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Hybrid Navier-Stokes/ANN solver for unsteady simulation of H2 flame

Francesco Cenvizo*, Luc Vervisch, Pascale Domingo
*Lead presenter: francesco.cenvizo@insa-rouen.fr
CORIA-CNRS, Normandie Université, INSA Rouen, France

Abstract

Data-driven methods have been introduced in numerical combustion to optimize computational efficiency by reducing the CPU time required for stiff chemistry integration [1, 2], and enhancing the physical modeling of effects caused by unresolved fluctuations in species concentrations and temperature, including multiphysics phenomena such as sooting flames [3]. In this study, neural networks are trained to assist in solving $\phi(\underline{x}, t)$, a thermochemical scalar representing species mass fractions, energy, or temperature. The scalar solution is advanced over n^o iterations by solving its transport equation. The $\phi(\underline{x}, t)$ values over these n^o iterations serve as inputs to a Reduced Order Model (ROM) framework. ROMs help in tackling the issue of modeling high-dimensional systems. Reduction is attained using Proper Orthogonal Decomposition (POD) [4] and dynamical modeling is attained via Long Short-Term Memory (LSTM) network [5]. The scalar at the $n^o + 1$ iteration is predicted by the framework (e.g. without resorting to the solving of the scalar balance equation). This strategy is first tested on a non-reactive Large Eddy Simulation (LES) of a cavity where air and H_2 are injected separately, then is verified on a Unsteady Reynolds Averaged Navier-Stokes (URANS) simulations of a non-premixed H_2-air flame stabilized downstream of the same cavity geometry, with *code_saturne*, under the hypothesis of infinitly fast chemistry. Results show that the network is capable of predicting the unsteady behavior of the turbulent system with decent accuracies, and very low error over the whole range of testing sequences, unseen during the training stage, with a CPU gain scaling as $1/4$ and $1/2$ respectively.

References

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