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Video Based Combustion State Identification for Municipal Solid Waste Incineration ⋆

Chenchen ZHOU* Yi CAO Shuanghua YANG*****

* *College of Chemical and Biological Engineering, Zhejiang University, Hangzhou, China & Institute of Zhejiang University-Quzhou,Quzhou,China (e-mail: zhou-cc@zju.edu.cn).*
** *College of Chemical and Biological Engineering, Zhejiang University, Hangzhou, China & Institute of Zhejiang University-Quzhou,Quzhou,China (e-mail: caoyi2018@zju.edu.cn).*
*** *College of Chemical and Biological Engineering, Zhejiang University, Hangzhou, China & Institute of Zhejiang University-Quzhou,Quzhou,China (e-mail: yangsh@zju.edu.cn).*

Abstract: As a means of secondary utilization of resources, waste incineration power generation has received more and more attention in recent years. However, due to various uncertainties, municipal solid waste(MSW) combustion is unstable. Owing to the large time-delay from the combustion state to conventional process measurements, it is difficult to reflect the combustion state of the incinerator. This paper uses a combustion video stream to identify the combustion state in real-time. The PCA-k-means clustering method is proposed to cluster different combustion states to distinguish abnormal flames from normal ones, which do not need any operators' attention. Based on the clustering, alarms on abnormal combustion states can be implemented to alert an operator to adjust incinerator operation conditions so that the desired combustion state can be achieved.

Keywords: Image processing, Fault detection, Fault identification, Combustion state identification, Refuse incineration operation

1. INTRODUCTION

With the development of the city, the amount of municipal solid waste(MSW) is increasing rapidly. Since MSWs occupy a large amount of valuable land space and deteriorate the surrounding environment, it has to be disposed of quickly. MSW incineration is the main way of MSW disposal. It recycles waste to generate electricity. However, the quality of waste classification and pretreatment methods before incineration are different all over the world. In some regions, due to poor waste classification, the calorific value, density, and viscosity of MSW are unevenly distributed. When incinerating such MSW, the quality of MSW combustion is difficult to be maintained. This, in turn, causes a low overall efficiency of the entire power generation plant operation.

To maintain MSW combustion in a desired state requires appropriate measurements. However, the measurement for direct monitoring of the state of MSW combustion in MSW incineration power plants is short due to its low-profit margin. Conventional process measurements, such as temperature of flue gas and steam flow, have a large time delay to monitor the combustion state, hence are not suitable for combustion state control in real-time. When the effect of a poor combustion state can be identified in-process measurements, the MSW which causes the consequence has already been removed from the combustion area.

A poor combustion state will not only impact on the operating profit but also the environment protection. An instability of the incineration process may cause secondary pollution. For example, if the temperature of the flue gas is not up to standard, dioxin will be produced, which will cause serious environmental pollution.

Therefore, it is very important to make MSW combustion stable. Nevertheless, since existing control systems could not consistently maintain a stable MSW combustion state, operators have to manually intervene the operation to avoid inadequate combustion. As long as the stability of MSW combustion increases, the quality of control throughout the process will improve significantly and the operator's work intensity will be greatly reduced.

Experienced operators can take action by observing the state of combustion. This suggests that a real-time image, such as a video stream, of combustion contains a lot of information which is useful for operating, such as the area of combustion. If the operator's experience is formalized, information and knowledge extracted from a combustion video stream can be used to enhance incineration control.

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There are many studies on combustion image processing reported in the literature. Most of them focus on monitoring of pulverized fuel combustion. Bai et al. (2017) applied random weight network techniques to monitor the combustion with the combustion image from an experimental device. Chen et al. (2011) considered the hidden Markov model to extract the features among spatial relationships. Zhou et al. (2002) used multiple charge-coupled device (CCD) cameras to reconstruct three-dimensional temperature distributions. Compared to pulverized fuels, MSW combustion is much less stable and harder to control. Besides, there are many types of poor combustion states, referred to as faults in the rest of the work, and some of them need no attention because they have little impact on the whole process or the duration of them is too short to react. So it is necessary to distinguish various faults in MSW combustion.

In general, a combustion video image contains rich information and has great potential. The current research is biased towards the monitoring of the combustion state, but there is little research on how to apply combustion images directly to control.

In this paper, a distinction is made among various states of combustion, such as uneven combustion and dirty lens. The idea of fault diagnosis is used to separate the normal situation from other various abnormal situations, to avoid class-imbalance caused by a few fault samples. An unsupervised method is employed to classify the combustion states. A classification model is trained off-line to distinguish combustion states online. The on-line application of the model can alert operators on abnormal combustion situations so that proper adjustment on incinerator operation can be manually made. The on-line application will further calculate knowledge about MSW incineration in order to improve the algorithm in the future so that closed-loop control of the incineration process can be eventually achieved.

The paper is structured as follows. After the introduction, knowledge-based combustion feature extraction is described briefly. Then PCA-k-means is described concisely as a method of clustering. Finally, knowledge-based combustion feature extraction and PCA-k-means method are applied to data collected from an MSW incinerator in Eastern China. The robustness of the proposed state clustering method is tested.

2. METHODOLOGY

Video images usually are high-resolution. But only a few features of the image play a major role. This work is to extract features to characterize the combustion state. Two ways are used to extract combustion video image features. As Fig. 1 shows, one of them is based on the knowledge of the operators, and establishing mathematical models to extract these features from the image. The other is to use the data-driven approach to consider the correlation between the image and the control target.

The first method is simpler, easier to operate, more understandable and more intuitive, but may lose some of the information that is valid for the control objectives. The second method is more complicated, but the use of image information is more thorough. This work uses the first approach experimentally to verify the feasibility of the overall approach.

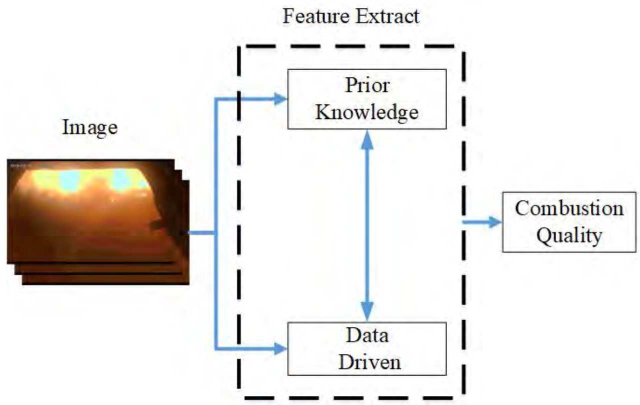

Fig. 1. Combustion feature extraction

2.1 Knowledge-based Combustion Feature Extraction

After a long period of experience accumulation, the operator can usually judge the combustion state by watching the flame through the monitoring window, and then adjust incinerator accordingly. After communicating with many experienced operators, the characteristics of the combustion are composed of three aspects: the brightness of combustion, position of combustion center, and the area of combustion.

The area of combustion To simplify the calculation, the RGB images are converted into a grays image. The number of pixels is used to represent the area of combustion A_f. The image is binarized through the Otus algorithm which is proposed by Yang et al. (2012) and divided the combustion region by selecting the appropriate threshold. Specifically, the input image can be binarized by the following transformation.

$$b(i,j) = \begin{cases} 1 & g(i,j) \geq T_h \\ 0 & g(i,j) < T_h \end{cases} \tag{1}$$

where $g(i,j)$ and $b(i,j)$ represents the input and output image's pixel of the i-th row and j-th column. T_h stands for the threshold.

And (2) is used to calculate A_f.

$$A_f = \sum_{i=1}^{n} \sum_{j=1}^{m} b(i,j) \tag{2}$$

The brightness of combustion The brightness of combustion usually reflects the temperature of combustion, which is important for the entire waste incineration process. Gray value is used to represent the brightness. The gray matrix of combustion G_f is constructed using the Hadamard product of the gray matrix of the image G and the binarized matrix B.

$$G_f = G \odot B \tag{3}$$

where $\odot$ represents the Hadamard product.

The position of combustion centre The centroid calculation method is referred to define the centre position of combustion as the gray scale centroid.

$$\begin{aligned} x_f &= \frac{\sum_{i=1}^{n}\sum_{j=1}^{m} i \times g_f(i,j)}{\sum_{i=1}^{n}\sum_{j=1}^{m} g_f(i,j)} \\ y_f &= \frac{\sum_{i=1}^{n}\sum_{j=1}^{m} j \times g_f(i,j)}{\sum_{i=1}^{n}\sum_{j=1}^{m} g_f(i,j)} \end{aligned} \tag{4}$$

where x_f and y_f is horizontal and vertical coordinates of the center position of combustion.

2.2 *k-means Clustering via Principal Component Analysis*

Based on the feature extracted above, the next step is to gain insight into data and identify a pattern. Clustering the data to find a natural classification of the combustion state is the main objective. k-means is a prototype-based clustering that is widely used in sociology, physics, biology, statistics and so on. k-means uses a greedy algorithm to minimize the sum of the squared error over all K clusters.

$$\min \sum_{k=1}^{K} \sum_{x_i \in c_k} \|x_i - \mu_k\|^2 \tag{5}$$

where c_k is the k-th cluster in clustering results. $\mu_k = \frac{1}{|c_k|}\sum_{x_i \in c_k} x_i$ is the mean of cluster c_k.

However, the data under normal conditions is much more than the others. Thus the unbalance data will seriously affect the effect of clustering. How to identify the normal conditions, in other words, is to identify the abnormality. It is consistent with the idea of fault diagnosis. In this paper, principal components analysis(PCA) is used to detect anomaly.

PCA is a method of multivariate statistical analysis. PCA is usually used for data reduction, information enrichment, or dimensionality reduction. It has already been successfully applied to detect and diagnose faults. Through linear transformation, PCA separates a plurality of indicators that are independent of each other and can fully reflect the overall information. It is convenient to further analyze the information of the original variables as much as possible, and they are not related to each other.

Data of n observations from m measurement variables stack the matrix $X \in \mathrm{R}^{n\times m}$. The linear variation matrix which is called the loading matrix is calculated via the Singular Value Decomposition (SVD).

$$X = U\Sigma V^T \tag{6}$$

where $U \in R^{n\times n}$ and $V \in R^{m\times m}$ are unitary matrices and the diagonal matrix $\Sigma \in \mathrm{R}^{n\times m}$ contains the non-negative real singular values of decreasing magnitude $(\sigma_1 \geq \sigma_2 \geq \ldots \sigma_m \geq 0)$. The V is the loading matrix.

$$T_{pc} = XP \tag{7}$$

where $P \in R^{m\times a}$ is the first a columns of V. The original space X is projected along P to get the principal component T_{pc}. Based on the assumption that the variables subject to Gauss distribution, Hotelling's T^2 statistic is employed to characterize normal states.

$$T^2 = x^T P \Sigma_a^{-2} P^T x \tag{8}$$

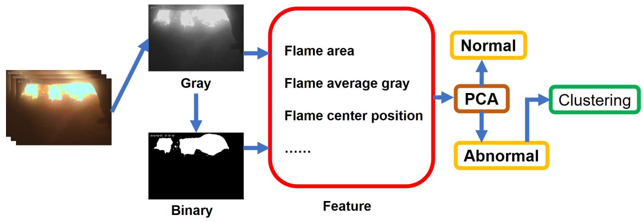

Fig. 2. Model training process

where Σ_a contains the first a rows and columns of Σ. The probability distribution is used to calculate the threshold for T^2 statistic.

$$T_\alpha^2 = \frac{(n^2-1)\,a}{n(n-a)} F_\alpha(a, n-a) \tag{9}$$

where $F_\alpha(a, n-a)$ is the upper $100\alpha\%$ critical point of the F-distribution with a and $n-a$ degrees of freedom. See MacGregor and Kourti (1995).

2.3 *Model Training Process*

As shown in Fig. 2, the raw image is first converted into a gray image and a binary image. Second, use the gray image and binary image to calculate the seven features which proposed in Section 2. And then, employ PCA to distinguish the normal and abnormal, and reduce dimension at the same time. Finally, principal components are put into the clustering model k-means.

3. CASE STUDY

3.1 *Case Background*

The data set used in this work comes from an MSW incinerator in Eastern China. This plant disposes of 1,350 tons of domestic MSW every day. As shown in Fig. 3, Area Blue is the drying area, Area Red is the incineration area, and Area Green is the burnout area. The gray area stands for the MSW. The camera monitors the area covered by the blue line. A continuous five hours video is used to train the model, and validate the method with another two and half hours of data.

3.2 *Combustion Feature Principal Component Extraction*

Using the method proposed in Section 2, the seven features of combustion are extracted.

As shown in Fig. 4, the original image signal is converted into a gray image firstly. And then, the Otus algorithm is used to calculate the optimal threshold to distinguish the flame area from other areas. Converting the gray image to the binary image through (1), and then by (2)-(4), the seven features of combustion are extracted.

After extracting features, (6)-(9) are applied to transform the extracted features into the principal component space.

And the number of retained PCs should be determined. There are several methods proposed for this task, such as screen tests, the average eigenvalue approach, and cross-validation, but none of them dominates. In this paper, the number of PCs that contributed over 90% of the total

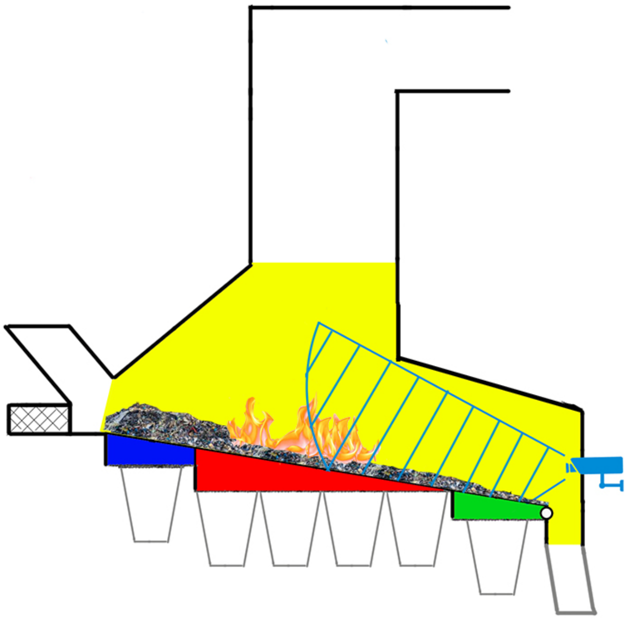

Fig. 3. Video shooting area

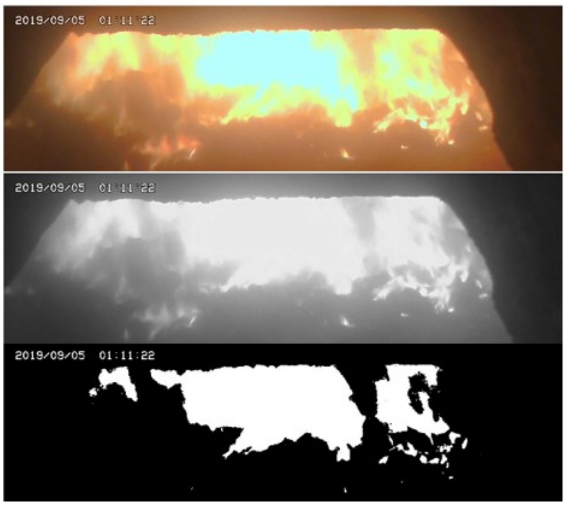

Fig. 4. Original combustion image to gray image and binarization

Table 1. Variance Contribution

Number of Principal Components	Variance Contribution	Cumulative Variance Contribution
1	63.42	63.42
2	23.66	87.08
3	11.05	98.14
4	1.652	99.79
5	0.152	99.94
6	0.051	99.99
7	0.004	100.0

variance were retained. As see in Table 1, although the two principal components do not reach 90%, three components are almost 100% and may contain noise. Therefore, two principal components are selected.

3.3 Combustion State Clustering Analysis

There are much more normal state samples than abnormal ones, underlined by the fact that MSW incineration is stable for most of the time. It will cause class-imbalance which will seriously damage the clustering effect. In this paper, a method is proposed to distinguish between normal and abnormal samples in an unsupervised way, by combining the idea of fault detection. The PCA, which is used in fault detection, is usually trained using normal states' data, and the appropriate confidence level is chosen to delineate the T^2 statistical limit. In the PCA subspace, the area with greater concentration is considered normal because the time of normal combustion is much longer than the abnormal combustion, and the normal combustion images look similar. On the contrary, there is a large difference between normal and abnormal combustion images. Therefore, the distance of each sample to the cluster centroid is measured by Hotelling's T^2 statistic. Assuming the distance obeys F-distribution, the appropriate confidence is chosen to determine the normal and abnormal boundaries, by observing the original image of the point near the decision boundary.

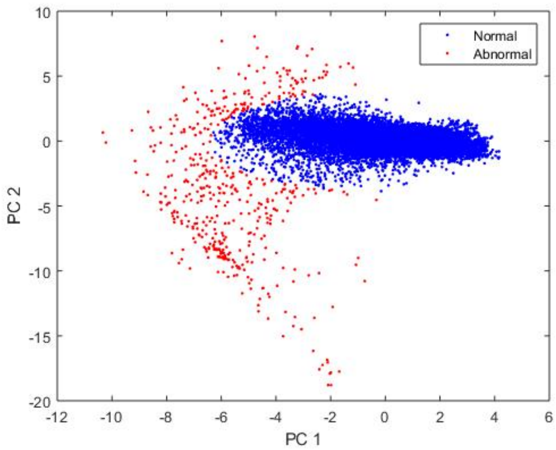

Fig. 5. Principal Component of Training Set

As see in Fig. 5, normal sample has high concentration. Abnormal combustion conditions are monitored at 99% confidence(Fig. 6) After pre-processing, the next step is to cluster the fault with k-means. Two types of index are proposed to determine the true number of clusters from the data itself. They are Davies-Bouldin Index (DBI) and Dunn Index (DI). Among many DBI and DI, the most widely used are sum of the squared errors (SSE) and Silhouette Coefficient. (See Tibshirani et al. (2001)) However, it is difficult to have a perfect mathematical criterion, because there is no clear definition of a 'cluster'. Yang et al. (2012) discusses a number of heuristics for estimating the cluster effect. In Fig. 7, when K is greater than 3, the SSE decrease amplitude reduces sharply. Because when K is smaller than the actual number of clusters, the increase of K will greatly increase the degree of polymerization of each cluster, so the decreased amplitude of SSE will be high, and when K reaches the number of real clusters, the degree of polymerization obtained by adding K is rapidly reduced. So 3 clusters are selected. The clustering results are shown in Fig. 8. Since the combustion video image can be directly observed with the naked eye for abnormality,

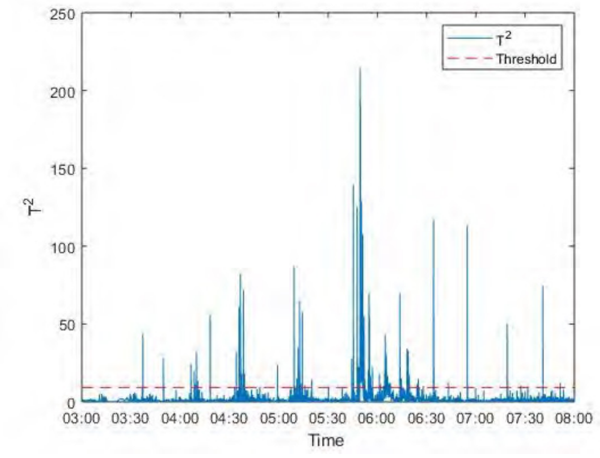

Fig. 6. Abnormal Monitoring of Training Set

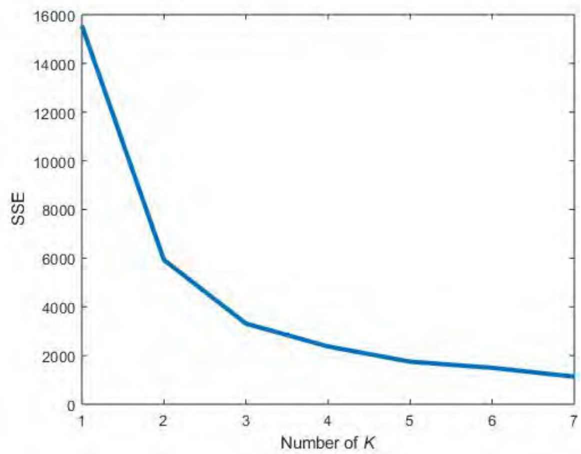

Fig. 7. SSE under different clusters of numbers

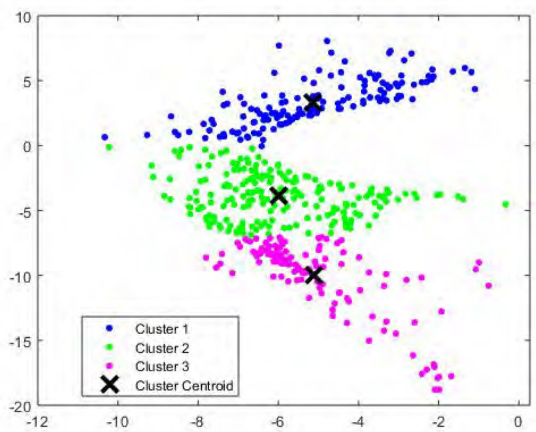

Fig. 8. Clustering for Training Set

the clustering result is checked by capturing an image of the corresponding time. In addition to the cluster of normal conditions, there are four clusters. Fig. 9 shows the effect of clustering.

By communicating with a skilled operator, Cluster 1 represents the offset of combustion, Cluster 2 and Cluster 3 represents flying ash. In practice, only the offset of combustion needs to be adjusted, and no other is needed. Therefore, it is only necessary to identify the space represented by Cluster 1 to recognize the combustion offset. By monitoring combustion status online, identifying combustion faults, and then alerting the operator to make adjustments to recover stable incineration. Therefore, an on-line application of this model can greatly alleviate the intensity of manual observation to monitor the combustion state.

Fig. 9. Three Clusters Image of Training Set

3.4 Test of Robustness

To test the robustness of PCA-k-means clustering model of combustion state, test samples are used to simulate real-time monitoring. The normalities and abnormalities are also distinguished by the same T^2 threshold, and then the k-means model obtained from the previous training is used for classification, and the results are shown in Fig. 10 and Fig. 11.

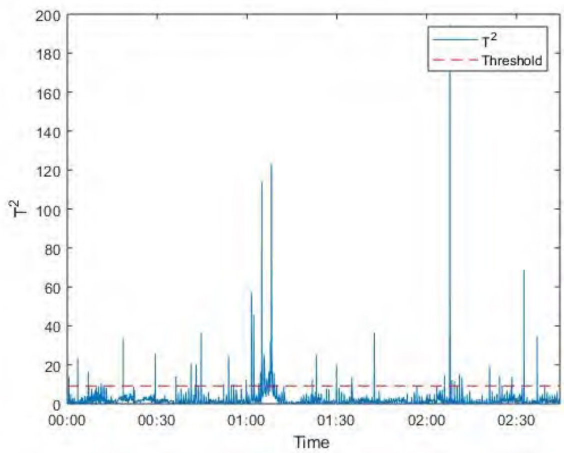

Fig. 10. Principal Component of Test Set

The combustion video images corresponding to test results of clustering are shown in Fig. 12. Finally, cross-compare the clustering results with the workers' experience results.

The results are shown in the table. Since Cluster 2 and Cluster 3 are consistent in practice, we will merge the two. The results are shown in Table 2. In the three-hour test, the identification of the offset has a low false alarm rate, but the identification of the ash flying still needs to be improved.

Table 2. Variance Contribution

	Ash Flying	Offset
total	71	7
correct	62	7
error	9	0
false alarm rate	12.7%	0%

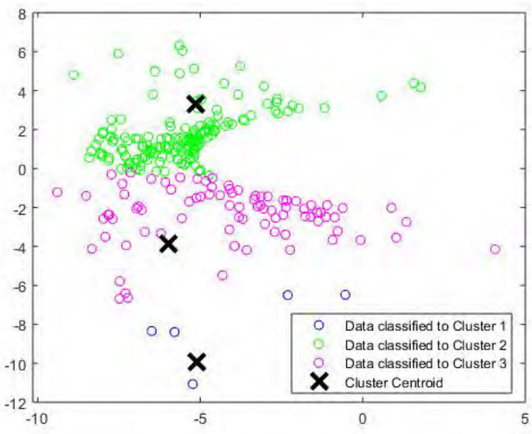

Fig. 11. Clustering for Testing Set

Fig. 12. Three Clusters Image of Testing Set

4. CONCLUSION

In this paper, a method that can identify abnormal combustion states in an unsupervised manner is proposed. After testing, the PCA-k-means method is demonstrated having good feasibility for the online monitoring of combustion state. However, in the actual test, Cluster 1 can be identified effectively, and can directly correspond to the abnormal combustion state in the real process. But the Clusters 2 and 3 belong to a same category in the real process. Fortunately, both cases do not need to be attended, and there is no need to distinguish between them in actual operation. Improvement in selection of combustion characteristics may be of use to overcome the problem The dynamic variation characteristics of combustion are not considered in this paper. In a future study, it is hoped that some methods of image processing and deep learning can be used to extract combustion features in a data-driven manner to further improve the reliability of the algorithm.

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