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Plasma two-fluid simulation using Physics-Informed Neural Networks

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Low temperature plasmas have diverse applications including plasma processing[1], electric thrusters[2], and fusion device wall modeling[3]. Among these, helicon plasma sources[4,5] are attracting attention for generating high density plasmas (~10^{19} m^{-3}). However, density limits have been observed in helicon plasmas, and a detailed understanding of the underlying mechanisms is essential for practical use. Modeling plasma-neutral interactions is important but computationally challenging due to the complex multiscale nature.

Physics-Informed Neural Networks (PINNs)[6] have emerged as a mesh-free approach for solving PDEs by embedding governing equations into the loss function, ensuring physical constraints without discretization. Compared to conventional methods, PINNs offer greater flexibility and efficiency by leveraging automatic differentiation and GPU-based parallel computing, making them suitable for large-scale plasma simulations. Despite their potential, few studies have used PINNs to explicitly address the complexities of electron and ion dynamics while considering their multiscale nature.

In this study, we establish a foundational framework for two-fluid modeling of electrons and ions using PINNs. We incorporate the fluid equations, initial conditions, and boundary conditions directly into the PINNs loss function, which is then minimized to obtain the simulation results (Figure 1). To handle the multiscale nature of electrons and ions, we apply appropriate normalization techniques that significantly improve learning stability and accuracy. We also find that specifying Dirichlet boundary conditions (fixed variable values) yields more accurate predictions than Neumann conditions (fixed derivatives). Even when using Neumann conditions, adding physical constraint terms to the loss function improves convergence and accuracy. Figure 2 illustrates the prediction results from the trained PINNs model under Dirichlet boundary conditions. Panels (a) and (b) compare the predicted electron density, ion density, and ion x-velocity at the initial and final normalized times, respectively, with exact numerical solutions. The predictions by PINNs (red lines) show good agreement with the exact solutions (blue lines), demonstrating that the method captures the essential features accurately. Panel (c) shows the time-space map of the relative error, confirming that errors remain low throughout the simulation domain.

References
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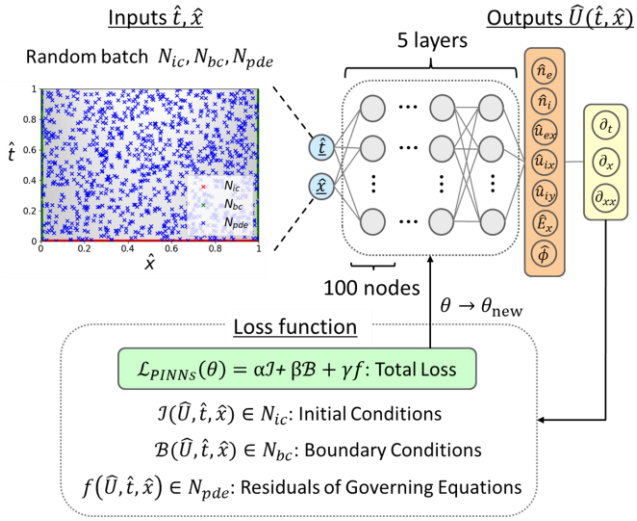

Figure 1. Neural Network architecture of this study. Training points for initial conditions (N_{ic}), boundary conditions (N_{bc}), and PDE residuals (N_{pde}) are sampled from the spatio-temporal domein and used to evaluate the loss function during training.

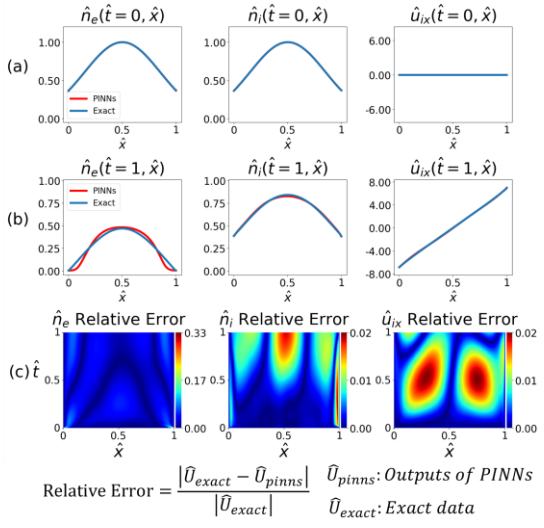

Figure 2. PINNs prediction results; (a) initial ($\hat{t} = 0$) and (b) final ($\hat{t} = 1$) snapshots, and (c) time-space map of relative error for electron/ion densities (n_e,n_i) and ion x-velocity (u_{ix}), with Dirichlet boundary conditions. Red lines: PINNs predictions; Blue lines: exact solutions obtained from conventional numerical methods.