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Robust Fault Detection and Diagnosis in Boiler Systems

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ABSTRACT

This paper gives a general survey of model-based fault detection and diagnosis methods. Specific applications of these ideas to boiler systems will also be discussed. A novel aspect of the fault detection technique described here is that it explicitly accounts for the effects of using simplified models and errors from linearizing a nonlinear system at an operation point. Inclusion of these effects is shown to lead to novel fault detection procedures which outperform existing methods when applied to typical fault scenarios in boiler systems.

1. INTRODUCTION

A fault may be defined as an abnormal change in the characteristics of a system which gives rise to undesirable performance. The diagnostic tasks can be classified into three components (Basseville, 1988; Frank, 1987; Isermann, 1984), namely

- fault detection – i.e. making a binary decision between fault and no fault;
- fault diagnosis – i.e. isolation the source of the fault; and
- failure evaluation – i.e. characterising the extent and significance of the failure.

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 has a significant bearing on minimizing the risk of catastrophic failures or on reducing maintenance costs (Yoon, 1993).

Two related approaches can be used for fault detection, namely, physical redundancy and analytical redundancy. The idea with physical redundancy is to use additional sensors to make independent measurements of the same parameter. In this way, sensor problems can be isolated by using a system of majority voting. The alternative is to use analytical redundancy where a model is used to interrelate two or more of the measured variables and the model parameters are then monitored to determine the influence of any faults. If a fault condition exists then significant departures from the model can be expected. In boiler 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.

The idea with analytic fault detection is to critically examine the model used to interrelate the measured variables. Under fault-free conditions, estimates of the model parameters can be made along with the expected variation in the parameters due to inaccuracies in the modelling process. Typical inaccuracies include effects of under-modelling (where a simplified model is used for convenience to approximate the real system), linearization errors and measurement noise. If over a period of time, the new estimates of the model parameters fall outside the expected fault-free range then a suspected fault condition exists. The particular way in which the estimated parameters vary from the nominal fault-free values will define a fault signature. This in turn can be used as an aid in diagnosing the cause of the suspected fault.

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 up to 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 high power settings.

Some indication of the difficulty involved in diagnosing faults from transient data can be seen from the following example. The steady state performance of a boiler can be defined within fairly close tolerances for a given operation condition. The uncertainty in the measured variables is minimized by allowing the boiler to stabilise for long enough to reduce bulk temperature effects and averaging the measurements over a reasonable sampling period. However, results obtained from transient responses for the same boiler do not produce a similar characteristic curve but exhibit different profiles for each transient depending on the ambient conditions and the operating technique used. This is not surprising because of the increased effect of the changes in bulk temperature on the transient behaviour compared to that of the steady-state. Furthermore, the effect of measurement noise in the transient case cannot be so easily filtered as in the steady-state case. Thus, it is important that the fault detection procedures are capable of distinguishing between model changes resulting from non-faulty conditions, such as changes in ambient conditions and/or operation procedures, and those introduced by faults.

2. SYSTEM DESCRIPTION AND PARAMETER ESTIMATION PROCEDURE

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:

$$y(k) = G(q^{-1})u(k) + G_{\Delta}(q^{-1})u(k) + G_{n\Delta}(q^{-1})u(k)^2 sign(u(k)) + v(k), \qquad (2.1)$$

where q^{-1} denotes the backward shift operator, G is the nominal model, G_{Δ} and $G_{n\Delta}$ denote the mismatched models due to undermodelling and linearization error, respectively, and v is the measurement noise. This system description is depicted by Fig. 1.

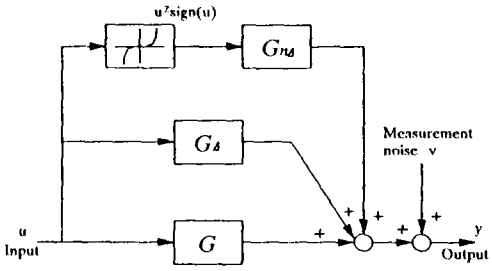

Fig. 1. System description.

The expansion given in (2.1) 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 (Ljung, 1987).

We assume that G, G_{Δ} and $G_{n\Delta}$ are stable and causal and that v is zero-mean white noise with variance σ_v^2. The nominal model is taken to be:

$$G(z^{-1}, \theta) = \frac{B(z^{-1}, \theta, N_B)}{F(z^{-1}, N_F)}, \qquad (2.2)$$

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

$$B(z^{-1}, \theta, N_B) := b_1 z^{-1} + b_2 z^{-2} + \cdots + b_{N_B} z^{-N_B}$$

$$F(z^{-1}, N_F) := 1 + f_1 z^{-1} + f_2 z^{-2} + \cdots + f_{N_F} z^{-N_F}$$

$$\theta := [\, b_1 \; b_2 \cdots b_{N_B} \,]^T .$$

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 (2.1) by adjusting the orders N_F and N_B. Basically, errors in the denominator polynomial are corrected by adjustments to the numerator polynomial.

Using the system description (2.1), the system output has the following form:

$$y(k) = B(q^{-1}, \theta, N_B)u_F(k) + \eta(k), \qquad (2.3)$$

where

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

$$\eta(k) := G_{\Delta}(q^{-1})u(k) + G_{n\Delta}(q^{-1})u(k)^2 sign(u(k)) + v(k). \qquad (2.4)$$

Using (2.4) and denoting the impulse response of G_{Δ} and $G_{n\Delta}$ as $\{h(\cdot)\}$ and $\{h_n(\cdot)\}$, respectively, $\eta(k)$ can be

expressed as

$$\eta(k) = \sum_{i=0}^{N_h-1} h(i)\,u(k-i) + \sum_{i=0}^{N_h^n-1} h_n(i)\,u^2(k-i)sign(u(k-i)) + v(k)\,, \quad (2.5)$$

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

Eq. (2.3) can be represented in standard linear regression form as

$$y(k) = \phi^T(k)\theta + \eta(k)\,, \quad (2.6)$$

where

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

We define the estimated parameter using ordinary least squares as

$$\hat{\theta} := arg\ min\left\{\frac{1}{N}\sum_{k=1}^{N}[\, y(k) - B(q^{-1}, \theta, N_B)u_F(k)\,]^2\right\}, \quad (2.7)$$

where N is the number of data available. Note that (2.7) 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 (2.2). Equation (2.3) and (2.5) can be rewritten compactly as follows

$$Y = \Phi\theta + S\,, \quad (2.8)$$

where

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

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

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

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

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

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

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

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

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

$$\hat{\theta} = (\Phi^T\Phi)^{-1}\Phi^T Y. \quad (2.9)$$

From (2.8) and (2.9) we can derive the following expression for the estimation error:

$$\tilde{\theta} := \hat{\theta} - \theta = (\Phi^T\Phi)^{-1}\Phi^T S. \quad (2.10)$$

Before we can proceed we need 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. We overcome this dilemma by adopting a Bayesian point of view. We assume that *a priori* knowledge is available which allows us to give a prior distribution to $\{h(\cdot)\}$ and $\{h_n(\cdot)\}$. This procedure is discussed in detail in (Goodwin and Salgado, 1989) where the term 'Stochastic Embedding' is used to describe the procedure of giving an *a priori* distribution to $\{h(\cdot)\}$. For our purposes here, we will simply assume knowledge of the mean and covariance function for these distributions. Given information about the second order statistics of h, h_n and v we can then 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 below.

3. 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 nonfaulty data and I_f corresponds to the suspected faulty data. The estimated parameter $\hat{\theta}$ may take different values on each experiment:

$$\hat{\theta} = \begin{cases} \hat{\theta}_n\,, & \text{for data set } I_n \\ \hat{\theta}_f\,, & \text{for data set } I_f\,. \end{cases} \quad (3.1)$$

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. We can formulate an appropriate test variable.

$$T_1 = (\hat{\theta}_n - \hat{\theta}_f)^T C^{-1} (\hat{\theta}_n - \hat{\theta}_f), \tag{3.2}$$

$$\begin{aligned} C &= Cov(\hat{\theta}_n - \hat{\theta}_f) = E[(\hat{\theta}_n - \hat{\theta}_f)(\hat{\theta}_n - \hat{\theta}_f)^T] \\ &= (Q_n - Q_f) C_h^o (Q_n - Q_f)^T + (Q_{nn} - Q_{nf}) C_{hn}^o (Q_{nn} - Q_{nf})^T \\ &\quad + (P_n + P_f)\sigma_v^2, \end{aligned} \tag{3.3}$$

where

$$\begin{aligned} &Q_i = P_i \Phi_i^T \Psi_i \quad , \quad Q_{ni} = P_i \Phi_i^T \Psi_{ni} \quad , \quad i = n, f \\ &P_i = (\Phi_i^T \Phi_i)^{-1} \quad , \\ &C_h^o = E[HH^T] \quad , \quad C_{hn}^o = E[H_n H_n^T] \quad . \end{aligned}$$

Here, E denotes the expectation with respect to the underlying probability space, and Φ, Ψ and Ψ_n are as in (2.8).

The first and second term on the right side of (3.3) 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 vanish. The third term on the right side of (3.3) corresponds to the measurement noise.

The stochastic assumptions corresponding to $\{h(\cdot)\}$ and $\{h_n(\cdot)\}$ would be to assume

$$E[h(k)h(j)] = r(k)\delta_{kj} \tag{3.4}$$

$$E[h(k)_n h(j)_n] = r_n(k)\delta_{kj}, \tag{3.5}$$

where

$$r(k) = \sigma_o^2 e^{-\beta k}, \qquad k = 0, 1, \cdots, N_h - 1 \tag{3.6}$$

$$r_n(k) = \sigma_n^2 e^{-\beta_n k}, \qquad k = 0, 1, \cdots, N_h^n - 1. \tag{3.7}$$

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 (3.4) and (3.5). 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 (3.4) and (3.5) 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:

$$\begin{bmatrix} \hat{\theta}_{FULL} \\ \hat{H} \end{bmatrix} = \begin{bmatrix} \Phi^T\Phi & \Phi^T\Psi \\ \Psi^T\Phi & \Psi^T\Psi \end{bmatrix}^{-1} \begin{bmatrix} \Phi^T \\ \Psi^T \end{bmatrix} Y. \tag{3.8}$$

Thus the inversion formula for a partitioned matrix gives

$$\hat{H} = (\Psi^T \Pi \Psi)^{-1} \Psi^T \Pi Y,$$

where

$$\Pi = I - \Phi(\Phi^T\Phi)^{-1}\Phi^T.$$

Also, for the model of Section 2,

$$E[(\hat{H} - H)(\hat{H} - H)^T] = (\Psi^T \Pi \Psi)^{-1}\sigma_v^2. \tag{3.9}$$

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 (3.9),

$$\begin{aligned} E[HH^T|Y] &= E[(\hat{H} - \hat{H} + H)(\hat{H} - \hat{H} + H)^T|Y] \\ &= \hat{H}\,\hat{H}^T + E[(\hat{H} - H)(\hat{H} - H)^T|Y] \\ &= \hat{H}\,\hat{H}^T + (\Psi^T \Pi \Psi)^{-1}\sigma_v^2 = C_h^a. \end{aligned} \tag{3.10}$$

From (3.8), (3.9) and (3.10), the linearization error covariance C_{hn}^a can also be derived

$$E[H_n H_n^T|Y] = \hat{H}_n \hat{H}_n^T + (\Psi_n^T \Pi \Psi_n)^{-1}\sigma_v^2 = C_{hn}^a, \tag{3.11}$$

where

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

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).

4. SIMULATION

To illustrate the application of the proposed method, a simulated fossil-fueled boiler-turbine-alternator 160 MW units is considered. The nonlinear 7th model presented by Bell and Åström is used in this paper. 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 and the drum water level deviation X_w as the output, an appropriate linearized nominal model is given as follows:

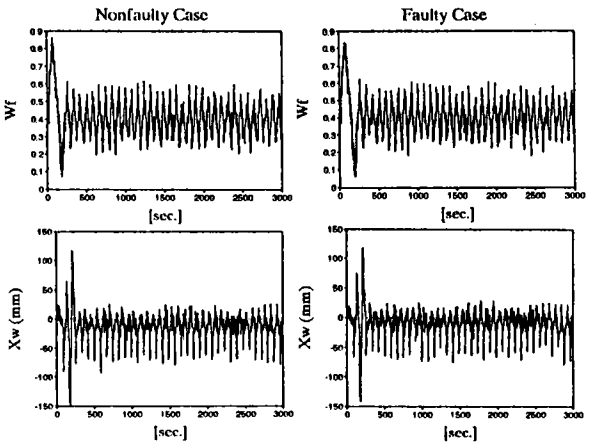

Fig. 2. A nonfaulty data set and a faulty data set.

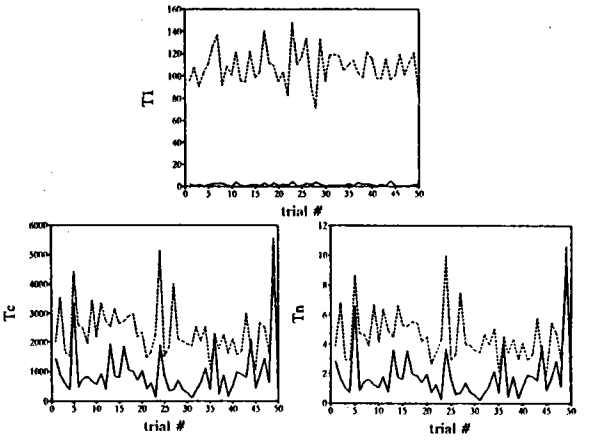

Fig. 3. Simulation results
(— nonfaulty case; --- faulty case).

Case	T_1	T_c	T_n
Nonfault	1.46 ± 1.26	922.94 ± 918.56	1.78 ± 1.76
Fault	108.16 ± 15.62	2376.77 ± 846.31	4.55 ± 1.66

Table 1. Summary of simulation results.

$$\Delta X_w(t) = \frac{b_{1c}p + b_{2c}}{p^2 + f_{1c}p + f_{2c}} \Delta W_f(t) , \qquad (4.1)$$

where p denotes the differential operator.

Taking noise and linearization errors into consideration, the underlying system can be described by the following discretized model similar to (2.1)

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

$$G(q^{-1}, \theta) = \frac{b_1 q^{-1} + b_2 q^{-2}}{1 + f_1 q^{-1} + f_2 q^{-2}} \qquad (4.2)$$

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: $N_B = 2$, $N_k = 10$, $N_k^n = 10$, and $N = 1000$. The input W_f was assumed to be corrupted by a white noise with variance $\sigma_u^2 = 0.05$, and measurement noise $v(\cdot)$ was chosen as $\sigma_v^2 = 9.54$.

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 (3.10) and (3.11).

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 Kumamaru, 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 (2.2) 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 (3.2) but it uses only the last two terms in (3.3) 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. Note that the cross validation test variable T_c and noise only test variable T_n do not perform satisfactorily for this problem.

5. CONCLUSIONS

A robust 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. 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.

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