International Conference on Numerical Combustion
Rome, Italy, October 14-17, 2025
www.icnc2025.com

A physics-constrained neural-network sub-grid-scale model for a flame in high-speed turbulence

Seung Won Suh[1]*, Jonathan MacArt[2], Luke Olson[1], and Jonathan Freund[1]
*Lead presenter: suh29@illinois.edu
[1] University of Illinois Urbana-Champaign, USA
[2] University of Notre Dame, USA

We develop a neural-network (NN) sub-grid-scale (SGS) model for a large-eddy simulation (LES) of turbulent reacting flows. The model is trained *a posteriori*, enabled by an adjoint method [1]. Specifically, the objective function measures the deviation of the model-predicted solution from some trusted data — a filtered direct numerical simulation (DNS) for this work. To maintain the model's role as a closure, a logistic NN activates or deactivates it depending on the trustworthiness of the resolved physics. Constraints needed for a physically realistic solution, including the scalar boundedness or Galilean invariance, are also imprinted in the model form. For demonstration, we compare LES of a premixed flame to a DNS with the filter and grid ratio of 16. The flame is statistically planar and propagates freely in a rectangular domain, governed by a single-species, single-step, and irreversible reaction. The upstream isotropic turbulence is intense enough to fold the flame in the DNS, but not in an LES without a proper closure, as the coarse grid cannot render the folding process in detail. Our model is trained to correct this: it promotes folding and also predicts the right amount of turbulent kinetic energy dissipation, thereby successfully representing both flame kinematics and turbulence in LES.

References

[1] J. Sirignano, J. F. MacArt, and J. B. Freund, "DPM: A deep learning PDE augmentation method with application to large-eddy simulation," *J. of Comput. Phys.* vol. 423, 109811, 2020.