A General Model Based Framework for Fault Accommodation

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A general fault accommodation system is proposed in this paper. Detailed accommodation strategies are presented for different types of faults. A combination of different diagnostic techniques involved in collective problem solving is used in the diagnosis module. A pseudo-measurement based Extended Kalman Filter (EKF) is used to perform the fault parameter estimation task for differential and algebraic equation systems. The fault accommodation problem is then formulated as a dynamic optimization problem. The system is demonstrated on the Model IV Fluid Catalytic Cracking Unit.

1. Introduction

Abnormal situations arise in chemical plants when the plants deviate from normal operational modes. An estimated $20 billion is lost annually by the petrochemical industry in the U.S. due to inadequate abnormal situation management (ASM). In order to achieve effective ASM, an operator has to perform such complex decision making tasks as detection of abnormalities, identification of the root causes of faults and their magnitudes, and planning of corrective actions under severe time constraints. An intelligent, real-time, computer-aided system is seen as a way to address ASM by providing real-time information, planning and executing corrective actions in the occurrence of abnormal situations.

FORMENTOR is an expert system for dealing with security control for petrochemical plants. A goal tree-success tree (GTST) [1] was built to represent the functional model of the process. A multi-layer model (MLM) was used to represent the structural and behavioral model of the process. One disadvantage of FORMENTOR is that it uses simple mathematical formulas to describe the relations among the variables. These formulas are not sufficient to capture the complex interactions that occur among the variables in chemical processes. Also as the diagnosis is largely qualitative in nature, it leads to lack of resolution [2]. The corrective actions are associated with different nodes in the GTST; this leads to the incompleteness and non-adaptability nature of this table-look-up strategy.

AEGIS is a large-scale intelligent refinery control system to either assist human operators, or automate certain plant procedures directly. The process knowledge in AEGIS is divided into three categories --- a structural model, a functional model and a malfunction hierarchy [3]. One disadvantage of AEGIS is that the analysis performed by the system is largely qualitative. In addition, the actions performed by the system are more reactive leading to aggressive corrective actions.

In this work, a general model based fault accommodation system is proposed and demonstrated. The proposed accommodation system includes five major components: data acquisition and validation, monitoring and fault diagnosis, identification and estimation, supervisory control and fault response, and control system.

2. Fault Accommodation System

In general, abnormal cases can be classified into the following three categories [2]: Gross parameter changes, structural changes, and malfunctioning sensors and actuators. According to this classification, the first type of faults will not change the structure of the process model. The identified fault parameters are assumed to remain constant over the time period of interest and a dynamic optimization is then solved to calculate the future profiles. However, such approaches are not capable of handling structural changes, or malfunctioning sensors and actuators. For the structural change faults, hard failures are often dealt with through the introduction of equipment redundancies. Sensor errors can be accommodated through data reconciliation and gross error detection. The details of the accommodation actions for various failures will be discussed later in this section.

A system for fault accommodation is proposed, it has five major components as shown in Figure 1: 1) data acquisition and validation module which performs the tasks of obtaining the measurements and rectifying the process data; 2) monitoring and fault diagnosis module which performs the tasks of detecting current process trends and faults; 3) fault identification and estimation module computes the magnitudes of the faults detected in previous module; 4) optimization module computes an optimal and feasible path for the process; and 5) control module implements the results obtained from the optimization module. Assume that the plant is represented by the following DAE system:

$$f_\xi(\dot{x}_\xi, x_\xi, y_\xi, u_\xi, d_\xi, t) = 0 \tag{1}$$

$$\phi_\xi(\dot{x}_\xi(t_0), x_\xi(t_0), y_\xi(t_0), t) = 0 \tag{2}$$

$$g_\xi(\dot{x}_\xi, x_\xi, y_\xi, u_\xi, d_\xi, t) \le 0 \tag{3}$$

where $x \in \Re^{n_x}$, $y \in \Re^{n_y}$, $u \in \Re^{n_u}$, and d_ξ are the differential, algebraic, control and disturbance/parameter vector, respectively, and ξ is the discrete mode.

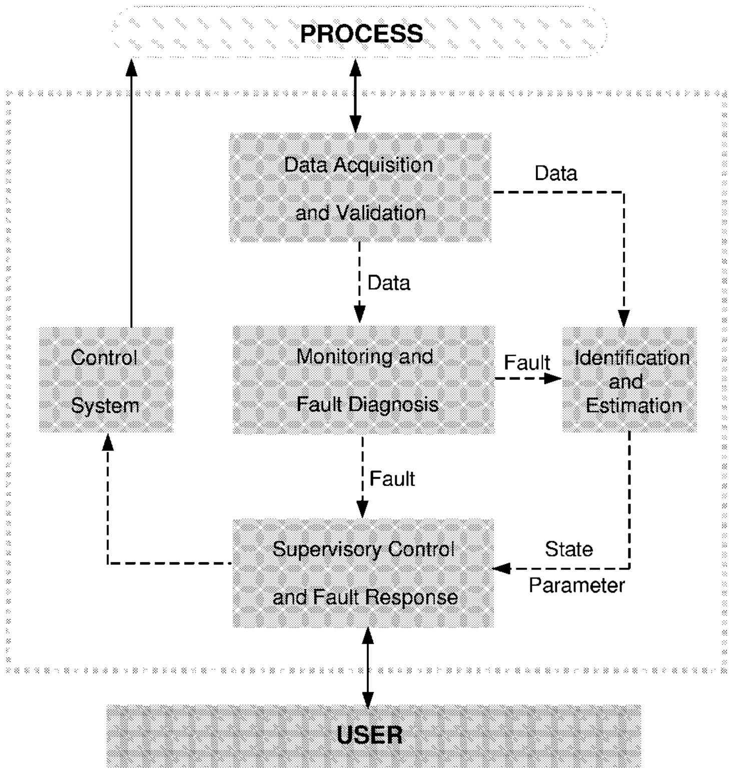

Figure 1: Tasks performed in computer-aided system for ASM

Gross Parameter Faults

In the case of gross parameter changes, the process model structure remains the same. The accommodation actions to be performed can be computed in two stages. (Feasibility stage) In the case that at least one of the constraints is violated, the following dynamic optimization problem is solved:

$$\min_{u(t),t_1} J = M \sum_{i=1}^{n_g} \int_{t_0}^{t_1} \max\{0, g_i\} \quad (4)$$

Subject to:

$$f(\dot{x}, x, y, u, d, t) = 0 \quad (5)$$

$$\phi(\dot{x}(t_0), x(t_0), y(t_0), t_0) = 0 \quad (6)$$

where M is a large number. In this stage, the goal is to drive the process into feasible region as soon as possible. If no single constraint is violated then this stage is skipped. How often this stage will be triggered depends on the efficiency of the fault detection module and the sensitivity of the process to the fault parameter or disturbance. (Optimality stage) In this stage, the focus is switched to the optimization of a performance index (profit, yield etc.) because the process is already inside the feasible region after the first stage. This is performed through the solution of the following dynamic optimization problem:

$$\min_{u(t),t_f} J = \varphi(x(t_f), t_f) + \int_{t_1}^{t_f} L(x, u, t) dt \quad (7)$$

Subject to:

$$f(\dot{x}, x, y, u, d, t) = 0 \quad (8)$$

$$g(\dot{x}, x, y, u, t) \le 0 \quad (9)$$

$$\phi(\dot{x}(t_1), x(t_1), y(t_1), t_1) = 0 \quad (10)$$

Structural Change Faults

For structural changes, the accommodation action to be performed not only depends on the equipment type and severity of the fault, but also on the location of the failed equipment. In process operations, some hard equipment failures will cause the shutdown of the equipment and concurrent startup of redundant equipment. Such situations are not considered in this work since the accommodation actions to be performed will automatically be taken care of by the existing interlock system in the plant. Instead, several other typical structural failures will be discussed in detail.

First, we consider the case of stuck valve. Once the valve fails to respond to the controller output, the position of the stuck valve V will stay at some fixed value $V_{curopen}$. When the valve sticks the process model should be augmented to include: $V = V_{curopen}$. This will cause the process model to lose one degree of freedom (DOF). This type of fault can be modeled using a disjunctive constraint by defining a new transition variable x_V:

$$x_V = \begin{cases} 1 & \text{If normal} \\ 0 & \text{If valve stuck} \end{cases}$$

and replacing the original constraint $V \in [V_L, V_U]$ by

$$x_V V_L + (1 - x_V) V_{curopen} \le V \le x_V V_U + (1 - x_V) V_{curopen} \quad (11)$$

The value of x_V is updated in the fault diagnosis module and $V_{curopen}$ is computed in the identification and estimation module. Thus, constraint (11) is just a lower and upper bound on variable V. Moreover the dynamic optimization problem to be solved does not contain any integer variables. Variable x_V only acts as a transition condition and its value is known before the optimization problem is solved.

When a pipe breaks or a vessel leak occurs, the corrective actions and the degree to which the fault affects the process depend on the severity of the situation. In a mild situation, the process model is still valid with minor modification. However, in a severe case, keeping the process in the feasible region becomes the important issue. The shutdown of part or even of the whole plant becomes options to be considered. For the broken pipe fault, a new flowrate variable with lower and upper bounds is introduced. Assuming that F is the flowrate before the leak occurs, then the leaking fault can be modeled by adding $F = \alpha F + F_l$, where F_l is the flowrate of the stream that leaks to the environment and α is a factor with value in the range [0

1]. Replacement of all occurrence of F in the process model by either $\alpha F+F_l$ or αF depends on whether F is in upstream or downstream of the leaking pipe.

In the case in which some equipment is shutdown because of equipment failure and no redundant equipment is available for immediate replacement, the model structure is changed. This can be viewed as the trigger of a transition to a new discrete mode. After removal of the equations related to equipment that is shutdown, the process model becomes: $f_\xi(\dot{x}_\xi, x_\xi, y_\xi, u_\xi, d_\xi, t) = 0$, where ξ denotes the new discrete mode of the system.

Sensor and Actuator Faults

Sensor bias faults can seriously degrade the performance of the control system through incorrect signal feedback. Three basic alternatives in accommodating such faults are: either remove the errors contained in the signals or discard the signals in question, or design a robust control system which is insensitive to the errors in the signals. The first approach is often realized through data reconciliation and rectification. The simultaneous approaches normally formulate the problem as a nonlinear program (NLP). Usually, this NLP approach is more robust than the EKF [4], but it is computationally expensive. For large-scale models, such approaches may have difficulties in obtaining estimates for on-line use. In this work, a pseudo-measurement strategy based EKF, called HEKF [5], is used to accommodate sensor biases. Simulation results show that the estimator is much more robust and efficient than the standard EKF and computationally more favorable than the NLP approaches.

3. FCCU Case Study

In this section, the application of fault accommodation scheme is illustrated on the Model IV FCCU for fault diagnosis, identification and dynamic optimization. Process fault diagnosis in the diagnosis module is performed using a combination of Signed Directed Graph (SDG) based method, Qualitative Trend Analysis (QTA) and Probability Density Functions (PDF) based statistical classifier. (See [6] for detailed description of these methods.) The simulation of FCCU is based on model equations given in [7]. Totally 87 different faults are simulated in CATSIM [8]. The accommodation simulation was done for 40 faults. These faults represent all different types of fault simulated in CATSIM and reflect the wide variety of faults that are encountered in refinery operations. In this section, some typical results will be presented.

(Example 1) A 5% increase in the coking factor of feed is introduced. Increase in coking factor is the only fault proposed by all three methods. The HEKF estimator correctly identified the magnitude of the coking factor in less than 10 sampling intervals. The result is shown in Figure 2. Figure 3 shows the setpoint trajectories of the three controlled independent variables. The accommodation actions recommended by the optimizer is to decrease the total inlet air flowrate from 75 lb/s to 71 lb/s while increase the pressures in regenerator and reactor and the differential pressure.

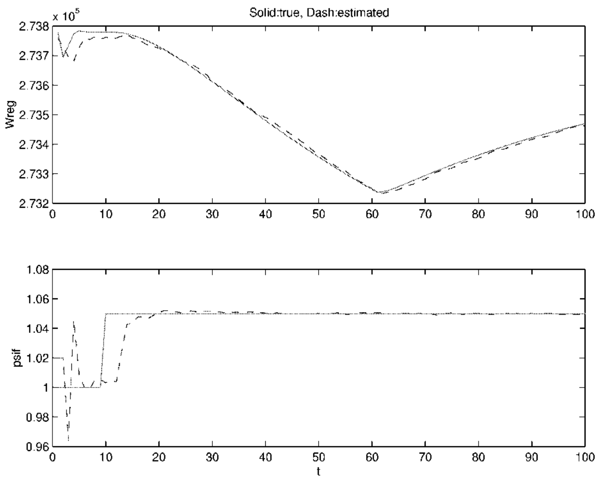

Figure 2: A 5% increase in coking factor

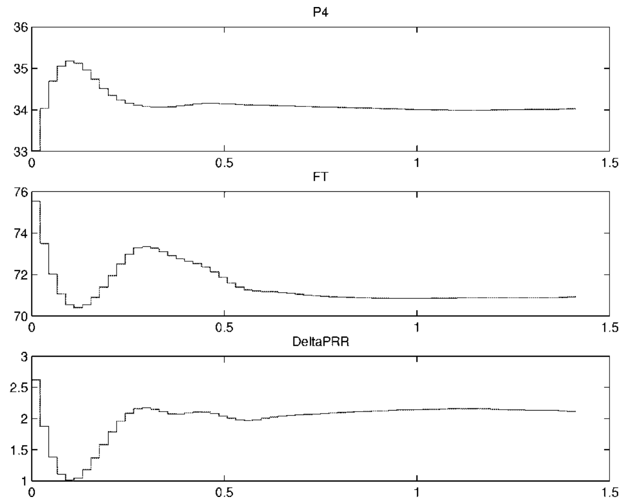

Figure 3: Setpoint profiles

(Example 2) The reactor fractionator pressure measurement (P_5) is biased by +10%. SDG was able to pick up this fault within 3 samples. Bias in the measured P_5 was removed through simultaneous data reconciliation and gross error detection technique, the HEKF. The estimated state and rectified measurements are shown in Figure 4.

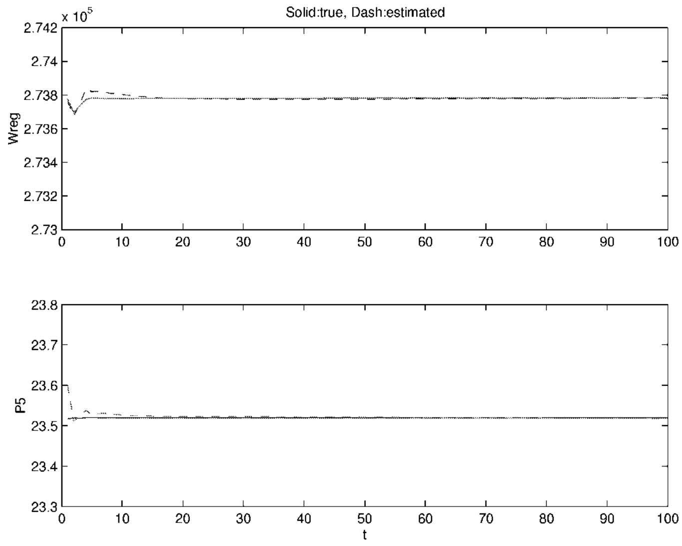

Figure 4: A 10% increase in reactor fractionator pressure measurement

4. Conclusion

A model based fault accommodation system is proposed in this paper. Disturbance and parameter faults can be accommodated through fault identification and dynamic optimization, sensor biases are accommodated through data reconciliation and gross error detection techniques. The actions recommended by the system are quantitative in nature. Moreover, the profile obtained is not only feasible but also optimal.

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