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Uncovering Flame Physics with Machine Learning

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Machine Learning (ML) is making a profound impact across a wide range of disciplines, from image and speech recognition to quantum computing. Within fluid mechanics, ML has led to significant progress in areas such as experimental diagnostics, numerical simulations, flow control, and weather forecasting. In the realm of turbulence and combustion modelling, numerous approaches have been explored, achieving remarkable success in different applications [1, 2].

Recently, ML-based methodologies have attracted growing interest as tools to investigate the physics of fluid mechanics systems [3], particularly in scenarios where traditional approaches face limitations. For instance, conventional statistical methods such as joint probability density functions might become unfeasible for highly dimensional datasets due to the need for unreasonably large volumes of data to obtain statistical convergence.

In this work, we apply Convolutional Neural Networks (CNNs) [4] to analyse various physical aspects of laminar and turbulent premixed hydrogen/air and methane/air flames. By training CNNs on data from turbulent methane flames at different Reynolds numbers (Re), filtered with the same filter over Kolmogorov scale ratio Δ/η, we observe that subgrid-scale flame wrinkling becomes independent of Re at sufficiently high values. For both laminar and turbulent premixed hydrogen flames, we find that the reaction rate can be accurately parametrised using only the progress variable C, provided that a three-dimensional neighbourhood of the C field is considered through convolution. This contrasts with classical pointwise tabulation methods, which typically require a second variable, such as the mixture fraction Z, to accurately model the reaction rate in lean hydrogen flames. Moreover, we identify the minimal spatial extent of the 3D neighbourhood required for accurate parametrisation, revealing not only that reaction rate information is inherently encoded in the C-field, but also the characteristic scale of the structures conveying this information. These findings demonstrate that ML-based methods can be effectively employed to uncover and interpret complex flame features.

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