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Deep learning-based prediction of flashback of swirling hydrogen-air flame

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Abstract. Lean-premixed hydrogen combustion has recently drawn attention as an environmentally friendly approach for aircraft gas turbine engines. However, the flame flashback is one major challenge associated with premixed hydrogen combustion. Flashback poses a critical risk to the combustor system and the safe operation of gas turbine engines, making accurate prediction of flashback behavior essential. Our recent work investigated the flashback phenomena of a lean-premixed hydrogen-air jet flame in the low-swirl combustor (LSC) using Large Eddy Simulation (LES). The present study focuses on developing a predictive model for flashback phenomena based on the LES data. An encoder-decoder architecture based on Convolutional Neural Network (CNN) is adopted to construct the model. Since the LES results proved that the flashback in LSC is core flow flashback, which is controlled by the competition between inflow velocity and turbulent burning velocity, the velocity in the streamwise direction along with key physical quantities affecting turbulent burning velocity are selected as input features to the CNN architecture, while its output is the flashback propensity at the subsequent time step. The results show that the proposed model successfully predicts flashback behavior in the next time step using current flame surface data despite the flame shape changing continuously.

1. Introduction

Lean-premixed hydrogen combustion has recently drawn attention as an environmentally friendly approach for aircraft gas turbine engines. However, one major challenge associated with premixed hydrogen combustion is the flame flashback into the injector. The primary cause of flashback is the high burning velocity of hydrogen fuel. Additionally, combustion instability, frequently problematic in hydrogen combustion, can trigger flashback. Flashback poses a critical risk to the combustor system and the safe operation of gas turbine engines, making accurate prediction of flashback behavior essential.

When designing combustors, flame behavior is analyzed using experiments and numerical simulations to verify combustor geometries and operating conditions that prevent flashback. However, experiments present safety challenges, and high-accuracy numerical simulations involve substantial computational costs, limiting their applicability. Recently, machine learning has attracted attention as a method to overcome these challenges. By learning complex nonlinear relationships from extensive experimental and numerical simulation data, machine learning is expected to enable rapid elucidation of flashback mechanisms and prediction of flame behavior.

Several previous studies have applied machine learning to flashback phenomena. For example, Chen *et al.* [1] predicted future flame shapes from experimental data of flashback in scramjet combustors and compared the accuracy of multiple deep learning models. Similarly, Leask *et al.* [2] applied neural networks to experimental data of flashback in a swirling combustor, developing a predictive model for flashback occurrence. However, since flashback behavior varies significantly depending on fuel properties and combustor geometry [3], it is essential to verify the mechanisms and prediction methods for diverse combustion modes.

More recently, Shoji *et al.* (Japan Aerospace Exploration Agency, JAXA) conducted experiments on flashback in a low-swirling hydrogen combustor [private communication], observing flashback originating from the burner center. Additionally, Kawai *et al.* [4] applied Large Eddy Simulation (LES) to the combustion field [5-8] investigated by Shoji *et al.*, accurately reproducing the flashback behavior and obtaining high-resolution combustion field data. In this study, a machine learning model is proposed to predict flashback propensity using the LES data.

2. Methodology

2.1. Data extraction

High-resolution data obtained from LES [4] is utilized to predict flame behavior during flashback. Figure 1 shows the time variation of the flame surface obtained by the LES. Flame surface is defined as the surface where the mass fraction of H_2O, which is the reaction progress variable used for analyzing premixed hydrogen-air combustion, equals 0.101. The premixed gas is ignited downstream of the injector exit and propagates upstream to reach the swirler. In this study, LES data is used from the time when the flame tip reaches the injector outlet to the time just before it reaches the swirler. The data extraction interval is set to $\Delta t = 0.1$ ms, and 355 samples are used for machine learning. 80% of the LES data are used for training and the remaining 20% are used for validation.

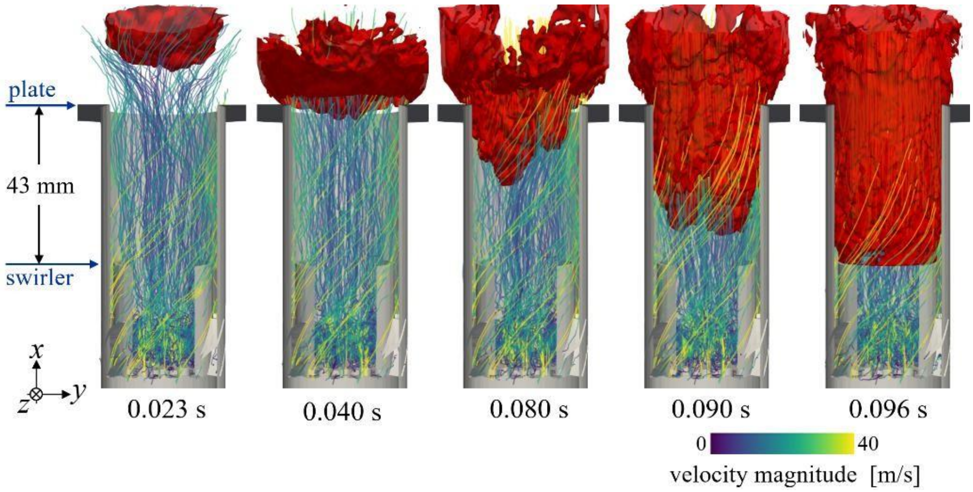

Figure 1: Temporal evolution of the flame surface (in red) and streamline.

Figure 2 provides a schematic diagram illustrating the data extraction method. The three-dimensional distribution of physical quantities near the flame surface is projected onto the y–z plane to extract two-dimensional data. The physical quantities used as explanatory variable data include the x-component of flow velocity at 0, 0.5, 1.0, and 2.0 mm upstream of the flame surface, as well as the equivalence ratio, pressure, density, temperature, heat release rate, circumferential velocity, vorticity, y-, and z-components of flow velocity, and x-, y-, and z-components of the unit normal vector of the flame surface. The objective variable, the flashback propensity Δx_{jk}^{t}, is defined as follows.

$$\Delta x_{jk}^{t} = x_{jk}^{t+\Delta t} - \bar{x}^{t} \tag{1}$$

Where x is a flame surface position in the mainstream direction, superscript denotes time, a subscript denotes position on the y-z plane, and $\bar{}$ is the spatial average. To eliminate the influence of the wall, data from the region around the axis of the combustor, i.e., $|y|, |z| \leq 9$ mm, are extracted.

To augment the dataset, each two-dimensional image is divided into four equally sized sub-images by splitting it along the vertical and horizontal axes. Each sub-image is then rotated by 0°, 90°, 180°, and 270°, respectively, resulting in a 16-fold increase in the number of images. Finally, standardization is applied.

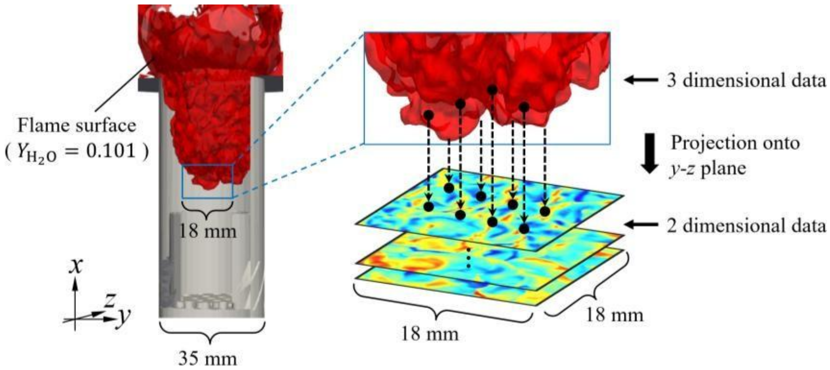

Fig. 2: Schematic diagram of the data extraction method.

2.2. *Model architecture*

The model architecture is based on an encoder-decoder structure designed for image-to-image regression tasks. The architecture is inspired by the conventional U-net [9]. While standard U-net models are primarily designed for classification tasks, the output structure is modified to accommodate the regression objective of this study. Figure 3 shows a schematic diagram of the model architecture. The encoder extracts hierarchical features from the input, while the decoder reconstructs the output image from these features. Skip connections are incorporated between corresponding layers of the encoder and decoder to preserve spatial information and improve gradient flow. Both the input and output are two-dimensional images with a resolution of 128 × 128 pixels. The training conditions are summarized in table 1.

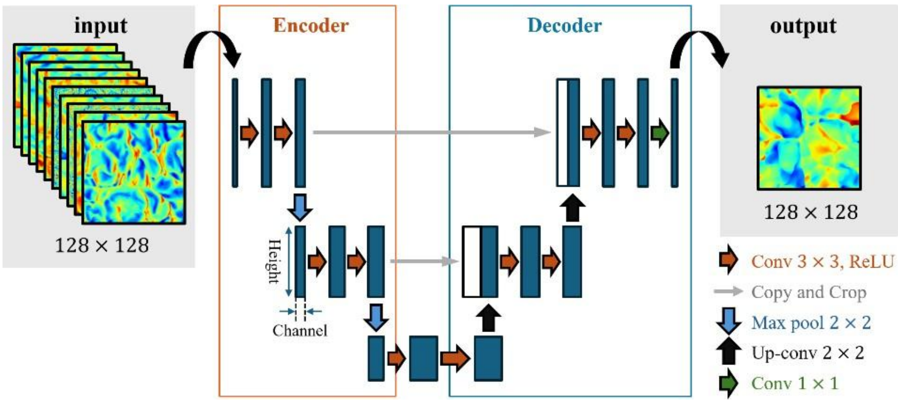

Figure 3: Schematic diagram of model architecture.

Table 1: Training conditions.

Library	PyTorch
Loss function	Mean Square Error (MSE)
Activation function	ReLU [10]
Optimizer	Adam [11]
Batch size	8
Learning rate	0.00001
Epoch	100
VRAM	24 GB, GDDR6 Memory
GPU	NVIDIA Quadro RTX 6000 GPU

3. Results and discussion

To evaluate the predictive accuracy of the flashback propensity, Figure 4 presents the spatial distribution of the ground truth and the predicted values obtained by the proposed model for the validation dataset. The results indicate that the proposed model largely reconstructs the flashback propensity, albeit with blurred boundary regions compared to the ground truth. Since this error may be attributed to the mean-square error loss function employed in this study, the accuracy may be further improved by modifying the loss function. To quantitatively assess the predictive accuracy of the proposed model, Figure 5 presents a scatter plot of the predicted value $\Delta\hat{x}$ versus the ground truth Δx. The color map represents the joint probability density estimated via kernel density estimation. The coefficient of determination R^2 = 0.80, confirms that the proposed model achieves high predictive accuracy in a quantitative sense.

The time required to predict the flashback propensity after a small time interval Δt is 972 seconds for LES, whereas it is only 0.93 seconds using the proposed model. This indicates that the prediction time using the machine learning model is approximately 1/1000th of that required for numerical simulations, leading to a significant reduction in computational cost. In summary, the proposed model successfully reproduces the flashback propensity obtained from LES while substantially reducing computational costs.

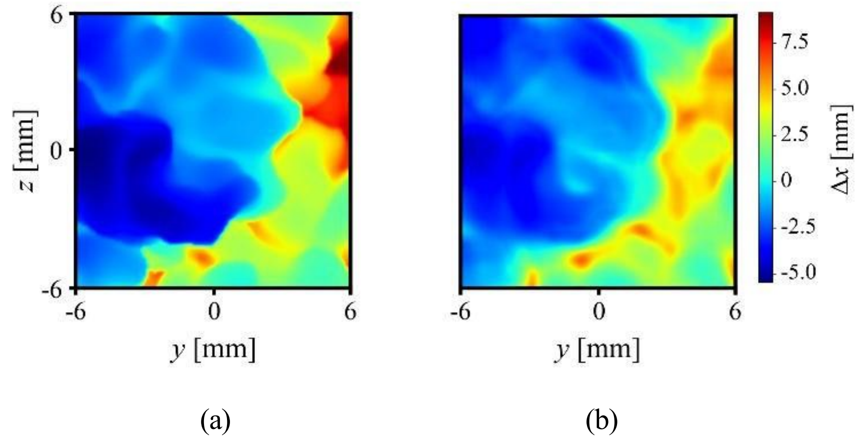

Figure 4: Comparison of distributions of the flashback propensity Δx. (a) Ture. (b) Predicted.

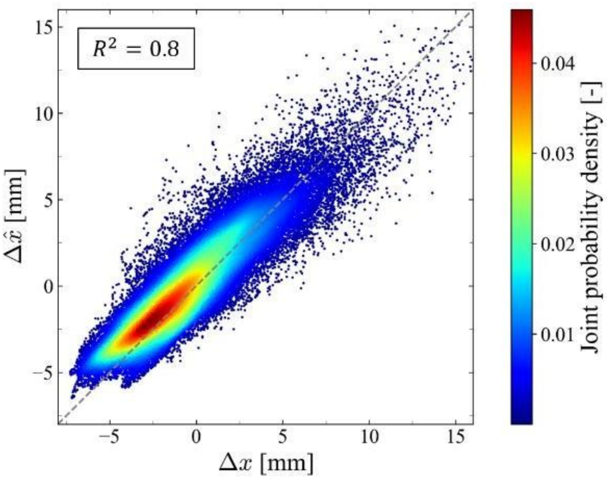

Figure 5: Scatter plot of predicted $\Delta\hat{x}$ versus true Δx values, colored by joint probability density.

4. Conclusions

This study introduced a machine learning model designed to predict flashback propensity by analyzing the distribution of physical quantities around the flame surface, utilizing high-resolution data obtained from LES of a low-swirling hydrogen-air flame. The proposed model demonstrated the ability to effectively replicate flashback propensity after a brief period while offering a more cost-efficient alternative to LES.

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