ID: 3153

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

Yuhang Luo[1*], Borui Jiang[1], Yifeng Zhang[2], Ling Ma[1], Binbin Wang[1,2], Shouzhi Wang[1], Yitan[1,2], Rui Chen[1]

[1]Startorus Fusion, Xi'an, China, [2] Department of Engineering Physics, Tsinghua University, Beijing, China

luoyh15@gmail.com*

ABSTRACT

- Equilibrium evolution and real-time reconstruction are critical challenges in magnetic confinement fusion, especially for the fast-changing plasmas in SUNIST-2.
- We present a Deep Operator Neural Network (**DeepONet)[1]** framework that unifies Grad–Shafranov constraints, and diagnostic data.
- Trained on only ~100 discharges, our model achieves **real-time reconstruction without labels** and shows strong generalization.
- This framework can also be extended to build plasma evolution models, enabling data-driven plasma control.

BACKGROUND

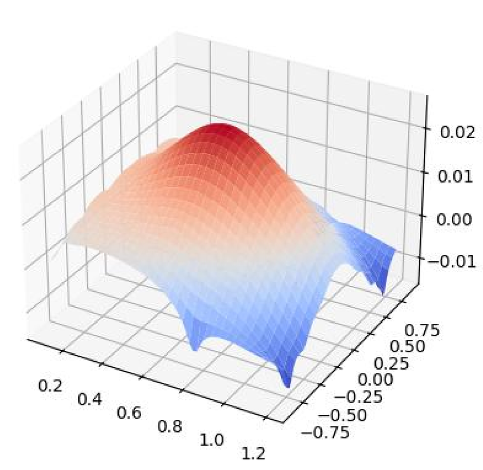
- Real-time control needs **real-time** equilibrium.
- SUNIST-2 plasmas change fast and violently.
- rt-EFIT limited by **speed–accuracy trade-off**.
- **Surrogate models** with neural networks → balance speed & accuracy, enable robust real-time reconstruction.

METHODS

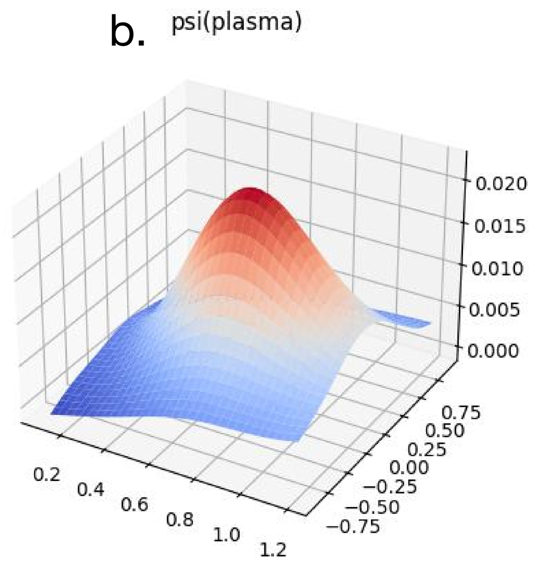
Dataset

- The dataset contains measured magnetic signals (**magnetic probes, flux loops, and Rogowski coils**) and **PF coil** data.
- A key trick is to predict **ψ contributed only by the plasma**, rather than the combined effect of plasma and coils. The reason is that the ψ landscape becomes much smoother when only the plasma contribution is considered (**a. plasma + coils vs. b. plasma only**), making it easier for the neural network to learn and fit.

a. psi(plasma+coils)



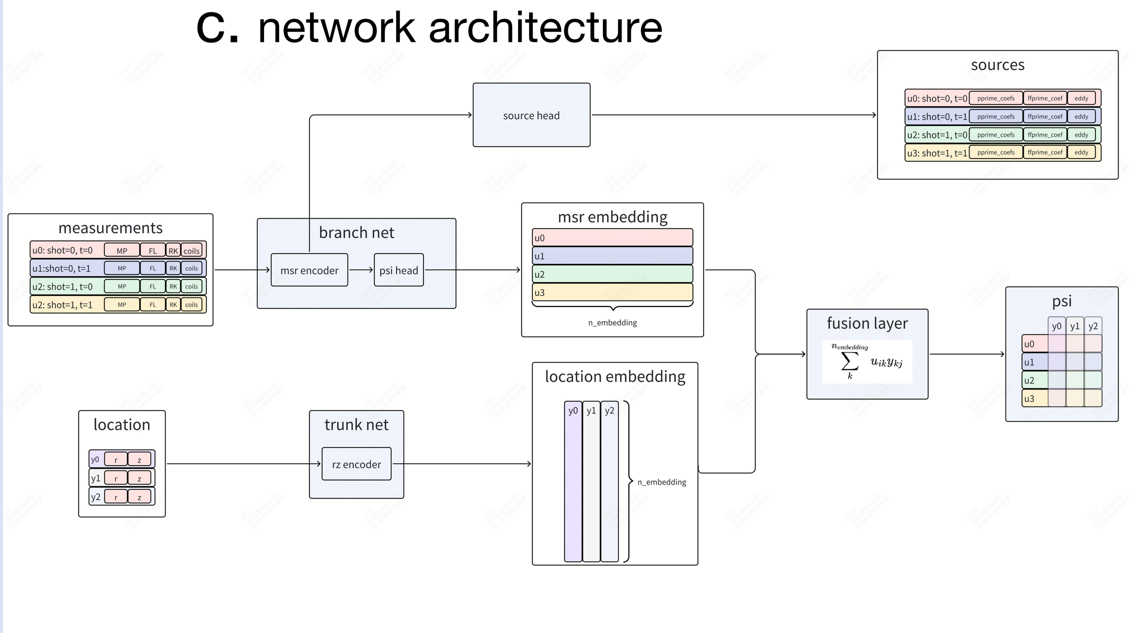
b. psi(plasma)



Network Architecture & Losses

- Our framework (c) builds upon GS-DeepNet[2] with some modifications. It adopts the **DeepONet paradigm**, with a branch network encoding measurement signals and a trunk network encoding spatial locations, which are fused to predict ψ. The fusion layer is implemented as a **simple Einstein summation**. **A shared encoder layer** (msr encoder in c) is introduced to enhance generalization.
- We use a polynomial basis for p' and ff', which is the same as the EFIT paradigm. The **source output** predicts the coefficients of p' and ff', as well as the eddy currents of the vacuum vessel.

c. network architecture



d. losses

losses

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

METHODS

- The loss function combines multiple components: data loss, physical loss, **least-squares loss**, and constraint loss. The least-squares loss, computed from the source output, replaces the conventional least-squares solving procedure used in EFIT.

- **Trainning Strategy**

We adopt a **stepwise training strategy**:

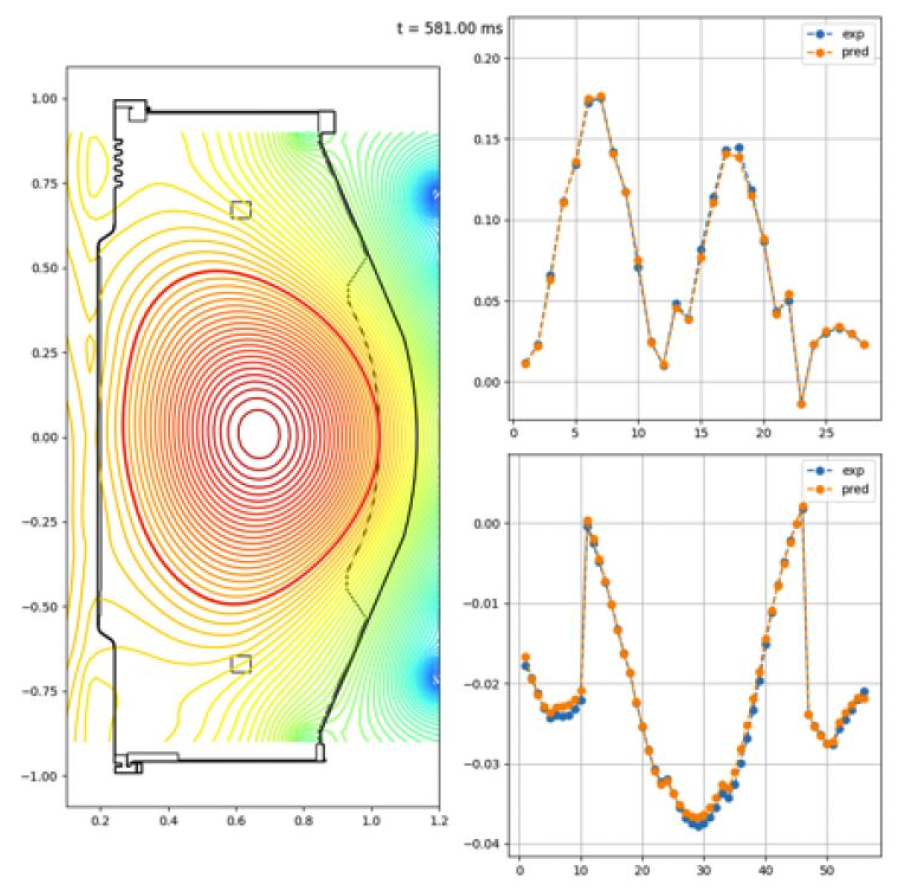
1. train ψ-related modules to capture equilibrium representation.
2. optimize source-related modules, and freeze the ψ-related modules.
3. jointly fine-tune all modules for end-to-end learning.

Thes strategy is really important to get a stable training result.

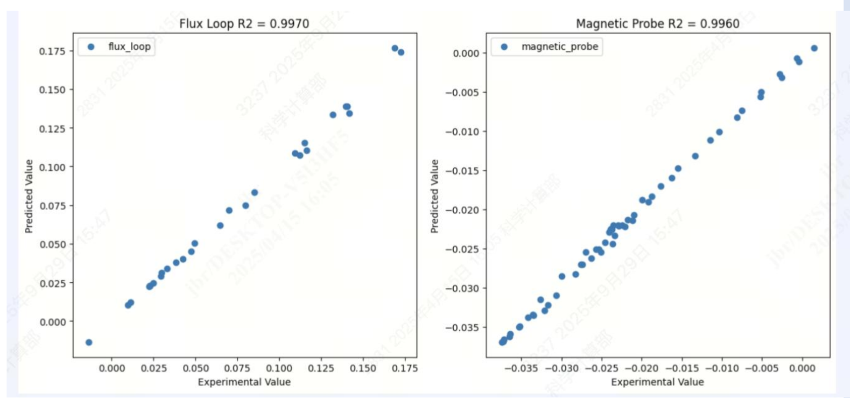
OUTCOME

Trainning Result

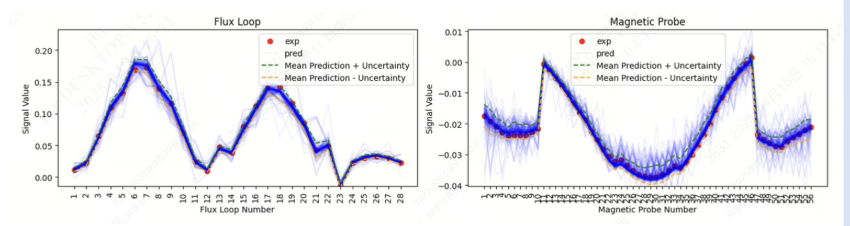
- Our PINN-based framework successfully reconstructs the plasma equilibrium in SUNIST-2 as shown in **f** (left panels). The measurement signals (right panels) exhibit excellent agreement between prediction and measurement.
- Quantitatively, the model achieves **R^2 = 0.9970** for flux loops and **R^2 = 0.9960** for magnetic probes as show in **g**, demonstrating high accuracy and robustness.
- Monte Carlo Dropout is employed to estimate prediction uncertainty, providing reliable error bounds as demonstrated in **h**.



f. psi prediction



g. R^2 of measurements



h. prediction uncertainty from monte carlo dropout

CONCLUSION & OUTLOOK

Conclusion

- **Source network** improves robustness over least-squares.
- **Plasma ψ separation** reduces training difficulty.
- **Stepwise training** accelerates convergence and improves stability.

Outlook

- **Temporal modeling** for better eddy current prediction and reconstruction continuity.
- **Unified framework** for equilibrium evolution and reconstruction.

ACKNOWLEDGEMENTS / REFERENCES

- [1] Lu, L., Jin, P., Pang, G. et al. Nat Mach Intell 3, 218–229 (2021).
- [2] Joung, S., Ghim, Y.C., Kim, J. et al. Sci Rep 13 , 15799 (2023).