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Closure models for simulations of drift wave turbulence

X. Garbet[1,2], K. Li[1], Y. Cho[1], Z. Qu[1], R. Varennes[1], C. Wan[1],
V. Grandgirard[2], Y. S. Ong[1], K. Lim[1], C. Guet[1]
[1] School of Physical and Mathematical Sciences, Nanyang Technological University, 637371 Singapore [2] CEA, IRFM, F-13108 Saint Paul-lez-Durance, France
e-mail (speaker):xavier.garbet@ntu.edu.sg

Closure models are commonly employed in Large Eddy Simulations (LES) of hydrodynamic turbulence. These models are usually driven by theoretical considerations – a common and quite successful example is the Smagorinsky model. This strategy has been much less utilized in plasma turbulence, one reason being the difficulty to elaborate theory-based closure models, and also the large number of possible closure schemes. One example is the identification of an eddy viscosity by Smith and Hammett to model the single field Hasegawa-Mima equation [1].

The objective of this work is to leverage recent developments in machine learning to identify relevant closure models for more complex systems than Hasegawa-Mima turbulence. In order to reduce computational cost, this methodology is applied to the 2D 2 field Hasegawa-Wakatani model [2], a minimal system with turbulent transport. Training of a neural network is performed with data from well resolved spectral Direct Numerical Simulations (DNS). Identification of a full closure scheme still represents a formidable task. The model is thus constrained by available Direct Interaction Approximation (DIA) theory, more precisely its Eddy Damped Quasi-Normal Markovian (EDQNM) version [3]. Under reasonable assumptions, DIA theory predicts a closure model with 6 diffusion and hyperdiffusion coefficients, which couple density and vorticity equations. The machine learning model is based on a Convolutional Long Short-Term Memory (ConvLSTM) architecture [4]. The identification of the six unknown coefficients is formulated as an inverse problem, following the framework of Physics-Informed Neural Networks (PINNs).

This model has been tested on low resolution LES simulations, which were compared to highly resolved DNS data. Agreement is found satisfactory for a broad range of input parameters (adiabaticity coefficient, and density gradient, see example Fig.1). Quite interestingly, it appears that viscosity is negative and hyperviscosity positive, in accordance with a previous Kraichnan's prediction for eddy viscosity in 2D turbulence [5]. In addition, cross-terms, i.e. density diffusion in vorticity equation, and vorticity diffusion in continuity equation, are small compared with diagonal coefficients. This result is consistent with findings from a 2-scale DIA study from Gürcan and co-workers [6].

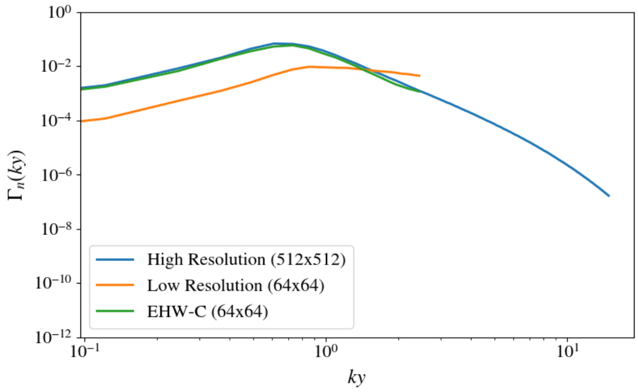

Fig. 1: Comparison of particle flux spectra computed from DNS (blue), low resolution simulations (orange) and LES with closure terms computed an ML algorithm (green).

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