Proceedings of the 1st international Symposium on AI and Fluid Mechanics
Abstract No S16 PO3

Physics-informed neural networks to solve 1D laminar flames

Jiahao Wu; Jiayue Liu; Su Zhang; Yuxin Wu*; Xin Li;

Department of Energy and Power Engineering, Key Laboratory for Thermal Science and Power Engineering of Ministry of Education, Tsinghua University, Beijing 100084, China

Abstract

One-dimensional (1D) laminar flames are essential for the study of flame limit, stretch, laminar flame speed (s_L), and flamelet tabulation. When solving the 1D laminar flames numerically, the unknown eigenvalues will make the problems ill-posed and the complex chemical reactions will further introduce high nonlinearity. This work illustrates how these issues can be addressed with physics-informed neural networks (PINNs), which is a new, differentiable, and mesh-free method for solving partial/ordinary differential equations (PDEs/ODEs). Compared to traditional methods, PINNs have no discretization errors and can more easily incorporate known data. By integrating the governing ODEs as a physical guide and treating the unknown eigenvalues as trainable parameters, the FlamePINN-1D framework is proposed to numerically solve the problems of 1D laminar flames. To enhance the learning robustness, some strategies are proposed, including the warmup pretraining, hard constraints, thin-layer normalization, and modified network architecture. Various problems have been tested, including the freely-propagating premixed flames and counterflow flames, with both simplified and detailed physical models. Results show that for forward problems, FlamePINN-1D can accurately solve the flame fields and infer the unknown eigenvalues (such as s_L) under the constraints of governing ODEs and boundary conditions. For inverse problems, FlamePINN-1D can accurately reconstruct the continuous fields and infer the unknown parameters (such as transport and chemical kinetics parameters) based on noisy sparse observations, indicating the possibility of optimizing chemical mechanisms from measurements of laboratory 1D flames. The proposed method demonstrates the ability of PINNs to solve complex combustion problems with ill-posed ODEs and highly nonlinear models, and the feasibility of PINNs to solve forward and inverse combustion problems in a unified manner.

Keywords: Physics-informed neural network (PINN); 1D laminar flames; Flow field reconstruction; Parameter inference