Boiler Leak Detection Using a System Identification Technique

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Boilers are important processes in chemical and refinery industries: they are normally operated for an extended period of time, leading to (water/steam) tube leaks because of aging and corrosion. To maintain production in normal and safe conditions, detecting the possible boiler leaks in time is crucial. In this paper, a process model is proposed to describe the boiler tube leak problem. On the basis of this model and the boiler characteristics, a least-squares method with a forgetting factor is derived to detect boiler leakage. The analysis of leak estimation properties for the proposed method is given under certain conditions of boiler operation. The applications based on both simulation and real plant data show that the proposed method is capable of detecting boiler leaks effectively and efficiently.

1. Introduction

Modern production equipment used in today's process industries is typically very complex. The operation of a highly automatic industrial system depends heavily on the status of equipment and the accuracy of measurement of process variables as well as the conditions of the various instruments. However, many factors such as disturbances, instrument errors, and process faults may cause abnormal operation of the industrial system. These issues motivate research on fault detection and diagnosis. There are three main approaches to fault detections, namely, the model-based method, the knowledge-based method, and the statistical analysis method.

The model-based method is the conventional method of fault detection and diagnosis which uses static or dynamic models of the process. It includes the observer-based method,1–3 the identification-based method,4,5 the subspace identification method,6 etc. This method can provide an efficient solution for most fault detection problems. But in some cases it cannot give correct detection results since the valid process mathematical model required in this technique is difficult to obtain in some industrial processes.

For a complex production process or a process with an unknown model, the knowledge-based method can be used to detect faults.5 The method can extract and employ the knowledge obtained from operators who have rich operational experience or have learned from the industrial operations. This technique includes the expert system method,7 the artificial neural network method,8 the wavelet and pattern recognition method,9 and the qualitative analysis method.10 In practical situations, a combination of the analytical and knowledge-based methods may be the most appropriate solution to some fault detection and diagnosis problem.

Statistical analysis methods have been employed for many years. Some of these methods are simple but are very effective for specific faults, including the limit checking method, frequency analysis method, data characteristics analysis method, etc. Currently, the principal-component analysis (PCA)11,12 and partial least-squares (PLS) analysis13,14 are popular multivariable statistical process monitoring techniques for processes with a large number of variables. Since PCA can effectively reduce monitored process dimensions, it is widely used in process monitoring and fault diagnosis.15–17

Water/steam leakages are typical faults that frequently occur in boiler systems. Despite their importance in industrial processes, their detection methods are rarely encountered in books or journals. They may be detected through gross error detection schemes designed for dynamic data reconciliation problems. Most methods for gross error estimation make use of statistical analysis techniques and system identification strategy.18–20 Narasimhan and Mah21 derived a generalized likelihood ratio method for identifying gross errors in steady-state chemical processes. For the problem of tank leak detection, a time-series based method, in which a Kalman filter is used, is developed by Chemielewski et al.22

However, the above methods based on steady state systems consider that every residual has the same contribution to the gross error detection. Since nonlinearity, time varying characteristics and many disturbances exist in boilers, it is difficult for those methods to provide satisfactory detection performance. Under such conditions, new residual information should be utilized more and past data should be gradually forgotten in the detection scheme. On the basis of the boiler process model and characteristics, a method with a forgetting factor is developed in this paper. It provides better identification results when there exist process disturbances and time-varying dynamics and gives an effective solution to the boiler leak detection problem.

The rest of this paper is organized as follows. In section 2, a typical boiler steam–water system is...
Figure 1. Boiler steam-water system and tube leakage problem.

The Syncrude Canada utility plant can be seen as an industrial co-generation system which utilizes a complex header system for steam distribution. This header system includes headers at four different pressure levels (900, 600, 150, and 50 psi). The 900# header receives steam from three utility-type boilers (such as the one described above) burning refinery gas, three CO-type boilers burning coke off gas and refinery gas, and two once-through steam generators (OTSG). The operation of the CO boilers is completely analogous to that of the utility boilers above-described. The steam is then distributed through the header system to numerous turbines to generate electricity.

It is clear from this description that the proper operation of the utility and CO boilers is vital to the normal operation of this large scale industrial system. A common occurrence in this type of plant is that the tubes in the risers and downcomers deteriorate due to aging as well as stress due to the heating process. This deterioration inevitably leads to leaks thus damaging the equipment and reducing the amount of steam generated which in turn originates a variety of problems in the normal plant operation. In the case of serious leakage it may lead to boiler shutdown. Thus, in the case of boiler water tube leaking, it is necessary to detect the problem as soon as possible.

3. Process Model and Estimation Method

(1) Boiler Steam Drum Model. Assuming that the mass flow in the downcomers is the same as that in the riser section, that is, the flow rate is uniform through a complete circulation path. Then, an overall material balance equation for the steam drum can be written as

\[ A_1 \frac{dD}{dt} + A_2 \frac{dP}{dt} + f = w_f - w_s \]  

(1)

where

\[ A_1 = \rho_1 - \rho_w, \quad A_2 = V_1 K_2 - V_2 K_1 \]

\[ w_f \] and \[ w_s \] are feedwater flow and steam flow, respectively; \( V_1 \) is the volume of the saturated liquid in the drum; \( V_2 \) is the volume of the steam in the drum and superheaters; \( \rho_1 \) is the liquid density; \( \rho_w \) is the steam density; \( P \) is the drum pressure; \( D \) is the liquid height; \( f \) is the boiler blow down flow; and

\[ dV_2/dt = A_0 (dD/dt); \quad K_1 = dP_1/dt = a_1 + a_2 P; \]

\[ K_2 = dP_2/dt = b_1 + b_2 P \]

where \( A_0 \) is drum section area, \( a_1, a_2, b_1, \) and \( b_2 \) are constants obtained by correlating the physical properties data. 23

Define

\[ x_{in} = w_f, \quad x_{out} = w_s \]

and

\[ \omega = -(A_1 A_0 (dD/dt) + A_2 (dP/dt)) \]

then the discrete time model for leak detection can be written as

\[ \theta(k) = x_{in}(k) - x_{out}(k) - f + \omega(k) \]  

(2)

where \( \theta \) is the leak amount and \( k \) is the sampling time.

From eq 2, we know that steam flow will be equal to feedwater flow only in the condition of \( f = 0 \), \( dD/dt = 0 \)
and \( \frac{dP}{dt} = 0 \); that is, the boiler system is in steady state. In practice, the steam flow and feedwater flow are generally not constant since persistent disturbances exist and the boiler loads change. From a material balance point of view, the steam flow plus blow down flow will not usually be instantaneously equal to the feedwater flow. However, the average of the steam flow plus blow down flow should be equal to (or almost equal to) the average of the feedwater flow in a certain time period, that is \( \omega(k) \) satisfies that \( \sum_{n=1}^{N} \omega(k) = \epsilon \), where \( \epsilon \) will be small if \( N = N_2 - N_1 \) is a large integer. In practice, measurement noise always exists. So, the process model in the presence of measurement noise can be written as

\[
\theta(k) = x_{in}(k) - x_{out}(k) - f + \omega(k) - \xi_{in}(k) + \xi_{out}(k)
\]

(3)

where \( x_{in} \) and \( x_{out} \) are the measured values for \( x_{in} \) and \( x_{out} \), respectively; \( \xi_{in} \) and \( \xi_{out} \) represent measurement noise with zero means for \( x_{in} \) and \( x_{out} \), respectively.

(2) Estimation Method. Leak is a persistent fault. From eq 3, we know that the leak amount \( \theta \) can be directly obtained under the ideal conditions, that is, no disturbances (\( \omega = 0 \) and \( f = 0 \)) and no measurement errors (\( \xi_{in} = 0 \) and \( \xi_{out} = 0 \)). In practice, measurement errors and/or disturbances always exist. Statistical analysis method or identification method must be used to solve the problem. In the presence of some temporary or time varying disturbances, the existing methods cannot often get satisfactory results for this problem. For this situation, the contribution of past residual information should be gradually reduced in leak detection. Thus, to enhance the accuracy of the identification of leaks, the forgetting factor should be introduced into the estimation scheme. On the basis of this idea, we can propose the following estimation scheme.

Let

\[
z(k) = x_{in}(k) - x_{out}(k) - f
\]

(4)

\[
\xi(k) = \xi_{in}(k) - \xi_{out}(k)
\]

(5)

\[
n(k) = \xi(k) + \omega(k)
\]

(6)

For \( N \) measurements (\( k = 1, 2, \ldots, N \)), we have

\[
Z_N = H_N \theta + n_N
\]

(7)

where \( Z_N = [Z(1), Z(2), \ldots, Z(N)]^T \), \( H_N = [1, 1, \ldots, 1]^T \), and \( n_N = [n(1), n(2), \ldots, n(N)]^T \). To get a forgetting factor algorithm, we introduce an ellipsoid factor \( \beta \) into the data vector \( Z_N \) and \( H_N \). Then

\[
\tilde{Z}_N = [\beta^{N-1}Z(1), \beta^{N-2}Z(2), \ldots, \beta Z(N-1), Z(N)]^T
\]

(8)

and

\[
H_N = [\beta^{N-1}, \beta^{N-2}, \ldots, \beta, 1]^T
\]

The model (eq 7) can be written as

\[
\tilde{Z}_N = \tilde{H}_N \theta + n_N
\]

(9)

where \( n_N = [\beta^{N-1}n(1), \beta^{N-2}n(2), \ldots, \beta n(N-1), n(N)]^T \). Let the object function be

\[
J(\theta) = (\tilde{Z}_N - \tilde{H}_N \theta)^T(\tilde{Z}_N - \tilde{H}_N \theta)
\]

(10)

Next, we will use a recursive algorithm to minimize the function (10). Taking the derivative of \( J(\theta) \) with respect to \( \theta \) and setting it to zero, we get

\[
\hat{\theta} = \tilde{H}_N^T \tilde{Z}_N
\]

(11)

Define \( \mu = \beta^2 \), \( P(k)^{-1} = \tilde{H}_N^T \tilde{H}_k \), and \( \hat{\theta} = \) estimation value of \( \theta \), then eq 10 can be written as a recursive algorithm

\[
\hat{\theta}(k) = \hat{\theta}(k - 1) + P(k)(z(k) - \hat{\theta}(k - 1))
\]

(12)

\[
P(k) = \frac{1}{\mu}(1 - \frac{P(k - 1)}{\mu + P(k - 1)})P(k - 1)
\]

(13)

where \( \mu \) is a constant forgetting factor and satisfies the limit condition \( 0 < \mu \leq 1 \).

The above algorithm, we have the following properties for boiler process:

**Theorem 1.** The boiler leak estimate of \( \theta \) given by (10) is approximately unbiased if \( \xi_{in}, \xi_{out} \), and \( \omega \) are statistically independent, and \( N \) is large enough. **Proof.** See Appendix A.

**Theorem 2.** For the boiler leak estimate of \( \theta \) given by (10), if \( \xi_{in}, \xi_{out} \), and \( \omega \) are statistically independent and \( E(\xi_{in} \xi_{in}^T) = E(\xi_{out} \xi_{out}^T) = E(\xi_{in} \xi_{out}^T) = 0 \) then

\[
\text{Cov}(\hat{\theta}) = \begin{pmatrix} r_{max} + & \omega_{max} + \frac{E_{max}^2}{N^2} \end{pmatrix}
\]

(14)

**Proof.** See Appendix B.

4. Simulation Experiment

A dynamic computer simulation model, named SYNSIM, for Syncrude utility system has been developed.23 The overall model includes submodels of the utility boilers, CO boilers and OTSG boilers with their controls, the 900#, 600#, 150#, and 50# headers and associated letdown system controls, the turbine-generator sets with their controls, and the plant electrical load with dynamic load-shedding. The SYNSIM model was developed with the purpose of studying the causes of certain upset conditions that have been sporadically detected, as well as using as a general tool for stability analysis. The model has been extensively tested, and correlation between measurements from the true plant outputs and predictions by SYNSIM are excellent. This model was used to obtain the simulations results presented here.

Boilers are inherent nonlinear processes and they often run in the condition of changing set points due to varying boiler loads. The change of boiler loads will cause the change of the water storage in boiler drum and pipes, which will affect the feedwater-steam balance relationship and then affect the result of leak detection. The change of unmeasured blow down flow and the existence of many disturbances in a boiler system will also affect the accuracy of leak detection. Thus, the leak detection scheme with a forgetting factor should be adopted to reduce the effects of these factors and enhance the accuracy of the leak detection.

The algorithm in (10) and (11) will be used to identify the boiler tube leaks, in which a constant forgetting factor is chosen as 0.9992. The measurement noise has zero mean and amplitude about 0.5% of measured signals. Load disturbance is zero mean and amplitude
about 1% of the actual load. We present the result in several cases.

Case 1. The boiler load varies around 80 kg/s, and the boiler tube leak is 0.3 kg/s. Figure 2 is the leak estimation curve, in which the estimated leaks using proposed method are 0.431 kg/s. If the leak is estimated using least-squares algorithm without the forgetting factor, then the estimated value of leak is 0.177 kg/s.

Case 2. The boiler load changes from 61 to 80 kg/s, and boiler tube leak is 0.5 kg/s. Figure 3 shows the leak estimation process, and the estimated leak using the proposed method is 0.564 kg/s. If the leak is estimated using least-squares algorithm without the forgetting factor, then the estimated value of the leak is 0.028 kg/s.

Case 3. The boiler load changes from 80 to 56 kg/s, and the boiler tube leak is 0.5 kg/s. Figure 4 shows the leak estimation process, and the estimated value of leak using proposed method is 0.606 kg/s. If the leak is estimated using the least-squares method without the forgetting factor, the leak estimated value is 1.024 kg/s.

From the above simulations, we find that the proposed scheme with forgetting factor gives much better identification results in the case of boiler load change, and the proposed scheme and the estimation scheme without forgetting factors have similar identification performances when the boiler load varies around some value.

5. Application Using Real Plant Data

The proposed method is used to detect boiler tube leak and steam leak based on real plant operation data supplied by Syncrude Canada, in which leaks took place in one CO boiler and two utility boilers.

The boiler tube or steam leak will affect the material balance relationship, which will result in the change of residual. However, often it is difficult to directly distinguish from the material balance error $\epsilon(k) = x_{in}(k) - x_{out}(k)$ (see Figures 5 and 6) whether leakage happens or not, especially when the leak is small. The existing leak detection methods used in Syncrude can detect the leak only when leak is larger than 2.5 kg/s. The method proposed in this paper can detect smaller leak and thus can give earlier leak warning for operators.

For industrial boiler processes, we need to select thresholds for each boiler due to different boiler load disturbances, unmeasured boiler blown flow and measurement noises. When the processed residual is larger than the threshold, a leak alarm will be triggered. The thresholds for the three boilers with Syncrude are listed in Table 1, which are settled based on the residual.
estimation values for about half-year fault-free data from Syncrude.

(1) CO Boiler Tube Leak Detection. A leak fault was detected in Figure 7 by using the proposed scheme. From this figure, we know that the CO boiler started to leak at the 7.3th day during the period, and the leak rate was 0.5–1 kg/s. The leakage can be found 0.3 days later after it leaked by using the scheme.

The continued leak detection curve for the boiler is given in Figure 8. Recorded data showed “shut down” for about 2 h after the end time of the curve in the Syncrude PI database.

It can be seen that the leak mount increased gradually from about 1.0 to 3 kg/s in Figure 9. At the 11.6th day, an operator found the leak problem in the boiler because of large leakage and began to shut down the boiler. Then the boiler tube had leaked for about 16.3 days.

(2) Utility Boiler A Tube Leak Detection. It can be seen from Figure 10 that the utility boiler A began to leak at the 6.9th day, and the leak amount was about 0.5–0.8 kg/s. This leak was detected 2 days later since it started to leak. Continuing from here, the leak amount was kept larger than 0.5 kg/s for 11 days (the curve is omitted here).

It shows that the leak continued for about another 12 days in Figure 11. The operator found the leak problem at the 11.75th day in the figure because the large leak took place. At this time, the utility boiler tube had leaked for about 29 days.

(3) Utility Boiler B Steam Leak Detection. The curve was varied before the seventh day in Figure 12 because the operator regulated the blow down flow in this period. At the 7.3th day in the plot, the curve suddenly went up to about 4 kg/s, which means the boiler steam leak rate was about 1.5 kg/s, and it was detected several hours later by using the proposed method. After this time, the steam leak was kept larger than about 1.5 kg/s for about 9.5 days (the plot is omitted here).

The next 4 days’ plot is given in Figure 13. It is easy to see that the steam leaked for about 2 days in the figure, and the operator found the leak problem on the second day. At this time, the steam leak had lasted for about 12.9 days.

6. Conclusion

In this paper, based on the characteristics and models of boiler systems, a practical approach to detect boiler
Figure 8. Continued leak detection for CO boiler.

Figure 9. Continued leak detection for CO boiler.

Figure 10. Utility boiler A leak detection.

Figure 11. Continued leak detection for utility boiler A.

Figure 12. Utility boiler B leak detection.
leak faults is developed. The method employs least squares with forgetting factors. The leak estimation properties of this method are analyzed under certain conditions. Simulations and applications in boiler leak detection show the feasibility and effectiveness of the method. The proposed method can improve the performance of the leak detections under the conditions of boiler load disturbances and can give operators earlier warning for boiler tube leak and steam leak problems.

Appendix A. Proof of Theorem 1

Proof. From eqs 5, 7, and 9, we find that

\[ \hat{\theta} = (H_N^T H_N)^{-1}H_N^T (H_N \theta - \bar{\omega}_N + \bar{\xi}_N) = \theta - (H_N^T H_N)^{-1}H_N^T \bar{\omega}_N + (H_N^T H_N)^{-1}H_N^T \bar{\xi}_N \]  

(A1)

where

\[ \bar{\omega}_N = [\beta^{N-1} \omega(1), \beta^{N-2} \omega(2), \ldots, \beta \omega(N-1), \omega(N)]^T \]

and

\[ \bar{\xi}_N = [\beta^{N-1} \xi(1), \beta^{N-2} \xi(2), \ldots, \beta \xi(N-1), \xi(N)]^T \]

Taking the expectation on both sides of the above equation, we get

\[ E\{\hat{\theta}\} = \theta - (H_N^T H_N)^{-1}H_N^T E\{\bar{\omega}_N\} + (H_N^T H_N)^{-1}H_N^T E\{\bar{\xi}_N\} \]  

(A2)

Since \( \bar{\xi}_{in} \) and \( \bar{\xi}_{out} \) are independent noises with zero mean, it follows that \( E\{\bar{\xi}\} = E\{\bar{\xi}_{in}\} - E\{\bar{\xi}_{out}\} = 0 \), and thus

\[ E\{\bar{\xi}_N\} = 0 \]  

(A3)

From the assumption below eq 1, we have

\[ E\{\omega_i\} \approx \frac{1}{N} \sum_{k=1}^{i} \omega(k) = \frac{\bar{\epsilon}_i}{N}, \quad i = 1, 2, \ldots, N \]  

(A4)

Let \( \epsilon_{max} = \max (|\beta^{N-1}|, 1, 1, \ldots, N) \), then

\[ (H_N^T H_N)^{-1}H_N^T E\{\bar{\omega}_N\} \leq \frac{1}{N} (H_N^T H_N)^{-1}H_N^T \epsilon_N \]

\[ \leq \frac{\epsilon_{max}}{N} \frac{\beta^{N-1} + \beta^{N-2} + \ldots + \beta + 1}{N} \leq \frac{\epsilon_{max}}{N} \frac{\beta^{N}}{N} + 1 \]

\[ \leq \frac{\sqrt{\mu}}{\mu + 1} \leq \frac{\epsilon_{max} \mu}{\sqrt{\mu}} \leq \frac{\epsilon_{max} \mu_{min}}{\mu_{min} + 1} \leq 2 \epsilon_{max} \]

where \( \epsilon_N = [\beta^{N-1} \epsilon(1), \beta^{N-2} \epsilon(2), \ldots, \beta \epsilon(N-1), \epsilon(N)]^T \)

Thus, from the above equations, (A2) and (A3), we obtain

\[ E\{\hat{\theta}\} = \theta - (H_N^T H_N)^{-1}H_N^T E\{\bar{\omega}_N\} \approx \theta - \frac{1}{N} (H_N^T H_N)^{-1}H_N^T \epsilon_N \]  

(A5)

therefore

\[ \lim_{N \to \infty} E\{\hat{\theta}\} \approx \theta - \lim_{N \to \infty} \frac{1}{N} (H_N^T H_N)^{-1}H_N^T \epsilon_N = \theta \]  

(A6)

From (A5) and (A6), we know that the estimation error of \( \hat{\theta} \) is less than \( 2 \epsilon_{max} / N \). If \( N \) approaches infinity, then the estimation error will approach zero. In this case, we conclude that the parameter estimation is approximately unbiased.

Appendix B. Proof of Theorem 2

Proof. From (A2) and the properties of \( \bar{\xi}_{in} \) and \( \bar{\xi}_{out} \), we have

\[ \text{Cov}\{\hat{\theta}\} = E\{(\hat{\theta} - E\{\hat{\theta}\})(\hat{\theta} - E\{\hat{\theta}\})^T\} = E\{(\theta - \hat{\theta} + (H_N^T H_N)^{-1}H_N^T E\{\bar{\omega}_N\}) \theta - \hat{\theta} + (H_N^T H_N)^{-1}H_N^T E\{\bar{\omega}_N\}^T\} \]

(B1)

Using (A1) and (B1), we get

\[ \text{Cov}\{\hat{\theta}\} = E\{(H_N^T H_N)^{-1}H_N^T \bar{\omega}_N - (H_N^T H_N)^{-1}H_N^T \bar{\xi}_N + (H_N^T H_N)^{-1}H_N^T E\{\bar{\omega}_N\} \theta - \hat{\theta} + (H_N^T H_N)^{-1}H_N^T E\{\bar{\omega}_N\}^T\} \]

\[ \leq (H_N^T H_N)^{-1}H_N^T \text{Cov}\{\bar{\omega}_N\} H_N^T (H_N^T H_N)^{-1} + 3 (H_N^T H_N)^{-1}H_N^T E\{\bar{\xi}_N\} \theta - \hat{\theta} + (H_N^T H_N)^{-1}H_N^T E\{\bar{\xi}_N\}^T \]

Because \( \bar{\xi}_{in} \) and \( \bar{\xi}_{out} \) are zero mean noises and statistically independent of \( H_N \) and \( \bar{\omega}_N \),

\[ \text{Cov}\{\hat{\theta}\} = (H_N^T H_N)^{-1}H_N^T \text{Cov}\{\bar{\omega}_N\} H_N^T (H_N^T H_N)^{-1} + 3 (H_N^T H_N)^{-1}H_N^T E\{\bar{\xi}_N\} \theta - \hat{\theta} + (H_N^T H_N)^{-1}H_N^T E\{\bar{\xi}_N\}^T \]

\[ \leq (H_N^T H_N)^{-1}H_N^T (\text{Cov}\{\bar{\omega}_N\} H_N^T (H_N^T H_N)^{-1}) + 3 (H_N^T H_N)^{-1}H_N^T \text{Cov}\{\bar{\xi}_N\} \theta - \hat{\theta} + (H_N^T H_N)^{-1}H_N^T \text{Cov}\{\bar{\xi}_N\}^T \]

\[ \leq (H_N^T H_N)^{-1}H_N^T (\text{Cov}\{\bar{\omega}_N\}) H_N^T (H_N^T H_N)^{-1} + 3 (H_N^T H_N)^{-1}H_N^T \text{Cov}\{\bar{\xi}_N\} \theta - \hat{\theta} + (H_N^T H_N)^{-1}H_N^T \text{Cov}\{\bar{\xi}_N\}^T \]

\[ = (H_N^T H_N)^{-1}H_N^T \text{Cov}\{\bar{\omega}_N\} H_N^T (H_N^T H_N)^{-1} + 3\epsilon_{max} \frac{\mu}{\mu + 1} \leq 3\epsilon_{max} \frac{\mu}{\mu + 1} \]

\[ \leq \frac{\beta^{N-1} + \beta^{N-2} + \ldots + \beta + 1}{N} \leq \frac{\beta^{N}}{N} + 1 \]

\[ \leq \frac{\mu}{\mu + 1} \leq \frac{\mu_{min}}{\mu_{min} + 1} \leq 2 \epsilon_{max} \]

where \( I_N \) is an unity matrix. This completes the proof.
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