Leakage Detection of Steam Boiler Tube in Thermal Power Plant Using Principal Component Analysis

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ABSTRACT

Tube leakage of steam boiler can decrease the whole efficiency of power plant cycle, and eventually cause an unscheduled shutdown. In this paper, we propose a leakage detection method for steam boiler tubes in thermal power plant (TPP) using principal component analysis and exponentially weighted moving average (EWMA). To determine the number of principal components, the cumulative percent variance technique is employed, and the Q statistic is used as the detection index. If the Q statistic of an unseen sample is larger than a predefined threshold value, the sample is detected as a fault sample and an alarm signal is generated. EWMA is used to reduce false alarms. To demonstrate the performance, we apply the proposed method to an unplanned shutdown case due to boiler tube leakage, which is collected from distributed control systems of 250 MW coal-fired TPP. The experiment results show that the proposed method can detect failure symptoms of the case successfully.

1. INTRODUCTION

In large-scale industrial processes (e.g., coal-fired thermal power plant (TPP)), online monitoring and fault diagnosis are indispensable for effective operation and maintenance; they provide potential benefits for improving safety, reliability and availability of the processes (Wang, Ma, and Wang, 2014). A fault is defined as an unpermitted deviation of at least one characteristic property or variable of the system from acceptable, usual, or standard behavior (Patan, 2008). In an early stage, the effects of a fault on system performance may be insignificant. However, if there are no proper corrective actions, the fault results in system malfunction and failure, and cause severe performance degradation and losses of life and property. A fault detection system can monitor the operating conditions of power plants and identify a fault at its earliest developing stage by analyzing complex and non-stationary patterns of process variables; thus, it can help operators to take proper actions in advance.

Boiler is important equipment in power plant, chemical and refinery processes. Boiler tube failures cause approximately 60% of boiler outages (An, Wang, Sarti, Antonacci, and Shi, 2011). The tube failures are the main factors that influence safe and economical operations of power plant. The timely detection of boiler tube leakages can reduce secondary damage and productivity losses caused by unscheduled shutdowns. In the following, we summarize several previous studies on boiler tube leakage detection.

Sun et al. (2002) developed a model-based least-squares algorithm with a time-varying forgetting factor for leak detection in boiler steam-water systems. Afgan et al. (1998) described the development of an expert system for detecting boiler tube leakage based on selected diagnostic variables obtained by radiation heat flux measurements. Zhang et al. (2015) used three-dimensional space location algorithm based on the time delay of arrival to determine the location of water-cooling wall tube leaks in real time. An et al. (2011) used a four-element acoustic array and a set of hyperbolic equations to locate boiler leaks. Widarsson and Dotzauer (2008) evaluated a new method for early warning to detect leakage of a typical recovery boiler using Bayesian network. Rostek et al. (2015) reported early detection and prediction of leaks in fluidized-bed boilers using artificial neural network (ANN). Sun et al. (2005) proposed a new preprocessing technique and dynamic principal component analysis (PCA) model for boiler leak detection.

When machine learning techniques such as ANN are used for fault detection, the difficulty lies in identifying significant inputs among many initial input candidates for effective learning. Furthermore, a number of models should be implemented for residual generation if the models have multi-input single-output structure. In this paper, we propose a PCA-based tube leakage detection method for steam boiler in TPP. PCA is a powerful tool capable of compressing data and reducing its dimensionality so that essential information is saved and easier to analyze than the original huge data set (Ajami and Daneshvar, 2012). In PCA, prior domain knowledge is not needed and historical data is only required for fault detection. PCA-based fault detection is performed by calculating detection indices using eigenvectors in the subspace of principal components (PCs). The PCA-based method has been widely applied for self powered neutron detectors, chiller systems, helical coil steam generator systems, pediatric emergency department and continuously stirred tank reactor (Peng, Li, and Wang, 2015; Beghi, Brignoli, Cecchinato, Menegazzo, Rampazzo, and Simmini, 2016; Zhao, and Upadhyaya, 2006; Harrou, Kadri, Chaabane, Tahon, and Sun, 2015; Harrou, Nounou, Nounou, and Madakyaru, 2013).

In this paper, to determine the number of PCs, cumulative percent variance (CPV) method is employed, and Q statistic and its smoothed value are used as detection indices. Using exponentially weighted moving average (EWMA), the smoothed value is calculated to consider the trend of the Q statistic (Harrou, Nounou, and Nounou, 2013). To verify the performance, we use an unplanned shutdown case due to boiler tube leakage in 250 MW coal-fired TPP. Experimental results show that the PCA-based method can successfully detect failure symptoms that appeared immediately before the shutdown. In addition, the results illustrate the validity of EWMA for fault detection.

The remainder of this paper is organized as follows. Section 2 explains the PCA-based fault detection method. Section 3 briefly summarizes the target system, i.e., 250 MW coal-fired TPP, and boiler tube leakage. In Section 4, we present the experimental results, and finally we give our conclusions in Section 5.

2. PRINCIPAL COMPONENT ANALYSIS

PCA is a multivariate statistical technique for dimensionality reduction of collected dataset. In PCA-based fault detection method, arbitrary m-dimensional vectors are projected onto a lower dimensional (i.e., l-dimension) subspace, and abnormal operating conditions are identified on the l-dimensional subspace.

2.1. Definition of PCA

Let $\mathbf{X} = [\mathbf{x}_1,..., \mathbf{x}_n]^T \in \Re^{n\times m}$ be a collected data matrix, where $\mathbf{X}$ is composed of m-dimensional n data vectors $\mathbf{x}_i \in \Re^m$. After applying z-score standardization to each dimension, $\mathbf{X}$ can be decomposed using singular value decomposition as follows:

$$\mathbf{X} = \mathbf{T}\mathbf{P}^T, \tag{1}$$

where $\mathbf{T} = [\mathbf{t}_1,..., \mathbf{t}_m] \in \Re^{n\times m}$ and $\mathbf{P} = [\mathbf{p}_1,..., \mathbf{p}_m] \in \Re^{m\times m}$ consist of score vectors $\mathbf{t}_j \in \Re^n$ and orthogonal loading vectors $\mathbf{p}_j \in \Re^m$, respectively. The vectors $\mathbf{p}_j$ are eigenvectors of covariance matrix $\mathbf{\Sigma}$ defined as

$$\mathbf{\Sigma} = \frac{1}{n-1}\mathbf{X}^T\mathbf{X} = \mathbf{P}\mathbf{\Lambda}\mathbf{P}^T, \tag{2}$$

where $\mathbf{P}\mathbf{P}^T = \mathbf{P}^T\mathbf{P} = \mathbf{I}_m$ and $\mathbf{\Lambda} = \mathrm{diag}(\lambda_1,..., \lambda_m)$ is diagonal matrix whose diagonal components sorted in descending order (i.e., $\lambda_1 >...> \lambda_m$) are eigenvalues of $\mathbf{\Sigma}$. The matrix $\mathbf{\Lambda}$ and λ_j are defined as (Joe Qin, 2013)

$$\begin{aligned} \mathbf{\Lambda} &= \frac{1}{n-1}\mathbf{T}^T\mathbf{T} = \mathrm{diag}\{\lambda_1,...,\lambda_m\}, \\ \lambda_j &= \frac{1}{n-1}\mathbf{t}_j^T\mathbf{t}_j. \quad (j = 1,...,m) \end{aligned} \tag{3}$$

In other words, λ_j is the variance of n projections of data vector $\mathbf{x}_i$, $i = 1,..., n$ onto eigenvector $\mathbf{p}_j$. In PCA, dimensionality reduction is performed by selecting l eigenvectors that correspond to largest l eigenvalues among m eigenvalues sorted in decreasing order.

2.2. Determining the number of PCs

The performance of PCA depends on the value for l, i.e., the retained number of PCs in the subspace. If the number of selected PCs is too small, important variations cannot be detected in the subspace and the performance deteriorates. On the other hand, if there are too many retained PCs, extraneous components could be considered. To select the proper number of PCs, several methods such as scree plot, CPV, cross validation, parallel analysis, sequential test, resampling and profile likelihood have been developed (Harrou et al., 2013). In this paper, the CPV method is employed and the CPV value is calculated as (Harrou et al., 2015)

$$CPV(l) = \frac{\sum_{k=1}^{l}\lambda_k}{\mathrm{tr}(\mathbf{\Sigma})}\times 100 = \frac{\sum_{k=1}^{l}\lambda_k}{\sum_{j=1}^{m}\lambda_j}\times 100. \quad l = 1,...,m \tag{4}$$

After calculating $CPV(l)$, $l = 1,..., m$, the value for l is determined by

$$l^* = \min\left(\{l \mid CPV(l) > CPV_{\mathrm{th}}\}\right), \quad l = 1, \ldots, m, \tag{5}$$

where CPV_{th} is a threshold value of $CPV(l)$ (e.g., 90%). When CPV_{th} is set as 90%, l PCs selected by eq. (4) capture more than 90% of total variations. After determining the number of PCs, $\mathbf{X}$ can be reformulated as

$$\mathbf{X} = \mathbf{T}\mathbf{P}^T = \left[\hat{\mathbf{T}} \vdots \tilde{\mathbf{T}}\right]\left[\hat{\mathbf{P}} \vdots \tilde{\mathbf{P}}\right]^T = \hat{\mathbf{T}}\hat{\mathbf{P}}^T + \tilde{\mathbf{T}}\tilde{\mathbf{P}}^T, \tag{6}$$

where $\hat{\mathbf{T}} = [\mathbf{t}_1, \ldots, \mathbf{t}_l] \in \Re^{n \times l}$ and $\tilde{\mathbf{T}} = [\mathbf{t}_{l+1}, \ldots, \mathbf{t}_m] \in \Re^{n \times (m-l)}$ consist of l retained PCs and $m-l$ ignored PCs, respectively, and $\hat{\mathbf{P}} = [\mathbf{p}_1, \ldots, \mathbf{p}_l]^T \in \Re^{m \times l}$ and $\tilde{\mathbf{P}} = [\mathbf{p}_{l+1}, \ldots, \mathbf{p}_m]^T \in \Re^{m \times (m-l)}$ are composed of l retained eigenvectors and $m-l$ ignored eigenvectors, respectively. Eq. (6) can be rewritten as

$$\mathbf{X} = \hat{\mathbf{T}}\hat{\mathbf{P}}^T + \tilde{\mathbf{T}}\tilde{\mathbf{P}}^T = \underbrace{\mathbf{X}\hat{\mathbf{P}}\hat{\mathbf{P}}^T}_{\hat{\mathbf{X}}} + \underbrace{\mathbf{X}\left(\mathbf{I}_m - \hat{\mathbf{P}}\hat{\mathbf{P}}^T\right)}_{\mathbf{E}}, \tag{7}$$

where $\hat{\mathbf{X}}$ is the approximated part by l retained PCs and $\mathbf{E}$ corresponds to the part of approximation error.

2.3. Detection indices

As described in eq. (7), an arbitrary m-dimensional data vector $\mathbf{x}$ can be decomposed into approximated part $\hat{\mathbf{x}}$ and error part $\tilde{\mathbf{x}}$. The norm of $\tilde{\mathbf{x}}$ is small when target system is normally operated, but its magnitude sharply increases when a system fault occurs. Q statistic measuring the magnitude of the size of $\tilde{\mathbf{x}}$ is defined as

$$Q = \|\tilde{\mathbf{x}}\|^2 = \left\|\left(\mathbf{I}_m - \hat{\mathbf{P}}\hat{\mathbf{P}}^T\right)\mathbf{x}\right\|^2. \tag{8}$$

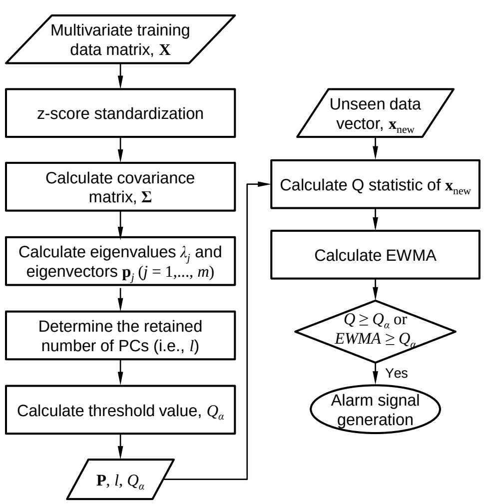


Fig. 1. PCA-based fault detection procedures.

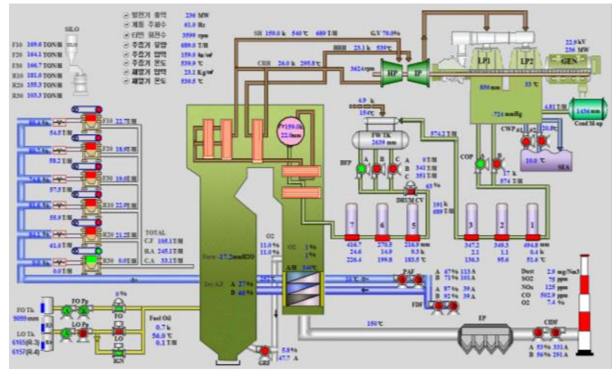


Fig. 2. An example of DCS screen for 250MW coal-fired power plant.

After calculating the Q statistic for an unseen data vector, an alarm signal is generated if the Q statistic is larger than or equal to a predefined threshold value. The threshold value of Q statistic, i.e., Q_α is defined as (Jackson, and Mudholkar, 1979)

$$Q_\alpha = \theta_1\left[\frac{c_\alpha\sqrt{2\theta_2 h_0^2}}{\theta_1} + 1 + \frac{\theta_2 h_0(h_0 - 1)}{\theta_1^2}\right]^{1/h_0}, \tag{9}$$

where $\theta_k = \sum_{j=l+1}^{m} \lambda_j^k$, k = 1, 2, 3, $h_0 = 1 - \frac{2\theta_1\theta_3}{3\theta_2^2}$, and c_α is the upper $(1-\alpha)$th percentile of normal distribution.

2.4. Summary of PCA-based fault detection procedures

Fig. 1 summarizes PCA-based fault detection procedure divided into training and test steps. In the training step, covariance matrix $\mathbf{\Sigma}$, its eigenvectors $\mathbf{p}_j$, the proper number of PCs and Q_α are sequentially calculated. In the test step, after calculating detection indices of an unseen vector $\mathbf{x}_{\mathrm{new}}$, alarm signal occurs if the detection indices are larger than or equal to the Q_α.

3. SUMMARY OF THE TARGET SYSTEM: 250 MW COAL-FIRED POWER PLANT

In this study, the target system is a 250 MW coal-fired TPP. Fig. 2 shows an example of distributed control system (DCS) screen. An unplanned shutdown data due to boiler tube leakage was collected from the DCS and is used to demonstrate the performance.

3.1. Coal-fired thermal power plant

In the coal-fired power plant, after transforming feedwater into steam by thermal energy produced from combustion of bituminous coal, electricity is generated by driving steam turbine and generator. Fig. 3 shows a simplified schematic diagram of the target TPP. (Yu, Jang, Yoo, Park, and Kim, 2016). Steam boiler raises steam by heating feedwater using thermal energy converted from fossil fuel. The steam boiler

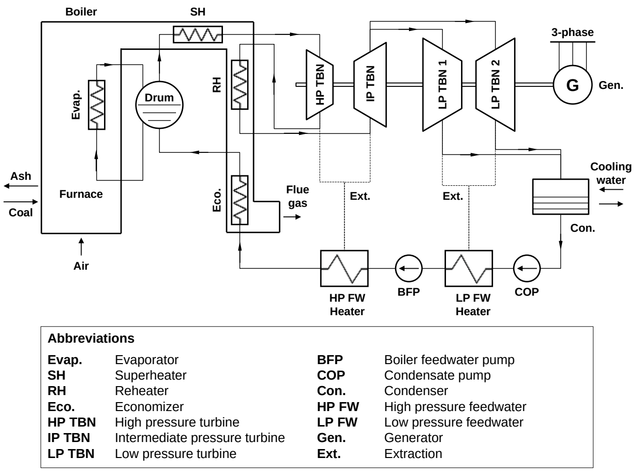


Fig. 3. Simplified schematic diagram of the coal-fired power plant.

follows the thermodynamic steam cycle, i.e., Rankine cycle, which is a practical implementation of the ideal Carnot cycle (Flynn, 2003). Steam, an important medium to produce mechanical energy, can be generated from abundant water, does not react much with materials of the power plant equipment and is stable at the required operation temperature in the power plant (Raja, 2006).

Bituminous coal pulverized in advance is transformed into thermal energy at the furnace of the steam boiler. Before flowing into drum, the feedwater is preheated by passing through a series of low- and high-pressure heaters and economizer. The heater and economizer raise the feedwater by extraction steam from turbine and high temperature flue gas, respectively. These preheating steps improve efficiency of the whole cycle. The drum supplies feedwater that will be converted into steam and temporarily stores the steam produced by evaporator. The saturated steam by evaporator contains a little moisture. Superheater converts the steam into high-purity and high pressure and temperature superheated steam that will be supplied to turbine.

In the turbine, the superheated steam expands, turbine blades are rotated and thermal energy is transformed into mechanical energy. The rotating turbine blades drives electric generator and three phase electric power is generated. After performing mechanical works at high pressure turbine, the steam is reheated by reheater and supplied to intermediate pressure turbine. The steam exiting from low pressure turbine is condensed into condensate water and it is stored at condenser's hotwell. The condensate water is boosted by condensate pump and passes through low pressure feedwater heater. And then, the water is deaerated by deaerator and boosted by feedwater pump. The boosted water passes through high pressure heater and economizer and is fed into the boiler again.

3.2. Boiler tube leakage

Failure of one or more tubes in the boiler can be detected by sound and either by an increase in make-up water requirement (indicating failure of water carrying tubes) or by an increased draft in the superheater or reheater areas (due to failure of superheater or reheater tubes) (Sarkar, 2015). The boiler tubes can be influenced by several damage processes such as inside scaling, waterside corrosion and cracking, fireside corrosion and/or erosion, stress rupture due to overheat and creep, vibration-induced and thermal fatigue cracking, and defective welds (Oakey, 2011).

The tube leakage from a pin-hole could be tolerated due to the adequate margin of feedwater and the leakage can be corrected after suitable scheduled maintenance. However, if the boiler is continuously operated with the leakage, much pressurized fluid leaks out eventually and severe damage to neighboring tubes occurs. The tube leakage of boiler, superheater and reheater could give rise to serious decline of efficiency. In the short term, the tube leakage of superheater and reheater is more fatal than that of boiler. When severe tube leakage happens, it is difficult to maintain the level of the boiler drum properly. If leaking water is spilled into furnace, combustion of coal is disturbed. In these cases, the plant should be shut down immediately.

4. EXPERIMENT RESULTS

In this section, the PCA-based fault detection method is applied to an unscheduled shutdown data due to boiler tube leakage. The aim of the method is to detect faults or failure symptoms just before the shutdown and prevent further deterioration of them. The collected dataset consists of 4320 training and 1054 test samples, respectively, and the monitored variables are summarized in Table 1. Each sample was recorded in discrete time intervals, i.e., 5 minute intervals, and the training samples are collected from normal target system. Among a large number of process variables, the

Table 1. Summary of monitored variables for boiler tube leakage detection.

Notation	Description	Unit
X_1	Generator output	MW
X_2	Steam flow	t/h
X_3	Main steam pressure	kg/cm^2
X_4	Main steam temperature	^{o}C
X_5	Reheater pressure	kg/cm^2
X_6	Reheater temperature	^{o}C
X_7	Furnace pressure	kg/cm^2
X_8	Drum level	m
X_9	Condenser pressure	kg/cm^2
X_{10}	Condenser make-up flow	t/h
X_{11}	Feedwater flow	t/h
X_{12}	Conductivity of condenser A	μmho
X_{13}	Conductivity of condenser B	μmho

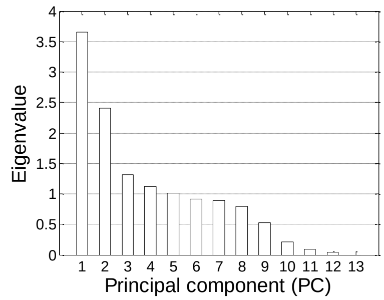


Fig. 4. Eigenvalues of each principal component.

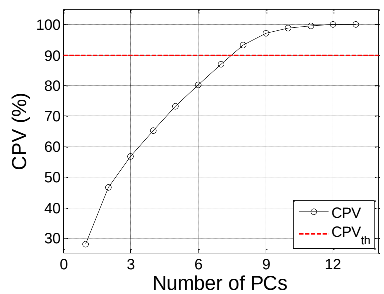


Fig. 5. Results of the CPV method for determining the retained number of PCs.

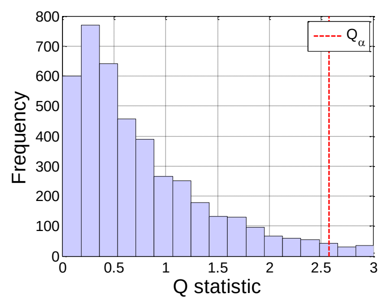


Fig. 6. Histogram of Q statistics for the training samples and Q_α.

monitored variables for boiler tube leakage detection are carefully selected by domain experts. After applying training step described in Fig. 1 to the training samples, the performance is validated using the test samples.

4.1. Results of the training step

The standardized fault-free training data is used to calculate covariance matrix, eigenvectors, the proper number of PCs and Q_α. Fig. 4 shows eigenvalues that correspond to 13 PCs. As shown in Fig. 4, the PCs from first to third capture approximately 60 percent of multivariate data information, i.e., important variations, while the PCs from 10th to 13th contain lower than 5 percent of the information. In other words, most important variations can be captured by several PCs and dimensionality reduction is also possible. In this paper, CPV method is employed for determining the proper number of PCs and Fig. 5 shows the results of the CPV method. In Fig. 5, CPV_{th} is set as 90% and indicated by horizontal dashed red line. The retained number of PCs is decided as 8 by eq. (5). The first eight PCs can capture 93.18 percent of entire variations. As described in eq. (8), Q statistic is calculated by only eight retained eigenvectors. After deciding the retained number of PCs, Q_α is calculated by eq. (9). Fig. 6 shows the histogram of Q statistics for the training samples and Q_α for fault detection. In Fig. 6, the value for α is set as 0.05 and the calculated value of Q_α is 2.5742 and indicated by a vertical dashed red line.

4.2. Results of the test step

In this subsection, the results of fault detection using the PCA-based method are presented. EWMA is used to generate alarm signals and its window size is set as 6, i.e., the six most recent Q statistics are considered. The detection indices are larger than or equal to a predetermined threshold value when the conditions of target system are abnormal. Fig. 7 shows Q statistics for the test samples and EWMA of them, and alarm signals without and with EWMA. In Fig. 7, shutdown time is indicated by vertical solid dashed red lines. In Fig. 7 (a), the horizontal dashed red line represents the predetermined value of Q_α and EWMA of Q statistics is indicated by solid purple line. The red points in Fig. 7 (b) and (c) represents alarm signals without and with EWMA, respectively. As shown in Fig. 7 (a) and (b), inconsistent false alarms can be easily removed using EWMA. The main reason for the improvements is that the trend from past to present can be considered for alarm signal generation. In Fig. 7 (a), failure symptom region where alarm signals occur intensively is indicated by transparent red region and its enlargement and corresponding alarm signals are shown in Fig. 8. As shown in Fig. 8, due to the sharp increases of detection indices, alarm signals are generated for about ten hours just before the unplanned shutdown.

4.3. Performance evaluation

In this subsection, using four measures, the results of performance comparisons for both indices, i.e., without and with EWMA, are presented. The four performance measures, i.e., accuracy (ACC), sensitivity (SEN), specificity (SPE), and precision (PRE), are defined as (Han, Kamber, and Pei, 2011)

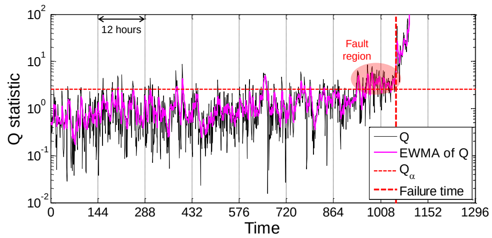
$$\mathrm{ACC} = \frac{TP + TN}{P + N}, \tag{10}$$

$$\mathrm{SEN} = \frac{TP}{P}, \tag{11}$$

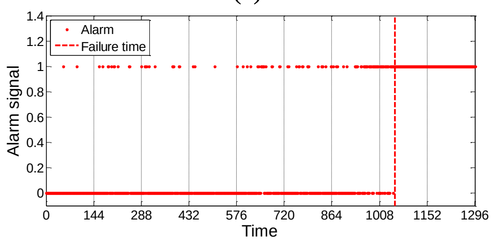
$$\mathrm{SPE} = \frac{TN}{N}, \tag{12}$$

$$\mathrm{PRE} = \frac{TP}{TP + FP}, \tag{13}$$

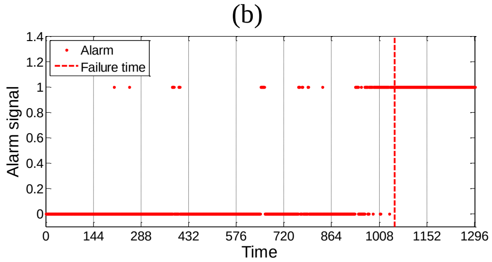
where



(a)

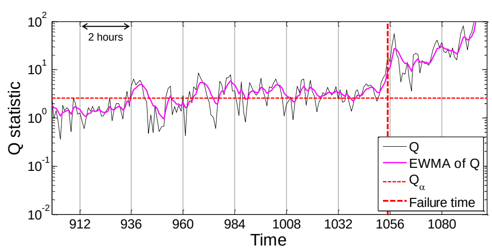


(b)

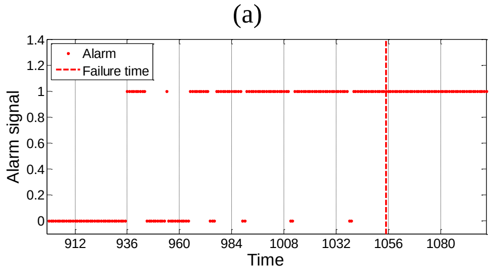


(c)

Fig. 7. (a) Q statistics and EWMA for the test samples on a semi-logarithmic scale (b) alarm signal without EWMA (c) alarm signal with EWMA.



(a)



(b)

Fig. 8. Enlargement of failure symptom region in Fig. 7 (a): (a) Q statistic and EWMA; (b) alarm signal with EWMA.

P the number of fault samples;
N the number of normal samples;
TP the number of samples that were correctly detected as fault samples;

Table 2. Performance comparisons (with EWMA vs. without EWMA).

	ACC	SEN	SPE	PRE
without EWMA	0.8786	0.6167	0.9122	0.4744
with EWMA	0.9412	0.7583	0.9647	0.7339
Improvements	7.12%	22.96%	5.76%	54.70%

TN the number of samples that were correctly determined as normal samples;
FP the number of samples that were incorrectly detected as fault samples;
FN the number of samples that were incorrectly determined as normal samples.

Table 2 lists the comparison results of fault detection performance using the four measures. It can be seen from the table that the results with EWMA show better performance than those without EWMA. The fact that both SEN and SPE are improved shows that the method with EWMA achieves better performance in both normal and abnormal regions. If Q statistic is used separately for alarm signal generation, it is assumed that those of present and past are independent each other; false alarm rate may increase because the trend of Q statistic is ignored. When EWMA of Q statistics is employed for detection index, false alarms were reduced since the tendency of Q statistics can be considered.

5. CONCLUSION

In this paper, PCA and EWMA were combined for detecting boiler tube leakage in TPP. To illustrate the performance, we applied the fault detection method to unplanned shutdown dataset collected from DCS of target TPP. The experimental results showed that the method can detect failure symptoms right before the shutdown successfully. Furthermore, fault detection with EWMA achieves better performance than those without EWMA. Since the states of tube leakage deteriorate gradually excluding sudden tube explosions, fault detection with EWMA is very effective.

In this paper, to demonstrate the performance, only one unplanned shutdown dataset was used. In future research, various shutdown dataset will be collected; the proposed method will be applied to the collected dataset and field application possibilities will be also examined. Moreover, we will develop a method that can consider different operating modes (e.g., free governor mode) for fault detection and diagnosis.

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