Modelling of space plasma from Vlasov to fluid: machine learning approach to the closure problem

Pietro Dazzi*[1], George Miloshevich[2], and Felipe Nathan De Oliveira Lopes[3]

[1]Centre for Mathematical Plasma-Astrophysics [Leuven] – Belgique
[2]KULeuven – Belgique
[3]Catholic University of Leuven - Katholieke Universiteit Leuven – Belgique

Résumé

Addressing many fundamental questions in space plasma physics requires numerical modelling. The most physically complete description is the kinetic approach, which tracks the full six-dimensional particle distribution function in phase space. While faithful, kinetic simulations are computationally expensive. An alternative is the fluid approach, where the distribution function is integrated over velocity space, reducing the dimensionality of the problem. However, this reduction introduces an additional problem: the resulting hierarchy of fluid equations is not closed, the evolution of lower order moments depend on the higher order ones. Thus, one has to introduce a closure relation.

We propose a data-driven solution to the closure problem, combining kinetic simulations with machine learning techniques. We perform an ensemble of two-dimensional, fully-developed plasma turbulence simulations using the hybrid particle-in-cell code Menura, varying two parameters (the ion parallel beta and the amplitude of initial magnetic field perturbations) to explore the variability of the Earth's (turbulent) magnetosheath. These kinetic simulations serve as ground truth for training three classes of machine learning architectures: Convolutional Neural Networks (CNN), Generative Adversarial Networks (GAN), and Fourier Neural Operators (FNO). Each model is tasked with learning an approximation of the pressure tensor closure from the plasma density, velocity, and electromagnetic fields on a two-dimensional grid.

The ultimate objective is a learned closure relation that captures the kinetic physics of the magnetosheath turbulence within a computationally efficient fluid framework. The generalization capability of the trained models is explicitly tested on plasma regimes not seen during training, to provide an independent (out-of-distribution) benchmark.

*Intervenant