PiMAPNet: A physics-informed multiscale-partitioning network for predicting dynamic behavior of reacting flows with application to hydrogen flames

Pushan Sharma[1], Wai Tong Chung[1], Matthias Ihme[1,2,3]*
*lead presenter: mihme@stanford.edu
1 Department of Mechanical Engineering, Stanford University, Stanford, CA 94305
2 Department of Energy Science and Engineering, Stanford University, Stanford, CA 94305
3 Department of Photon Science, SLAC National Accelerator Laboratory, Menlo Park, CA 94025

Common data-driven models for predicting chemical reacting flows suffer from error accumulation, divergence from expected physical behavior, and poor generalizability. To address this, we present Physics-informed hybrid Multiscale and Partitioned Network (PiMAPNet), a physics-informed machine learning (ML) strategy for generating multi-scale and multi-physics predictions by integrating low-resolution physics-based models with neural networks. PiMAPNet combines a state-space decomposition of hydrodynamic (velocity and pressure) and thermochemical (temperature and species mass fractions) quantities for improved predictions of multiphysical processes with a mixture-of-experts (MoE) architecture that partitions the thermochemical state-space. We demonstrate this ML framework on a reacting hydrogen/air jet flame configuration. Results demonstrate that both the purely data-driven ML model and a traditional physics-informed ML approach could not represent the entire state-space, which resulted in unphysical behavior in long-term predictions. In contrast, the MoE-based PiMAPNet achieves higher accuracy and demonstrates improved robustness over extended time windows and out-of-distribution scenarios. We show that PiMAPNet offers faster inference compared to numerical simulations with comparable accuracies in multiple physical quantities.