CONSIDERATIONS ABOUT APPLICATION OF ADAPTIVE FAULT DETECTION SCHEMES TO A POWER PLANT

BADEA ADRIAN, GRIGORE ROXANA

University Politehnica Bucuresti, University of Bacau

Abstract. In this paper are presented theoretical results regarding the design of an adaptive fault detection scheme. The issue of robustly detecting system faults in the presence of modeling errors is also addressed. It is presented the importance of application of adaptive detection scheme to a power plant.

Keyword. Power plant, fault detection and diagnosis, adaptive fault detection scheme,sliding mode observer

1. INTRODUCTION

The power plants represents system involving many electrical and mechanical components whose operation must be planned, monitored, analyzed and controlled. The amount of information to be processed will continue to increase for a number of reasons.

An important requirement is an increased reliability of the plant. This leads to a desire for fault detection and fault tolerant control schemes, with the purpose handling eventual faults as fast as possible, in order to shorten or avoid periods where the plants have to be closed down.

The power plant is a complex nonlinear dynamic system. The dynamic characteristics of the power plant change considerable as the operating load varies. Thus a model which accurately represents the system dynamics al full load may not accurately represents the system dynamics at other operating load. The power plant system dynamics has hard nonlinearities and is also subjected to degradation due to phenomena such as heat exchanger fouling.

For the improvement of reliability, safety and efficiency advanced methods of supervision detection and fault diagnosis become increasingly important for power plants. The performances of a fault detection and diagnosis system (FDD) are giving by [1]:

- Detection promptitude- faults detection very quickly after its happened;
- Sensitivity to fault- FDD system ability to detect small errors;
- Robustness- FDD system ability to operate in the presence of noise;
- Correctitude – avoidance of incorrect identification of fault components;
- Classification error estimate-the diagnostic system could provide a priori estimate on classification error that can occur;

- Adaptability –FDD system ability to adapt at process;
- Explanation facility-FDD system ability to explain how the fault originated and propagated to the actual situation;
- Modeling requirements- the modeling effort should be minimal possible ;
- Storage and computational requirements;
- Multiple fault identification – FDD system ability to identify multiple faults.

In the last years a lot of different approaches for fault detection using mathematical models have been developed [2; 3;4]. The task consists of the detection of faults in the processes, actuators and sensors by using the dependencies between different measurable signals. These dependencies are expressed by mathematical process models.

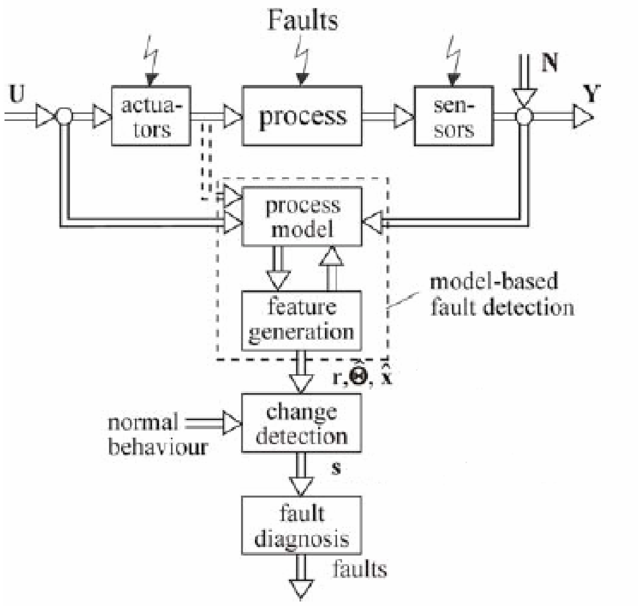

Figure 1. The basic structure of model-based fault detection

Figure 1 shows the basic structure of model-based fault detection. Based on measured input signals U and output signals **Y** the detection methods generate residuals **r**, parameter estimates **Θ** or state estimates $\hat{x}$, which are called features. By comparison with the normal features, changes of features are detected, leading to analytical symptoms **s**.

2. ADAPTIVE FAULT DETECTION SCHEMES

Consider a dynamic system with modeling errors and system faults represented by:

$$\dot{x} = Ax + Bu + \Psi(y,u) + J_1\varepsilon_1 + M_1 f_1 \tag{1}$$

$$y = Cx + M_2 f_2 \tag{2}$$

Where $x \in R^n, u \in R^m, y \in R^p$ represents the states, inputs, outputs of system. The term *Ψ(y,u)* represents known nonlinear inputs to the system. The modeling errors and the error distribution matrix are represented by $\varepsilon_1 \in R^q$, $J_1 \in R^{n\times q}$, respectively. The matrices $M_1 \in R^{n\times s}$ and $M_2 \in R^{p\times t}$ represents the distribution of the fault f_1 and f_2.

An adaptive fault detection scheme offers significant advantages in cases where the accurate characterization of the modeling errors is not known. The operation of fault detection scheme is divided into two phases:

- Learning phase;
- Fault detection phase.

In the learning phase all the discrepancies between the model and the system are attributed to modeling errors. The characteristics of the modeling errors are analyzed and the fault detection scheme adapts the fault detection algorithm to recognize the modeling errors. In some cases the model may be adapted to give a better representation of the actual system. In the learning phase it is assumed that the input is sufficiently rich to excite all the dynamics associated with the modeling errors.

In the fault detection phase the discrepancies between the model and the system are compared with the data collected during the learning phase and any new discrepancies are attributed to a fault in the system.
The schemes used in the adaptive or learning phase can be classified into two major categories:

- Pattern classification schemes;
- Function approximation schemes.

The pattern classification schemes facilitate robust fault detection by distinguishing modeling error and fault signatures. The function approximation schemes facilitate robust fault detection by adapting the model to obtain a better representation of the system.

Sliding mode observer is a high performance state estimator well suited for non-linear uncertain systems with partial state feedback. The sliding function of this observer is the estimation error of the available output. The basic sliding mode structure consists of switching terms added to a conventional Luenberger observer.

For the system described by equations 1 and 2, when there are no faults presented, the dynamics of the sliding mode observer and the estimation error dynamics are represented by [6]:

$$\dot{\hat{x}} = (A - LC)\hat{x} + Bu + \Psi(y,u) + \bar{J}KT_s \qquad (3)$$

$$\dot{\tilde{x}} = \dot{x} - \dot{\hat{x}} = (A - LC)\tilde{x} + J_1\varepsilon_1 - \bar{J}KT_s \qquad (4)$$

Where $\hat{x}$ is the estimate of the states and $\tilde{x}$ is the estimation error. The matrix $\bar{J}$ is obtained by augmenting zero columns to the J_1 matrix so that the columns dimension of $\bar{J}$ equals the row dimension of C.

The output error $\tilde{y}$ is defined as the difference between the actual system outputs and the estimated system outputs:

$$\tilde{y} = y - C\hat{x} \qquad (5)$$

The vector T_s is obtained by scaling each element of $\tilde{y}$ and taking the *tanh* of each element.

$$T_s(i) = \tanh(\frac{\tilde{y}(i)}{\mu_i}); \mu_i > 0, i = 1,...., p \quad (6)$$

where $\tilde{y}(i)$ represents the i^th element of vector $\tilde{y}$. The scaling term μ_i determines the size of the boundary layer within which the out put errors will be constrained. The matrix K is a diagonal matrix with diagonal elements.

The stability and the convergence of the state estimates are guaranteed using Lyapunov techniques. Consider a positive definite function:

$$V(\tilde{x}) = \frac{1}{2}\tilde{x}^T\tilde{x} \quad (7)$$

The derivative of the candidate Lyapunov function is:

$$V(\tilde{x}) = \frac{1}{2}\tilde{x}^T\tilde{x} = \tilde{x}^T(A - LC)\tilde{x} + \tilde{x}^T J_1\varepsilon_1 - \tilde{x}^T K T_s(i) \quad (8)$$

The Lyapunov stability theorem requirs the function $V(\tilde{x})$ to have continous first partials with the respect to $\tilde{x}$. This requires $J\varepsilon_1$ to be a smooth function.

4. CONCLUSIONS

System failures in power plant can results in serious accidents because of the large amounts of energy transfer, high temperatures and pressure involved in power plant operation.

It is thus essential for an on-line process monitoring system to be an integral part of any power plant control system.

The implementation of this modern technique requires a significant amount of computing resources, efficient data storage and retrieval capabilities and the archival of huge amounts of historic data of plant condition.

REFERENCES

[1]V.Venkatasubramanian, s.a. *A review of process fault detection and diagnosis, Part I:Quantitative model-based methods*, Computers and Chemical Engineering 27 (2003), 293-311

[2] R. Isermann, *"Supervision, Fault-Detection and Fault-Diagnosis Methods - An Introduction*", Control Eng. Practice, vol. 5, no. 5, pp. 639-652, (1997).

[3]. I.Fagarasan, P.Arsene, S.Iliescu, *Fault Detection and Isolation of sensors faults using model based methods,* Control Engineering an Applied Informatics, vol.4, no.2, 37-46

[4]. P.M. Frank*, Fault Detection in Dynamic Systems using Analitical and Knowledge-Based Redundancy,* Automatica, vol.26,nr.3,1990

[5].Babu, M.Shailesh, *Adaptive Networks for fault Diagnosis and Process Control*, internet

[6].Sreedhar, B.Fernandez, G.Y. Masada, *Sliding Mode Observers with ART Neural Network for Robust Fault Detection in Dynamics Systems,* Proceedings of the 1993 Artificial Neural Networks in Engineering Conference, St.Louis, 1993

[7].I.Dumitrache, s.a., *Automatizari electronice*, Editura Didactica si Pedagogica, Bucuresti, 1993