

Robust On-Line Fault Detection Method for Boiler Systems

보일러 시스템의 견실한 실시간 이상검출법

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요 약 : 본 논문은 불확정 시스템의 견실한 이상검출기법의 적용을 위한 실시간 이상검출기법에 대하여 다루며 대상 시스템은 산업용보일러 시스템이다. 본 논문에서 기술된 이상검출기법은 Kwon (1994) 등에 의하여 이미 제시된바 있는 견실한 이상검출기법의 오프라인 배치 처리 알고리즘을 실시간 적용을 위해 확장된 것이며 모델링 오차에 의한 불확실성, 비선형 시스템을 특정 동작점에서 선형화 하는 과정에서 발생하는 선형화 오차, 잡음등을 고려하였고, 보일러 시스템을 대상으로 한 모의 실험을 통해 본 알고리즘의 우수성을 보였다.

Keywords : fault detection; on-line algorithm; modelling errors; nonlinear systems

I. Introduction

There exists a vast amount of literature on the topic of fault detection and diagnosis. For example, fault detection method based on parameter estimation are described in (Geiger, 1984; Isermann, 1986; Kitamura 1989; Zhang *et al.*, 1992). A very general approach is presented in (Basseville *et al.*, 1986) which considers a general class of recursive parameter estimation procedures. There are also many other alternative formulations - see for example the extensive literature provided in the survey papers by Willsky(1976), Isermann(1984), Basseville(1988) and Frank(1987, 1988). These methods have been successfully applied in a variety of practical cases.

The purpose of the current paper is to focus attention on the problem of modelling error. Many authors (*e.g.*, Basseville and Benveniste, 1983; Kosut and Walker, 1984; Basseville *et al.*, 1986; Basseville, 1988; Lou *et al.*, 1986) refer to the importance of this problem, and recently Kwon *et al.* (1994) have proposed a robust fault detection method importance of this problem, and recently Kwon *et al.* (1994) have proposed a robust fault detection method. Besides the robustness issue, the issue of computational complexity should be considered in the fault detection problem since it is closely related with the rapid response to occurrence of a fault. In off-line problems the fault detection is based on observations over the complete time interval of interest, and in on-line problems the detection decision must be made rapidly at each time moment based on past observations. From the off-line point of view, multiple

changes may be found by global search; From the on-line viewpoint, the changes are assumed to be detected one after another. The needs in real-time applications have stimulated the development of an on-line fault detection method.

The fault detection method in the current paper would be described via a computer simulation using *MATLAB* to a practical boiler-turbine system. In boiler-turbine systems, models can be used to relate various control input variables to various outputs. For example, changes in inputs, such as fuel flow and valve geometry, can be related to changes in the outputs typically, drum water level and pressures and temperatures throughout the steam wall. Typical faults that can occur in boiler systems include fuel nozzle clogging, pump fault, leaking, coking, valve fault, turbine blade fault, sensor fault, actuator fault and controller fault. Clearly accurate detection and diagnosis of these faults play an important role in minimizing the risk of catastrophic failures or on reducing maintenance costs (Yoon, 1993).

The key ingredient in an analytical redundancy approach is the mathematical model used to interrelate the measured variables. A typical model for a drum-type boiler can have at most fourteen inputs and outputs with fourteen or more state variables. In addition, a non-linear model is usually required to describe the complex mass, energy and thermodynamic relationships over the full power range of a boiler system. Thus, to gain insight into the fault detection problem it is generally desirable to simplify the equations to something more manageable. Typically, linear models of order two or three are employed containing one or two inputs and outputs. The structure and the number of parameters to be used in these simplified models may depend on the operation conditions, for example, the most suitable model at part power may differ from that required at

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high power settings.

This paper is organized as follows: In Section 2, the model mismatch problem due to undermodelling and linearization error is briefly described and the nonrecursive and recursive parameter estimation procedures are summarized. In Section 3, off-line and on-line fault detection methods are proposed. In Section 4, the fault detection methods proposed are applied to a boiler-turbine system to illustrate the effective performance of the proposed methods. The conclusions are summarized in Section 5.

II. System description and parameter estimation

1. System description

The basic premise of this paper is that all mathematical models are only approximate description of real systems. As alluded previously, the major sources of modelling errors are measurement noise, undermodelling and linearization errors. Thus the model mismatch can be represented by the following system description based on a Taylor series expansion of input-output relationship:

$$y(k) = G(q^{-1})u(k) + G_d(q^{-1})u(k) + G_{nd}(q^{-1})u(k)^2 \text{sign}(u(k)) + v(k), \quad (1)$$

where q^{-1} denotes the backward shift operator, G is the nominal model, G_d and G_{nd} denote the mismatched models due to undermodelling and linearization error, respectively, $\text{sign}(\cdot)$ is the *sign* function, and v is the measurement noise. This system description is depicted by Fig. 1.

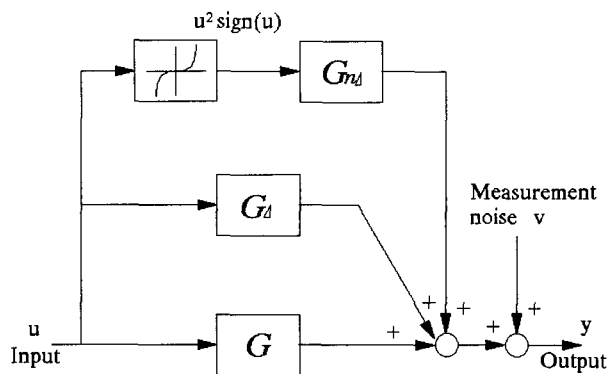


Fig. 1. System description.

The expansion given in (1) can be justified either in terms of linearization about an operation point or via a description of a nonlinear system in which the nonlinearity is represented as a static element on the input side as in the Hammerstein model (Ljung, 1987). It is here assumed that G , G_d and G_{nd} are stable and causal and that v is zero-mean white noise with variance σ_v^2 . The nominal model is taken

to be:

$$G(z^{-1}, \theta) = \frac{B(z^{-1}, \theta, N_B)}{F(z^{-1}, N_F)}, \quad (2)$$

where $F(z^{-1}, N_F)$ is a predetermined denominator and

$$\begin{aligned} B(z^{-1}, \theta, N_B) &= b_1 z^{-1} + b_2 z^{-2} + \dots + b_{N_B} z^{-N_B} \\ F(z^{-1}, N_F) &= 1 + f_1 z^{-1} + f_2 z^{-2} + \dots + f_{N_F} z^{-N_F} \\ \theta &= [b_1 \ b_2 \ \dots \ b_{N_B}]^T. \end{aligned}$$

The denominator $F(z^{-1}, N_F)$ can be determined from *a priori* information about the system, *e.g.*, approximate values of dominant poles or by some prior estimation experiments on the system. Note that any linear stable system can be always approximated by the nominal model (1) by adjusting the orders N_F and N_B . Basically, errors in the denominator polynomial are corrected by adjustments to the numerator polynomial (Salgado, 1989; Makila 1990).

2. Non-recursive parameter estimation

Using the system description (1), the system output has the following form:

$$y(k) = B(q^{-1}, \theta, N_B)u_F(k) + \eta(k), \quad (3)$$

$$u_F(k) = \frac{1}{F(q^{-1}, N_F)} u(k) \quad (4)$$

Using (4) and denoting the impulse response of G_d and G_{nd} as $\{h(\cdot)\}$ and $\{h_n(\cdot)\}$, respectively, $\eta(k)$ can be expressed as

$$\begin{aligned} \eta(k) &= \sum_{i=0}^{N_h-1} h(i) u(k-i) \\ &+ \sum_{i=0}^{N_h^n-1} h_n(i) u^2(k-i) \text{sign}(u(k-i)) + v(k), \end{aligned} \quad (5)$$

where it has been assumed that $u(k) = 0$ for $k \leq 0$, $h(k) = h_n(k) = 0$ for $k < 0$. $h(\cdot)$ and $h_n(\cdot)$ have the finite duration N_h and N_h^n , respectively.

(3) can be represented in standard linear regression form as:

$$y(k) = \phi^T(k) \theta + \eta(k), \quad (6)$$

$$\phi(k) = [u_F(k-1) \ u_F(k-2) \ \dots \ u_F(k-N_B)]^T.$$

The estimated parameter using ordinary least squares is defined as follows:

$$\hat{\theta} = \arg \min \left\{ \frac{1}{N} \sum_{k=1}^N [y(k) - B(q^{-1}, \theta, N_B)u_F(k)]^2 \right\}, \quad (7)$$

where N is the number of data available. Note that (7) corresponds to output error minimization. However, the ordinary least squares method can be used to solve this problem due to the special form of the representation (2). (3) can be rewritten compactly as follows:

$$Y = \Phi\theta + S, \quad (8)$$

where

$$S = \Psi H + \Psi_n H_n + V$$

$$Y := [y(1) \ y(2) \ \cdots \ y(N)]^T$$

$$\Phi := \begin{bmatrix} u_F(0) & u_F(-1) & \cdots & u_F(1-N_B) \\ u_F(1) & u_F(0) & \cdots & u_F(2-N_B) \\ \vdots & \vdots & \ddots & \vdots \\ u_F(N-1) & u_F(N-2) & \cdots & u_F(N-N_B) \end{bmatrix}$$

$$\Psi := \begin{bmatrix} u(1) & 0 & \cdots & 0 \\ u(2) & u(1) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ u(N) & u(N-1) & \cdots & u(N-N_h+1) \end{bmatrix}$$

$$\Psi_n :=$$

$$\begin{bmatrix} u^2(1)\text{sign}(u(1)) & 0 & \cdots & 0 \\ u^2(2)\text{sign}(u(2)) & u^2(1)\text{sign}(u(1)) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ u^2(N)\text{sign}(u(N)) & u^2(N-1)\text{sign}(u(N-1)) & \cdots & u^2(N-N_h^*+1)\text{sign}(u(N-N_h^*+1)) \end{bmatrix}$$

$$H := [h(0) \ h(1) \ \cdots \ h(N_h-1)]^T$$

$$H_n := [h_n(0) \ h_n(1) \ \cdots \ h_n(N_h^*-1)]^T$$

$$V := [v(1) \ v(2) \ \cdots \ v(N)]^T.$$

The nominal parameter vector θ can be estimated by the ordinary linear least squares method as follows:

$$\hat{\theta} = (\Phi^T \Phi)^{-1} \Phi^T Y. \quad (9)$$

From (8) and (9) we can derive the following expression for the estimation error:

$$\tilde{\theta} := \hat{\theta} - \theta = (\Phi^T \Phi)^{-1} \Phi^T S. \quad (10)$$

3. Recursive parameter estimation

For the recursive parameter estimation, (3) can be rewritten as (11), which is the standard linear regression form:

$$y(k) = \phi^T(k) \theta(k) + \phi^T(k) H(k) + \phi_n^T(k) H_n(k) + V(k), \quad (11)$$

where

$$\phi(k) := [u_F(k-1) \ u_F(k-2) \ \cdots \ u_F(k-N_B)]^T$$

$$\phi(k) := [u(k) \ u(k-1) \ \cdots \ u(k-N_h+1)]^T$$

$$\phi_n(k) := [u^2(k)\text{sign}(u(k)) \ u^2(k-1)\text{sign}(u(k-1)) \ \cdots \ u^2(k-N_h^*+1)\text{sign}(u(k-N_h^*+1))]^T.$$

The nominal parameter vector can be estimated by ordinary linear least squares method:

$$\hat{\theta}(k) = P(k) \Phi^T(k) Y(k), \quad (12)$$

where

$$\Phi(k) := [\phi^T(1) \ \phi^T(2) \ \cdots \ \phi^T(N)]^T$$

$$P(k) := [\Phi^T(k) \Phi(k)]^{-1} = \left[\sum_{i=1}^k \phi(i) \phi^T(i) \right]^{-1} \quad (13)$$

The recursive parameter estimation algorithm can

be then evaluated by the ordinary recursive least squares method (Ljung, 1987) as follows:

$$\hat{\theta}(k) = \hat{\theta}(k-1) + K(k) e(k) \quad (14)$$

$$K(k) = P(k) \phi(k) = P(k-1) \phi(k) [I + \phi^T(k) P(k-1) \phi(k)]^{-1} \quad (15)$$

$$e(k) = y(k) - \phi^T(k) \hat{\theta}(k-1) \quad (16)$$

$$P(k) = [P(k-1)^{-1} + \phi(k) \phi^T(k)]^{-1}. \quad (17)$$

Now, it is necessary to say something about the unmodelled impulse responses $\{h(\cdot)\}$ and $\{h_n(\cdot)\}$. It would not make sense to assume these were known since they would then hardly qualify as being unmodelled dynamics. This dilemma can be solved by adopting Bayesian point of view. One approach is based on the stochastic embedding technique (Goodwin and Salgado, 1989) which is used to describe the procedure of giving an *a priori* distribution to $\{h(\cdot)\}$ and $\{h_n(\cdot)\}$. Another approach proposed by Kwon *et al.* (1994) uses some experimental data to evaluate the expected value of the estimation error, $E[\tilde{\theta} \tilde{\theta}^T]$. This will be the basis of the fault detection method to be described next.

III. Fault detection method

In the fault detection procedure, we shall use the test variable based on the covariance of the estimation error between two experiments. Thus in the sequel we assume that we have access to two sets of data I_n and I_f , where I_n corresponds to non-faulty data and I_f corresponds to the suspected faulty data. The estimated parameter $\hat{\theta}$ may take different values on each experiment:

$$\hat{\theta} = \begin{cases} \hat{\theta}_n, & \text{for data set } I_n \\ \hat{\theta}_f, & \text{for data set } I_f, \end{cases} \quad (18)$$

where $\hat{\theta}$ denotes the estimated values of θ . We also assume that H , H_n and V are uncorrelated between one another.

The fault detection procedure now amounts to comparing $\hat{\theta}_n$ and $\hat{\theta}_f$ and to decide if the observed changes can be explained satisfactorily in terms of the effects of noise, undermodelling and nonlinearity. If not, then we may conclude that a system fault has occurred. The covariance function of $(\hat{\theta}_n - \hat{\theta}_f)$ under nonfaulty condition will be used in this paper as measures of the uncertainty due to noise, undermodelling and nonlinearity.

1. Non-recursive scheme

The test variable for the fault detection can be formulated as follows:

$$T_1 = (\hat{\theta}_n - \hat{\theta}_f)^T C^{-1} (\hat{\theta}_n - \hat{\theta}_f), \quad (19)$$

where

$$\begin{aligned} C &= \text{Cov}(\hat{\theta}_n - \hat{\theta}_f) = E[(\hat{\theta}_n - \hat{\theta}_f)(\hat{\theta}_n - \hat{\theta}_f)^T] \\ &= (Q_n - Q_f)C_h^o(Q_n - Q_f)^T \\ &\quad + (Q_{nn} - Q_{nf})C_{hn}^o(Q_{nn} - Q_{nf})^T + (P_n + P_f)\sigma_v^2, \\ Q_i &= P_i\Phi_i^T\Psi_i, \quad Q_{ni} = P_i\Phi_i^T\Psi_{ni}, \\ P_i &= (\Phi_i^T\Phi_i)^{-1}, \quad i = n, f \\ C_h^o &= E[HH^T], \quad C_{hn}^o = E[H_nH_n^T]. \end{aligned} \quad (20)$$

Here, E denotes the expectation with respect to the underlying probability space, and Φ , Ψ and Ψ_n are as in (8).

The first and second term on the right side of (20) account for the effects of undermodelling, nonlinearities and the difference in input signals for the two experiments. Note that if there is neither undermodelling nor nonlinearity, or if the inputs are identical, these terms will be vanished. The third term on the right side of (20) corresponds to the measurement noise.

The stochastic assumptions corresponding to $\{h(\cdot)\}$ and $\{h_n(\cdot)\}$, which implies exponentially bounded unmodelled dynamics, would be to assume

$$E[h(k)h(j)] = r(k)\delta_{kj} \quad (21)$$

$$E[h(k)_n h(j)_n] = r_n(k)\delta_{kj}, \quad (22)$$

where

$$r(k) = \sigma_o^2 e^{-\beta k}, \quad k = 0, 1, \dots, N_h - 1 \quad (23)$$

$$r_n(k) = \sigma_n^2 e^{-\beta_n k}, \quad k = 0, 1, \dots, N_h^n - 1. \quad (24)$$

This assumption can be found in some literature on robust adaptive control and estimation (de Souza *et al.*, 1988; Middleton *et al.*, 1988; Goodwin and Salgado, 1989). If σ_o^2 , σ_n^2 , β and β_n were known as prior information, then C_h^o and C_{hn}^o could be directly calculated by (21) and (22). Even if they were not known, σ_o^2 , σ_n^2 , β and β_n could be estimated from a sequence of prior experiments on nonfaulty systems based on the simple description (21) and (22) since $2/\beta$ and $2/\beta_n$ can be considered as the 'average' time constant for the class of unmodelled and linearization error dynamics, respectively (Kwon and Goodwin, 1990; Merrington *et al.*, 1991).

If prior information about the likely undermodelling and linearization error are not available, then H and H_n can be estimated from the available data, where the maximum likelihood technique has been used instead of the least-squares technique here (Kwon *et al.*, 1994). Firstly, the estimate of H can be evaluated by full model:

$$\begin{bmatrix} \hat{\theta}_{FULL} \\ \hat{H} \end{bmatrix} = \begin{bmatrix} \Phi^T\Phi & \Phi^T\Psi \\ \Psi^T\Phi & \Psi^T\Psi \end{bmatrix}^{-1} \begin{bmatrix} \Phi^T \\ \Psi^T \end{bmatrix} Y. \quad (25)$$

Thus the inversion formula for a partitioned matrix gives

$$\begin{aligned} \hat{H} &= (\Psi^T\Pi\Psi)^{-1}\Psi^T\Pi Y, \\ \Pi &= I - \Phi(\Phi^T\Phi)^{-1}\Phi^T. \end{aligned}$$

Also, for the model of Section 2.,

$$E[(\hat{H} - H)(\hat{H} - H)^T] = (\Psi^T\Pi\Psi)^{-1}\sigma_v^2. \quad (26)$$

If H is considered as a realization of a random variable, provided the noise is gaussian, then \hat{H} and $(\Psi^T\Pi\Psi)^{-1}\sigma_v^2$ can be viewed as the *a posteriori* mean and covariance of the conditional distribution for H , given the data Y . Under these conditions, from (26),

$$\begin{aligned} E[H\hat{H}^T|Y] &= E[(\hat{H} - \hat{H} + H)(\hat{H} - \hat{H} + H)^T|Y] \\ &= \hat{H}\hat{H}^T + E[(\hat{H} - H)(\hat{H} - H)^T|Y] \\ &= \hat{H}\hat{H}^T + (\Psi^T\Pi\Psi)^{-1}\sigma_v^2 = C_h^a. \end{aligned} \quad (26)$$

From (25), (26) and (27), the linearization error covariance C_{hn}^a can also be derived

$$\begin{aligned} E[H_n\hat{H}_n^T|Y] &= \hat{H}_n\hat{H}_n^T + (\Psi_n^T\Pi\Psi_n)^{-1}\sigma_v^2 \\ &= C_{hn}^a, \end{aligned} \quad (28)$$

$$\hat{H}_n = (\Psi_n^T\Pi\Psi_n)^{-1}\Psi_n^T\Pi Y.$$

Provided an independent data set is used to estimate C_h^a and C_{hn}^a , then the common symbol C_h and C_{hn} will be used to denote C_h^o and C_{hn}^o (when *a priori* data about H_n is used) or C_h^a and C_{hn}^a (when *a posteriori* data about H_n is used).

2. Recursive scheme

The fault detection method in Section (18) is based on a set of measurements, and it is not suitable for real-time application. It is therefore desirable to make a suitable reformulation of the algorithms in order to provide efficient procedures in real-time applications. On-line fault detection method is to be derived from the recursive parameter estimation algorithm of (14)–(17). The test variable (19) can be rewritten as follows:

$$T_1(k) = [\hat{\theta}^* - \hat{\theta}'(k)]^T C^{-1}(k) [\hat{\theta}^* - \hat{\theta}'(k)], \quad (29)$$

where the subscripts n and f mean set of the normal and faulty data, respectively, and

$$\begin{aligned} C(k) &= [Q_n - Q_f(k)] C_h^o [Q_n - Q_f(k)]^T \\ &\quad + [Q_{nn} - Q_{nf}(k)] C_{hn}^o [Q_{nn} - Q_{nf}(k)]^T \\ &\quad + [P_n + P_f(k)] \sigma^2 \\ Q_f(k) &= P_f(k)\Phi_f^T(k)\Psi_f(k), \end{aligned} \quad (30)$$

$$Q_{nf}(k) = P_f(k) \Phi_f^T(k) \Psi_{nf}(k) \quad (31)$$

$$P_i(k) = [\Phi_i^T(k) \Phi_i(k)]^{-1} = \left[\sum_{i=1}^k \phi_i(i) \phi_i^T(i) \right]^{-1}, i = n, f$$

$$\Psi_f(k) = [\phi_f^T(1) \quad \phi_f^T(2) \quad \cdots \quad \phi_f^T(N)]^T$$

$$\Psi_{nf}(k) = [\phi_{nf}^T(1) \quad \phi_{nf}^T(2) \quad \cdots \quad \phi_{nf}^T(N)]^T$$

The model mismatching error covariances, C_h and C_{hn} , can be determined once by (20)-(21) or (27)-(28) as mentioned in the previous section. Note that in (30) P_n , Q_n and Q_{nn} can be computed by *a priori* information or experimental data which are given from the normal data. Note the algebraic similarity with the least squares estimate. Going through the derivation of the RLS algorithm, it can be seen that the estimates $Q_f(k)$ and $Q_{nf}(k)$ in (31) can be computed recursively as follows: Using the relations

$$\begin{aligned} Q_f(k) &= P_f(k) \left[\sum_{i=1}^k \phi_f(i) \phi_f^T(i) \right] \\ &= P_f(k) \left[\sum_{i=1}^{k-1} \phi_f(i) \phi_f^T(i) + \phi_f(k) \phi_f^T(k) \right] \\ \sum_{i=1}^{k-1} \phi_f(i) \phi_f^T(i) &= P_f(k-1)^{-1} Q_f(k-1) \\ &= P_f(k)^{-1} Q_f(k-1) - \phi_f(k) \phi_f^T(k) Q_f(k-1), \end{aligned}$$

it follows that

$$\begin{aligned} Q_f(k) &= Q_f(k-1) - P_f(k) \phi_f(k) \phi_f^T(k) Q_f(k-1) \\ &\quad + P_f(k) \phi_f(k) \phi_f^T(k) \\ &= Q_f(k-1) + P_f(k) \phi_f(k) [\phi_f^T(k) - \phi_f^T(k) Q_f(k-1)] \\ &= Q_f(k-1) + K_f(k) \varepsilon_f(k), \end{aligned} \quad (32)$$

where the terms $P_f(k)$ and $K_f(k)$ can be determined by (15)-(17) from the suspected faulty input-output data. The prediction error gives the following form:

$$\varepsilon(k) = \phi_f^T(k) - \phi_f^T(k) Q_f(k-1), \quad (33)$$

and $Q_{nf}(k)$ is evaluated by the similar procedure as that of $Q_f(k)$ which is proposed above.

IV. Simulations

To illustrate the application of the proposed method, a simulated fossil-fueled boiler-turbine-alternator of 160 MW units is considered. A nonlinear 7th order model presented by Bell and Åström (1987) is used in this paper. Details of the unit are available in Eklund (1971). The unit is still in operation for peak load purpose in Malmo Sweden.

1. Boiler model

The nonlinear model of a boiler system has been proposed by Bell and Åström (1987) as follows:

$$\begin{aligned} \dot{x}_1 &= -0.0018 U_2 \cdot P^{1.125} + 0.9 U_1 - 0.15 U_3 \\ \dot{x}_2 &= [(0.73 U_2 - 0.16) P^{1.125} - P_o] / 10 \end{aligned}$$

$$\dot{x}_3 = (141 U_3 - Q_s) / 85$$

$$\dot{x}_4 = (A_l - x_4) / 10$$

$$\dot{x}_5 = (1000(A_l - x_4) - x_5) / 10$$

$$\dot{x}_6 = (U_3 - x_6) / 20$$

$$\dot{x}_7 = (3.55 Q_s - x_7) / 20,$$

and the outputs are taken as follows:

$$Y_1 = P = x_1$$

$$Y_2 = P_o = x_2$$

$$Y_3 = X_w = 50(V_{wd} - 66),$$

where the first three state variables x_1 , x_2 and x_3 are the drum steam pressure (kg/cm^2), the electrical output (MW) and the drum/riser fluid density (kg/cm^3), respectively, and the last four state variables x_4 , x_5 , x_6 and x_7 are auxiliary states in order to predict the drum water level shrink/swell for changes in the fuel flow. U_1 , U_2 and U_3 are the inputs, namely the fuel flow, control and feedwater actuator positions, respectively, which are normalized. The simple actuator dynamics which are the input constraints are given below:

$$|\dot{U}_1| \leq 0.007/\text{sec}, \quad 0 < U_1 \leq 1$$

$$-2/\text{sec} \leq \dot{U}_2 \leq 0.02/\text{sec}, \quad 0 \leq U_2 \leq 1$$

$$|\dot{U}_3| \leq 0.05/\text{sec}, \quad 0 \leq U_3 \leq 1.$$

The output Y_3 is the drum water level deviation about mean (mm). Q_s , A_l and V_{wd} are the steam mass flow rate (kg/cm^2), the steam quality (*Vol. Ratio*) and the volume of water in drum (m^3), respectively. The boiler model is implemented by SIMULINK in this paper.

2. Nonlinear simulation

Boiler-turbine models are highly nonlinear, and thus simplified linearized models are usually employed. For example, taking the fuel flow W_f as the input U_1 and the drum water level deviation X_w as the output Y_3 , an appropriate linearized nominal model is given as follows:

$$\Delta X_w(t) = \frac{b_{1c} p + b_{2c}}{p^2 + f_{1c} p + f_{2c}} \Delta W_f(t), \quad (34)$$

where p denotes the differential operator.

Taking noise and linearization errors into consideration since (34) is the linearized nominal model for the nonlinear boiler system, the underlying system can be described by the following discretized model similar to (1).

$$\Delta X_w(k) = G(q^{-1}, \theta) \Delta W_f(k) + G_{nd}(q^{-1}) [\Delta W_f(k)]^2 + v(k)$$

$$G(q^{-1}, \theta) = \frac{b_1 q^{-1} + b_2 q^{-2}}{1 + f_1 q^{-1} + f_2 q^{-2}}. \quad (35)$$

A nonfaulty data set and a faulty data set with -5%

change in the control upper bound were obtained from a full nonlinear simulation with sampling time $T_s = 3$. The following constants were chosen: $N_B = 2$, $N_h^n = 10$, and $N = 1000$. The input W_f was assumed to be corrupted by a white noise with variance $\sigma_u^2 = 0.05^2$, and measurement noise $v(\cdot)$ was chosen as $\sigma_v^2 = 9.54^2$. The fixed denominator was taken by a prior experiment with nonfaulty data as $f_1 = -0.7317$ and $f_2 = -0.0277$. The undermodelling and linearization error have been evaluated by (27) and (28).

The test variable T_1 has been adopted for fault detection, and another test variable T_c given by a standard cross validation test (Söderström and Kumamuru, 1985) has been also applied for the sake of comparison, where

$$T_c := \|Y_n - \Phi_n \hat{\theta}_f\|_2^2 - \|Y_n - \Phi_n \hat{\theta}_n\|_2^2,$$

and an ARMA (Auto-Regressive Moving Average) model has been taken as the nominal model, which is similar to (2) but its denominator is not necessarily an optimal one, but it is included as being representative of the kind of test frequently used in practice. Also, other test has been performed using the same ARMA model as that of T_c and accounting for only the variance error due to noise. This test variable has been denoted here as T_n . Note that T_n is defined by the similar form to that of (19) but it uses only the last two terms in (20) for the computation of C , and the estimated parameter change in ARMA parameters instead of numerator parameters in T_1 . It is also noted that T_n accounts for the error due to noise alone and is one kind of the well-known χ^2 test variable.

The simulation results are shown in Fig. 3 and summarized in Table 1. These results show that the proposed fault detection method works very well even under the effect of linearization error, i.e., has the robustness against the linearization error. That is because the method accounts for the effect of modelling linearization errors. Note that, on the other hand, the cross validation test variable T_c and noise only test variable T_n do not perform satisfactorily for this problem. Since they do not account the effect of modelling error or linearization error.

The simulation has also been done to show the performance of the on-line fault detection method. The same values and conditions are used here in order to set the same environments. The simulation result is shown in Fig. 4, and this result shows that the on-line method has also good performance similarly as the off-line method. However, other test variables T_c and T_n have not been accounted here

since they are not suitable for on-line problems.

V. Conclusions

A robust on-line fault detection method for uncertain systems having undermodelling, linearization errors and noise has been proposed. The key feature of this method is that it accounts for the effects of noise, model mismatch and linearization errors and can be applied to on-line fault detection problem. Some simulations applied to boiler-turbine systems show that the proposed method works well and outperform existing methods. This improvement is a consequence of the fact that the proposed method explicitly accounts for the effects of undermodelling and linearization errors in nonlinear systems and that it provides the on-line algorithm for real-time applications.

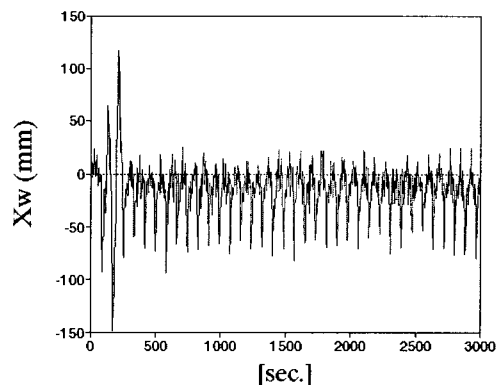
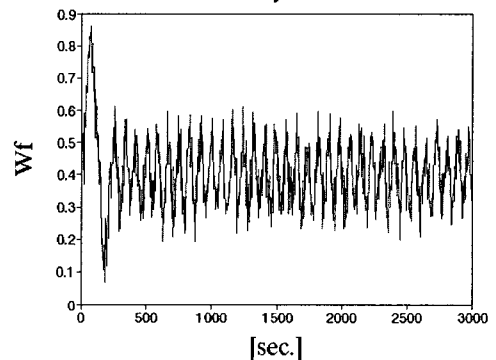
The further research will be put emphasis upon MIMO system and the optimization of calculation for real time application.

References

- [1] M. Basseville, "Detection of changes in signals and systems - A survey," *Automatica*, vol. 24, pp. 309-326. 1988.
- [2] M. Basseville and A. Benveniste, "Design and comparative study of some sequential jump detection algorithms for digital signals," *IEEE Trans. Acoust., Speech, and Signal Processing*, vol. 31, 512-535. 1983.
- [3] M., Baseville, A. Benveniste and G. V. Moustakides, "Detection and diagnosis of abrupt changes in modal characteristics of non-stationary digital signals," *IEEE Trans. Inform. Theory*, vol. 32, pp. 412-417. 1986.
- [4] R. D. Bell and K. J. Åström, "Dynamic models for boiler-turbine-alternator units: Data logs and parameter estimation for a 160MW unit," *Technical Report*, Dept. of Automatic Control, Lund Institute of Technology of Lund, Sweden. 1987.
- [5] C. E. de Souza, G. C. Goodwin and D. Q. Mayne, "An adaptive control algorithm for linear systems having unknown time delay," *Automatica*, vol. 24, pp. 327-342. 1988.
- [5] K. Eklund, "Linear drum boiler-turbine models," *Report TFRT-1001*, Dept of Automatic Control, Lund Institute of Technology, Sweden. 1971.
- [6] P. M., Frank, "Fault diagnosis in dynamic systems via state estimation - A survey," In: *System Fault Diagnostics, Reliability and Related Knowledge-Based Approaches*, (S. Tzafestas *et al.*, Ed), vol. 1, pp. 35-98. 1987.
- [7] P. M., Frank, "Fault diagnosis on the basis of dynamic process of models," *Proc. of the 12th IMACS world Congress on Scientific Compu-*

- tation, Paris, July 18-22, 1988, vol. 2, pp. 414-419. 1988.
- [8] G. Geiger, "Fault identification of a motor-pump system using parameter estimation and pattern classification," *Proc. 9th IFAC World Congress*, Budapest July 1984, Pergamon Press, Oxford. 1984.
- [9] G. C. Goodwin, M. Gevers and B. Ninness. "Quantifying the error in estimated transfer function with application to model order selection," *IEEE Trans. Automatic Control*, vol. 37, pp. 913-928. 1992.
- [10] G. C. Goodwin and M. E. Salgado. "A stochastic embedding approach for quantifying uncertainty in the estimation of restricted complexity models," *Int. J. of Adaptive Control and Signal Processing*, vol. 3, pp. 333-356. 1989.
- [11] R. Isermann, "Process fault detection based on modelling and estimation methods- A survey," *Automatica*, vol. 20, pp. 387-404. 1984.
- [12] R. Isermann, "Process fault diagnosis with parameter estimation methods," *Proc. of 7th IFAC/IFIP Conference on Dig. Comp. Applic.*, Wien 1986, Pergamon Press, Oxford. 1986.
- [13] M. Kitamura, "Fault detection in nuclear reactors with the aid of parametric modelling methods. In: *Fault diagnosis in dynamic systems; Theory and applications*," (R. Patton *et al.*, Ed.), Prentice Hall, U.K., 1989.
- [14] R. L. Kosut and R. A. Walker. "Robust fault detection; The effect of model error," *Proc. of Amer. Contr. Confr.*, pp. 1094-1096. 1986.
- [15] O. K. Kwon and G. C. Goodwin. "A fault detection method for uncertain systems with unmodelled dynamics, linearization errors and noisy inputs. *Proc. 11th IFAC World Congress*, vol. 8, pp. 68-73, Tallinn, Estonia. 1990.
- [16] O. K. Kwon, G. C. Goodwin and W.H. Kwon "Robust fault detection method accounting for modelling errors in uncertain systems," *Control Engineering Practice*, vol. 2, pp. 763-771. 1994.
- [17] L. Ljung, *System Identification: Theory for the User*, Prentice Hall, Inc., Englewood Cliffs, N.J. 1987.
- [18] X. C. Lou, A. S. Willsky and G. C. Verghese "Optimally robust redundancy relations for failure detection in uncertain systems," *Automatica*, vol. 22, pp. 333-344. 1986.
- [19] P. M. Makila, "Approximation of stable systems by Laguerre filters," *Automatica*, vol. 26, pp. 333-345, 1990.
- [20] G., Merrington, O. K. Kwon, G. C. Goodwin and B. Carlsson. "Fault detection and diagnosis in gas turbines," *Trans. of ASME, J. of Engineering for Gas Turbines and Power*, vol. 113, pp. 276-282, 1991.
- [21] R. H., Middleton, G. C. Goodwin, D. Q. Mayne and D. J. Hill. "Design issues in adaptive control," *IEEE Trans. Automat. Contr.*, vol. 33, pp. 50-58, 1988.
- [22] S. Nold and R. Isermann. "Identifiability of process coefficients for technical failure diagnosis," *Proc. 25th IEEE CDC Conference*. Athens. Dec., 1986.
- [23] M. E. Salgado, *Issues in Robust identification*, Ph. D. Thesis, University of Newcastle, Australia. 1989.
- [24] T. Söderström and K. Kumamaru. "On the use of Kullback discrimination index for model validation and fault detection," *Report UPTEC 8520R*, Uppsala University, Sweden. 1985.
- [25] B. Wahlberg, "System identification using Laquerre models," *IEEE Trans. Automatic Control*, vol. 36, pp. 551-562, 1991.
- [26] J. L. Weiss, "Threshold computation for detection of failures in SISO systems with transfer function errors," *Proc. of Amer. Contr. Confr.*, pp. 2213-2218, 1988.
- [27] A. S. Willsky, "A survey of design methods for failure detection in dynamic systems," *Automatica*, vol. 12, pp. 601-611, 1976.
- [28] I. S. Yoon, "R & D Planning on development of automatic control system for energy savings and management," *Research Project Report under contract with KEMC*. 1993.

Nonfaulty Case



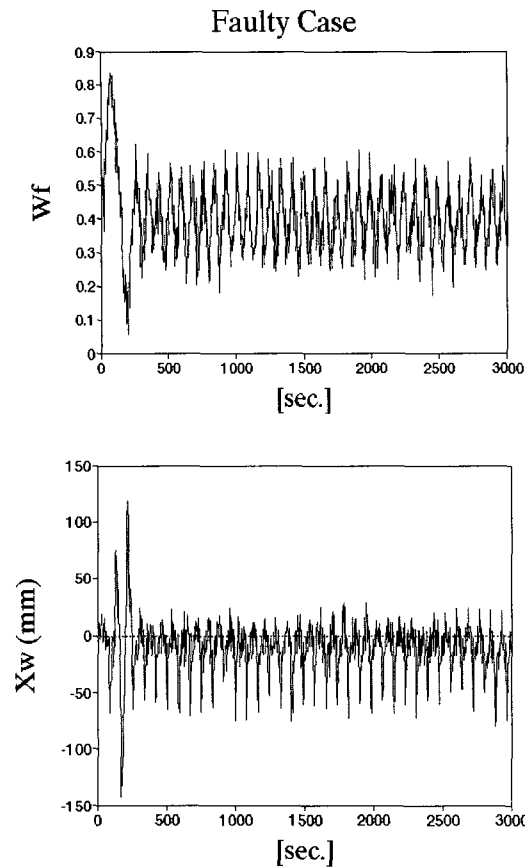
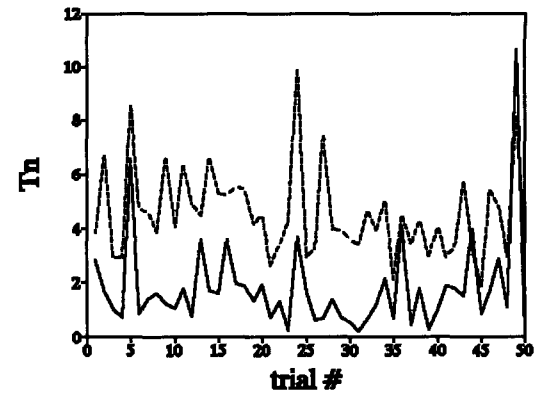
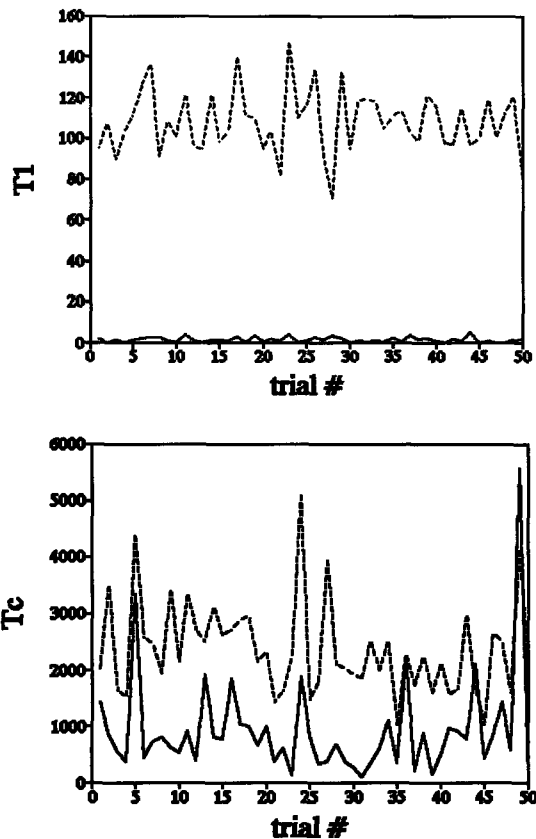


Fig. 2. A nonfaulty data set and a faulty data set.



(— nonfaulty case; --- faulty case)
Fig. 3. Simulation results (Off-line method).

(— nonfaulty case; --- faulty case)

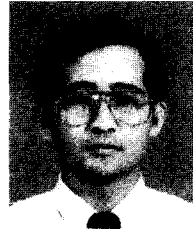
Fig. 4. Simulation results of on-line method.

Table 1. Summary of simulation results.

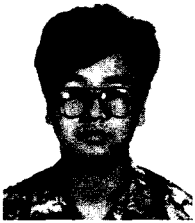
Case	T_1	T_c	T_n
Non faulty	1.46 ± 1.26	922.94 ± 918.56	1.78 ± 1.76
Faulty	108.16 ± 15.62	2376.77 ± 846.31	4.55 ± 1.66

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