Leveraging Physics-Constrained Deep Learning to Accelerate Integrated Modeling of Tokamak Disruptions.

Research on mitigating damage from tokamak disruptions is limited by the inability of experiments to access relevant plasma conditions expected in future devices. Additionally, the multi-physics nature of disruptions makes first-principles modeling computationally prohibitive for many-query analyses, which requires a self-consistent treatment of plasma power balance, magnetohydrodynamic (MHD) activity, and runaway electron (RE) formation. To this end, we present a novel path towards an efficient and high-fidelity integrated model of a tokamak disruption. This approach leverages an adjoint treatment of the relativistic Fokker-Planck equation [1] together with recent innovations in physics-constrained deep learning. While incorporating a fully kinetic description of RE formation and evolution, the adjoint formulation of the relativistic Fokker-Planck equation employed is tailored to only predict quantities of interest needed to close the coupled MHD-RE system such as RE density or current. It is shown that such an adjoint problem can be solved across a broad range of plasma conditions using a Physics-Informed Neural Network (PINN) [2]. The resulting surrogate allows for near instantaneous online predictions of RE density, while incorporating a fully kinetic description of RE physics including essential physical processes such as partial screening and radiation. As an initial application, the RE surrogate is coupled with a reduced yet fully self-consistent model of a tokamak disruption. This efficient integrated model is used to explore the high-dimensional space of potential disruption mitigation strategies, thus motivating a path towards accelerating disruption research.

[1] C. F. Karney and N. J. Fisch, The Physics of Fluids **29**, 180 (1986).

[2] J. S. Arnaud, T. B. Mark, and C. J. McDevitt, Journal of Plasma Physics **90**, 905900409 (2024).