Research Article

Model-Based Water Wall Fault Detection and Diagnosis of FBC Boiler Using Strong Tracking Filter

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Fluidized bed combustion (FBC) boilers have received increasing attention in recent decades. The erosion issue on the water wall is one of the most common and serious faults for FBC boilers. Unlike direct measurement of tube thickness used by ultrasonic methods, the wastage of water wall is reconsidered equally as the variation of the overall heat transfer coefficient in the furnace. In this paper, a model-based approach is presented to estimate internal states and heat transfer coefficient dually from the noisy measurable outputs. The estimated parameter is compared with the normal value. Then the modified Bayesian algorithm is adopted for fault detection and diagnosis (FDD). The simulation results demonstrate that the approach is feasible and effective.

1. Introduction

Fluidized bed combustion (FBC) boiler, the most popular clean coal combustion technology in power and chemical industries [1], facilitates burning a wide variety of fuels with high combustion efficiency, especially for the low-grading coal. The technology burns fuel at temperatures from 800 to 950°C, a range where nitrogen oxide (NO_x) formation is much lower than that in traditional pulverized coal boiler [2]. The fluidized bed has several potential advantages in CO_2 capture from flue gas [3]. In addition, water-wall slagging is significantly eliminated due to the combustion condition of lower temperature. Furthermore, soot formation can be attenuated with the appropriate distributor plate layout. However, wastage of tube materials, both refractory and metallic, is more prominent than pulverized coal boiler because the particulates in the fluidization state strike and rub the tube more fiercely and frequently. It has become a source of concern for FBC boilers because it is responsible for water-wall burst and even undesired shutdowns.

A great deal of research has been done in an effort to further understand metal wastage in fluidized bed combustion environments and to find solutions to ease it. It is generally acknowledged that tube wastage is caused by simultaneous

corrosion and erosion. In [4, 5], the erosion-prone areas were identified in circulating and bubbling fluidized bed boilers and described current methods for erosion protection. The wastage rate was most significant in the water wall around the bed region, decreasing with increasing height [6]. The rate of tube erosion is usually a complex function of characteristics of the coal particulates, that is, shape, strength, size, composition, and ash content, such as SiO_2 , Al_2O_3 , and Fe_2O_3 [7]. Most researches [4–8] of tube wear have been conducted for exploration of erosion mechanism to improve boiler design. However, there have been few reports on online monitoring of erosion occurring during runtime. In [9], the method by ultrasonic thickness gauge was introduced to investigate tube wastage patterns successfully. But the increased equipment cost and integration difficulties limit its broad application in industry.

An alternative monitoring method based on boiler dynamic model and optimal estimation theory was introduced in this paper. By delving into the performance characteristics of FBC boiler, we can deduce that the global wastage or deposition rate of water wall could be expressed equally as the variation of the overall heat transfer coefficient regardless of its cause. Hence the problem of thickness measurement and detection was reconstructed as a parameter

estimation issue. This critical parameter can be assumed as an extended state, which would be estimated with other state variables simultaneously in an augmented nonlinear model. Specifically, the observability of augmented system should be examined, which serves as a necessary precondition of the proposed software redundancy method other than hardware-based measurement method.

The conventional linear estimation theory was proposed by Kalman [10] and then developed into nonlinear version in NASA, named “extended Kalman filter” (EKF) which was widely applied in the aerospace and navigation areas. However, in most industrial cases, the EKF method is of poor robustness against model mismatches [11], which can only give a biased state estimation and even may quickly diverge, owing to its linearization. We propose to adopt a new filter, called a strong tracking filter (STF) [12], which can overcome the above-mentioned flaws of EKF. In STF, the mean square of estimated residues is minimized based on the orthogonality principal. Thus the Kalman gain can be adjusted in real time to track the actual states. This approach is applicable to joint states and parameters estimation with unknown changing laws.

In the current paper, Section 2 is devoted to a brief introduction to the structure and model of a bubbling fluidized bed combustor. The outline of STF is presented in Section 3. After introducing an FDD strategy based on modified Bayes’ classification algorithm, computer simulation results are given in Section 4 to show the effectiveness of the proposed approach. Section 5 is the conclusions and future work. The strategy in this paper is also applicable for circulating fluidized bed (CFB) boiler if the corresponding dynamic model can be provided with acceptable accuracy.

2. System Description and Analysis of FBC Boiler

2.1. Overview of Fluidized Bed Combustion Technology. Fluidized beds find widespread application in industrial applications because of their favorable heat transfer properties. With appropriate upward-blowing primary air velocity to suspend solid fuels, there are tumbling action and bubble formation, which provides more effective combustion and heat transfer. The bed of solid particles exhibits the properties of a boiling liquid and assumes the appearance of a fluid—“bubbling fluidized bed.” The schematic of a FBC boiler is shown in Figure 1.

As shown in Figure 1, a mixture of inert/sorbent bed material and solid fuel is fluidized by the primary air entering from below. Secondary air is injected above the fuel bed to ensure complete gas burning out. But the total amount should be limited due to economic efficiency. The heat released in combustion is captured by heat exchangers and used for the generation of steam.

2.2. Global Dynamic Model of Bubbling FBC Boiler. The full-order dynamic model of FBC has been set up for mechanism study, but it is not suitable for fault detection and state estimation because of the complexity. The classical bubbling

FIGURE 1: A schematic of a typical FBC plant.

FBC model was originally formulated in [13] based on mass and energy balances, which was verified by experimental data. To strike a balance between fidelity and simplicity, the model was further modified as follows [14].

Dynamics of fuel inventory W_C [kg]:

$$\frac{dW_C(t)}{dt} = (1 - V) Q_C(t) - Q_B(t). \quad (1)$$

Dynamics of bed oxygen content C_B [Nm^3/Nm^3]:

$$\frac{dC_B(t)}{dt} = \frac{1}{V_B} [C_1 F_1(t) - Q_B(t) X_C - C_B(t) F_1(t)]. \quad (2)$$

Dynamics of freeboard oxygen content C_F [Nm^3/Nm^3]:

$$\begin{aligned} \frac{dC_F(t)}{dt} = \frac{1}{V_F} \{ & C_B(t) F_1(t) + C_2 F_2(t) \\ & - V Q_C(t) X_V - C_F(t) [F_1(t) + F_2(t)] \}. \end{aligned} \quad (3)$$

Dynamics of bed temperature T_B [K]:

$$\begin{aligned} \frac{dT_B(t)}{dt} = \frac{1}{C_I W_I} \{ & H_C Q_B(t) + c_1 F_1(t) T_1 \\ & - \alpha_{Bt} A_{Bt} [T_B(t) - T_{Bt}] - c_F F_1(t) T_B(t) \}. \end{aligned} \quad (4)$$

Dynamics of freeboard temperature T_F [K]:

$$\begin{aligned} \frac{dT_F(t)}{dt} = \frac{1}{C_F V_F} \{ & V Q_C(t) + c_1 F_1(t) T_1 \\ & - \alpha_{Bt} A_{Bt} [T_B(t) - T_{Bt}] - c_F F_1(t) T_B(t) \}. \end{aligned} \quad (5)$$

Dynamics of thermal power P [MW]:

$$\frac{dP(t)}{dt} = \frac{1}{\tau_{\text{mix}}} [P_C(t) - P(t)], \quad (6)$$

where the combustion rate in bed Q_B [kg/s] is $Q_B(t) = (W_C(t)/t_C)(C_B(t)/C_1)$ and the combustion power P_C [MW] is $P_C(t) = 10^{-6}[H_C Q_B(t) + H_V V Q_C(t)]$. Here, other detailed variable nomenclatures and fine-tuned model parameter values have been given in [14]. In this FBC process, the manipulated inputs $\mathbf{u}$ are fuel feed Q_C [kg/s], primary air flow F_1 [Nm³/s], and secondary air flow F_2 [Nm³/s]; the controlled variables are power P , bed temperature T_B , and freeboard oxygen content C_F ; freeboard temperature T_F is also a measurable output in addition to the 3 controlled variables. Hereby a canonical nonlinear model can be established from (1)–(6):

$$\begin{aligned} \dot{\mathbf{x}} &= f(\mathbf{x}, \mathbf{u}), \\ \mathbf{y} &= h(\mathbf{x}), \end{aligned} \quad (7)$$

where $\mathbf{x} = [W_C \ C_B \ C_F \ T_B \ T_F \ P]^T$, $\mathbf{u} = [Q_C \ F_1 \ F_2]^T$, and $\mathbf{y} = [T_B \ P \ T_F \ C_F]^T$.

3. Strong Tracking Filter Based State Estimation

3.1. Extension and Discretization. If soot formation or erosion occurs in water wall tube, the corresponding heat transfer coefficient will change due to variation of thermal conduction resistance. However, it is impossible to obtain the heat transfer coefficient h_B by measurement. We can estimate the variation of h_B by using methods based on joint state and parameter estimation. Considering the influence of noise, and assuming h_B as an extended state, the augmented model can be discretized as

$$\begin{aligned} \mathbf{z}(k+1) &= f_e(\mathbf{z}(k), \mathbf{u}(k)) + \mathbf{w}_k, \\ \mathbf{y}(k+1) &= h_e(\mathbf{z}(k+1)) + \mathbf{v}_{k+1}, \end{aligned} \quad (8)$$

where $\mathbf{z}(k) = [\mathbf{x}(k) \ h_B(k)]^T$ is the augmented state by assuming $h_B(k+1) = h_B(k)$. Thereby, functions f_e and h_e can be derived from (7) by Euler methods. $\mathbf{w}_k$ and $\mathbf{v}_k$ are the process and observation noises which are both assumed to be zero mean multivariate Gaussian noises with covariances Q_k and R_k , respectively.

3.2. Basic Principals of STF. It is well known that the extended Kalman filter (EKF) can be used [15] for the joint estimation of the systems described by (8), which can be summarized as the following formulas.

Predicted state:

$$\hat{\mathbf{z}}_k^- = f_e(\hat{\mathbf{z}}_{k-1}^+, \mathbf{u}_{k-1}). \quad (9)$$

Predicted covariance:

$$P_k^- = F_{k-1} P_{k-1}^+ F_{k-1}^T + Q_{k-1}. \quad (10)$$

Measurement residual:

$$\boldsymbol{\gamma}_k = \mathbf{y}_k - h_e(\hat{\mathbf{z}}_k^-). \quad (11)$$

Kalman gain:

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + R_k)^{-1}. \quad (12)$$

Updated state:

$$\hat{\mathbf{z}}_k^+ = \hat{\mathbf{z}}_k^- + K_k \boldsymbol{\gamma}_k. \quad (13)$$

Updated covariance:

$$P_k^+ = (I - K_k H_k) P_k^-, \quad (14)$$

where the superscripts $-$ and $+$ represent the values before and after measurement correction, respectively. F_k and H_k are the state transition and observation matrices by linearizing f_e and h_e at each time step.

However, in most cases, especially for industrial fault diagnostics, the EKF has the following flaws:

- (i) poor robustness against model mismatches;
- (ii) sensitivity to the statistics of the initial states and noise;
- (iii) weak tracking ability to the suddenly changing states.

All these drawbacks will be more prominent especially when filter approaches steady, as shown in the next subsection. The essential reason accounting for the phenomenon is that the optimal Kalman gain is actually calculated by open-loop method in spite of updating process in state correction. According to the original paper [10] regarding linear filtering, the predicted covariance and Kalman gain both depend on the model and initial parameter settings of P_0 , Q_k , and R_k . The Kalman gain K_k will approach zero after long-time steadiness and then EKF will lose tracking ability when process uncertainty occurs.

For this reason, Zhou and Frank proposed a strong tracking filter (STF) in [12]. By introducing a diagonal matrix Λ_k to (10),

$$P_k^- = \Lambda_k F_{k-1} P_{k-1}^+ F_{k-1}^T + Q_{k-1}; \quad (15)$$

the Kalman gain can be adjusted online to maintain the strong tracking ability of filters. The suboptimal fading factors Λ_k can be obtained recursively by solving the following equations:

$$\begin{aligned} E[(\mathbf{z}_{k+1} - \hat{\mathbf{z}}_{k+1}^+)^T (\mathbf{z}_{k+1} - \hat{\mathbf{z}}_{k+1}^+)] &= \min, \\ E[\boldsymbol{\gamma}_{k+1}^T \boldsymbol{\gamma}_{k+1+j}] &= 0; \quad j = 1, 2, \dots \end{aligned} \quad (16)$$

The second equation of (16) is named orthogonality principle, whose physical meaning is that the residual error series should be made mutually orthogonal at each step, so that the rich information in the residual error series could be extracted. For deduction details, see [12].

FIGURE 2: Simulation comparison of estimated states.

FIGURE 3: The structure of closed-loop fault detection and diagnosis.

3.3. Open-Loop Simulation and Comparison. In this part, an open-loop simulation on FBC plant (7) was conducted without joint estimation. In the simulation, EKF and STF shared the same set of filter parameters with initial states deviating from the actual value. The simulation results are shown in Figure 2. In simulating process, the input variable (fuel feed Q_C) increased by 25% at $t = 1000$ s; the state variable (fuel inventory W_C) dropped suddenly at $t = 2000$ s. In addition, there is a mutation in heat transfer coefficient h_B at $t = 3500$ s.

As shown in Figure 2, the adjective “strong” in STF implies (i) faster rate of convergence in the presence of initial error (see Figure 2(a)), (ii) stronger tracking ability to the abrupt changing states regardless of dynamic or stationary fashion, and (iii) better robustness to modeling error (Figures 2(c), 2(d), and 2(e), titles: “freeboard” and “temperature”).

4. FDD of Water Wall

4.1. Strategy of Fault Detection. Once the erosion or soot formation occurs, it will grow more and more serious. Hence, it is necessary to detect the fault in time. Assume the fault is a drift-type process. While the boiler is running at normal state, the heat transfer parameter is

$$h_B(k) \sim N(h_B^0, \sigma_0^2), \quad (17)$$

where h_B^0 is the normal operating value and σ_0^2 is the reasonable variation which is acceptable for engineering. The modified Bayes' algorithm is adopted for fault detection.

Define

$$\begin{aligned} \mu_{h_B}(k) &= \frac{1}{N} \sum_{j=1}^N \hat{h}_B^+(k-j), \\ \sigma_{h_B}^2(k) &= \frac{1}{N-1} \sum_{j=1}^N [\hat{h}_B^+(k-j) - h_B^0]^2, \end{aligned}$$

$$\begin{aligned} \sigma_{h_B}^2(k) &= \frac{1}{N-1} \sum_{j=1}^N [\hat{h}_B^+(k-j) - \mu_{h_B}(k)]^2, \\ d(k) &= \frac{\sigma_{h_B}^2(k)}{\sigma_0^2} - \ln \frac{\sigma_{h_B}^2(k)}{\sigma_0^2} - 1, \end{aligned} \quad (18)$$

where N is the preselected data window and d is named detection parameter. When the boiler operates well, d is close to zero. As soon as the fault occurs, d will be soaring sensitively. When a threshold β_0 is defined, the strategy of fault detection is, thus, obtained:

$$d(k) > \beta_0, \quad (19)$$

where β_0 can be selected by operating experience. With smaller β_0 , smaller faults can be detected, but more false alarms occur. On the other hand, with larger β_0 , only relative larger fault can be detected, and missing alarms will increase.

4.2. Closed-Loop Structure of Fault Diagnosis. In [16], the authors proposed a multivariable coordinated control method of FBC boiler based on LSSVM-GPC, which can control output power and bed temperature well by regulating fuel feed and primary air flow. Here, a PI controller was applied in the secondary air flow-freeboard oxygen content loop. Based on the above discussion, a closed-loop fault detection and diagnosis strategy was developed under the control framework, as shown in Figure 3, where the strong tracking filter was used to estimate state variables and heat transfer coefficient dually based on (8).

4.3. Numerical Simulation. The simulation time is 14000 s. A load-up command was given with setpoints of P and T_B rising to 30 MW and 850°C, respectively, while the setpoint of C_B was kept constant.

Suppose soot was deposited gradually in water wall at $t = 2000$ s and then was cleaned up by soot blower at $t = 7000$ s. After 1000 seconds, tube erosion of water wall occurred due to severe attrition. Let $\Lambda_k = \lambda_k I_7$; that is, the STF based on multiple fading factors deteriorates to a single fading factor which also has good tracking ability. The closed-loop simulation results were shown in Figures 4–6.

It can be seen from Figure 4 that STF can track all the state variables with almost no errors under the condition of joint estimation while EKF is more sensitive to model mismatch (see Figures 4(a) and 4(b)). Figure 5(a) shows the overwhelming superiority of STF in tracking time-varying heat transfer coefficient with unknown changing laws while the EKF can be used to estimate constant parameters only. Figure 5(b) shows that the fading factor λ_k can be increased rapidly once model mismatch happens. Thus the Kalman gain can be adjusted in real time, which accounts for the strong tracking ability essentially.

As shown in Figure 6, the detection parameter d is hypersensitive to water wall fault, which grows exponentially once fault happens. The incipient fault can be detected at an early stage. For example, the soot formation fault is detected at

FIGURE 4: States estimation of closed-loop simulation.

FIGURE 5: Heat transfer coefficient estimation.

FIGURE 6: A semilog graph of detection parameter d .

$t = 5493$ s with estimated fault amplitude, -19.9 . The erosion fault is detected at $t = 10006$ s with estimated fault amplitude, 19.8 (see Figure 5(a)). The estimation accuracy of the fault amplitude is 66.4% and 99.3%, respectively. It is possible to detect a fault earlier if we select a lower threshold, but the rate of false alarm will correspondingly increase.

5. Conclusion and Future Work

Because the security and reliability of FBC boiler are becoming more and more important, and the erosion is one of the most common faults of FBC boiler, it is urgent to investigate further the erosion fault of FBC. The STF is adopted for joint estimation due to the virtue of strong robustness against model mismatch and strong tracking of drifting states, as well as jumping states even when the filter is stable. According to the estimated heat transfer coefficient, the soot formation and erosion can be detected based on the modified Bayes' algorithm. At last, the simulation results demonstrate that the approach is feasible and effective. The line of research will lead to the future work in comprehensive fault detection and

diagnosis and fault-tolerant control by incorporating other common faults, such as sensor and actuator faults.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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