NEURAL NETWORK REDUCED MODELS FOR PLASMA TURBULENCE

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1. INTRODUCTION

In magnetic fusion plasmas, turbulence transport primarily determines plasma confinement time and, ultimately, fusion yield. Understanding and predicting turbulence fluxes is crucial for the success of fusion energy. Traditionally, this challenge has been addressed through computationally expensive numerical simulations.

In this synopsis, we leverage recent advances in neural networks (NNs) to develop data-driven closure and surrogate models. Our NN-based large-eddy closure model accurately recovers the turbulence spectrum and flux while requiring only 1/8 of the resolution in each direction, leading to a speed-up of at least a factor of 10. Meanwhile, our NN-based surrogate model successfully captures the complex interplay between turbulence and zonal flows, even in the presence of strong stochasticity.

2. LARGE EDDY SIMULATIONS OF DRIFT WAVE TURBULENCE

Closure models are commonly employed in Large Eddy Simulations (LES) of hydrodynamic turbulence. This strategy has been much less utilized in plasma turbulence. The objective of this work is to leverage recent developments in machine learning to identify relevant closure models for the 2D 2-field Hasegawa-Wakatani model [1], a minimal system with turbulent transport. Under reasonable assumptions, the Direct Interaction Approximation (DIA) theory [2] predicts a closure model with 6 diffusion and hyperdiffusion coefficients, which couple density and vorticity equations. These 6 coefficients are identified by a physics-informed neural operator approach. Training of the neural network is performed with data from highly resolved spectral Direct Numerical Simulations (DNS).

This model has been tested on low resolution LES simulations on a 64*64 grid, which were compared to DNS highly resolved data with a 512*512 grid. Agreement is found satisfactory for a large set of input parameters (adiabaticity coefficient, and density gradient), as demonstrated in Figure 1, while directly reducing the resolution to 64*64 in DNS leads to discrepancies. Quite interestingly, it appears that viscosity is negative and hyperviscosity positive, in accordance with an old prediction from Kraichnan [3] for eddy viscosity in 2D turbulence. In addition, cross-terms, i.e. density diffusion in vorticity equation, and vorticity diffusion in continuity equation, are found to be significant, in agreement with DIA theory.

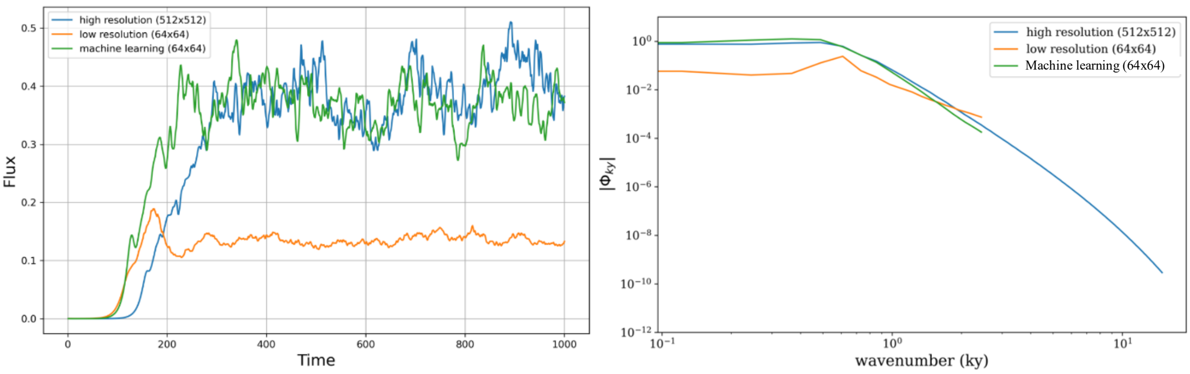

Figure 1 (Left) The volume averaged particle flux as a function of time for high resolution DNS, low resolution DNS, and low-resolution LES with parameters identified by machine learning. (Right) The spectrum of electrostatic potential as a function of azimuthal wave number k_y for the three different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

3. STOCHASTIC SURROGATE MODEL FOR THE TURBULENCE-ZONAL FLOW DYNAMICS

The predator-prey model of turbulence and zonal flows [4] is simple but efficient. Although features of such a model can be qualitatively identified from the phase lag between the turbulence energy and zonal flow energy, the direct extraction of model parameters from data is complicated. The interplay is stochastic, as turbulence itself is inherently random and nonlinear. An example from a DNS simulation of the modified Hasegawa-Wakatani model is shown in Figure 2.

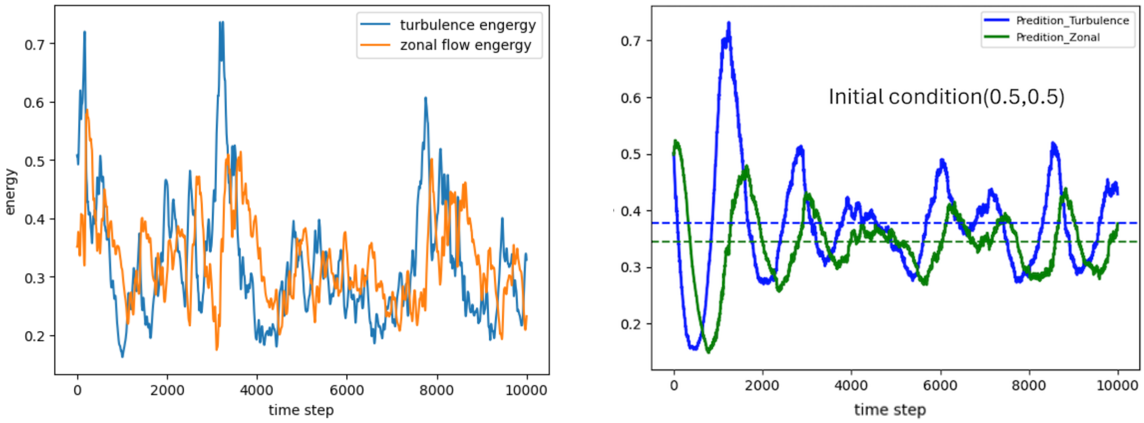

Figure 2 (Left) Turbulence and zonal flow energy from DNS. (Right) Reconstruction from the NN-SDE.

We propose to construct a neural-network stochastic differential equation (NN-SDE) from data, which takes the form

$$dE_T = g_{11}(E_T, E_Z)dt + g_{21}(E_T, E_Z)dW,$$
$$dE_Z = g_{12}(E_T, E_Z)dt + g_{22}(E_T, E_Z)dW,$$

where E_T and E_z are turbulence and zonal flow energy, respectively. The g functions are neural networks, and dW is a Gaussian white noise. We managed to learn the g functions from a number of DNS for the same condition but with different random seeds. An example of the reconstructed predator-prey trajectory is presented in Figure 2, showing similar features to DNS including the stochastic dynamics. The histogram of E_T and E_z is also in good agreement with data.

4. CONCLUSION

In this work, we have demonstrated the effectiveness of neural network reduced models for plasma turbulence transport. Our approach successfully integrates machine learning techniques with physics-based models to enhance the efficiency and accuracy of turbulence simulations. The neural-network-based closure model significantly reduces computational costs while maintaining high-fidelity predictions of turbulence flux and spectra. Additionally, our stochastic surrogate model effectively captures the intricate dynamics of turbulence-zonal flow interactions, reinforcing the utility of data-driven methods in plasma physics.

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