P 11: Codes and Modeling I

Time: Tuesday 16:30–17:40 Location: ELP 6: HS 3

Invited Talk P 11.1 Tue 16:30 ELP 6: HS 3

Collaboration on RDM in low-temperature plasma physics
— •Marina Prenzel[1], Kerstin Sgonina[2], and Markus Becker[3] — [1]Research Department Plasmas with Complex Interactions, Ruhr-University Bochum (RUB) — [2]Institute of Experimental and Applied Physics, Kiel University (CAU) — [3]Leibniz Institute for Plasma Science and Technology (INP)

The dynamic research environments in low-temperature plasma physics, including plasma sources and instrumentation often developed in the course of research, have historically lacked standardized research data management (RDM). The absence of established standards not only complicates the implementation of structured RDM, but also hinders data comparability and reusability, impeding the seamless transfer of research outcomes to new plasma applications. In response to these challenges, research groups at INP, RUB and CAU have started a collaborative initiative to develop common standards and tools for comprehensive data documentation.

This contribution provides an update on the current status of these collaborative efforts, focusing on the practical implementation of data management standards in laboratory settings and presenting real-world examples from different research groups.

The presentation aims to underscore the significance of structured RDM in low-temperature plasma physics and its concrete implications for advancing research outcomes in this field.

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P 11.2 Tue 17:00 ELP 6: HS 3

Learning physics-based reduced models from data for the Hasegawa-Wakatani equations
— •Constantin Gahr[1], Ionuţ-Gabriel Farcaş[2], and Frank Jenko[1] — [1]Max-Planck-Institute for Plasma Physics, 85748 Garching, DE — [2]Oden Institute for Computational Engineering & Sciences, Austin, TX 78712, US

This presentation focuses on the construction of non-intrusive Scientific Machine-Learning (SciML) Reduced Order Models (ROMs) for nonlinear, chaotic plasma turbulence simulations. In particular, we propose using Operator Inference (OpInf) to build low-cost physics-based ROMs from data for such simulations. As a representative example, we focus on the Hasegawa-Wakatani (HW) equations used for modeling two-dimensional electrostatic drift-wave plasma turbulence. We first use the data obtained via a direct numerical simulation of the HW equations starting from a specific initial condition and train OpInf ROMs for predictions beyond the training time horizon. In the second, more challenging set of experiments, we train ROMs using the same data set as before but this time perform predictions for six other initial conditions. Our results show that the OpInf ROMs capture the important features of the turbulent dynamics and generalize to new and unseen initial conditions while reducing the evaluation time of the high-fidelity model by up to six orders of magnitude in single-core performance. In the broader context of fusion research, this shows that non-intrusive SciML ROMs have the potential to drastically accelerate numerical studies, which can ultimately enable tasks such as the design and real-time control of optimized fusion devices.

P 11.3 Tue 17:25 ELP 6: HS 3

Solving the Parametric Boltzmann Equation for Electrons Using Physics-Informed Neural Networks
— •Ihda Chaerony Siffa[1], Detlef Loffhagen[1], Markus M. Becker[1], and Jan Trieschmann[2] — [1]Leibniz Institute for Plasma Science and Technology (INP), Greifswald, Germany — [2]Kiel University, Kiel, Germany

The coupling of fluid-Poisson models for low-temperature plasma simulations with the Boltzmann equation of electrons is often needed to ensure the reliability of such models. A direct coupling is, however, often too expensive with respect to calculation time. The pre-calculation of look-up tables for the electron transport and rate coefficients as a function of the reduced electric field strength or mean electron energy is therefore a common practice. In this work, we present a way to parametrically solve the electron Boltzmann equation in two-term approximation using the so-called Physics-Informed Neural Networks (PINNs). PINNs are a mesh-free method and provide differentiable solutions with the potential to ultimately predict electron properties more efficiently than traditional Boltzmann solvers. Presently, the artificial neural network surrogate model takes into account two inputs, the kinetic energy of electrons and an additional input parameter, which represents either the reduced electric field or the mean electron energy, and outputs the isotropic component of the electron velocity distribution function. This contribution discusses the advantages and limitations of the present approach, and gives an outlook for future work.