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Dynamic features and combustion state identification of burner flames in a 660 MW coal-fired boiler

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Abstract: The combustion state of burners in coal-fired boilers is crucial for furnace efficiency and safety. However, relying solely on static flame features limits the ability to capture flame dynamics and accurately assess combustion stability. To address these limitations, an improved Non-Smooth Data optical flow method is proposed for extracting flame dynamics. This method performs multi-scale estimation via an image pyramid, capturing motion features and reducing errors from limited spatial resolution. A Lorentzian robust function and noise-adaptive parameter are introduced to suppress disturbances from illumination changes, blurred boundaries and weak textures. An adaptive regularisation strategy is proposed to further enhance performance under varying load conditions. The proposed method is experimentally validated on a 660 MW opposed-fired boiler. The results show that under stable combustion, its fluctuation range remains within a narrow band regardless of load level, indicating good consistency. However, when mismatches occur in the regulation of air and coal feed rates, the flame structure becomes significantly disordered and the optical flow field shows intense disturbances. Therefore, the proposed dynamic features can

sensitively and effectively reflect abnormal combustion conditions, providing a reliable set of quantitative indicators and methodological support for real-time monitoring and stability diagnostics of burner flame behaviour in coal-fired boilers.

Keywords: Coal-fired power plant; Burner; Flame stability; Improved NSD; Dynamic features.

1. Introduction

In the context of promoting green and low-carbon development, coal-fired power plants must enhance their peak-shaving capabilities to accommodate the integration of renewable energy sources and ensure the stable operation of the power grid [1,2]. However, the peak-shaving process significantly alters the furnace combustion state, making burner flames a critical factor affecting combustion efficiency and operational safety. Flame instability can lead to localized overheating and uneven temperature distribution, which deteriorates overall combustion performance and increases pollutant emissions [3,4]. Therefore, accurate flame monitoring at the burner level is essential for ensuring the safe, environmentally friendly and efficient operation of power plants [5,6].

With the advancement of digital imaging technology, flame imaging-based monitoring methods have been widely applied under various fuel types and complex combustion conditions due to their non-intrusive nature, high sensitivity and fast response [7-10] to determine combustion states by extracting flame features [11] such as geometric parameters [12], luminous intensity [13], oscillation characteristics [14] and texture features [15]. For instance, Gaidhane et al. [16] established a relationship between combustion states and flame contour and area using local binary patterns, dual-thresholding and Levenberg-Marquardt optimization techniques. Sun et al. [17] quantitatively investigated the oil flame's stability based on Hue-Saturation-Intensity (HSI) color space components, flame brightness and length. Chi et al. [18] calculated the oscillation frequency,

fluctuation ratio and combustion kinetic energy of the flame and observed that they are most sensitive to coal type and therefore serve as indicators of ignition stability in coal-fired flames. Yang et al. [19] proposed a method for extracting flame texture features in industrial boilers using Gabor filters and gray-level co-occurrence matrix (GLCM)-based techniques. This approach enhances flame texture and converts it into scalar statistical values, which are then used to predict key combustion indicators such as flue gas O₂ concentration and NO_x emissions, thereby reflecting the air–fuel ratio and combustion efficiency under the different operating conditions.

Recently, data-driven methods have also been applied to monitor the combustion states [20–22]. For example, Lyu et al. [23] employed a deep belief network (DBN) to extract global features of flame based on statistical indicators for flame state monitoring. Zhou et al. [24] proposed a convolutional neural network (CNN) to extract flame features for predicting the thermoacoustic state of the flame. Qiu et al. [25] applied a convolutional autoencoder (CAE) to extract flame features and then an unsupervised clustering method was used to classify the combustion states. Han et al. [26] utilized a stacked sparse autoencoder to extract flame features and identified combustion stability based on the sum of squared prediction errors. The aforementioned approaches primarily rely on single-frame static image feature extraction without fully considering the dynamic characteristics of the flame, which limits the accuracy and adaptability of combustion states identification.

To reveal the dynamic patterns of combustion processes, in recent years, studies on flame dynamics have also been conducted in both methodological frameworks and applications. Common approaches include the frame differencing method [27], background subtraction [28] and optical flow analysis [29]. Among them, the optical flow method estimates pixel motion by analyzing

temporal variations in pixel intensity across image sequences, allowing the assessment of flame movement in successive frames, which is particularly important for detecting abnormal combustion behavior. Rinsurongkawong et al. [30] employed the classical Lucas-Kanade (L-K) optical flow algorithm, combined with background subtraction, color filtering and region growth rate analysis, to achieve real-time flame detection. However, this method is sensitive to background movements and lighting conditions, which can easily lead to false alarms. Harlapur et al. [31] further analyzed flame motion features in video sequences and differentiated flame from non-flame objects based on distinct motion patterns, thereby improving flame region identification and reducing interference from other moving targets. Nevertheless, these approaches face limitations under complex environments or turbulent flame conditions, where detection accuracy is susceptible to the disordered motion of flames. To enhance the analysis of complex flame dynamics, Khondaker et al. [32] proposed an enhanced Lucas-Kanade-Tomasi (LKT) optical flow algorithm, which improved the ability to capture turbulent flame characteristics and provided a refined analysis of irregular flame motion. Considering the challenges posed by brightness variation, complex boundary disturbance and high saturation regions in flame images, Mueller et al. [33] proposed the Non-Smooth Data (NSD) optical flow method, enhancing the algorithm's applicability to dynamic flame scenarios. In addition, strong background illumination and noise in complex environments often introduce errors in flame and smoke detection. To overcome these issues, Kikuta et al. [34] integrated optical flow variance and (Hue-Saturation-Value) HSV color space features. By analyzing the unique color and motion characteristics of flames and smoke, their method improved detection accuracy under sunlight interference, effectively reduced missed and false alarms in external environment fire detection, and reduced both false positives and false negatives. For

dynamic target recognition under complex scenarios, Wu et al. [35] developed a two-stage real-time video smoke detection framework. In the first stage, dense optical flow was used to extract motion information and locate potential smoke regions. In the second stage, a convolutional neural network (CNN) was employed to classify and verify these candidate regions. By combining traditional motion analysis with deep learning-based feature learning, the framework achieves more accurate and robust detection of dynamic smoke targets. Moreover, to realize real-time flame tracking and expansion rate estimation, Kaliyev et al. [36] introduced region growth analysis based on color space and optical flow features. This approach enabled the precise localization of ignition points within video frames and the dynamic monitoring of flame expansion velocity and motion status, thereby improving the real-time performance and reliability of the monitoring system. To directly capture in-furnace flame dynamics based on optical flow, Wang et al. [37] calculated optical flow vectors within flame regions of video frames to analyze the pulsation behavior of flames in two-dimensional images and proposed an optical flow pulsation evaluation model to assess the combustion stability of gas flames quantitatively. Furthermore, Wang et al. [38] combined optical flow with multi-scale feature extraction techniques to improve the robustness and adaptability of flame detection. They successfully extracted dynamic features under various operating conditions from gas flame images and demonstrated the sensitivity and effectiveness of these features in flame diagnostics.

Although optical-flow-based methods have been applied to forest fire and smoke monitoring, most of these applications are conducted in relatively open environments. In such scenarios, the motion velocity of flames or smoke is usually relatively low, and the contrast between the target and the background is comparatively clear, making the inter-frame motion easier to identify. However,

conventional optical flow methods still face difficulties when dealing with high-speed motion. Optical flow estimation is generally based on the assumptions of brightness constancy and small inter-frame displacement. When the target moves rapidly, the displacement between adjacent frames may become too large, resulting in inaccurate pixel correspondence, motion blur, and unreliable gradient information. Consequently, spurious or distorted optical-flow vectors may be generated. This issue becomes more pronounced for burner flames in coal-fired boilers. In practical furnace environments, the pulverized coal–air mixture is injected into the furnace at high velocity from the burner outlet, resulting in rapid flame motion and strong deformation. Meanwhile, the internal boiler environment is highly complex, with strong background radiation and pulverized-coal particle interference, leading to blurred flame boundaries. These factors further reduce the reliability of optical-flow estimation. Therefore, how to obtain a reliable optical-flow field for high-speed burner flames in coal-fired boilers and further extract effective dynamic features remains an unresolved issue.

This study focuses on the optical-flow-based dynamic feature extraction of burner flames in an actual 660 MW opposed-fired coal-fired boiler. Compared with existing studies, the novelty and methodological improvements of this work are mainly reflected in the following aspects:

1. This study obtains burner flame image sequences from an actual 660 MW opposed-fired coal-fired boiler under practical variable-load operating conditions. Different from studies on general flames, laboratory-scale flames, fire/smoke detection, or static flame image features, this work characterizes the dynamic behavior of large-scale pulverized-coal boiler burner flames under load variation and air–coal regulation conditions.
2. The conventional NSD optical flow method is improved by introducing an image pyramid

strategy, a Lorentzian robust function, and an adaptive regularization parameter. These improvements enhance the robustness of optical-flow estimation for flame images with rapid motion, blurred boundaries, brightness fluctuations, and local disturbances.

3. Dynamic features, including optical-flow velocity, direction, and pulsation energy, are further extracted from the improved optical-flow field to characterize flame stability and identify combustion states. These features provide a more detailed description of burner flame motion behavior than conventional flame presence detection or static image analysis.

2. Combustion state identification

Fig. 1 illustrates an improved Non-Smooth Data (NSD) optical flow method for estimating the optical flow vector field in an opposed-fired boiler burner and to reveal the flames' dynamic characteristics. The 660 MW opposed-fired boiler flames are captured using an imaging system and then converted into grayscale images of the same size. An image pyramid structure [39] is used to perform hierarchical optical flow estimation across multiple resolution levels. A top-down, layer-by-layer iterative optimization strategy is employed, starting from the downsampled low-resolution level and progressively refining the flow estimation, which effectively alleviates the accuracy degradation caused by high-velocity flame. To address the challenges of abrupt brightness variations and blurred flame boundaries within the furnace, a Lorentzian-based robustness enhancement function is introduced. This function behaves approximately quadratically for small gradients, thereby preserving normal structural information in the image. For large gradients, it increases slowly, effectively suppressing the influence of outliers and mitigating the interference of local extreme gradients in optical flow estimation. Meanwhile, to accommodate flame morphology variations under fluctuating load conditions in coal-fired boilers, an adaptive parameter adjustment

mechanism is developed. The regularization parameter is dynamically modulated based on the magnitude of the image spatial gradient, reducing smoothness constraints in high-gradient edge regions while enhancing regularization in low-gradient, homogeneous areas. This strategy improves the generalization capability of the model across varying loads and complex flame structures. Dynamic features of the combustion process are further extracted from the constructed optical flow vector field. Dynamic features such as optical flow pulsation energy, velocity, and direction are used to characterize combustion stability under different load conditions. The combustion states are then identified by evaluating the defined combustion stability range and the fluctuation amplitude of the optical flow pulsation energy.

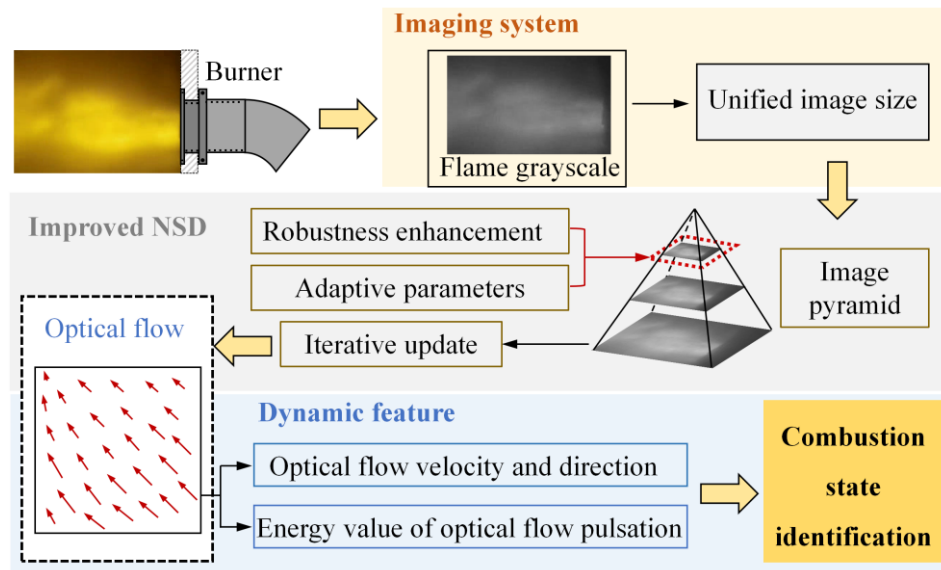


Fig.1. Overview architecture of the flame dynamic feature extraction method

2.1 Conventional optical flow estimation method

Optical flow estimation describes the motion characteristics of objects along the temporal dimension by calculating the correspondence of pixels between adjacent frames in an image sequence. Based on the assumption of intensity constancy, this process typically posits that the brightness of a given object remains constant across consecutive frames.

As shown in Figure 2, the pixel intensity at point A is denoted as $I(x, y, t)$, where (x, y) represents the spatial coordinates and t represents time. Specifically, x and y denote the horizontal and vertical pixel directions in the flame image, respectively, rather than the physical width, depth, or height directions of the boiler furnace. The optical flow vector (u, v) indicates the pixel displacement in the horizontal and vertical directions. In the optical flow constraint model, the image gradients in the x , y and t directions are denoted as I_x , I_y , and I_t , respectively. Point A in frame 1 moves to position B in frame 2, where the pixel intensity becomes $I(x + dx, y + dy, t + dt)$. Based on the brightness constancy assumption, the fundamental optical flow constraint can be derived as follows [40]:

$$I(x, y, t) = I(x + dx, y + dy, t + dt) \quad (1)$$

$$I_x u + I_y v + I_t = 0 \quad (2)$$

The above equations provide only a single constraint at each pixel, whereas there are two unknown variables to be solved u and v . As a result, the problem is inherently ill-posed, leading to the so-called aperture problem. That is, only the component of the optical flow along the direction of the image gradient can be computed, while the complete motion vector cannot be uniquely determined.

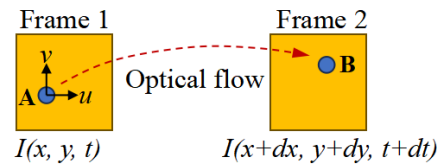


Fig.2. Schematic diagram of optical flow motion

However, conventional optical flow methods are generally based on a smoothness assumption, which presumes that object motion in image sequences is continuous and coherent. However, when dealing with dynamic, non-rigid targets such as flames, particularly in boundary regions exhibiting

rapid motion or deformation, these methods often fail to accurately estimate motion vectors, resulting in distorted optical flow near the edges.

2.2 Improved Non-Smooth Data (NSD)-based optical flow estimation method

To address the challenges of motion estimation under non-smooth boundary conditions, the NSD optical flow method is proposed for dynamic objects with complex boundaries [33]. This approach can effectively capture deformations, local disturbances, and boundary perturbations near the boundaries of non-rigid objects, while reducing the excessive smoothing of local motion details caused by global smoothness constraints. Therefore, it can significantly enhance the adaptability of optical flow estimation to non-smooth motion fields.

The optical flow energy function needs to be reconstructed for the NSD optical flow method and a non-smooth regularization strategy is incorporated to handle irregular motion in flame-saturated regions. The corresponding variational formulation is defined by Equation (3).

$$\min_{\vec{u}} \frac{1}{2} \int_{\Omega} \int_0^1 (I_t + \nabla I \cdot \vec{u})^2 + \alpha \|\vec{u}\|_2^2 dt dx dy \quad (3)$$

where $\vec{u}$ denotes the optical flow vector, I_t represents the temporal gradient of the image, ∇I is the spatial image gradient and α is the regularization parameter. This energy function preserves the data term, which measures the discrepancy between the estimated optical flow and the brightness constancy assumption (i.e., the temporal change of image intensity should be consistent with the motion field). By retaining this term, the method ensures that the computed flow remains faithful to the observed image sequence.

Since saturated pixels can generally be regarded as maintaining constant intensity, the NSD optical flow method still relies on the brightness constancy assumption as a constraint. To accommodate locally discontinuous motion caused by strong disturbances at flame boundaries, the

NSD optical flow method is explicitly formulated as a non-smooth model, avoiding the boundary blurring effects introduced by global smoothness constraints in conventional optical flow approaches. In this method, the norm $\|\vec{\mathbf{u}}\|_2^2$ serves to regularize the magnitude of the optical flow vector without enforcing spatial smoothness. As a result, the direction of the optical flow is entirely driven by variations in image intensity, while its magnitude is constrained to prevent excessive motion estimates. The corresponding mathematical formulations are given in Equations (4) and (5).

$$\frac{\partial L}{\partial u} = (I_t + \nabla I \cdot \vec{\mathbf{u}})I_x + \alpha u = 0 \quad (4)$$

$$\frac{\partial L}{\partial v} = (I_t + \nabla I \cdot \vec{\mathbf{u}})I_y + \alpha v = 0 \quad (5)$$

In boilers, the pulverized coal-air mixture is injected into the furnace at high velocity from the burner outlet, resulting in rapid changes in flame boundaries and morphology. This rapid jetting behavior reduces the accuracy of the NSD method in estimating flame optical flow. To address this issue, an image pyramid algorithm is introduced to enable multi-scale analysis of flame images by constructing hierarchical representations at different resolutions. Specifically, the original image is first downsampled to generate lower-resolution versions, where optical flow is first estimated to capture coarse motion patterns. As the resolution gradually increases, the estimation is refined progressively, allowing for a more detailed analysis of flame motion. This layer-wise estimation approach effectively reduces errors introduced by high-resolution images. In particular, for flames with high-speed motion, it improves the ability to capture both global and fine-scale motion features.

The original image is denoted as I_0 , which corresponds to the 0th layer of the image pyramid. Each subsequent image I_k ($k = 1, 2, \dots, K$) is generated by first applying a Gaussian filter to the preceding layer I_{k-1} to suppress high-frequency noise, followed by downsampling. This iterative process continues until the resolution of the top layer I_K becomes sufficiently small, resulting in a

multi-scale image sequence arranged from high to low resolution. The Gaussian filtering process [41] applied to the upper layer image is described in Equations (6) and (7).

$$G_{\sigma}(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \quad (6)$$

$$I'_{k-1}(x, y) = \sum_{m=-1}^1 \sum_{n=-1}^1 G_{\sigma}(m, n) \cdot I_{k-1}(x + m, y + n) \quad (7)$$

where I'_{k-1} denotes the filtered image from the $(k-1)$ th layer. $G_{\sigma}(x, y)$ represents a two-dimensional Gaussian function, which serves as the convolution kernel for image smoothing. The parameter σ is the standard deviation of the Gaussian filter and determines the degree of smoothing applied to the image. The Gaussian filter assigns weights to each pixel in the neighborhood such that pixels further from the current pixel have a smaller influence. The variables m and n denote the spatial offsets in the Gaussian kernel, which span the local neighborhood around the current pixel. Gaussian filtering is used to suppress high-frequency noise and fine details in the image, thereby preventing aliasing artifacts during the subsequent downsampling process.

Furthermore, the image $I_k(x, y)$ is obtained by downsampling the Gaussian-smoothed image $I'_{k-1}(x, y)$, as defined in Equation (8).

$$I_k(x, y) = \frac{1}{4} \sum_{i=0}^1 \sum_{j=0}^1 I'_{k-1}(x + i, y + j) \quad (8)$$

where, i and j represent the indices in the x and y directions of the image, respectively, and are used to select a fixed-size pixel block for processing. During the downsampling process, the image size is reduced by half. Thus, the offsets i and j range from 0 to 1, corresponding to the four pixels within each 2×2 region.

The core of optical flow estimation at each pyramid level lies in solving the horizontal and vertical components u and v of the optical flow at each pixel. Through iterative processing across

pyramid layers, the optical flow is progressively updated, as shown in Equations (9) and (10). On this basis, Equations (4) and (5) are reformulated to obtain the optical flow increment Δu and Δv at each level. After several iterations, a stable optical flow estimation is achieved for the current layer, as expressed in Equations (11) and (12).

$$u_k = u_{k-1} + \Delta u \quad (9)$$

$$v_k = v_{k-1} + \Delta v \quad (10)$$

$$\Delta u = -\frac{\rho \cdot I_x I_t}{\|\nabla I\|_2^2 + \alpha} \quad (11)$$

$$\Delta v = -\frac{\rho \cdot I_y I_t}{\|\nabla I\|_2^2 + \alpha} \quad (12)$$

where ρ denotes the Lorentzian robustness function [42] as shown in Equation (13), which is introduced to address stability in optical flow estimation caused by dust particles and varying background illumination within the furnace. To enhance the robustness of optical flow methods in flame detection, this function serves as an effective approach for noise suppression and feature enhancement. In addition, a noise parameter ε is introduced to control sensitivity to noise. By dynamically adjusting ε , the method can be adapted for varying noise levels, thereby improving the stability of optical flow computation. Specifically, ε can be tuned based on the estimated image noise level to ensure stable performance under high-noise conditions.

$$\rho = \log \left(\left(\frac{I_t}{\varepsilon^2} + 1 \right) \right) \quad (13)$$

During the detection of boiler flames, the dynamic characteristics of the flame vary with changes in boiler load. To accommodate such variations, an adaptive regularization parameter α is introduced [43], as shown in Equation (14). This parameter is dynamically adjusted based on the image gradient, thereby enhancing the algorithm's adaptability under various load conditions.

$$\alpha' = \alpha \cdot \left(1 + \exp \left(-k \cdot \sqrt{I_x^2 + I_y^2} \right) \right) \quad (14)$$

Accurate construction of the optical-flow vector field is essential for the subsequent extraction of flame dynamic features. To evaluate the performance improvement and applicability of the proposed method over the conventional NSD method, the conventional NSD optical-flow method was reproduced under the same experimental condition and compared with the improved NSD method proposed in this study. Figure 3 presents a comparative study of the optical flow estimation for flames in a coal-fired boiler between the conventional NSD method and the proposed improved NSD method. Where (a) shows the original flame image and (b) presents the optical flow field estimated by the conventional NSD method. It can be observed that the conventional approach generates a dense distribution of flow vectors across the entire image, including saturated, high-intensity, and background regions, resulting in a considerable number of motion estimates that lack physical significance. Consequently, the actual flame structure and texture become difficult to discern, and only a coarse representation of the global flow direction is obtained. The result of the improved NSD method is presented in (c). Compared with the conventional approach, the improved method not only preserves the dominant motion trends of the flame but also effectively suppresses spurious optical flow in non-flame regions and significantly enhances the response to boundary perturbations and internal deformations, thereby providing a clearer and more physically consistent characterization of the flame motion. Specifically, (d) and (e) present a detailed comparison of the optical flow estimates obtained by the two methods at the same spatial location. Regions 1 through 4 correspond to different parts of the flame structure, including the flame root, the main combustion zone, and the flame boundary. The conventional NSD method yields relatively uniform but low-detail flow distributions, which are insufficient to capture flame pulsation or morphological changes. The improved method, however, effectively captures local disturbances along the flame edges as

well as dynamic texture features within the flame. These results validate the effectiveness of incorporating image pyramids, the Lorentzian robustness function and the adaptive regularization parameter, which together contribute to notable improvements in both the accuracy and robustness of optical flow estimation.

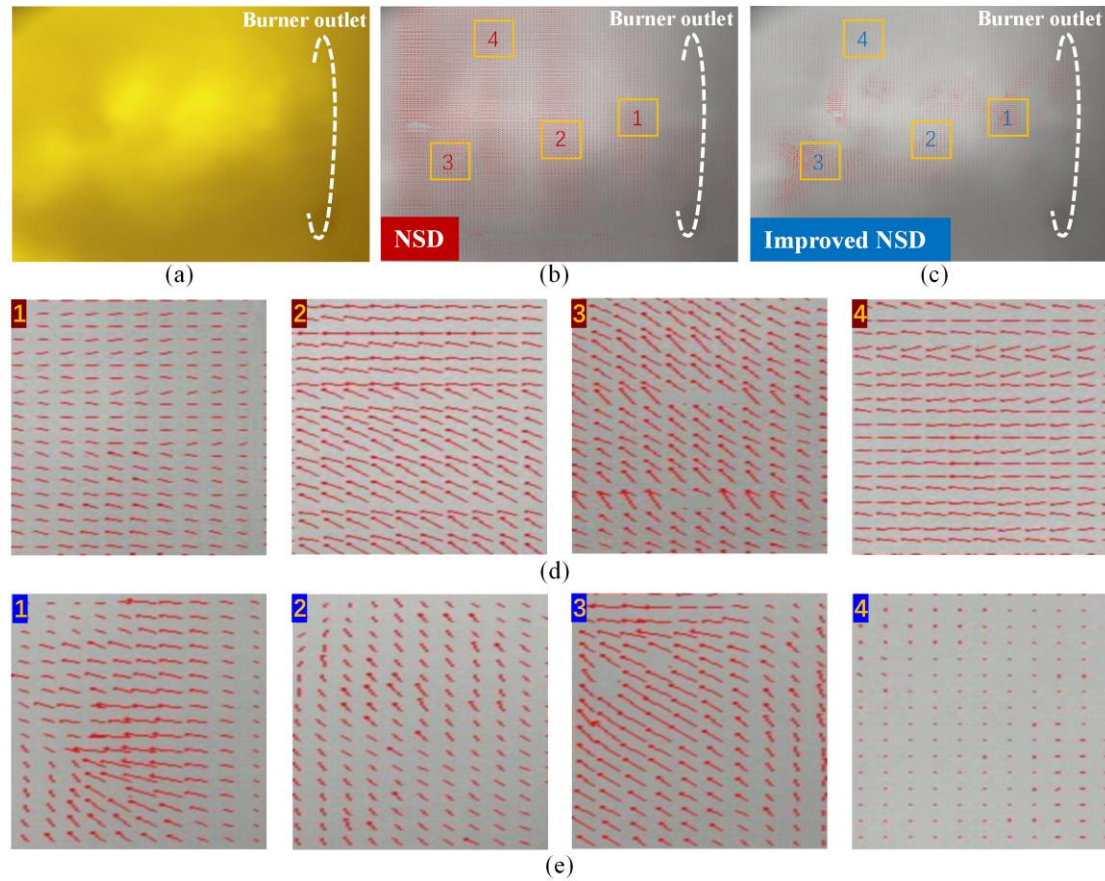


Fig.3. Comparison of optical flow estimation before and after NSD improvement, (a) original flame image, (b) conventional NSD, (c) proposed NSD, (d) optical flow estimated by the conventional NSD and (e) optical flow estimated by the proposed NSD.

2.3 Dynamic flame features extraction

In coal-fired power plant boilers, flames propagate rapidly, and both brightness and geometric features of the flame exhibit significant fluctuations during transient combustion processes. Especially during the unstable combustion stages, the optical flow vectors change in direction and

magnitude between consecutive image frames. The optical flow vectors not only capture the motion trajectory of the flame within the image sequence but also provide visual information about the flame propagation direction and velocity. To systematically characterize the combustion state and assess flame stability, five key parameters are extracted from the optical flow vector field, serving as dynamic descriptors of flame behavior.

Among these, flame velocity and direction are the key dynamic features of the flame. Through layer-by-layer iterative optimization, the optical flow vector d_i at feature point i in the base-level original flame image is obtained, where the magnitude of d_i represents the optical flow velocity at that point, as defined in Equation (15).

$$d_i = \|\mathbf{u}_i\| = \sqrt{u_i^2 + v_i^2} \quad (15)$$

Furthermore, by comparing the angle between the optical flow direction and the burner injection direction, it is possible to determine whether flame propagation deviates from the intended flow path. For the swirl burner investigated in this study, the burner injection direction refers to the main axial direction of the primary air–pulverized coal jet entering the furnace from the burner outlet, namely the direction along the burner centerline. During the operation of swirl burners, variations in primary air velocity, secondary air volume and coal feed rate may lead to an expansion of the flame recirculation zone or even result in flame impingement on the furnace wall. To quantify this deviation, the burner injection direction is defined as the reference direction, with angles in the same direction considered positive and those in the opposite direction considered negative. The burner injection direction is calculated by Equation (16).

$$\theta_i = \begin{cases} \arctan(v_i/u_i) & (u_i > 0, v_i > 0) \\ \pi/2 + |\arctan(v_i/u_i)| & (u_i > 0, v_i < 0) \\ \arctan(v_i/u_i) & (u_i < 0, v_i > 0) \\ -\pi/2 - \arctan(v_i/u_i) & (u_i < 0, v_i < 0) \end{cases} \quad (16)$$

where u_i and v_i represent the horizontal and vertical components of the optical flow at a pixel i in the base-level original image, respectively.

Four statistical dynamic features of the flame are quantitatively derived from the optical flow vectors of all n feature points in a single flame image frame: the mean velocity (a_n) and velocity variance (b_n), and the mean (c_n) and variance (d_n) of the flow directions. The corresponding formulas are provided in Equations (17)-(20) [44].

$$a_n = \frac{1}{n} \sum_{i=1}^n d_i \quad (17)$$

$$b_n = \frac{1}{n-1} \sum_{i=1}^n (d_i - a_n)^2 \quad (18)$$

$$c_n = \frac{1}{n} \sum_{i=1}^n \theta_i \quad (19)$$

$$d_n = \frac{1}{n-1} \sum_{i=1}^n (\theta_i - c_n)^2 \quad (20)$$

On the other hand, the dynamic variations of the flame during combustion are manifested as continuous fluctuations in the optical flow vector field. These optical flow pulsations not only reflect the inherent instability of the flame but also contain information about local combustion intensity and disturbance energy. Therefore, this study introduces the optical flow pulsation energy value ω as a key parameter for quantifying the intensity of flame dynamics. This parameter characterizes the level of pulsation activity and provides a quantitative basis for evaluating combustion stability, as defined in Equation (21).

$$\omega = \frac{\sum_{i=1}^n I \cdot \|\mathbf{u}_i\|_2^2}{2n} \quad (21)$$

where I denotes the grayscale intensity of the flame image, $\mathbf{u}_i$ is the optical flow vector at the i -th point, and n represents the total number of pixels within the flame region of the image. The L2 norm is used to represent the optical flow pulsation energy at each pixel in the flame image and the average level of optical flow pulsation in each frame is quantified by the expected energy

value across all flame-region pixels.

3. Experiments on a 660MW coal-fired boiler

Experiments were conducted on a 660 MW opposed-fired boiler equipped with swirl burners featuring rich-lean fuel separation. The selection of this boiler as the experimental object is mainly based on its engineering representativeness and practical operating characteristics. This type of boiler is widely used in large-scale coal-fired power generation units and frequently participates in deep peak shaving and load variation during actual operation. Under variable-load conditions, the air-coal ratio in the burner region may become mismatched. In particular, for swirl burners, variations in air flow rate and coal feed rate may lead to flame deflection or local combustion instability. Therefore, selecting burner flames from an actual 660 MW opposed-fired coal-fired boiler as the research object can more realistically reflect the combustion-state variations of large-scale coal-fired boilers under variable-load operating conditions and help verify the applicability of the proposed method in engineering applications.

The flame image acquisition system was installed at the flame observation port and consisted mainly of an optical probe and a CCD camera. As shown in Fig. 4, the optical probe has a field of view of 110° , ensuring coverage of a sufficiently wide combustion region. It should be clarified that the monitored location is representative of the local combustion state of the observed burner, rather than the whole furnace combustion zone. For the opposed-fired boiler investigated in this study, radiation from the background combustion region or the opposite-side flame may be superimposed along the line of sight and affect the captured pixel intensity to some extent. However, since the optical lens was directed toward the target burner flame region near the corresponding burner outlet, the captured radiation signal was mainly dominated by the target flame itself. In addition, the flame

generated from the swirl burner is a three-dimensional flame body with a certain spatial thickness and swirling morphology, rather than a thin two-dimensional structure, which further reduces the influence of background flame radiation within the selected field of view. Therefore, although line-of-sight superposition may exist, its influence on the optical-flow-based dynamic features extracted in this study is relatively limited. The CCD camera captures flame images at a frame rate of 25 frames per second. To prevent image distortion or saturation, the exposure time was set to 150 μ s. Air cooling was employed to protect the imaging equipment and ensure its stable operation under high-temperature conditions.

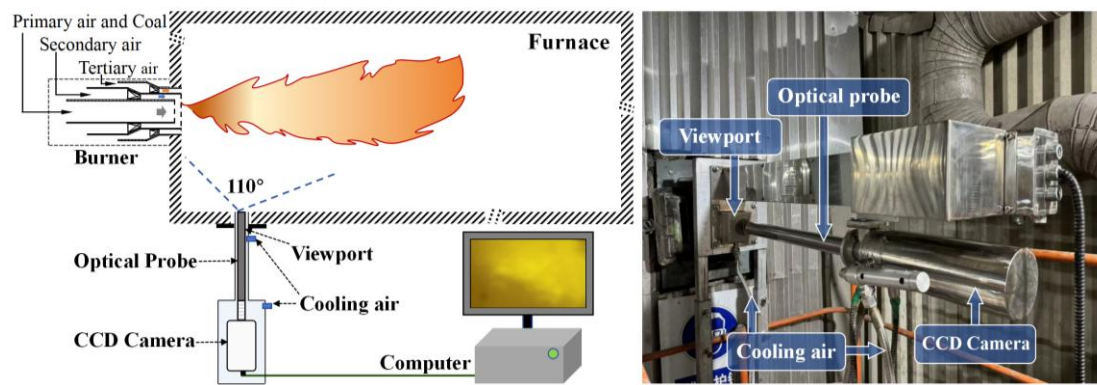


Fig. 4. Experimental setup of the flame imaging system.

Optical flow characteristics of the flame during boiler load reduction were analyzed at four operating loads: 570 MW, 470 MW, 370 MW, and 270 MW. The boiler is operated starting at a higher load and then gradually reduced to lower loads. At each load, flame image sequences were continuously captured for 20 seconds (25 frames/second) to compute the subsequent construction of optical flow vector fields and dynamic feature extraction analysis.

Table 1 presents the actual operating parameters under four representative conditions during the load reduction process. It should be noted that these operating parameters are not direct input variables for the optical-flow calculation, but are used to define different experimental operating

conditions and to help explain the relationship between air-coal regulation and flame dynamic behavior. In practical boiler operation, boiler load, coal feed rate, primary air velocity, and secondary air volume do not follow a strictly linear proportional relationship. Therefore, a reduction in boiler load does not mean that the coal feed rate and air supply should be reduced in the same proportion. The operating parameters listed in Table 1 were obtained from actual boiler operation records rather than from ideal proportional scaling. It can be observed that as the boiler load decreases, both the coal feed rate and the secondary air volume decline accordingly, while the primary air velocity increases. This control strategy is commonly adopted in practical power plant operations to ensure flame stability under low-load conditions. When the fuel supply and secondary air are reduced, increasing the primary air velocity helps maintain sufficient jet momentum at the burner outlet, thereby effectively preventing flame detachment or backflow.

Table 1: Operating parameters under different conditions

	Load	Coal feed rate	Primary air speed	Secondary air volume
	(MW)	(T/H)	(m/s)	(m³/min)
Condition 1	570	38	25.5	120
Condition 2	470	35	26.5	110
Condition 3	370	33	27.2	90
Condition 4	270	30	28.3	80

4. Results and discussion

4.1 Optical flow estimation under different loads

As boiler load decreases, the combustion characteristics of the burner flame vary significantly with changing operating conditions. Flame images were collected under four different load

conditions, as illustrated in Table 1, and optical flow analysis was performed to investigate the flame motion behavior across multiple operating scenarios. It should be noted that the flame images presented for the four load conditions were selected from temporally continuous flame image sequences rather than isolated single frames. During the acquisition period, the flame morphology under each operating condition remained relatively stable, and the selected images are representative of the overall flame behavior at the corresponding load.

Figure 5 presents the flame image and corresponding optical flow analysis results obtained at the burner outlet under a load of 570 MW, with a secondary air flow rate of 120 m³/h and a coal feed rate of 38 t/h. (a) shows the original flame image, (b) illustrates the optical flow vector field, and (c) provides the local details of the optical flow field at different characteristic regions to further reveal the motion features of the flame. In the flame root region (Regions 1 and 2), pulverized coal is injected into the furnace from the burner and is rapidly ignited due to the high furnace temperature. As a result, the optical flow vectors in these regions are relatively small, indicating stable combustion at the flame root. The direction of the optical flow vectors aligns with the injection direction of the burner, further confirming that the combustion state at the flame root is consistent with the current operating condition. In the main combustion region (Region 3), the flame is fully developed and unburned coal particles are almost absent. Consequently, there are no significant grayscale gradient variations in the image. This uniform grayscale distribution results in stable and evenly distributed optical flow vectors, further indicating that the combustion in this region is sufficient and steady, with no evident fluctuations or instability. In the flame boundary (Region 4), the optical flow vectors point toward the left, suggesting that the boundary combustion is complete and there is no sign of coal particle backflow or incomplete combustion. This observation further

validates the adequacy and stability of combustion under high-load conditions, demonstrating that the burner operates effectively at high load, with a reasonable flame spread.

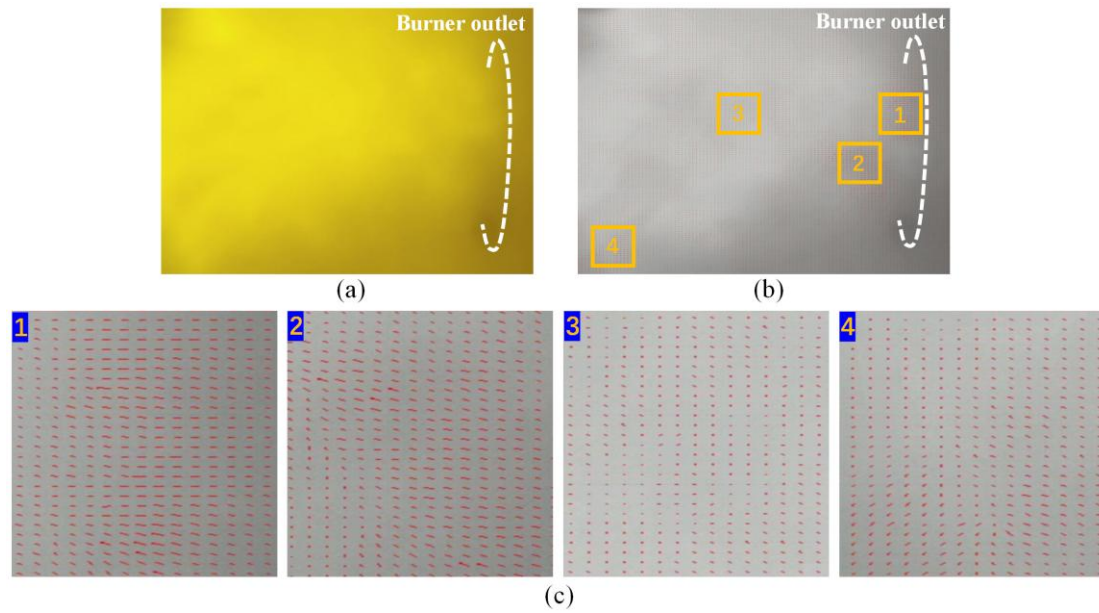


Fig. 5. Flame optical flow vector field under 570 MW load, (a) original flame image, (b) optical flow field, (c) detailed optical flow characteristics in different regions.

Figure 6 presents the flame image and corresponding optical flow analysis results obtained at the burner outlet under a load of 470 MW, with a secondary air flow rate of 105 m³/h and a coal feed rate of 36 t/h. (a) shows the original flame image, (b) illustrates the optical flow vector field distribution, and (c) highlights local details of the optical flow field at selected regions. Under these operating conditions, the flame exhibits intense combustion, and the optical flow vectors are primarily concentrated in the lower part of the combustion region, a phenomenon closely associated with the operating principle of the rich–lean separated swirl burner. These dynamic features can be clearly visualized through the optical flow analysis, providing an intuitive representation of the flame motion characteristics. In the flame root region (Region 1), the optical flow vectors predominantly point to the left, consistent with the burner’s injection direction. Compared to the 580 MW condition, the flame in this region is more strongly influenced by unburned pulverized coal

jets, resulting in more pronounced optical flow variations. In the coal-rich regions (Regions 2 and 3), the boundary between the flame and coal particles is clearly defined, with noticeable changes in the optical flow direction. The arrows point toward the flame zone, indicating that flame–coal interactions are more prominent in these areas. The magnitude and direction of the optical flow reflect the spatial distribution of coal and flame, as well as the dynamic evolution of flame propagation. In contrast, Region 4 lies within the main combustion zone of the flame, where the optical flow vectors are sparse and of low magnitude. This suggests that the flame in this area maintains a relatively stable structure, with a continuous and complete combustion process, and no significant disturbances or reverse flows are observed.

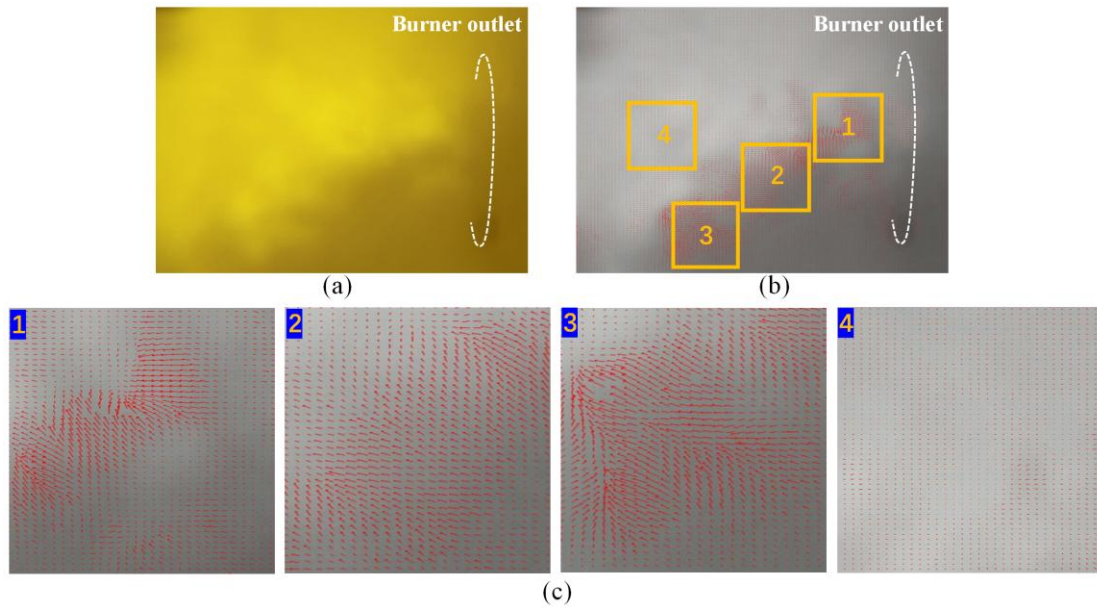


Fig. 6. Flame optical flow vector field under 470 MW load, (a) original flame image, (b) optical flow field, (c) detailed optical flow characteristics in different regions.

Figure 7 presents the flame image and optical flow analysis results obtained at the burner outlet under a load of 370 MW, with a secondary air flow rate of 90 m³/h and a coal feed rate of 30 t/h. Panel (a) shows the original flame image, panel (b) illustrates the optical flow vector field, and panel (c) provides local details of the optical flow field at representative regions. Under these operating conditions,

the combustion region exhibits an interlaced distribution of flame and pulverized coal, with the upper portion dominated by flame and the lower portion by unburned coal particles. This stratified distribution is attributed to the design characteristics of the rich–lean swirl burner, where the dense-phase coal stream is directed upward and the lean-phase stream downward. From Region 1 to Region 2, the optical flow directions of the flame are consistent with the actual injection direction of the burner, indicating that the pulverized coal–air mixture flows and combusts stably along the designed trajectory. Region 2 is characterized by minimal optical flow variation in the center and more intense variation around the periphery, reflecting the combustion process of coal particles within the flame texture. In the lower coal-rich zone, the optical flow vectors are small, indicating that the pulverized coal in this region remains stable and no explosive combustion has occurred. As the coal particles move, Regions 3 and 4, located at the interface between the flame and coal regions, reflect the particle trajectories through the direction of the optical flow vectors. These vectors point toward the flame zone, indicating that the coal particles gradually migrate into the flame region under the influence of airflow and are ignited once the ignition conditions are met.

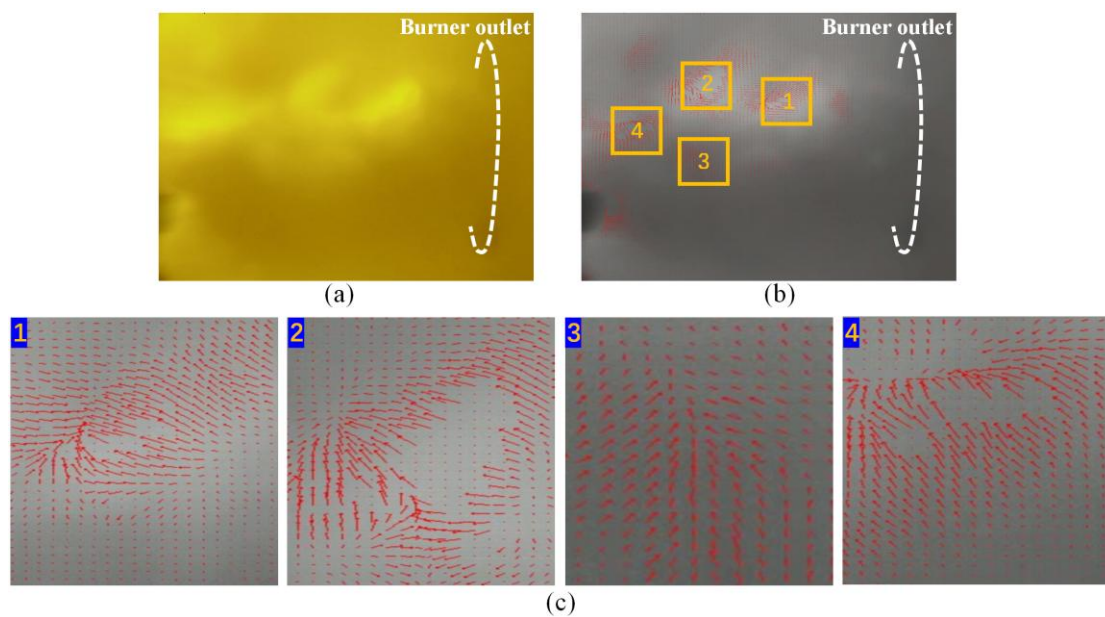


Fig. 7. Flame optical flow vector field under 370 MW load, (a) original flame image, (b) optical flow

field, (c) detailed optical flow characteristics in different regions.

Figure 8 presents the flame image and optical flow analysis results obtained at the burner outlet under a load of 270 MW, with a secondary air flow rate of 70 m³/h and a coal feed rate of 30 t/h. (a) shows the original flame image, (b) illustrates the optical flow vector field, and (c) highlights local details of the optical flow field at representative regions. Compared with the combustion state at 350 MW, the flame and pulverized coal remain interlaced; however, the flame-dominated area has further decreased, whereas the coal-rich region has become more pronounced, indicating a lower degree of combustion completeness under this operating condition. In Regions 1 and 2, the optical flow vectors align with the combustion direction. In contrast, in Regions 3 and 4, the vectors are oriented opposite to the burner injection direction, pointing toward the flame zone. This distribution is primarily attributed to the contraction of the flame region and reduction in the main combustion volume under low-load conditions. As a result, unburned pulverized coal surrounding the flame is driven by airflow and converges toward the remaining high-temperature zone, forming inward-pointing optical flow vectors. This phenomenon indicates that even under flame contraction, the transport of coal particles remains directional and the surrounding fuel continues to participate in combustion. This process helps maintain the continuity of reactions within the main combustion zone.

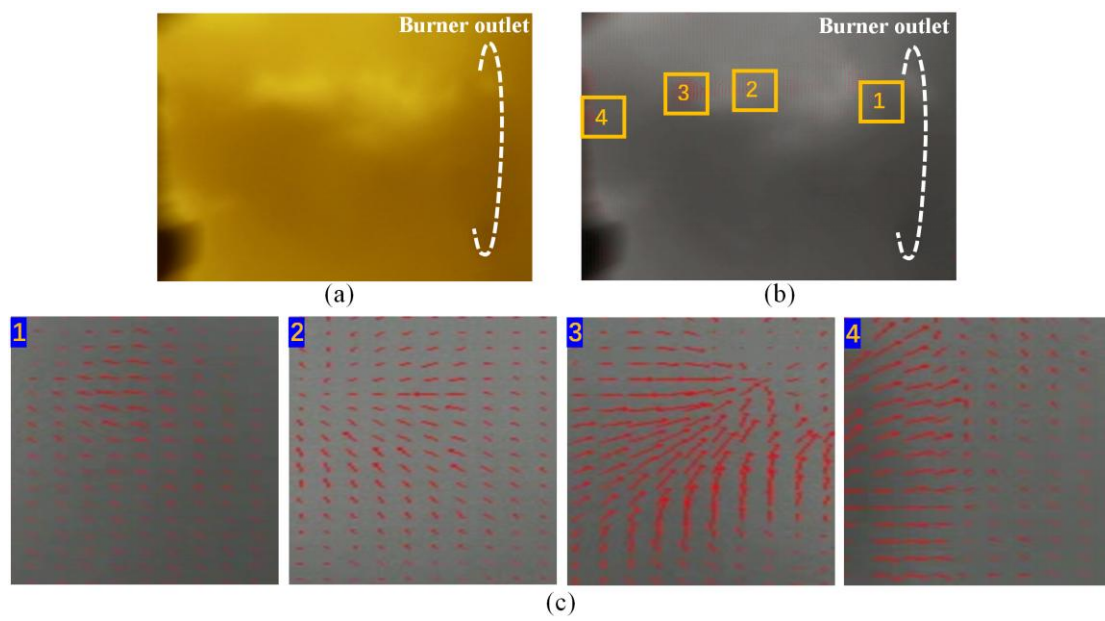


Fig. 8. Flame optical flow vector field under 270 MW load, (a) original flame image, (b) optical flow field, (c) detailed optical flow characteristics in different regions.

4.2 Combustion state identification under different loads

Flame image acquisition and analysis were conducted under four different load conditions. For each condition, a 20-second sequence of flame images was continuously captured under stable combustion, with an image frame rate of 25 fps. Based on optical flow estimation between adjacent frames, combined with the five dynamic flame features proposed in this study, a dynamic characterization of the combustion state under varying loads was achieved. Since the optical flow estimation is based on frame-to-frame differencing, 24 sets of dynamic feature values can be computed per second, enabling the construction of a time-series distribution that describes the flame evolution behavior for each operating condition.

Figure 9 illustrates the variation trend of the optical flow pulsation energy ω under different load conditions. For ease of numerical representation and comparison, ω is expressed in units of $\times 10^5$. In the subsequent analysis, all related values are reported using only the coefficient, with the exponential part omitted for brevity. Based on the distribution of optical flow pulsation energy under

stable conditions at each load, corresponding stability intervals are further defined, as shown in Table 2. The overall results indicate that as the boiler load decreases, the overall combustion intensity of the flame gradually weakens, as reflected by the continuous decline of ω . Meanwhile, the fluctuation range corresponding to each load remains within 0.2, demonstrating that under stable combustion conditions, each load has its specific ω interval, which can therefore serve as an important reference standard for evaluating combustion states.

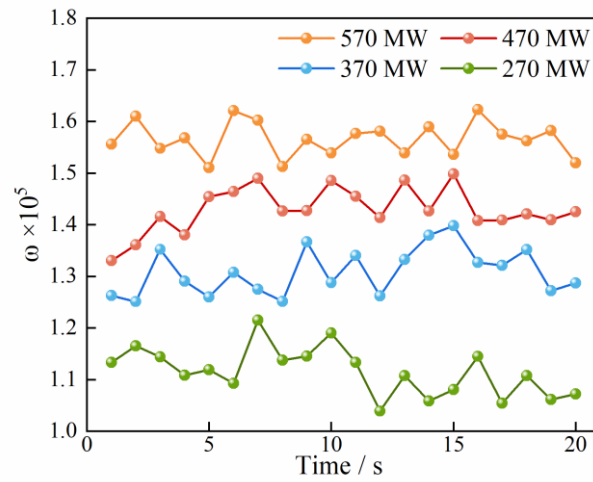


Fig.9 . Optical flow pulsation values energy (ω) under different load conditions

Table 2: Overview of average optical flow pulsation energy (ω) under different conditions

	Load (MW)	Average ω ($\times 10^5$)	Fluctuation range ($\times 10^5$)
Condition 1	570	1.55	[1.50-1.63]
Condition 2	470	1.43	[1.32-1.48]
Condition 3	370	1.31	[1.24-1.40]
Condition 4	270	1.12	[1.02-1.22]

Figure 10 illustrates the variation trends of four statistical indicators: the mean velocity (a_n), the velocity variance (b_n), the mean flow direction (c_n), and the direction variance (d_n). Under the 570 MW load condition, the value a_n reaches its minimum, which is primarily attributed to the

intense combustion at high load. In this condition, pulverized coal particles injected from the burner combust rapidly and completely, resulting in a saturated flame region in the image with minimal grayscale gradients, thereby leading to smaller optical flow variations. As the load decreases, the coal region gradually expands, and the flame zone, coal particle region and flame texture area in the image exhibit more pronounced grayscale gradients. This leads to increased optical flow velocity variations.

At load levels of 470 MW, 370 MW, and 270 MW, the primary air velocities were 26 m/s, 26.5 m/s, and 27 m/s, respectively. Although the measured optical flow velocity does not directly represent the true physical flame speed, its variation trend still reflects the dynamic changes in flame imagery under the given operating conditions. The trend of the b_n curve further supports this observation: as the load decreases, the variation in optical flow velocity increases, indicating that the combustion state—characterized by the interaction between flame and pulverized coal—becomes more complex under lower load conditions compared to high-load operation.

In addition, the analysis results of c_n and d_n show that the flame direction angle θ is primarily concentrated between 1.3 and 1.5 radians (53° – 55°), indicating that the flame generally propagates toward the upper-left direction, which is consistent with the actual flame orientation in the furnace. Under high-load conditions, the flame angle exhibits greater stability, whereas as the load decreases, slight fluctuations in the flame direction are observed. This phenomenon further confirms the influence of load variation on the dynamic characteristics of the flame.

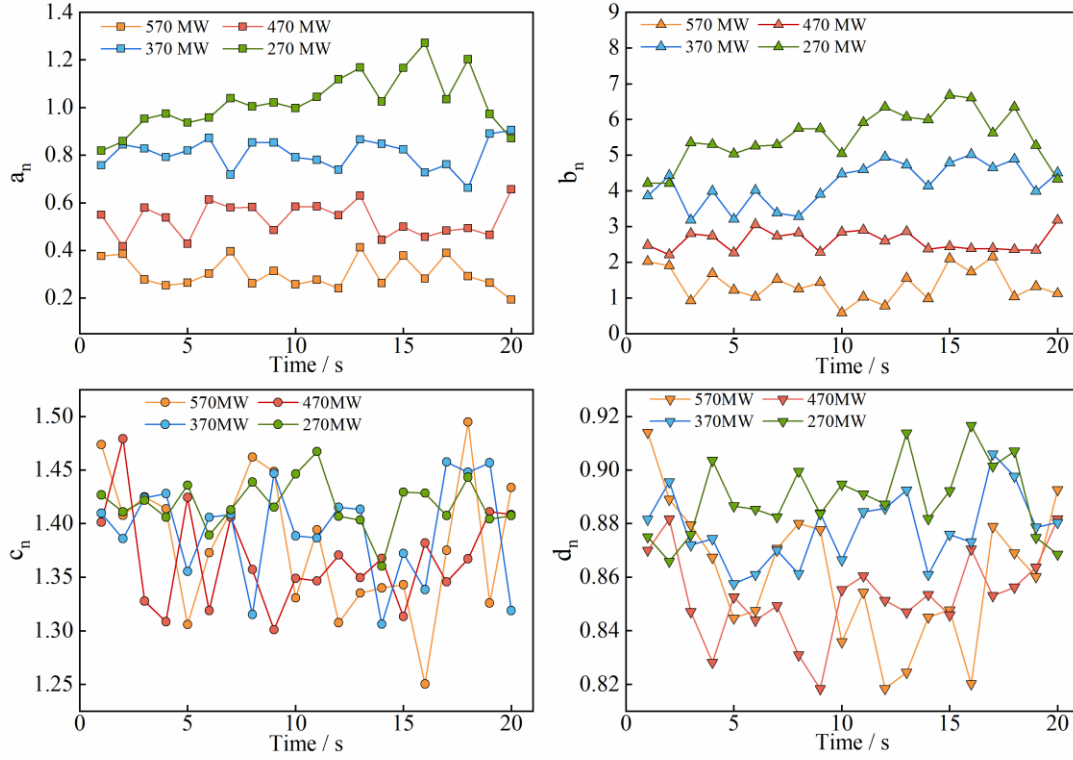


Fig. 10. Optical flow velocity and direction features of the flame

4.3 Unstable combustion identification based on the dynamic features

The regulation of coal-fired power plant boilers is inherently complex and improper adjustments may alter the combustion state, or in more severe cases, compromise the safe operation of the boiler. During deep peak-shaving operations, the boiler load was reduced to 270 MW. Figure 11 presents the flame image and corresponding optical flow analysis results observed under this low-load condition. (a) shows the original flame image, (b) illustrates the optical flow vector field, and (c) highlights local details of the optical flow field at representative regions. It should be noted that the 270 MW condition shown in Fig. 11 is different from the stable 270 MW condition shown in Fig. 8. Although both figures were obtained at the same boiler load, the corresponding flame images exhibit significantly different combustion characteristics. Under low-load operation, the flame area is expected to decrease compared with high-load conditions; however, a visible and continuous flame region should still exist near the burner outlet. In Fig. 11, no obvious luminous

flame region can be observed near the burner outlet. Instead, the burner outlet region is largely occupied by pulverized coal particles, indicating delayed ignition and poor combustion organization. It should also be emphasized that this abnormal condition was not an instantaneous phenomenon observed in a single frame. Throughout the entire 20 s flame image sequence, the burner outlet region was continuously dominated by pulverized coal injection. Therefore, this condition was identified as an abnormal combustion state under low-load operation. At this stage, the injected pulverized coal particles fail to ignite promptly, resulting in an expansion of the unburned coal zone. The optical flow vectors are primarily concentrated along the upper edge of the flame. Prolonged operation under such low-load conditions, characterized by a large unburned coal region, tends to cause coal particle accumulation near the burner outlet. If the local temperature rises abruptly, instantaneous ignition may be triggered, posing a potential risk of detonation or explosive combustion.

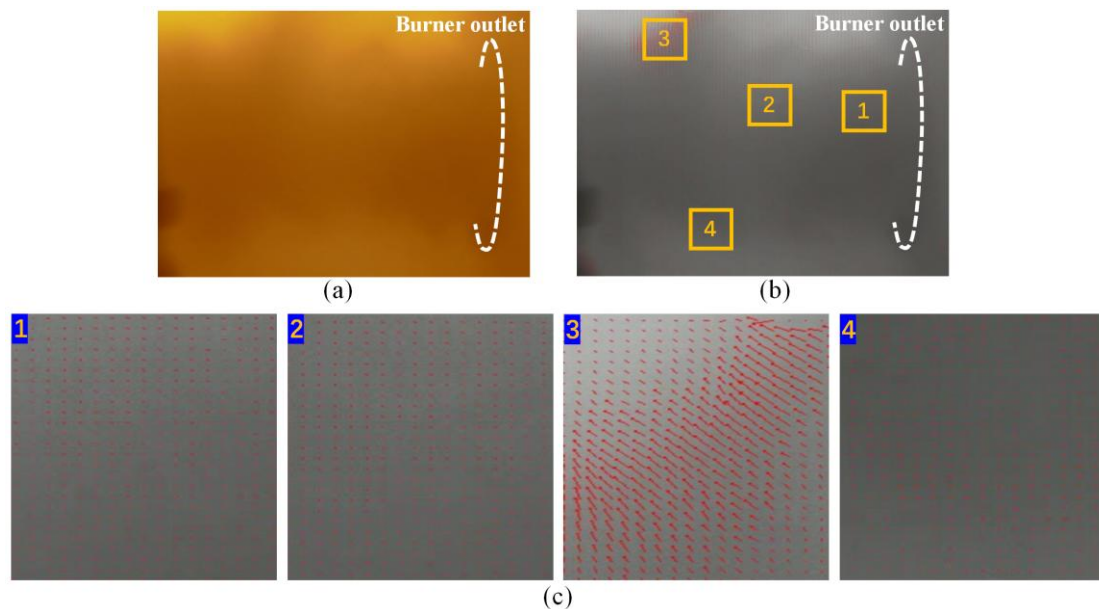


Fig. 11. Optical flow vector field of unstable combustion at 270 MW (a) original flame image, (b)

optical flow field, (c) detailed optical flow characteristics in different regions.

Figure 12 compares the variation ω between stable and abnormal combustion states at a

270 MW load. During abnormal combustion, although the fluctuation range of ω remains around 0.2, the overall value is clearly below the lower limit of the previously defined stable combustion interval. This indicates that the presence of an enlarged unburned coal particle region at the burner outlet leads to a reduction in flame energy pulsation. By further comparing the variations of a_n and b_n , it can be observed that a_n exhibits slight fluctuations around 0.3, which is significantly lower than the average level under normal 270 MW load conditions. In contrast, the velocity variance b_n remains relatively stable, showing no significant fluctuation.

Based on image observations and optical flow analysis, it can be concluded that when the burner outlet region is completely covered by the dark-core zone, the pulverized coal particles fail to ignite promptly, leading to reduced activity in the main flame region. Consequently, both the optical flow pulsation energy ω and the mean velocity a_n decrease simultaneously. Meanwhile, the stable behavior of the velocity variance b_n further indicates that this condition is not a transient disturbance but rather exhibits a certain degree of persistence, suggesting a tendency to evolve into a sustained abnormal combustion state.

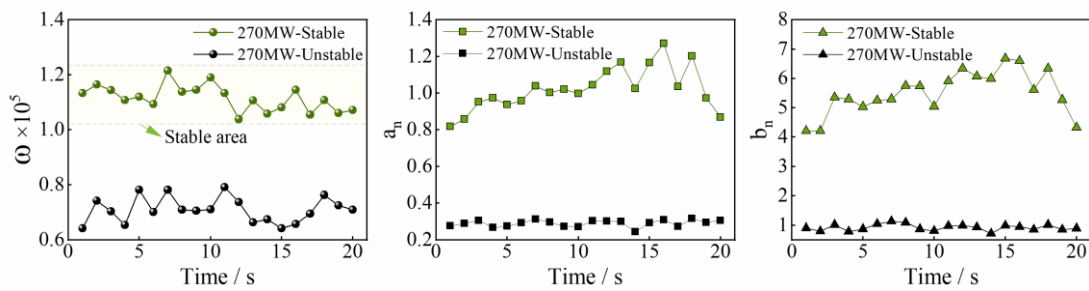


Fig. 12. Comparison of dynamic features during unstable combustion at 270 MW

Figure 13 presents the actual operating parameters under the abnormal combustion condition at 270 MW. The combustion state is influenced by the coupling of multiple operating variables and this effect becomes particularly significant under deep peak-shaving conditions, where the impact on flame morphology and combustion stability is more pronounced. As shown in Figure 12(a), the

secondary air volume for this burner layer experienced a substantial drop under the 270 MW condition, falling sharply from 85 m³/min (during stable operation) to 53 m³/min—a reduction of nearly 40%. At the same time, both the primary air velocity and the coal feed rate were higher than those typically observed under normal low-load conditions. In theory, moderately increasing the coal feed rate under low-load conditions helps maintain the pulverized coal concentration in the furnace, thereby enhancing flame intensity to prevent flameout. However, in this abnormal case, a significant mismatch between operating parameters is observed: the insufficient secondary air volume fails to supply adequate oxidizer to complete combustion, while the elevated coal feed rate increases the fuel burden, further aggravating combustion instability. Additionally, the higher primary air velocity accelerates the injection of pulverized coal into the furnace, causing the ignition point to shift forward and further contributing to the expansion of the unburned coal particle region.

Comprehensive analysis indicates that this abnormal condition results from an imbalance in the proportional relationship among primary air velocity, secondary air volume and coal feed rate. Under this load condition, the relatively high primary air velocity and coal feed rate must be supported by sufficient secondary air to provide the necessary oxidizer for stable combustion. Once the secondary air volume becomes insufficient, the limited supply of combustion-supporting air can easily trigger non-steady combustion phenomena such as flame displacement, forward shifting of the ignition point, and expansion of the unburned coal particle region. In severe cases, these issues may even pose a risk of furnace detonation.

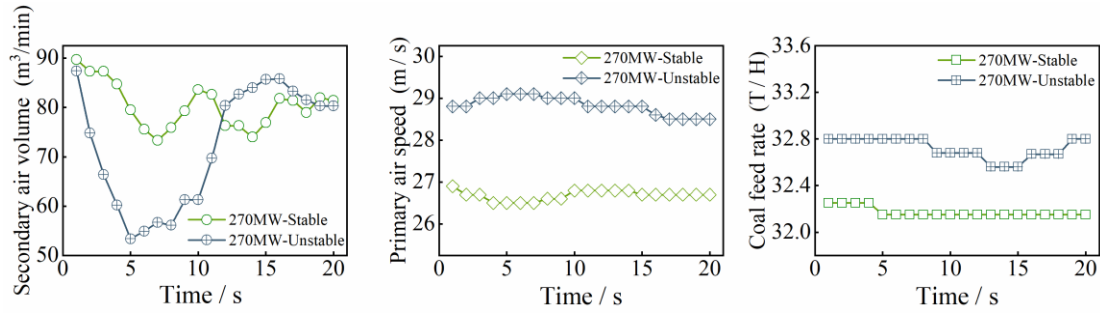


Fig. 13. Comparison of operating parameters during unstable combustion at 270 MW

Figure 14 illustrates an abnormal combustion condition observed during high-load boiler operation, with a typical manifestation of flame impingement on the water-cooled wall. (a) shows the original flame image, (b) illustrates the optical flow vector field, and (c) provides local details of the optical flow field at representative regions. In this case, a large amount of pulverized coal particles and flame jets deviate from the intended injection path and shift toward one side of the furnace, intensely impinging on the water wall near the camera-facing side. This deviation and impingement not only increase the thermal load and erosion risk of the water wall but also reflect significant disruption in the furnace's internal airflow organization.

The corresponding optical flow vector field clearly shows that some coal particles and flame plumes move in a direction opposite to the main injection axis of the burner, exhibiting a characteristic backflow toward the camera. Compared with the orderly vector field observed under stable combustion conditions, the optical flow vectors in each frame during this abnormal state appear highly disordered with dispersed directions and large amplitude fluctuations, demonstrating typical features of an unstable flow field.

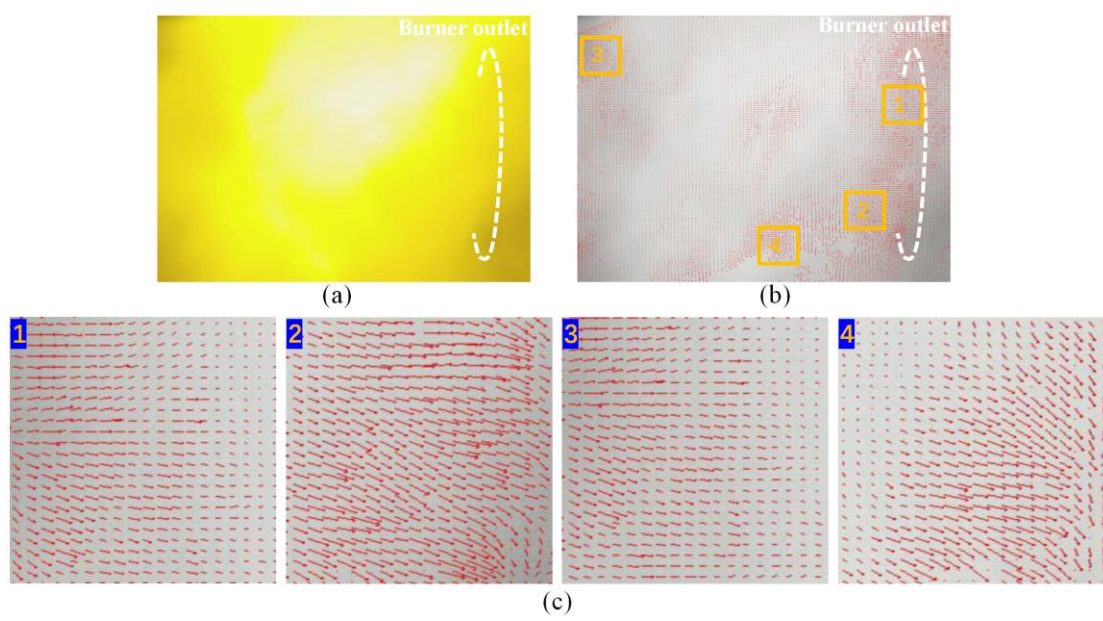


Fig. 14. Optical flow vector field of operational load 570 MW (a) original flame image, (b) optical flow field, (c) detailed optical flow characteristics in different regions.

Figure 15 illustrates the temporal variation of the optical flow pulsation energy ω under a boiler load of 570 MW, comparing the stable combustion condition with an abnormal state characterized by flame deflection and impingement on the water-cooled wall. Under stable combustion, ω fluctuates within a narrow range of 1.5–1.65. In contrast, the abnormal condition exhibits significantly stronger fluctuations, with a maximum variation approaching 0.4. Some instantaneous values exceed the upper bound of the stable range, reaching up to approximately 1.8, while others drop below 1.45, indicating substantial instability in the flame behavior. The sharp increases of ω are primarily attributed to the intense combustion of coal particles occurring near the water-cooled wall. In this condition, the flame propagates along the wall-adjacent region with a trajectory more closely aligned with the CCD camera's optical axis. This results in a localized surge in image brightness and greater apparent pixel motion due to the reduced distance, thereby producing larger optical flow vectors and increased ω values. Conversely, the observed low ω values are associated with the presence of coal dust or unburned particles recirculating and striking

the water wall, some of which adhere to the lens surface. This partial obstruction of the flame region leads to reduced image brightness and loss of texture detail, weakening the optical flow estimation and resulting in ω values falling below the lower bound of the stable range.

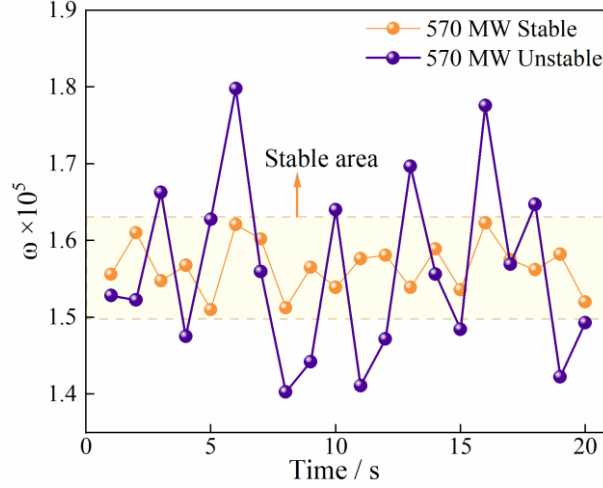


Fig. 15. Comparison of optical flow pulsation energy (ω) at operation load 570 MW

As shown in Figure 16, under the combustion instability condition at 570 MW, the mean optical flow velocity a_n is significantly higher than that under stable operation. This is primarily due to the recirculating coal particles and flame fronts burning close to the water-cooled wall, which are also closer to the CCD camera. The reduced distance enhances both local image brightness and apparent motion, thereby increasing the amplitude of optical flow variations. Meanwhile, the velocity variance b_n exhibits pronounced fluctuations under abnormal conditions, indicating instability in the gas-particle flow near the water wall. Regarding the mean flow direction c_n , a large number of negative values are observed during the unstable state, suggesting that the dominant flow direction is opposite to the burner injection direction and consistent with the presence of reversed or recirculating flow patterns. In contrast, under stable combustion c_n remains consistently positive, reflecting a high degree of directional coherence. Furthermore, the trend of the directional variance d_n reveals that under stable conditions, the fluctuation of flame angles is

relatively small and the direction distribution is more concentrated. Under unstable conditions, however, the distribution of optical flow directions becomes more dispersed, indicating enhanced flow disturbance and directional instability.

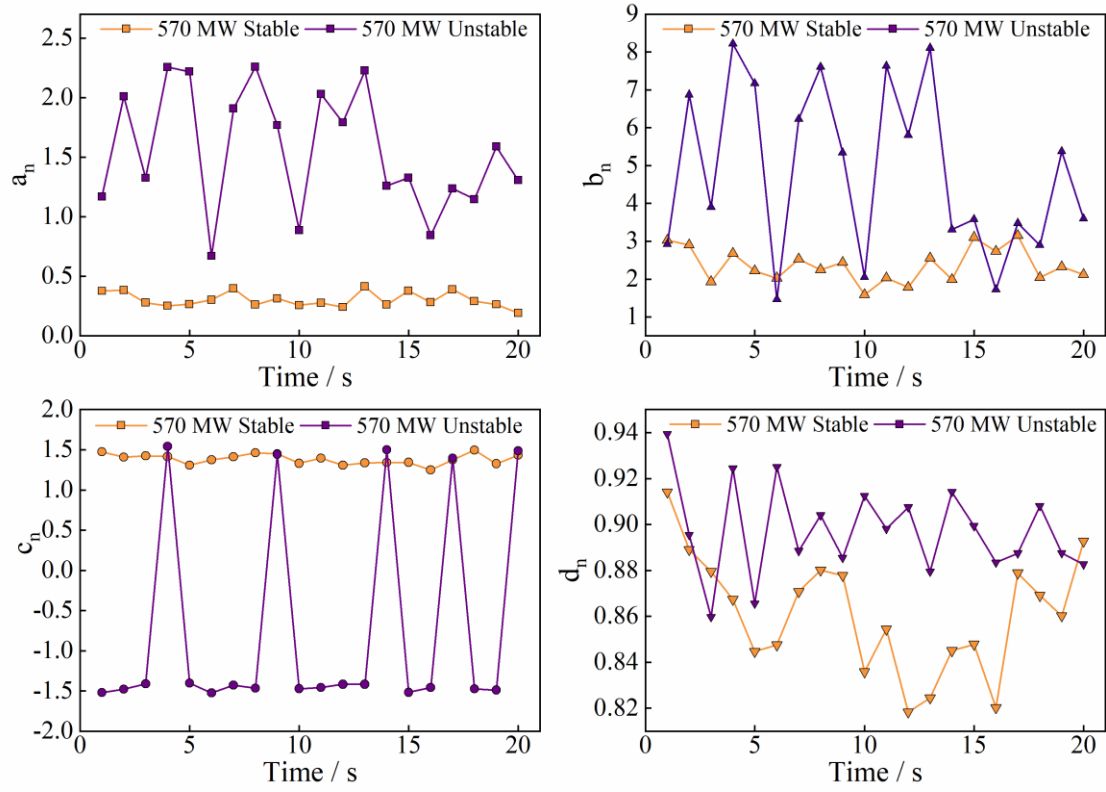


Fig.16. Comparison of dynamic features at operation load 570 MW

Figure 17 illustrates the variation in boiler operating parameters associated with combustion instability under the 580 MW condition. During stable combustion, the coal feed rate is 37 T/h, the secondary air volume is maintained at approximately 120 m³/min and the primary air velocity is around 25.4 m/s. These parameters are well-balanced, supporting stable flame behavior. However, under the abnormal combustion condition, significant parameter mismatches occur: the secondary air volume drops sharply to approximately 80 m³/min, the primary air velocity decreases to 24.8 m/s, while the coal feed rate increases to 39 T/h. Under this scenario, the amount of combustion air per unit of pulverized coal becomes insufficient, resulting in a reduced oxygen concentration, which

inhibits complete combustion. Additionally, the reduction in primary air velocity lowers the momentum of the carrier flow, compromising the stability of coal particle injection. More critically, the reduced secondary air volume directly weakens the swirl intensity. Swirl burners rely on the rotational flow generated by secondary air to stabilize flame anchoring and maintain combustion stability. When the swirl is weakened, the flame's divergence angle increases, making it more prone to shifting toward the furnace wall and forming asymmetric flame structures. This process is also confirmed by flame imaging and optical flow analysis, which reveal that the primary combustion zone expands toward the furnace boundaries, with portions of the flame and coal particles migrating toward and propagating along the near-wall region.

In summary, this abnormal condition is not caused by a single variable but results from an air–coal mismatch characterized by a combination of high coal feed rate, low primary air velocity, and low secondary air volume. This mismatch leads to flame displacement, structural instability, and disturbed combustion behavior.

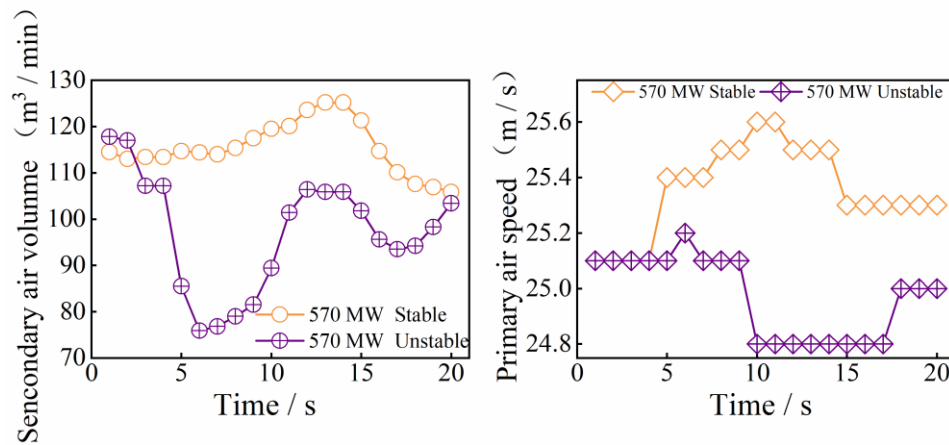


Fig. 17. Comparison of operating parameters at operation load 570 MW

5. Conclusions

This study proposes an improved NSD optical flow method that integrates an image pyramid

strategy, a robust enhancement function and an adaptive adjustment mechanism. An optical flow vector field is constructed by this method to enable visual characterization of the dynamic behavior of burner flames in coal-fired power plant boilers. Dynamic flame features are further extracted to identify combustion states under varying load conditions. The key findings are as follows:

- Based on the analysis of stable combustion under different load conditions, the fluctuation range of optical flow pulsation energy is generally confined within 0.2, indicating strong consistency and stability. This range can therefore serve as a reference interval for combustion stability. Under abnormal conditions, significant deviations are observed at 270 MW. The pulsation energy decreases to ~ 0.7 with weakened flame motion and expanded unburned coal regions; at 570 MW, the peak reaches 1.8 with flame deflection and wall impingement. These results confirm that the extracted dynamic features are strongly correlated with combustion stability and can effectively identify unstable combustion.
- Combined analysis of the operating parameters and the optical flow field indicates that unstable combustion conditions are often linked to mismatches in the regulation of key operational parameters. Under low-load conditions, weakened combustion intensity combined with reduced secondary air leads to insufficient oxygen for coal combustion, resulting in the expansion of unburned coal regions and diminished flame activity at the root. Under high-load conditions, although the furnace environment is favorable for combustion, a lack of sufficient secondary or primary air disrupts the aerodynamic swirl required for flame stability, leading to lateral flame deflection and wall impingement, thus increasing operational risks.
- The method proposed in this study effectively addresses optical flow estimation errors caused by rapid flame motion and blurred boundaries. However, the optical-flow vectors obtained

from flame images describe the apparent motion of flame structures in the two-dimensional image plane, rather than the real three-dimensional velocity field inside the furnace. Therefore, the dynamic features extracted in this study are more suitable for relative combustion-state evaluation and stability monitoring, rather than direct quantitative measurement of the physical flame velocity.

- Future work will focus on the coupling of dynamic and static flame features to achieve a more comprehensive analysis of flame states. In addition, the load-dependent stable intervals of optical-flow pulsation energy will be further refined as preliminary warning thresholds for abnormal combustion. Long-term multi-source time-series operating data will also be combined with flame dynamic features to develop a more reliable early prediction model for combustion instability.

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