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Full Length Article

Multi-mode combustion process monitoring on a pulverised fuel combustion test facility based on flame imaging and random weight network techniques

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ABSTRACT

Combustion systems need to be operated under a range of different conditions to meet fluctuating energy demands. Reliable monitoring of the combustion process is crucial for combustion control and optimisation under such variable conditions. In this paper, a monitoring method for variable combustion conditions is proposed by combining digital imaging, PCA-RWN (Principal Component Analysis and Random Weight Network) techniques. Based on flame images acquired using a digital imaging system, the mean intensity values of RGB (Red, Green, and Blue) image components and texture descriptors computed based on the grey-level co-occurrence matrix are used as the colour and texture features of flame images. These features are treated as the input variables of the proposed PCA-RWN model for multi-mode process monitoring. In the proposed model, the PCA is used to extract the principal component features of input vectors. By establishing the RWN model for an appropriate principal component subspace, the computing load of recognising combustion operation conditions is significantly reduced. In addition, Hotelling's T^2 and SPE (Squared Prediction Error) statistics of the corresponding operation conditions are calculated to identify the abnormalities of the combustion. The proposed approach is evaluated using flame image datasets obtained on the PACT 250 kW Air/Oxy-fuel Combustion Test Facility (PACT 250 kW Air/Oxy-fuel CTF). Variable operation conditions were achieved by changing the primary air and SA/TA (Secondary Air to Territory Air) splits. The results demonstrate that, for the operation conditions examined, the condition recognition success rate of the proposed PCA-RWN model is over 91%, which outperforms other machine learning classifiers with a reduced training time. The results also show that the abnormal conditions exhibit different oscillation frequencies from the normal conditions, and the T^2 and SPE statistics are capable of detecting such abnormalities.

1. Introduction

In power generation industries, boilers are required to operate under optimised conditions to maintain high combustion efficiency and low emissions. Abnormal combustion states caused by drifts or faults in a combustion system can result in not only reduced efficiency and increased emissions but also enormous negative 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 exacerbated this issue [1,2]. Hence, the combustion process monitoring has received considerable attention.

Flame imaging incorporating soft-computing algorithms is considered to be a promising technical approach to monitoring the combustion process as it provides the operators with reliable, 2-D (two-dimensional) measurements about the furnace [3]. Several studies have been carried out for combustion process monitoring based on flame imaging techniques. Sun et al. [1] applied KPCA (Kernel Principal Component Analysis) for the diagnosis of abnormal operation conditions on a heavy oil-fired combustion test facility. Chen et al. [4] proposed an online predictive technique

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for furnace performance monitoring based on dynamic imaging and the combination of Hidden Markov Model and multiway PCA. Li et al. [3] and Chen et al. [5] constructed an extreme learning machine using flame image features to recognise the burning state (i.e., over burning, normal burning, or under burning) in a rotary kiln. Wang and Ren [6] also suggested a flame imaging and machine learning based method for recognising combustion conditions in a pulverised coal-fired rotary kiln. These methods are designed for detecting the process under individual operation conditions, i.e., the single-mode process where only a normal condition is considered.

However, modern combustion systems often operate under variable conditions (i.e., multi-mode process) according to the demand for energy. This means that the combustion process can be normal or abnormal under each condition. The single-mode process monitoring method will fail to distinguish abnormalities from normal deviations in a multi-mode process. Therefore, multi-mode process monitoring techniques are required to recognise reliably the operation condition and assess the state (normal or abnormal) of the process under variable operation conditions. Existing multi-mode monitoring approaches can be divided into three categories, i.e. global-model, adaptive-model and local-model. The global-model builds generally an uniform model for all operations to achieve the process monitoring. Shang et al. [7] used slow feature analysis and classical statistics for the concurrent monitoring of operation condition deviations and process dynamics anomalies. Ma et al. [8] and Wang et al. [9] employed the standardisation method to transform the multi-mode data to an uniform distribution, which then incorporates a PCA model for the fault detection of multi-mode processes. Whereas, describing all kinds of operation conditions through an uniform model is challenging, especially for the conditions with significant distinction. The adaptive model adjusts model parameters adaptively and updates the model with operation conditions [10,11]. Lee et al. [10] extracted process knowledge based on if-then rules for detecting the change in operation conditions. Ge and Song [12] proposed an adaptive local model approach to online monitoring of nonlinear multiple mode processes with non-Gaussian information. In an adaptive model, the modelling update speed is essential and the monitoring performance is mainly determined by the model selection. In a multi-mode combustion process, however, some conditions show significant differences and the dynamic behaviours of flames lead to the complexity of the features extracted from flame images. It is thus very difficult to build appropriate global or adaptive models to achieve multi-mode process monitoring in a combustion system. The local model recognises the operation conditions using clustering methods and builds multiple models for each operation condition to assess the state. Feital et al. [13] presented a multimodal modelling and monitoring method for multivariate multimodal processes based on the maximum likelihood PCA and a component-wise identification of operating modes. Yang et al. [14] proposed an aligned mixture probabilistic PCA to exploit within-mode correlations for the fault detection of multi-mode chemical processes. However, in flame imaging based combustion monitoring, the features extracted from flame images, which are considered as input variables, suffer from various noises from either the imaging system or the combustion process as well as abnormalities in the combustion process. As a consequence, it is challenging to determine the most suitable model for every new sample using the existing multi-mode monitoring approaches. Appropriate methods are therefore required for recognising the combustion operation conditions and detecting the combustion state.

In this paper, a flame imaging and PCA-RWN (PCA-Random Weight Network) based multi-mode technique is proposed to achieve combustion process monitoring under variable conditions. In the PCA-RWN model, a global PCA model for all operation conditions is built to extract the features from flame images, and an RWN model is constructed for recognising the operation conditions. Cross-validation is used to select the optimal number of principal components of the PCA and the hidden nodes of the RWN. The PCA-RWN model can reduce significantly the computing overhead of the RWN model. This is achieved by dividing the inputs of the RWN model into a PCA based feature space and the optimised number of principal components are adaptively selected to obtain the optimal recognition performance of operation conditions. Following the recognition of the operation condition, Hotelling's T^2 and SPE are used to detect the combustion abnormalities. The performance of the proposed technique is evaluated using flame images obtained on the PACT 250 kW Air/Oxy-fuel CTF at the UKCCSRC PACT (Pilot Scale Advanced Capture Technology) Core Facilities. Experimental results show that the proposed PCA-RWN based multi-mode process monitoring method is feasible and effective for detecting the abnormalities of combustion processes under variable operations.

2. Methodology

2.1. Overall strategy

Fig. 1 shows the scheme of the PCA-RWN based multi-mode combustion process monitoring method. The scheme has three main steps, i.e. feature calculation, feature extraction and process monitoring. Firstly, flame images are pre-processed to reduce the noises by employing a moving average filter. Filtered flame images are then used to compute the colour and texture features of the flame. Secondly, the PCA model is built to extract the useful feature variables from the calculated features of the filtered flame images. Principal component feature spaces with different numbers of principal components are then considered, and the extracted features with various dimensions are taken as the inputs of the RWN model to perform the fitting tasks. Subsequently, processing is taken to search for the minimum-error and to select the well-trained RWN with the optimal numbers of principal components and hidden nodes according to the fitting errors of the RWN model. By using the certain well-trained PCA-RWN, the combustion operation condition of the targeted test flame image is recognised, and multiple variable statistics indices, the T^2 and SPE (Squared Prediction Error), are finally calculated to identify the state.

2.2. Principal component analysis based feature extraction

In general, as one essential step in the flame visualisation, flame images are segmented to identify the flame regions using edge detection or other grey-level threshold methods [15]. Regarding coal combustion under variable operation conditions, it is very challenging to allocate precisely the boundary of the flame region in a very short time due to the dynamic nature of the flame. The inaccurate segmentation of the flame region will lead to inaccurate feature extraction, and thus poor monitoring performance. In this study, therefore, the colour and texture features of flame images are computed without any prior image segmentation. In this way, the adverse effects of flame image processing are significantly reduced. The colour features and texture features are calculated as follows:

Step 1. Original flame images need to be filtered to reduce noise using a moving average filter [16]. The i-th filtered image, $\bar{\boldsymbol{I}}_i$, is represented as,

$$\bar{\boldsymbol{I}}_i = \frac{1}{w}\sum_{\tau=0}^{w-1}\boldsymbol{I}_{i-\tau}, \tag{1}$$