A Physics-Informed Neural Network for Real-Time, Data-Efficient Plasma Equilibrium Reconstruction in SUNIST-2

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Equilibrium evolution and real-time reconstruction of Tokamak plasmas represent pivotal challenges in magnetic confinement fusion research. During SUNIST-2 discharges, rapid and drastic changes in plasma position, shape, and topology impose stringent demands on the speed and capability of equilibrium reconstruction. Conventional numerical approaches, which typically require independent modeling frameworks for solving forward (equilibrium evolution prediction) and inverse (equilibrium reconstruction) problems, suffer from limitations such as low computational efficiency and inadequate data assimilation capabilities. With the rapid advancement of deep learning, Physics-Informed Neural Networks (PINNs)[1] have demonstrated remarkable potential in unifying the solutions to both forward and inverse problems, potentially addressing SUNIST-2's equilibrium reconstruction requirements. However, it is well-known that neural network training typically demands large-scale datasets, and SUNIST-2's rapid iteration cycles further impose significant requirements on data standardization and quality control. In this work, we implement multi-time equilibrium reconstruction through PINNs that simultaneously satisfy the current diffusion equation, circuit equations for dynamic evolution, as well as Grad-Shafranov (GS) equation constraints and diagnostic data compatibility, thereby integrating forward evolution modeling with experimental data assimilation. Furthermore, we demonstrate that PINN-based surrogate models enable real-time equilibrium reconstruction without relying on traditional reconstruction results as training labels. Remarkably, the model exhibits strong generalization capabilities when trained on a small historical dataset (approximately 100 discharges). Looking ahead, we aim to leverage the PINN framework to enable precise predictions of plasma equilibrium evolution, with the ultimate goal of enhancing the accuracy and robustness of real-time control and optimization in fusion devices. This study establishes a novel paradigm integrating physics-driven constraints and data-driven techniques for unified plasma modeling in fusion applications.

Keywords: PINNs, surrogate models, equilibrium reconstruction

[1] Cuomo, S., Di Cola, V.S., Giampaolo, F. *et al.* Scientific Machine Learning Through Physics–Informed Neural Networks: Where we are and What's Next. *J Sci Comput* 92, 88 (2022). https://doi.org/10.1007/s10915-022-01939-z