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**Condition Monitoring of Combustion Processes Through Flame Imaging and Kernel Principal Component Analysis**

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This article presents a methodology for the diagnosis of abnormal conditions in a combustion process through flame imaging and kernel principal component analysis (KPCA). A digital imaging system is used to capture real-time flame images and radiation signals, from which flame characteristics such as flame area, brightness, non-uniformity, and oscillation frequency are quantified. These characteristics are used as the variables to establish the KPCA model of the combustion process. With the use of Hotelling’s T² and Q statistics, the monitoring of abnormal conditions of the combustion process is achieved. Unlike the traditional principal component analysis (PCA) method, the KPCA method is capable of dealing with nonlinear data via nonlinear mapping, which projects the original nonlinear input space into a high-dimensional linear feature space. The effectiveness of the methodology is demonstrated by applying the approach to processing the data obtained on a 9MWth heavy oil fired combustion test facility. Experimental results obtained show that the KPCA method outperforms the traditional PCA in discriminating between the normal and abnormal combustion conditions, even in cases where the number of training samples is limited.

Keywords: Combustion process; Condition monitoring; Digital imaging; Fault detection; Flame monitoring; Hotelling’s T² statistic; KPCA; Q statistic

INTRODUCTION

In power generation industries, boilers are required to operate under optimum conditions to maintain high combustion efficiency and low atmospheric emissions. Abnormal conditions caused by drifts or faults in a combustion system would result in not only low efficiency and high emissions but also enormous impact on the health of the system. The recent trend of using a variety of fuels, including low quality coals, coal blends, and co-firing biomass and coal, has further deteriorated this issue.
Therefore, reliable online monitoring and fault detection techniques are desirable for the optimized operation and control of a combustion process.

Traditional statistical process control techniques, which are used to detect the occurrence of abnormal events in a process, adopt univariate control charts such as Shewhart, Exponentially Weighted Moving Average chart (EWMA), and Cumulative Sum chart (CUSUM). A problem with these techniques is that they chart only a small number of process variables and examine them one at a time. These techniques are inadequate for most modern process industries (MacGregor and Kourti, 1995). A more reliable diagnosis of an abnormal occurrence requires the simultaneous analysis of various process variables, which would demand an enormous amount of data processing and system response time. An alternative approach is to use multivariate statistical process control (MSPC) techniques (Bersimis et al., 2007), which utilize statistical modeling to reduce the information collected from process variables. The widely used MSPC techniques include principal component analysis (PCA), partial least square (PLS), and independent component analysis (ICA) (Kourti, 2005; Lee et al., 2004b; Lieftucht et al., 2006; Qin, 2003; Zuo et al., 2005). Among these techniques, PCA is the most common one due to its capability of extracting the main structure of high-dimensional and noisy data (Cho et al., 2005). The most extensive applications of PCA-based process monitoring have been found in the manufacturing industry for product quality control (Simoglou et al., 2000). Efforts have also been devoted to apply the PCA to combustion process monitoring. Zhao et al. (2008) proposed a PCA-based fault detection and diagnosis framework for the early fault detection and diagnosis in a municipal solid waste (MSW) incinerator for improved safety and continuity of the furnace. Tavares et al. (2011) also reported the application of the PCA and PLS to the continuous process control of an MSW moving grate-type incinerator, where the monitoring, fault detection, and diagnosis of the process were achieved based on the information extracted from historical data. However, in the aforementioned cases, supervising a combustion process is realized through the measurements of global variables such as air/fuel flow rates, steam pressure, and flue gas compositions, which provide a limited representation of the process inside the furnace. Previous research has suggested that the reliable identification of anomalous or off-design operation in a combustion system can be achieved by analyzing the sensorial information of the flame (Ballester and García-Armingol, 2010; Hernández and Ballester, 2008). On the other hand, the characteristics of individual flames in a multiburner system may behave very differently from that estimated from global variables, and consequently, the drift or malfunction of an individual burner can go unnoticed until the problem becomes serious (Ballester and García-Armingol, 2010). Furthermore, the PCA-based process monitoring techniques as mentioned above rely on the assumption that the process data are linear. They may not perform well in a nonlinear case, such as a combustion process.

As the central reaction zone of a combustion process, a flame contains valuable and instantaneous information about the combustion process. In the last decade, a number of techniques for monitoring and characterizing flame have been developed. Among them, optical sensing and imaging techniques (Barlow, 2007; Huang et al., 2000; Kohse-Höinghaus et al., 2005; Lu et al., 2004; Yan et al., 2002) are widely used for a variety of applications. While laser-based techniques require seeding or external
illumination, which poses significant challenges in applying those techniques for routine operation in industry, direct imaging techniques capture the radiation naturally emitted by a flame and have been recognized as one of the most suitable approaches for use in practical furnaces. The direct imaging techniques are capable of providing temporal and spatial characteristics of the flame, which make it possible to use such information to establish a model for early diagnosis of abnormal conditions in a combustion process. This article presents a methodology for the online condition monitoring of a combustion process through direct flame imaging and application of the KPCA technique. Flame characteristic parameters, including flame area, brightness, non-uniformity, oscillation frequency, etc., which were measured using a digital imaging system (Sun et al., 2011), are used as the process variables. The performance of the KPCA is evaluated and compared with that of the PCA on a 9MWth heavy oil fired combustion test facility (Sun et al., 2011).

METHODOLOGY

General Principle

Figure 1 shows the technical strategy for the KPCA-based online condition monitoring of a combustion process. The work flow can be described briefly as follows. First, optical sensorial information, including flame images and radiation signals, is captured by using a digital imaging system. Flame characteristics are then extracted from the optical sensorial information. Due to the complexity of a combustion process, such flame characteristics are generally nonlinearly correlated. By using the kernel method, these nonlinear flame characteristics are virtually mapped into a high-dimensional linear feature space, where the kernel principal components of these mapped flame characteristics are derived. Following that, the $T^2$ and $Q$ statistics of the kernel principal components are used for detecting the occurrence of abnormal events in the combustion process. An abnormal condition is identified if both the $T^2$ and $Q$ statistics exceed their confidence limits. The high-dimensional linear feature space (defined by a KPCA model) and the confidence limits of the $T^2$ and $Q$ statistics are obtained through a KPCA modeling procedure, also known as a training procedure, which should be conducted in advance under the normal combustion condition.

Flame Characteristic Parameters

As mentioned above, in the present study, the optical sensorial information of the flame is obtained using a digital imaging system. The system uses a rigid probe
with a 90° viewing angle to guide the light of the flame into the imaging unit, where the light is then split into two parts through a beam splitter. The first part is captured by a digital RGB color camera with a resolution of 1280(H) × 1024(V) pixels, while the second part is received by three photodetectors, which cover ultraviolet, visible, and infrared bands, respectively. The flame images and radiation signals captured are processed in parallel in embedded processing boards, and the results are transmitted to the host computer via an Ethernet cable. A detailed description of the digital imaging system can be found in Sun et al. (2011).

**Geometric and luminous parameters.** From the flame images, a number of geometric and luminous parameters are extracted (Lu et al., 2004), including the following:

- **Luminous region** ($R_f$): Calculated by counting the number of pixels within a flame image (FI) with an appropriate threshold, $\delta$, i.e.,
  \[
  R_f = \sum_{i \in \text{FI}} \sum_{j \in \text{FI}} \left\{ \begin{array}{ll} 1, & \text{if } G(i,j) \geq \delta \\ 0, & \text{other} \end{array} \right. 
  \]  
  \hspace{1cm} (1)
  
  where $G(i,j)$ is the gray-level intensity of the $i^{th} - j^{th}$ element of the flame image, and $\delta$ is the threshold that is used to define the luminous region.

- **Brightness** ($B_f$): Defined as the averaged gray-level intensity of the flame within the luminous region normalized to the maximum gray-level intensity of the camera, i.e.,
  \[
  B_f = \frac{1}{|R_f|} \sum_{i \in R_f} \sum_{j \in R_f} \frac{G(i,j)}{255} \times 100\% 
  \]  
  \hspace{1cm} (2)

- **Non-uniformity** ($U_f$): Represented by the mean intensity deviation of individual pixels from the flame brightness within its luminous region, i.e.,
  \[
  U_f = \frac{1}{R_f B_f} \sum_{i \in R_f} \sum_{j \in R_f} \left| \frac{G(i,j)}{255} - B_f \right| \times 100\% 
  \]  
  \hspace{1cm} (3)

**Time and frequency parameters.** From flame radiation signals, characteristic parameters are extracted in time, frequency, and joint time-frequency domains:

- **Time domain parameters** include DC, AC, skewness, and kurtosis. The DC and AC indicate the intensity and fluctuations of the flame, respectively. The skewness and kurtosis are measures of the asymmetry and peakedness of the probability distribution of the signal in the time domain, respectively. These parameters are given by
  \[
  \overline{S} = \frac{1}{N} \sum_{i=1}^{N} S_i
  \]  
  \hspace{1cm} (4)
\[ \hat{S} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (S_i - \bar{S})^2} \]  

(5)

\[ S_{ke} = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{S_i - \bar{S}}{S} \right)^3 \]  

(6)

\[ K_{ur} = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{S_i - \bar{S}}{S} \right)^4 \]  

(7)

where \( S_i \) is the \( i \)th sample point of a flame radiation signal, and \( N \) is the signal length.

- Frequency domain adopts the power-density-weighted average frequency, known as the flame oscillation frequency (Huang et al., 1999). The oscillation frequency, \( F \), is defined as

\[ F = \frac{\sum_{i=1}^{M} p_i f_i}{\sum_{i=1}^{M} p_i} \]  

(8)

where \( f_i \) is the \( i \)th frequency component, \( p_i \) is the power density of \( f_i \), and \( M \) is the total number of frequency components.

- In the joint time-frequency domain, flame parameters are extracted using wavelet analysis. Wavelet algorithms process a signal at different resolutions and thus have advantages in analyzing situations where the signal contains discontinuities and sharp spikes (Graps, 1995). In the present study, one-dimensional Daubechies wavelet db1 (Daubechies, 1990) is performed to decompose the flame signals to six levels, corresponding to seven different frequency bands, as illustrated in Table 1. The energy contained in each band is taken as the characteristic parameter of that band, i.e.,

\[ E_j = \sum_{i=1}^{N_j} \text{Coef}_j(i)^2 \]  

(9)

where \( j = A_6, D_6, D_5, \ldots, D_1 \); \( \text{Coef}_j(i) \) is the \( i \)th coefficient at band \( j \); and \( M_j \) is the number of coefficients at band \( j \). The seven bands correspond to detail coefficients at levels 1~6 and approximation coefficients at level 6.

<table>
<thead>
<tr>
<th>Wavelet subspace</th>
<th>A_6</th>
<th>D_6</th>
<th>D_5</th>
<th>D_4</th>
<th>D_3</th>
<th>D_2</th>
<th>D_1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency range (Hz)</td>
<td>0~7</td>
<td>8~15</td>
<td>16~31</td>
<td>32~63</td>
<td>64~127</td>
<td>128~255</td>
<td>256~511</td>
</tr>
</tbody>
</table>
The Algorithm of KPCA

A detailed description of the KPCA can be found in Schölkopf et al. (1998) and Lee et al. (2004a). Given a set of nonlinear data with a zero mean, \( x_k \in \mathbb{R}^m, k = 1, \ldots, N \), \( \sum_{k=1}^{N} x_k = 0 \), the key idea of the KPCA is to project \( x_k \) in the input space into a high-dimensional space, known as a feature space, through nonlinear mapping \( \Phi(\cdot) \), so that the mapped data \( \Phi(x_k) \) in the feature space can be linearly distributed. Kernel-based methods allow that the dot product of two vectors \( \Phi(x_i) \) and \( \Phi(x_j) \) in the feature space can be calculated as a function of corresponding vectors \( x_i \) and \( x_j \), i.e.,

\[
\langle \Phi(x_i), \Phi(x_j) \rangle = k(x_i, x_j)
\]  

(10)

thus, there is no need to explicitly define or carry out the nonlinear mapping \( \Phi(\cdot) \). Function \( k(\cdot, \cdot) \) is called the kernel function. There are a number of representative kernel functions, such as polynomial, sigmoid, and radial basis kernels (Boser et al., 1992). In this study, the radial basis function, which has fewer hyper-parameters and numerical difficulties than other kernel functions, is used, i.e.,

\[
k(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{\epsilon}\right)
\]  

(11)

The computation of the eigenvectors in the feature space is similar to that of the PCA. The covariance matrix \( \mathbf{C} \) in the feature space can be expressed as

\[
\mathbf{C} = \frac{1}{N} \sum_{i=1}^{N} \Phi(x_i)\Phi(x_i)^T
\]  

(12)

where it is assumed that the mapped data in the feature space are centered, i.e., \( \sum_{k=1}^{N} \Phi(x_k) = 0 \). The diagonalization of the covariance matrix \( \mathbf{C} \) requires solving eigenvalue equation:

\[
\lambda \mathbf{v} = \mathbf{C} \mathbf{v}
\]  

(13)

where \( \lambda \geq 0 \) and \( \mathbf{v} \) represent eigenvalue and eigenvector, respectively, and it is assumed that \( \mathbf{v} \) is normalized, i.e., \( \langle \mathbf{v}_k, \mathbf{v}_k \rangle = 1 \), for all \( k = 1, \ldots, N \). Equation (13) is equivalent to

\[
\lambda \langle \Phi(x_k), \mathbf{v} \rangle = \langle \Phi(x_k), \mathbf{C} \mathbf{v} \rangle, k = 1, \ldots, N
\]  

(14)

Because all solutions of \( \mathbf{v} \) with \( \lambda \neq 0 \) lie in the span of \( \Phi(x_1), \ldots, \Phi(x_N) \), there exist coefficients \( \beta_i \) (\( i = 1, 2, \ldots, N \)) such that

\[
\mathbf{v} = \sum_{i=1}^{N} \beta_i \Phi(x_i).
\]  

(15)
Substituting Eqs. (12) and (15) into Eq. (14) yields
\[ \lambda \sum_{i=1}^{N} \beta_i \langle \Phi(x_k), \Phi(x_j) \rangle = \frac{1}{N} \sum_{i=1}^{N} \beta_i \left( \sum_{j=1}^{N} \Phi(x_k) \langle \Phi(x_k), \Phi(x_j) \rangle \langle \Phi(x_j), \Phi(x_i) \rangle \right) \quad (16) \]
for all \( k = 1, \ldots, N \). It is clear that, in Eq. (16), only the computations of the dot products of the mapped vectors in the feature space are required, which can be done easily through the kernel function as illustrated in Eq. (10).

To obtain coefficients \( \beta_i (i = 1, 2, \ldots, N) \), define an \( N \times N \) kernel matrix \( K \) by its \( i \)th – \( j \)th element \( K_{ij} \),
\[ K_{ij} = \langle \Phi(x_i), \Phi(x_j) \rangle \quad (17) \]

Then, Eq. (16) can be rewritten as
\[ \lambda \sum_{i=1}^{N} \beta_i K_{ki} = \frac{1}{N} \sum_{i=1}^{N} \beta_i \sum_{j=1}^{N} K_{kj} K_{ji} \quad (18) \]
for all \( k = 1, \ldots, N \). This leads to
\[ \lambda \mathbf{K} \mathbf{\beta} = \frac{1}{N} \mathbf{K}^2 \mathbf{\beta} \quad (19) \]
where \( \mathbf{\beta} = [\beta_1, \ldots, \beta_N]^T \). The solution of Eq. (19) can be found through solving the eigenvalue problem, i.e.,
\[ \lambda \mathbf{\beta} = \frac{1}{N} \mathbf{K} \mathbf{\beta} \quad (20) \]
Let \( \lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_N \) and \( \mathbf{\beta}^1, \mathbf{\beta}^2, \ldots, \mathbf{\beta}^N \) represent the eigenvalues and corresponding eigenvectors of the Eq. (20), respectively, then the kernel principal components vector \( \mathbf{t} \) of a test vector \( \mathbf{x}_t \) can be calculated by projecting \( \Phi(\mathbf{x}_t) \) onto the eigenvectors of the feature space, i.e.:
\[ t_k = \langle \mathbf{v}_k, \Phi(\mathbf{x}_t) \rangle = \sum_{i=1}^{N} \beta_i^k \langle \Phi(\mathbf{x}_i), \Phi(\mathbf{x}_t) \rangle \quad (21) \]
where \( \beta_i^k \) is the \( i \)th element of the eigenvector \( \mathbf{\beta}^k \) in Eq. (20); \( k = 1, \ldots, p \); and \( p \) is the number of kernel principal components retained.

It should be noted that the assumption \( \sum_{k=1}^{N} \Phi(\mathbf{x}_k) = \mathbf{0} \) in Eq. (12) can be realized by substituting the kernel matrix \( \mathbf{K} \) with
\[ \mathbf{\tilde{K}} = \mathbf{K} - \mathbf{1}_N \mathbf{K} - \mathbf{K} \mathbf{1}_N + \mathbf{1}_N \mathbf{K} \mathbf{1}_N \quad (22) \]
where \( \mathbf{1}_N \in \mathbb{R}^{N \times N} \) and all elements of \( \mathbf{1}_N \) have the same value of \( 1/N \). The assumption \( \langle \mathbf{v}_k, \mathbf{v}_k \rangle = 1 \) for all \( k = 1, \ldots, N \) in Eq. (13) can be realized through scaling the corresponding eigenvector \( \mathbf{\beta}^k \) by factor \( 1/\sqrt{\lambda_k} \).
KPCA for Combustion Condition Monitoring

As mentioned in the section “General Principle,” the KPCA model should be trained before it can be used for online combustion condition monitoring. This is achieved by using the above-described algorithm to process the flame characteristics obtained under the normal combustion condition to derive the kernel matrix \( K \) in Eq. (17), and its eigenvalues \( \lambda_1, \ldots, \lambda_N \) and eigenvectors \( \mathbf{b}_1, \mathbf{b}_2, \ldots, \mathbf{b}_N \) in Eq. (20). The derived information defines the KPCA model of the combustion process under the normal condition.

Once the KPCA model is trained, the occurrence of abnormal conditions can be judged by computing the variation of new data within the model, as well as the fitness of the new data to the model. Suppose the kernel principal components vector of new data \( \mathbf{x}_{\text{new}} \) is denoted as \( t = [t'_1, \ldots, t'_p] \) where \( t' \) is derived from Eq. (21). The variation of \( \mathbf{x}_{\text{new}} \) within the KPCA model can be assessed by Hotelling’s \( T^2 \) statistic, known as Mahalanobis distance, i.e.,

\[
T^2 = \left[ t'_1, \ldots, t'_p \right] \Lambda^{-1} \left[ t'_1, \ldots, t'_p \right]^T
\]

(23)

where \( \Lambda^{-1} \) is the diagonal matrix of the inverse of eigenvalues \( (\lambda_1, \ldots, \lambda_p) \). The goodness-of-fit of \( \mathbf{x}_{\text{new}} \) to the KPCA model can be assessed by \( Q \) statistic, known as squared prediction error (SPE) (Lee et al., 2004a):

\[
Q = \sum_{j=1}^{n} t_j^2 - \sum_{j=1}^{p} t_j^2
\]

(24)

An abnormal condition is identified if both \( T^2 \) and \( Q \) statistics exceed their confidence limits. The confidence limit of \( T^2 \) statistic can be obtained by the means of \( F \)-distribution, i.e.,

\[
T^2_{p,N,\alpha} \sim \frac{p(N - 1)}{N - p} F_{p,N-p,\alpha}
\]

(25)

where \( F_{p,N-p,\alpha} \) is the \( F \)-distribution with \( p \) and \( N \) degrees of freedom with the significance level of 100(1–\( \alpha \))%. In this study, \( p \) is the number of PCs and \( N \) is the number of samples in the KPCA model. The confidence limit of \( Q \) statistic can be computed from its approximate distribution \( Q_\alpha \sim gX^2_\nu \), i.e.,

\[
Q_\alpha = \theta_1 \left[ 1 + \frac{\theta_2 h_0 (h_0 - 1)}{\theta_1^2} + \frac{z_\alpha \sqrt{2 \theta_2 h_0^2}}{\theta_1} \right]^{\frac{1}{h_0}}
\]

(26)

where \( \theta_1 = \sum_{i=p+1}^{N} \lambda_i, (i = 1, 2), h_0 = 1 - (2\theta_1 \theta_2 / 3\theta_2^3) \), and \( z_\alpha \) is the standard normal deviate corresponding to the upper 100(1–\( \alpha \))%. 
RESULTS AND DISCUSSIONS

In order to evaluate the effectiveness of the proposed methodology, experimental tests were carried out on an industrial-scale heavy-oil-fired combustion test facility (CTF). The CTF has a capacity of 9MWth with a horizontally oriented cylindrical combustion chamber (1.3 m in inner-diameter and 11 m in length). The furnace features a highly controllable low-NOx burner with three air supplies, i.e., primary, secondary, and tertiary air. The probe of the flame imaging system was inserted into the furnace through a side sighting tube close to the front wall, so that the flame root is viewable.

Flame data were collected under a total air flow rate of 9100 Nm$^3$h$^{-1}$ (primary air: 17%, secondary air: 43%, and tertiary air: 40%). An abnormal condition was created by setting the swirl vane position of the secondary air (SA) deviated from its baseline configuration of 65 mm. Flame images and radiation signals were simultaneously captured using the flame imaging system under both normal and abnormal conditions. Figures 2 and 3 show the typical flame images and radiation signals obtained under these two conditions, respectively. For each condition, a total of 150 data samples were collected. Each sample, also known as an observation, contains 27 flame characteristic parameters, as described in the section “Flame Characteristic Parameters.” Both visible and infrared signals were used (but the ultraviolet signal was too weak to be detected in the case studied).

For comparison purposes, 70% of data taken under the normal condition were used as the training data to build the KPCA and the PCA models. The KPCA was carried out based on the approach as described in the section “The Algorithm of KPCA.” The PCA was performed through the single value decomposition of input matrix $X$, i.e.:

$$X = USV^T$$

where $X_{n \times m}$ represents $n$ observations of $m$ variables, $S_{m \times m}$ is the diagonal matrix with standard deviations of the variables in descending order on its diagonal, and $U_{n \times m}$ and $V_{m \times m}$ are orthonormal matrices (Jackson, 1991). To reduce the number of variables in $X$, the small values of variance in $S$ are regarded as noises and neglected in the PCA. In the present study, the first 10 principal components, which represent more than 85% of variation in the original 27 variables, were used.

![Figure 2](image-url)  
(a) Normal condition  
(b) Abnormal condition

Figure 2 Typical flame images taken during the tests. (Figure is provided in color online.)
Figures 4 and 5 show the results of the trained PCA and KPCA models for monitoring the combustion process. The corresponding 95% confidence limit is plotted as the dash line in each figure. The first 30 test samples were obtained under the normal condition, while the remainder were from the abnormal condition. It can be seen that both the KPCA and the PCA can correctly detect the occurrence of the deliberately created abnormal event. However, in comparison with the PCA, the KPCA exhibits clearly a better performance in several aspects. The relative differences of the KPCA statistics between the normal and abnormal conditions are much higher than that of the PCA in both $T^2$ and $Q$ statistics. This implies that the nonlinear KPCA model performed better in illustrating the discrepancy between the normal and abnormal conditions. Furthermore, the PCA produced noticeable false warnings, especially the $Q$ statistic (Figure 4b), while the KPCA shows no false warnings at all. (A false warning is an indication of abnormal events from the normal condition, and the false warning rate is defined as the ratio of the number of false warnings to the number of test samples.) This problem with the PCA may be caused by the assumption of the PCA that the data in the input space are linear, which may not reflect the truth. Another important factor that may be relevant to this problem is the size of the training samples. The number of samples used to
establish the PCA model may not be sufficient to represent the characteristics of the normal condition.

In order to investigate the impact of the size of the training samples on the accuracy of the fault detection of both models, the data set of the normal condition (a total of 150 samples) was divided randomly into two parts, i.e., the training set \( t\% \), and the test set \( 1-t\% \). Different percentages of the training set, varying from 30% to 90%, were created. For each percentage, the same procedure was repeated 100 times in order to eliminate possible errors due to erroneous samples. Figure 6 shows the variation of the averaged false warning rate with the size of the training set. It can be seen that the false warning rates of the \( T^2 \) statistic for both models are less affected by the size of the training set, about 4% in the PCA model and 0% in the KPCA model. The false warning rate of the Q statistic in the PCA model decreases gradually with the percentage of the training data, reaching the minimum of 15% at the training set size of 90%, while the KPCA model gives consistently a 0% false warning. The results suggest that the KPCA model can give not only a better representation of the flame characteristic parameters but also a good performance even when the number of the training samples is limited.

Figure 5 Combustion process monitoring charts by using KPCA.

Figure 6 Variation of false warning rate with the size of training set.
The occurrence of the abnormal condition detected by the KPCA was confirmed by the NO\textsubscript{x} emissions in flue gas, which were taken by a gas analyzer concurrently during the tests. As shown in Figure 7a, the NO\textsubscript{x} emissions increased by 5\% in the abnormal condition in comparison to the normal condition.

In addition, the changes caused by the abnormal condition can also be observed in the optical sensorial data captured from the flame, for example, the flame temperature and the power spectral density (PSD) estimates of the flame radiation signals. Figure 7b shows the variations of the flame temperature under the tested conditions. The flame temperature here is derived from the captured flame images based on the two-color method (Sun et al., 2011; Zhao and Ladommatos, 1998). To represent the results statistically, 20 instantaneous readings were used to compute the mean and standard deviation of each data point. A greater fluctuation of the flame temperature (indicated as increased standard deviations) has been observed in the abnormal condition. Figures 7c and 7d illustrate the PSD estimates of the flame radiation signals in the visible and infrared bands, respectively. It has been found that, in both spectral bands, the average amplitude of the low-frequency components in the abnormal condition is much higher than that in the normal condition, while the high-frequency components appear to be similar in both conditions. Previous research has suggested that the low frequency components in the PSD estimates of a flame radiation signal reflect the flame geometrical pulsation caused by aerodynamic influences, while the high-frequency components indicate the variations in the heat release rate of the flame (Jones, 1988). Therefore, the results of PSD
estimates of the flame radiation signals have revealed an increased geometrical fluctuation of the flame in the abnormal condition.

The results of the flame temperature and PSD have also demonstrated the necessity of simultaneously analysing multiple variables for the combustion process monitoring. As illustrated by the error bars in Figures 7b–7d, the instantaneous values of the flame temperature and PSD fluctuated markedly under both conditions due to the dynamic nature of the flame. The fluctuation resulted in the overlapping of the results between the normal condition and the abnormal condition, which implies that an indication of abnormal conditions through the univariate analysis would not be as prompt and reliable as that through the KPCA method based on simultaneous statistical analysis of multiple variables.

CONCLUSIONS

The early detection of an abnormal condition in a combustion process has been realized through the flame monitoring and application of the KPCA technique. Instead of using global variables, which provide the limited description of a combustion process, the present work utilizes the optical sensorial information directly captured from the flame by a digital imaging system to establish the KPCA model. With the use of Hotelling’s $T^2$ and $Q$ statistics, the detection of an abnormal condition in the combustion process has been achieved. The test results obtained from a 9MW$_{th}$ heavy oil combustion test facility have demonstrated the effectiveness and potential of the KPCA method for combustion condition monitoring. It has been found that, in comparison to conventional PCA approaches, the proposed KPCA model gives a better performance in discriminating between the normal and abnormal conditions, even in cases where the number of training samples is limited. This is ascribable to the adoption of the kernel method in the KPCA, which is capable of handling non-linear relationships between the process variables.

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