CONFERENCE PRE-PRINT

A PHYSICS-INFORMED NEURAL NETWORK FOR REAL-TIME, DATA-EFFICIENT PLASMA EQUILIBRIUM RECONSTRUCTION IN SUNIST-2

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Abstract

Equilibrium evolution and real-time reconstruction are critical challenges in magnetic confinement fusion, particularly for the fast-changing plasmas in SUNIST-2. We present a physics-informed Deep Operator Neural Network (DeepONet) framework that integrates Grad–Shafranov constraints with diagnostic measurements. Trained on only ~100 discharges, our model achieves label-free, real-time reconstruction while demonstrating strong generalization across discharges. Key innovations include predicting plasma-only contributions to the poloidal flux ψ, employing a source network to replace the conventional least-squares procedure, and using a stepwise training strategy for stable convergence. This framework is extendable to plasma evolution modeling, offering a promising path toward data-driven plasma control.

1. INTRODUCTION

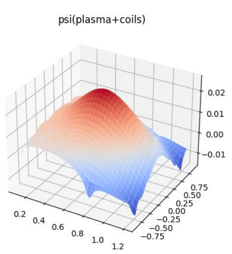
Accurate and fast equilibrium reconstruction is essential for real-time control of tokamak plasmas. SUNIST-2 plasmas evolve rapidly and violently, which challenges traditional iterative solvers like real-time EFIT (rt-EFIT), due to the intrinsic trade-off between computational speed and spatial/temporal accuracy.

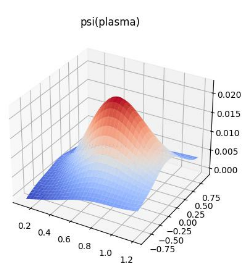
Data-driven surrogate models, particularly neural networks, provide a promising alternative. By learning from diagnostic measurements and embedding physics constraints, these models can achieve both high accuracy and real-time performance, enabling robust control of fast-evolving plasmas.

2. METHODDS.

2.1 Dataset Construction

The dataset includes measurements from magnetic probes, flux loops, Rogowski coils, and PF coil currents. A crucial preprocessing step is separating the plasma-only contribution to the poloidal flux ψ. Removing the coil contribution produces a smoother ψ landscape, facilitating neural network training and improving predictive accuracy.



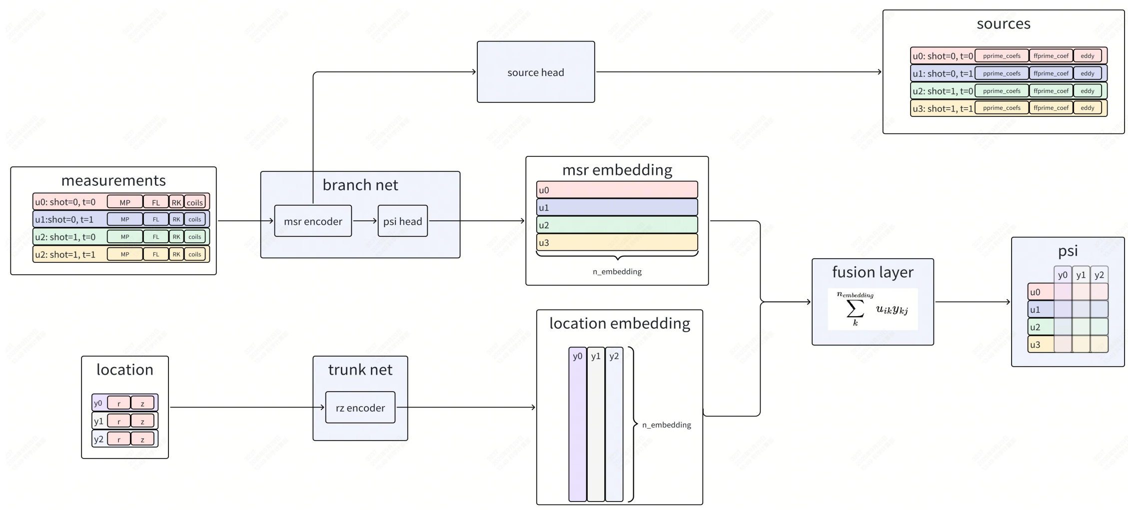


.2 Network Architecture

Our framework builds upon GS-DeepNet, adopting the DeepONet paradigm:

- Branch network: Encodes diagnostic measurements.

- Trunk network: Encodes spatial coordinates (R, Z).
- Fusion layer: Implements an Einstein summation to predict ψ.
- Shared encoder: Enhances generalization across discharges.

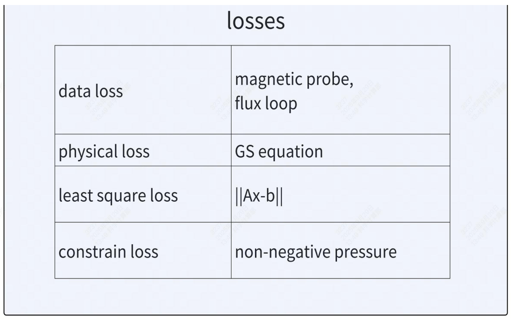


A polynomial basis is used for p’ and ff’ (consistent with EFIT). The source network predicts coefficients of p’, ff’, and eddy currents of the vacuum vessel. Replacing the conventional least-squares solver with the source network improves robustness against parameter sensitivity.

2.3 Loss Function

The loss function combines multiple components:

- Data loss (match to diagnostic measurements)
- Physical loss (Grad–Shafranov constraints)
- Least-squares loss (computed from source network outputs)
- Constraint loss (boundary and regularization terms)


losses

data loss	magnetic probe, flux loop
physical loss	GS equation
least square loss	||Ax-b||
constrain loss	non-negative pressure

2.4 Stepwise Training Strategy

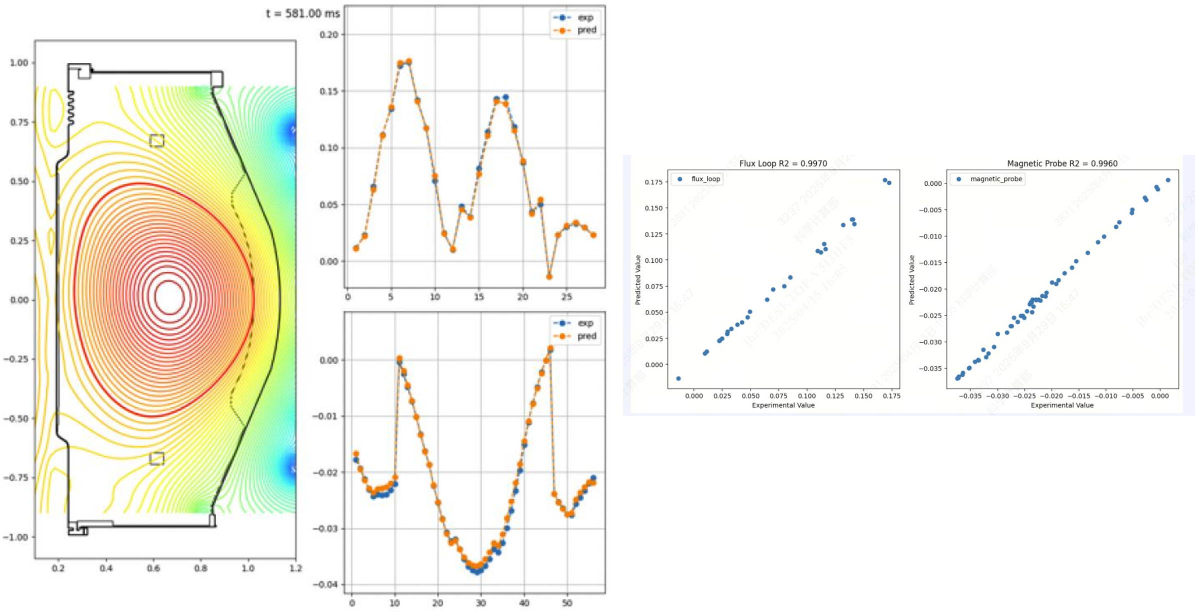
To ensure stable convergence:

1. Train ψ-related modules to capture the equilibrium representation.
2. Train source-related modules while freezing ψ-related modules.
3. Jointly fine-tune all modules for end-to-end learning.

This phased approach reduces training difficulty and accelerates convergence.

3. RESULTS

3.1 Equilibrium Reconstruction



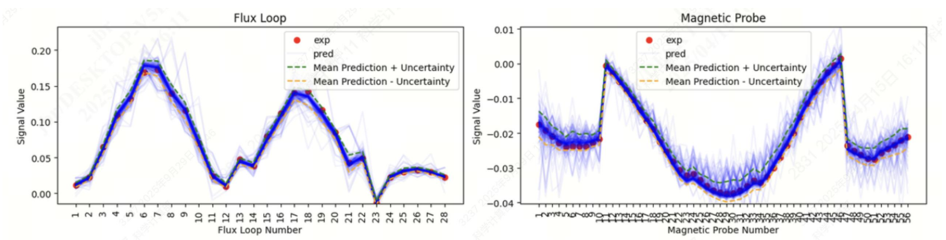
The framework successfully reconstructs plasma equilibria in SUNIST-2. Predicted diagnostic signals show excellent agreement with measurements (R^2 = 0.9970 for flux loops, R^2 = 0.9960 for magnetic probes), demonstrating high accuracy and robustness.

3.2 Inference Performance

A single reconstruction on a 65×65 grid takes ~0.1 ms on an NVIDIA RTX 3070 Ti, meeting real-time control requirements at kHz rates.

3.3 Uncertainty Quantification

Monte Carlo Dropout provides prediction uncertainty estimates, yielding reliable error bounds useful for control applications.



4. DISCUSSION AND CONCLUSION

We developed a physics-informed, dual-network surrogate model for real-time equilibrium reconstruction. Key improvements include:

- Source network replacing least-squares fitting, enhancing robustness.

- Plasma-only ψ separation, reducing learning complexity.
- Stepwise training strategy, improving stability and convergence.

Outlook: Future work will incorporate temporal modeling (e.g., RNNs or transformers) for smoother eddy current prediction and reconstruction continuity, aiming toward a unified framework for equilibrium evolution and reconstruction.

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[2] Joung, S., Ghim, YC., Kim, J. et al. GS-DeepNet: mastering tokamak plasma equilibria with deep neural networks and the Grad–Shafranov equation. Sci Rep 13, 15799 (2023). https://doi.org/10.1038/s41598-023-42991-5