industry. Model based fault detection and diagnosis systems have found extensive use because of the fast response to abrupt failure and the implementation of the model based FDI in real-time algorithms.
The most common methods for model based FDI are either based on state or parameter estimation. A comprehensive review of the different FDI methods and their applicability to a given physical system has been presented in Isermann (1994). The methods based on observers are rather well developed, especially for the linear systems. Various types of observers were created according to the nature of the considered problem. More recent work treats theoretical development for fault detection and isolation methods of nonlinear systems (García and Frank, 1997; Frank *et al.*, 1999; Hammouri *et al.*, 1999; Nijmeijer and Fossen, 1999;

De Persis and Isidori, 2001; Zhang, 2000; Chen and Saif, 2005; Li and Dahhou, 2007)

In this paper, we treat the actuator and the sensor with constant value faults for a class of nonlinear system (Sastry and Bodson, 1989). The proposed FDI method (Fragkoulis *et al*, 2010 and 2011) treats not only single faults but multiple ones as well and can guarantee a quite satisfactory isolation speed. A filter has been used to transform the sensors faults problem to an actuators faults problem. Next, a method based on adaptive observers has been developed where one observer has been designed for each element (actuators and sensors). Finally, we propose a structured residual to facilitate the procedure of the fault isolation.

The paper is organized as follows. In section 2, we present the class of the nonlinear systems that we study and the different faulty models. In section 3, we reformulated the sensor fault problem to an actuator fault one and we give the FDI and identification strategy for actuators and sensors faults. In section 4, we briefly describe the bioethanol process and we present the simulation results for this model in the case of single and multiple faults. Finally, conclusion and perspectives end the paper.

2 NONLINEAR FAULTY MODEL

2.1 *Class of nonlinear model*

We consider the following class of nonlinear models:

$$\begin{cases} \dot{x} = f(x) + g(x)u \\ y = Cx \end{cases} \tag{1}$$

where $f(x)$ is a nonlinear vector function from $\Re^n$ to $\Re^n$, $g(x) \in \Re^{n \times m}$ is a matrix function whose elements are nonlinear functions, $x \in \Re^n$ is the state vector, $u \in \Re^m$ is the input vector, $C \in \Re^{p \times n}$ is a matrix and $y \in \Re^p$ is the system output. Throughout this paper, we assume that only constant value faults can occur on the actuators or the sensors (pumps run off is the most common fault in bioprocess). The fault detectability in nonlinear systems can be found in (Rios Bolivar, 2001). If the fault f_i is detectable, the residuals $r_i(t)$ can be obtained by the difference between the faulty output $y(x_0, x, u, f_i)$ and the output without a fault $y(x_0, x, u, 0)$, which is:

$$r_i(t) = y(x_0, x, u, f_i) - y(x_0, x, u, 0) \tag{2}$$

Consequently, an unspecified residual $r_i(t)$ is a function of time which is ideally zero for the no fault case and different from zero when a fault occurs. The detectability of a fault in nonlinear systems is a function as well of the system's structure as of the control input. In the case of an actuator fault, the fault f_i becomes f_{ai} and in the case of a sensor fault it becomes f_{si}.

2.2 *Actuator faulty model*

When actuator faults occur we have $u_j^f(t) = u_j(t) + f_{aj} = \theta_{aj}(t)$ for $t \geq t_f$, $j \in 1, 2, \cdots m$, and $\lim_{t \to \infty} | u_j(t) - \theta_{aj}(t) | \neq 0$, where f_{aj} is a constant and $u_j^f(t)$ is the actual output of the j^{th} actuator when it is faulty, while $u_j(t)$ is the expected healthy output. The corresponding faulty model for nonlinear systems (1) is:

$$\begin{cases} \dot{x} = f(x) + \sum_j g_j(x) u_j + F_a f_a \\ y = Cx \end{cases} \tag{3}$$

Where $g(x) = (g_1(x) \cdots g_m(x))$, F_a is the fault distribution matrix and we consider that the fault vector $f_a \in \Re^m$ is a limited signal where $\|f_a\| \leq M_a$ (M_a is a positive known constant).

2.3 *Sensor faulty model*

When sensor fault occur we have $y_j^f(t) = y_j(t) + f_{sj} = \theta_{sj}(t)$ for $t \geq t_f$, $j \in 1, 2, \cdots m$, and $\lim_{t \to \infty} | y_j(t) - \theta_{sj}(t) | \neq 0$, where f_{sj} is a constant and $y_j^f(t)$ is the actual output of the j^{th} sensor when it is faulty, while $y_j(t)$ is the expected healthy output. With this formulation the faulty model is:

$$\begin{cases} \dot{x} = f(x) + \sum_j g_j(x) u_j \\ y = Cx + F_s f_s \end{cases} \tag{4}$$

Where F_s is the fault distribution matrix and we consider that the fault vector $f_s \in \Re^p$ is also limited by a constant M_s as in the previous case.

In the proposed approach we will transform the sensors to virtual actuators (cf. section 3.2) of an extended nonlinear model of the same class as in (3). With this transformation, the actuator and sensor faults can be represented by the same faulty model, thus:

$$\dot{x} = f(x) + \sum_{j \neq l} g_j(x) u_j + g_l(x) \theta_l \tag{5}$$

Where the fault is located in the l^{th} element.

3 FDI AND IDENTIFICATION STRATEGY

3.1 *Proposed strategy*

Figure 1 presents the scheme with various elements in order to monitor actuators and sensors of the system. The vector u_{cal} represents the input vector of the actuators, f_a is the fault vector and u is the actuators output vector.

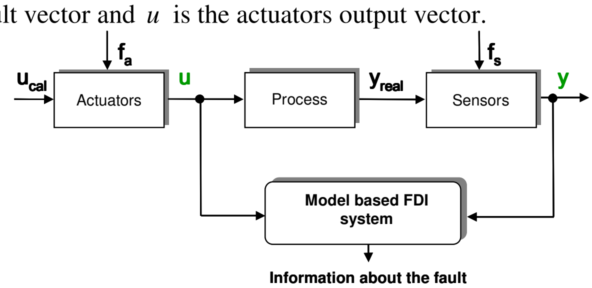

Fig.1 Actuators and sensors signals