Reconstructing High-fidelity Plasma Turbulence with Data-driven Tuning of Diffusion in Low Resolution Grids

Kunpeng Li[a], R. VARENNES[a], Z.S. QU[a], Y.W. CHO[a], K. LIM[a], X. GARBET[a], Y.S. ONG[b]

[a] *School of Physical and Mathematical Sciences, Nanyang Technological University, Singapore, Singapore*

[b] *College of Computing and Data Science, Nanyang Technological University, Singapore, Singapore*

1. Introduction

In magnetic fusion plasmas, turbulence dictates plasma confinement time and ultimately limits fusion yield. Accurate prediction and control of turbulent transport are essential for the advancement of fusion energy. Traditionally, this has relied on high-fidelity numerical simulations, but their prohibitive computational cost and time requirements pose a major challenge.

Here, we capitalize on recent advances in neural networks (NNs) to develop data-driven closure and surrogate models. Our NN-based large-eddy closure model accurately captures the turbulence spectrum and flux while operating at just one-eighth of the spatial resolution in each direction, achieving a speed-up of at least a factor of 10. This approach offers a significant step toward efficient and scalable turbulence modeling in fusion plasmas.

2. Large Eddy Simulation of Drift Wave Turbulence

Closure models are essential in Large Eddy Simulations (LES) of hydrodynamic turbulence, where theoretical approaches, such as the Smagorinsky model, have seen considerable success. However, their application to plasma turbulence remains limited, largely due to the complexity of formulating theory-based closures and the vast number of possible schemes. A notable exception is the eddy viscosity model proposed by Smith and Hammett for the single-field Hasegawa-Mima equation [1].

Here, we leverage recent advances in machine learning to identify effective closure models for more complex plasma turbulence systems. To mitigate computational cost, we focus on the two-dimensional, two-field Hasegawa-Wakatani model [2]—a minimal yet representative system of turbulent transport. A neural network is trained on high-resolution spectral Direct Numerical Simulations (DNS) to infer closure models, guided by constraints from Direct Interaction Approximation (DIA) theory [3]. Under reasonable assumptions, DIA predicts a closure model with six diffusion and hyperdiffusion coefficients, coupling density and vorticity dynamics.

The resulting model is tested in LES at reduced resolution and validated against high-fidelity DNS data. The proposed closure achieves robust agreement across a broad parameter space, including variations in the adiabaticity coefficient and density gradient. Notably, the inferred viscosity is negative and the hyperviscosity positive, aligning with Kraichnan's prediction [4] for eddy viscosity in two-dimensional turbulence. Interestingly, cross-terms—such as density diffusion in the vorticity equation and vorticity diffusion in the continuity equation—appear to have negligible influence, despite their prominence in DIA predictions. These findings highlight the potential of machine learning in developing physics-informed closure models for plasma turbulence.

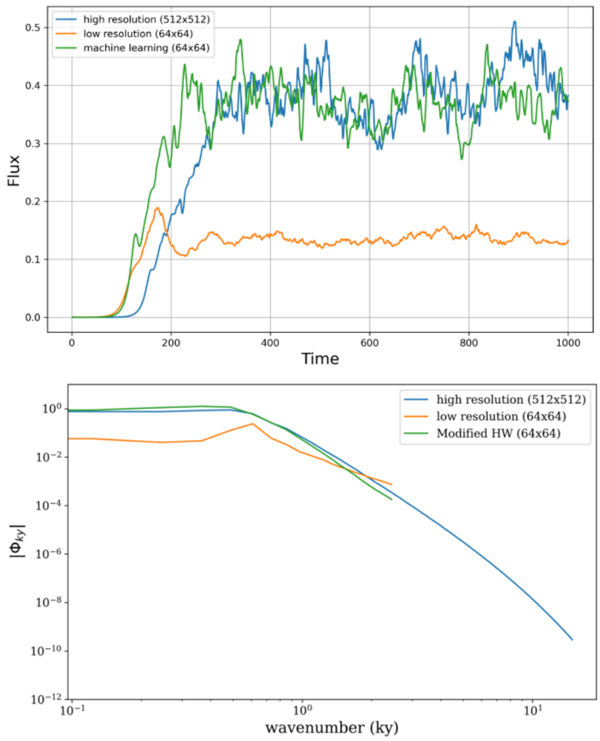

Fig. 1: (Up) The volume averaged particle flux as a function of time for high resolution DNS, low resolution DNS, and low-resolution LES with parameters identified by machine learning. (Down) The spectrum of electrostatic potential as a function of azimuthal wave number ky for the three different cases.

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