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PHYSICS- AND NUMERICS-AWARE AI FOR REAL-TIME COMPUTATIONAL FLUID DYNAMICS

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ABSTRACT

Artificial intelligence and machine learning are increasingly being explored as tools for accelerating computational fluid dynamics (CFD), but their use in practical flow simulation remains limited by fundamental questions of stability, conservation, accuracy, and generalization. Purely data-driven surrogate models can provide fast predictions, yet they often fail when deployed beyond the training distribution, under different discretizations, geometries, boundary conditions, or flow regimes. This minisymposium will focus on physics- and numerics-aware AI methods for real-time CFD: approaches that learn from, augment, or emulate numerical solvers while retaining the physical and numerical structure needed for reliable simulation.

The minisymposium will bring together recent developments at the interface of scientific machine learning, numerical analysis, and computational fluid mechanics. Topics of interest include model-constrained (physics- and numerics-aware) learning for dynamical systems, neural tangent-slope and time-integration-aware surrogate models, graph neural networks for unstructured meshes, neural approximations of finite-volume and discontinuous Galerkin discretizations, learned Riemann solvers and numerical fluxes, AI-assisted stabilization and shock capturing, data randomization and regularization for long-time prediction, and uncertainty-aware or reliability-oriented machine learning for flow simulation. Particular attention will be given to methods that remain compatible with classical explicit or implicit time integration schemes, preserve conservation or discretization structure, and generalize across meshes, geometries, initial conditions, boundary conditions, and physical parameters.

A central theme is that reliable AI for CFD should not merely replace numerical solvers as black boxes. Instead, emerging methods can be designed to learn computationally expensive components of discretized models, such as tangent slopes, fluxes, volume corrections, closure terms, or coarse-to-fine corrections, while embedding physical and numerical constraints during training. Such approaches are especially relevant for real-time simulation, design optimization, control, uncertainty quantification, and digital-twin applications, where repeated high-fidelity CFD solves are often prohibitively expensive.

The objective of this minisymposium is to provide a forum for researchers developing mathematically informed, physically constrained, and computationally efficient AI techniques for fluid dynamics. Contributions may include methodological advances, theoretical analysis, algorithmic design, benchmark studies, and applications to compressible and incompressible flows, shock-dominated flows, turbulent flows, aerodynamics, geophysical flows, and multiphysics problems. By highlighting the interaction between AI, numerical discretization, and flow physics, the minisymposium aims to identify promising directions toward trustworthy, generalizable, and deployable AI-accelerated CFD.