OBSERVER-BASED SUPERVISION AND FAULT DETECTION OF A FCC UNIT MODEL PREDICTIVE CONTROL SYSTEM

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Abstract: This work is concerned with the design of a fault detection and isolation (FDI) system to monitor malfunctions in sensors and actuators of a fluid catalytic cracking (FCC) unit model predictive control (MPC) system. The control system is based on an infinite-horizon MPC algorithm. The fault detection scheme is developed based on two banks of robust observers, while the fault isolation task is done employing a structured residual approach. The models used in the control and in the FDI of the FCC unit are obtained by using subspace identification methods. The effectiveness of the proposed strategy is verified through numerical simulations carried out on a dynamical model of an industrial FCC unit under abrupt fault in its control devices.

Keywords: Fluid catalytic cracking, Fault detection and isolation, Model predictive control, Unknown input observers, Subspace model identification.

1. INTRODUCTION

Market globalization has induced the high level of automatization in chemical and petrochemical plants. As an example, nowadays there is no petroleum refiner that does not use advanced process engineering, such as advanced control systems, to improve process operations (Moro, 2003). In these cases and under normal situations, the control system acts partly as operators to keep a satisfactory production process. Nevertheless, recent catastrophic accidents, namely the explosion at the Kuwait Petrochemical's Mina Al-Ahmedhi refinery in 2000, which resulted in about $400 million in damages, and the explosion at the offshore oil platform P-36 of Petrobras, Brazil, in 2001, with estimated loss about $5 billion (Venkatasubramanian, 2003), have shown that advanced control systems may not be sufficient to deal with abnormal situations.

Although these catastrophic accidents are infrequent and represent extreme cases within the spectrum of major abnormal situations, minor accidents are very common with significant economic, safety and environment effects. According to Cochran *et al.* (1996), the inability of automated control systems and plant operators to deal with abnormal situations cost the U.S. economy at least $20 billion annually, about half of which in direct losses related to petrochemical companies alone. Similar cases, cost the British economy up to $27 billion per year (Laser, 2002). Estimates indicate that elimination of all abnormal situations in the petrochemical industry could increase profits up to 5% (Harrold, 1998).

The performance of a control system depends on other control devices, namely sensors (to read the data that it receives) and actuators (to execute the commands that it issues). Obviously, any abnormal situation (or fault) in these devices or in the plant itself, can significantly affect the performance of the control system. For instance, a biased sensor lead the process to an operating point far from its optimal one and a stuck valve lead to a loss of control effectiveness. In any case, the control system can, eventually, hide a gradual fault incident till the failure of control is unavoidable and, in other cases, sudden faults can be amplified by the closed-loop control, inducing to premature plant shutdown, with loss of productivity, loss of expensive equipment and possible damage to human health and environment. Therefore, it is important to supervise the production process, as well as to detect faults while the plant is still operating in a controllable region, to support operators to deal with abnormal situations promptly. In this sense, fault diagnosis or fault detection and isolation (FDI) can be seen as part of a large scheme for optimal process operation.

There are several methods for FDI and they can be grouped into three general categories: quantitative model-based methods, qualitative model-based methods and process history based methods (Venkatasubramanian, 2003). Quantitative model-based FDI techniques, namely parity space approach, observer-based approach and parameter estimation approach, have received considerable attention in recent years. These approaches are based on the concept of *analytical redundancy* which makes use of a mathematical model of the process to obtain measurement estimates. The inconsistencies between the estimated and actual behaviors are *residuals* or fault indicators, which reflect the abnormal situation of the supervised process. Next, the residuals are analyzed aiming at the localization of the fault. Although there is a close relationship among the quantitative model-based FDI techniques, observer-based approach have become the most popular and important method for model-based FDI (Frank and Ding, 1997), especially within the automatic control community.

On the other hand, petroleum refining is one of the major industrial enterprices worldwide. It is a very competitive and specific market, where little improvements in the operation of the processes may lead to large economical benefits. The functional heart of a petroleum refinery, and the most economically critical component, is the FCC unit. It is operated to convert heavy petroleum fractions into light and more valuable hydrocarbon products, such as gasoline and LPG. It involves a highly nonlinear, slow and multivariable process, with strong interactions among its variables, subject to a number of operational constraints, and working at high temperatures and pressures, with a slate of fires and explosions arising from malfunctions. This complex characteristic together with its economic significance makes the FCC unit a potential candidate and challenging problem to the application of advanced process engineering tools. Although numerous papers have been written concerning different modelling approaches, advanced control (predominantly model predictive control, MPC) and optimization systems for the FCC unit, only few have treated about the application of FDI to the FCC system. Among these, Yang *et al*. (2000) use an approach based on neural network, Heim *et al*. (2003) use causal and knowledge based models, Huang *et al*. (2003) use an heuristic-based extended Kalman filter, Sundarraman and Srinivasan (2003) use a trend analysis-based approach and Wang *et al* (2003) use a recursive partial least squares (PLS) algorithm. A common feature in all these works is that the FDI system is mainly directed to detect process parameter faults and the FCC unit operates under conventional regulatory control. The only work available in the literature, in which the system is controlled by MPC was presented by Pranatyasto and Qin (2001). They propose an algorithm based on principal component analysis (PCA) for self-validating sensors in a FCC unit.

The present paper focuses on the design of a FDI system for the sensors and actuators of a FCC unit under MPC control. Closed-loop systems are vulnerable to faults and these are in general difficult to handle. In addition to the well-known damages, faults in control devices may cause structural changes of the process model as well. Two separated banks of robust observers are built for fault detection (FD) in the inputs and outputs of the FCC system. Both are based on the unknown input observers (UIO) theory. Fault isolation is obtained through a structured residual approach. The models used in the control and in the FDI system of the FCC unit are obtained by subspace identification methods. In the context of this study it is used the FCC RECOPE benchmark.

2. THE FCC UNIT DYNAMIC MODEL

The FCC RECOPE benchmark is basically the same as the one presented by Moro and Odloak (1995) for the FCC unit Kellog Orthoflow model F, and it has become a standard for validation of FCC control structures in the Petrobras's refineries. A simplified schematic diagram of this process is shown in figure 1. The process is constituted of three major parts, the riser, the reactor and the regenerator. At nominal steady-state conditions, the air flowrate to the regenerator is $u_1 = 221$ ton/h, the regenerated catalyst valve opening $u_2 = 82\%$, the total feed flowrate (gasoil + deasphalted heavy oil) introduced into the riser is $u_3 = 9700\,\mathrm{m}^3$/d and the temperature of the total feed flowrate is $u_4 = 235$ °C. For the stable operation of the FCC unit, the benchmark includes necessarily a conventional regulatory control system, based on three PI controllers (not shown in figure 1), aiming at to keep the differential pressure between reactor and regenerator, the catalyst inventory in the reactor, and the suction pressure of the wet gas compressor at 0.65 kgf/cm^2, 90 ton. and 1.0 kgf/cm^2, respectively.

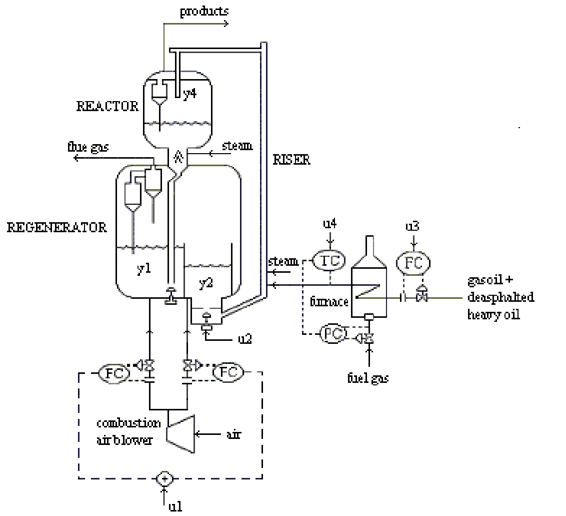

Fig. 1. Scheme of the FCC Kellog Orthoflow model F

The benchmark, represented by a 9x9 MIMO system, with 26 ODE's and 74 linear and nonlinear algebraic equations, was validated with industrial data from the FCC unit of the Petrobras's Henrique Lajes (REVAP) refinery in São José dos Campos. This simulator was written in language C and implemented in Simulink/Matlab™ platform by the RECOPE process control group, and it can be downloaded from *www.enq.ufrgs.br/recope/FCC/*. The model equations and the process parameters are here omitted but they can be found in Moro and Odloak (1995).

3. THE MPC CONTROL SYSTEM

MPC, or model-based predictive control (MBPC) or receding (moving) horizon control, is currently the most widely implemented advanced control system for process plants. It has several advantages over other control techniques because it incorporates an explicit process model into the control calculation and because of its close relationship with on-line optimization, which allows it to deal with multivariable process, coupling, inverse response, time-delays, process constraints, modelling uncertainties and measurement errors. MPC's are commonly found in the medium level of a plant-wide control scheme. A survey summarizing about 4500 successful MPC industrial applications is presented by Qin and Badgwell (2003).

Since a robust controller can desensitize fault effects and make the FDI very difficult (Chen and Patton, 1999), in this paper it is used the nominal version of the robust infinite-horizon MPC (IHMPC) controller proposed by Rodrigues and Odloak (2003).

3.1 The IHMPC algorithm

There are plenty of papers on MPC algorithms and their application to FCC units. When compared to other MPC algorithms, the IHMPC has the following advantages (Rodrigues and Odloak, 2003):

- The IHMPC is based on a class of output prediction oriented model (OPOM), where the state-space model of the process is modified to represent the output as a continuous function of time. With this model, for a finite control horizon, the infinite output horizon MPC cost function can be integrated explicity. The approach becomes more efficient as the computation of the control sequence does not include the solution of the Lyapunov equation to compute the terminal state penalty. The on-line solution of this equation may be time consuming for large systems.
- The cost function is modified by inclusion of slack variables in the output error. This is done to overcome the problem of an unbounded cost due to offset in the controlled outputs or unfeasibility of the infinite-horizon control problem. The cost function is minimized by using linear matrix inequalities (LMI) tools.
- It is not necessary to known the system steady state. Hence, the IHMPC can be applied for the servo problem as for the regulator problem.

3.2 Control structure for the FCC unit

The FCC control is by definition a multivariable one rather than a multiloop control. Nevertheless, the control performance of a FCC process highly depends on the control structure selection. This problem has been addressed by several authors, mainly focusing on possible combinations of manipulated and controlled variables for exact and partial control.

In this paper, the control structure is based on the original version of the MPC controller proposed for the FCC unit of the REVAP refinery. From this scheme we consider only a 4x4 MIMO control system, where the inputs or manipulated variables are as described in Section 2, and the outputs or controlled variables are: the temperature of the regenerator 1st stage dense phase (y_1), the temperature of the regenerator 2nd stage dense phase (y_2), the estimated cracking reaction severity (y_3) and the riser (reactor) temperature (y_4). The control objetive for the FCC unit is to stabilize the process despite undesired disturbances by keeping the outputs on their steady-state conditions, i.e. $670.14\,°C$, $700.88\,°C$, 77.5% and $542.2\,°C$, respectively. In the implementation of the IHMPC algorithm, $T = 3$ min and $m = 2$. For more information, see Sotomayor *et al*. (2004).

3.3 Controller model identification

The MPC requires a process model to represent the dynamical input-output behavior and it should be as simple as possible. In the industrial practice, a simple process model with two or three parameters are adjusted to produce the step response for the MPC controller. In this case, sixteen 2nd order SISO models are obtained by individually exciting the inputs with m-level pseudo-random signals (around $\pm 2\,\%$ their nominal values) and using the MOESP subspace identification method (Verhaegen and Dewilde, 1992) to identify initial models and to improve them by the PEM method of the System Identification Toolbox/Matlab™. These models are then converted to extract coefficients of the step response function, which are required by the IHMPC.

4. THE FDI SYSTEM

4.1 UIO and FD system based on UIO

Unknown input observers (UIO) are well known from the control theory. They constitute a class of robust observers that under certain conditions allow one to decouple the effect of unknown inputs (or disturbances) on the estimate of the true state. With slight modifications, they can be used to solve the disturbance decoupled residual problem in FD systems. Consider a dynamic system described by a discrete-time LTI model with an *additive* unknown disturbance as follows:

$$\begin{aligned} x_{k+1} &= Ax_k + Bu_k + Ed_k \\ y_k &= Cx_k \end{aligned} \qquad (1)$$

where x is the state vector, u is the input vector, y is the output vector and d is the unknown input. A, B, C and E are known matrices with appropriate dimensions. The structure of a full-order UIO is described by:

$$\begin{aligned} z_{k+1} &= Fz_k + TBu_k + Ky_k \\ \hat{x}_k &= z_k + Hy_k \end{aligned} \qquad (2)$$

where z is the state of the UIO, $\hat{x}$ is the estimated state vector, whilst F, T, K and H are matrices to be designed to achieve unknown input decoupling and other design requirements. When the observer (2) is applied to system (1), the estimation error ($\in_k = x_k - \hat{x}_k$) will approach to zero asymptotically if the following relationships hold true (Chen and Patton, 1999):

$$\left.\begin{aligned} T &= I - HC \\ TE &= 0 \\ F &= TA - K_1C \\ K_2 &= FH \\ K &= K_1 + K_2 \end{aligned}\right\} \qquad (3)$$

It can be shown that if $rank(CE) = rank(E)$ then $H = E(CE)^+$, where ($^+$) denotes the Moore-Penrose pseudo-inverse. If the pair (C, TA) is observable, an UIO exists and F can be easily stabilized by a K_1 obtained using the pole placement routine in the Control System Toolbox/Matlab™. By employing the UIO structure for FD purposes, now called UIFDO, the residual (r) is generated as shown in figure 2.

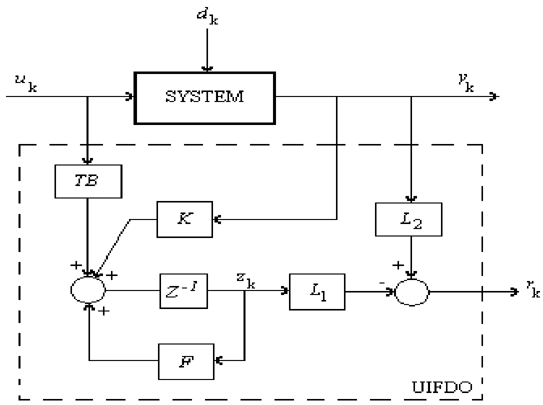

Fig. 2. Structure of the FD structure based on UIO

In figure 2, $L_1 = C$ and $L_2 = I - CH$. Note that by setting $T = I$, $H = 0$ and $E = 0$, the observer (2) is the classical Luenberger observer (LO).

4.2 FD model identification

The use of a simple process model for FDI applications may constitute a source of false alarms, which can corrupt the performance of the FD system to such an extent that it may even become totally useless. Therefore, it is necessary to obtain a highly precise process model (Frank *et al*., 2000).

In this case, a 13^{th} order MIMO linear state-space model, that reproduces very well the main dynamical characteristics of the process, is obtained by using the MOESP algorithm. The model order is chosen by applying the optimal statistical Akaike's information criterion (Akaike, 1973). The identification procedure was carried out in open-loop, by simultaneously exciting the control inputs with m-level pseudo-random signals (around $\pm 2\,\%$ their nominal values). To improve the model, the single-loop PI control signals are considered as inputs, and the temperature of the regenerator 1^{st} stage dilute phase and the temperature of the regenerator general dilute phase are also considered as outputs. For more details, see Sotomayor *et al*. (2003).

4.3 FDI schemes and results

The main task of robust fault detection is to generate residual signals. To facilitate fault isolation, here it is used a structured residual approach, i.e. each residual is designed to be sensitive to a certain group of faults and insensitive to others. Taking into account these sensitivity and insensitivity properties, the fault isolation is possible. The ideal case is to make each residual only sensitive to a particular fault and insensitive to all other faults. However, this ideal situation is normally difficult to achieve. According to Chen and Patton (1999), an alternative solution is to make each residual to be sensitive to all the faults except a particular fault. Moreover, as full insensitivity is difficult to achieve, the fault isolation task is obtained by choosing adequate thresholds.

Consider the open-loop system represented in (1) with possible sensor (output) and actuator (input) faults, which can be described as follows:

$$\begin{aligned} x_{k+1} &= Ax_k + Bu_k + Ef_{a,k} \\ y_k &= Cx_k + f_{s,k} \end{aligned} \tag{4}$$

where f_a and f_s denote actuator and sensor faults.

.1) Sensor FDI scheme

To uniquely detect and isolate a fault concerning one of the four sensors of the FCC control system, a bank of four LO, in a DOS (dedicated observer scheme) configuration (Wünnenberg, 1990), is used. It is assumed that the actuators are fault-free (i.e. $f_a = 0$). Figure 3 shows the absolute value of the residuals responses for the case of a single abrupt fault (bias) in each sensor, occurring at $t = 100$ min, with magnitude of +5%, +5%, +5% and +1% of the output value, respectively.

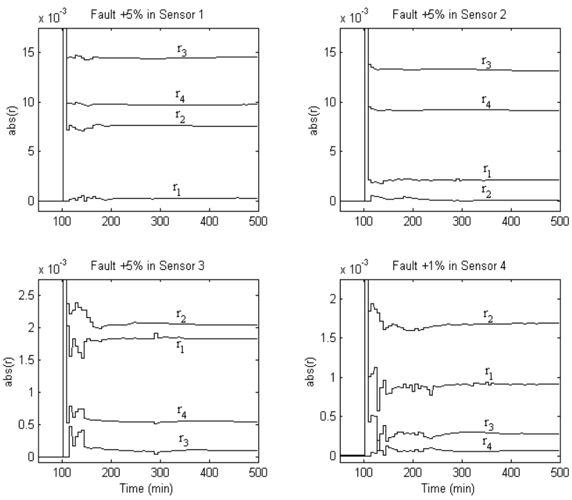

Fig. 3. Residual responses for faults in sensors.

Biased sensors lead to the saturation of controlled actuators. For example, a fault of +5% in sensor 2 is alarmed by the residuals r_1, r_3 and r_4 which are sensitive and not by the residual r_2 that is insensitive. The IHMPC tries to compensate this situation saturating input u_3. However, an acceptable control of the output variables is not achieved since bias appear in all the outputs.

.2) Actuator FDI scheme

To uniquely detect and isolate a fault concerning one of the four actuators of the FCC control system, a bank of four UIFDO, in a GOS (generalized observer scheme) configuration (Wünnenberg, 1990), is used considering that the sensors are fault-free (i.e. $f_s = 0$). Here, matrix E is one of the first four columns of the matrix B. Figure 4 shows the absolute value of the residuals responses for the case of a single abrupt fault (bias) in each actuator, occurring at $t = 100$ min, with magnitude of +5%, +10%, +5% and +5% of the input value, respectively.

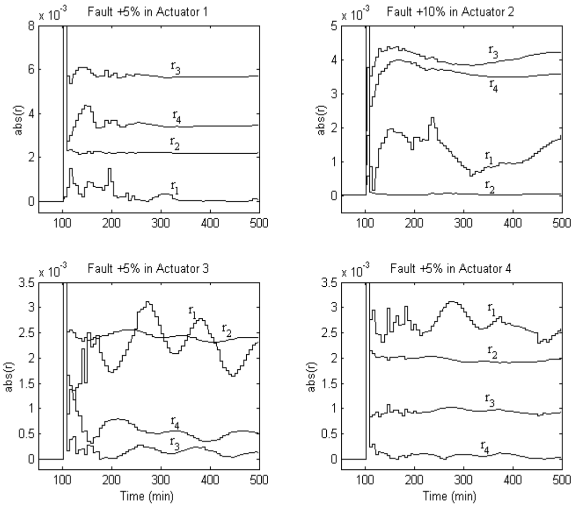

Fig. 4. Residual responses for faults in actuators.

For example, for a fault of +5% in actuator 1, the residuals r_2, r_3 and r_4 are sensitive and the residual r_1 is insensitive. In partial combustion mode, this fault scenario drives the process to the full combustion mode, severely affecting the quality of products. The IHMPC will try to revert this situation decreasing, mainly, the control signal of actuator 1. However, if the fault becomes more severe, the control fails and can cause a disastrous break down of the production.

It is necessary to state that in both presented cases, the fault is detected before the first 10 minutes after the fault occurrence. The instantaneous peaks in figures 3 and 4 are generated by the abrupt fault ocurrence and they can be considered as an incipient FD system.

To summarize the obtained results, table 1 shows the fault signatures in the structured residuals form.

Table 1. Structured residuals of the FDI system

	Sensor FDI scheme				Actuator FDI scheme			
	$f_{s,1}$	$f_{s,2}$	$f_{s,3}$	$f_{s,4}$	$f_{a,1}$	$f_{a,2}$	$f_{a,3}$	$f_{a,4}$
r_1	0	1	1	1	1	1	1	1
r_2	1	0	1	1	1	1	1	1
r_3	1	1	0	1	1	1	1	1
r_4	1	1	1	0	1	1	1	1
r_1	1	1	1	1	0	1	1	1
r_2	1	1	1	1	1	0	1	1
r_3	1	1	1	1	1	1	0	1
r_4	1	1	1	1	1	1	1	0

1=sensitive, 0=insensitive

5. CONCLUSIONS

Fault diagnosis in a FCC unit is an important task. Although, disturbances and parameter changes can be compensated by the advanced control system, the performance of the FCC control system is highly dependent of sensors and actuators. The timely detection of malfunctions in these control devices can help operators to avoid disastrous consequences. In this paper, we have presented a robust observer-based FDI system for a FCC unit under MPC control. It is shown that abrupt fault in a sensor or an actuator was accurate and rapidly detected. Later, the FDI information will be used for controller reconfiguration. The integration FDI-IHMPC provides a useful framework for an active fault tolerant MPC control. MPC seems a natural and promising basis for it.

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