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RECONSTRUCTING THE PLASMA BOUNDARY WITH A REDUCED SET OF DIAGNOSTICS

M. STOKOLESOV, M.R. NURGALIEV, I. KHARITONOV, E. ADISHCHEV, D. SOROKIN
Next Step Fusion, Luxembourg

Introduction

Present-day tokamaks rely on equilibrium reconstruction codes that fit magnetic measurements to solutions of the Grad–Shafranov equation. While effective today, this approach may face limitations in future fusion power plants, where diagnostic access is restricted by shielding and larger machine size increases computational demands. Machine learning (ML) offers a path forward by enabling fast, data-driven plasma boundary reconstruction without depending on full diagnostic coverage. In this work, we focus on reconstructing the last closed flux surface using reduced magnetic datasets, demonstrating that surrogate models can provide accurate, real-time boundary estimates and robust fallback options when diagnostics are limited or degraded.

A total of 5 NN models trained on various input feature sets are considered:

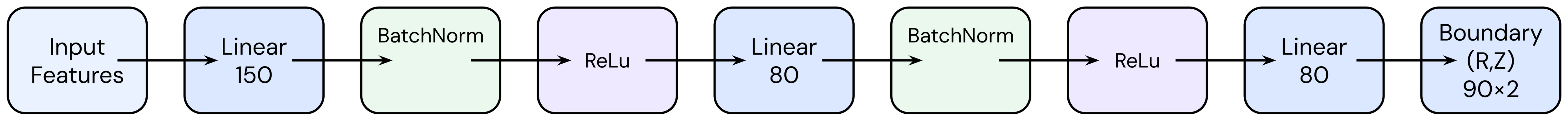
1. $[I_{PF\text{-}coil}]$ — least informed model
2. $[I_{PF\text{-}coil}] + I_p + V_{loop}$

more about these two models in Stokolesov et.al. JoPP 2025 (accepted)

3. $[I_{PF\text{-}coil}] + I_p$ + [ψ-loops]
4. $[I_{PF\text{-}coil}] + I_p + [B_p\text{-probes}]$
5. $[I_{PF\text{-}coil}] + I_p + [B_p\text{-probes}]$ + [ψ-loops] — baseline model

ML models training

- Output: vector of size $\mathbf{N_c = 2 \cdot N_p = 180}$, where N_p = 90 points describe the boundary.
- Dataset: matrix (N, $D+N_c$), standardized inputs and outputs.
- Architecture: FCNN with 2 hidden layers (150, 80 neurons), ReLU activations, batch normalization.
- Training: Mean Squared Error (MSE) loss, Adam optimizer (lr = 1×10^{-4}).
- Cross-validation: plasma shapes grouped by triangularity → 12 sets. Shape-balanced splits → ~80/10/10 train/val/test.
- Final evaluation: additional test set (2024–2025 discharges), balanced to ~70/10/20.



Dataset

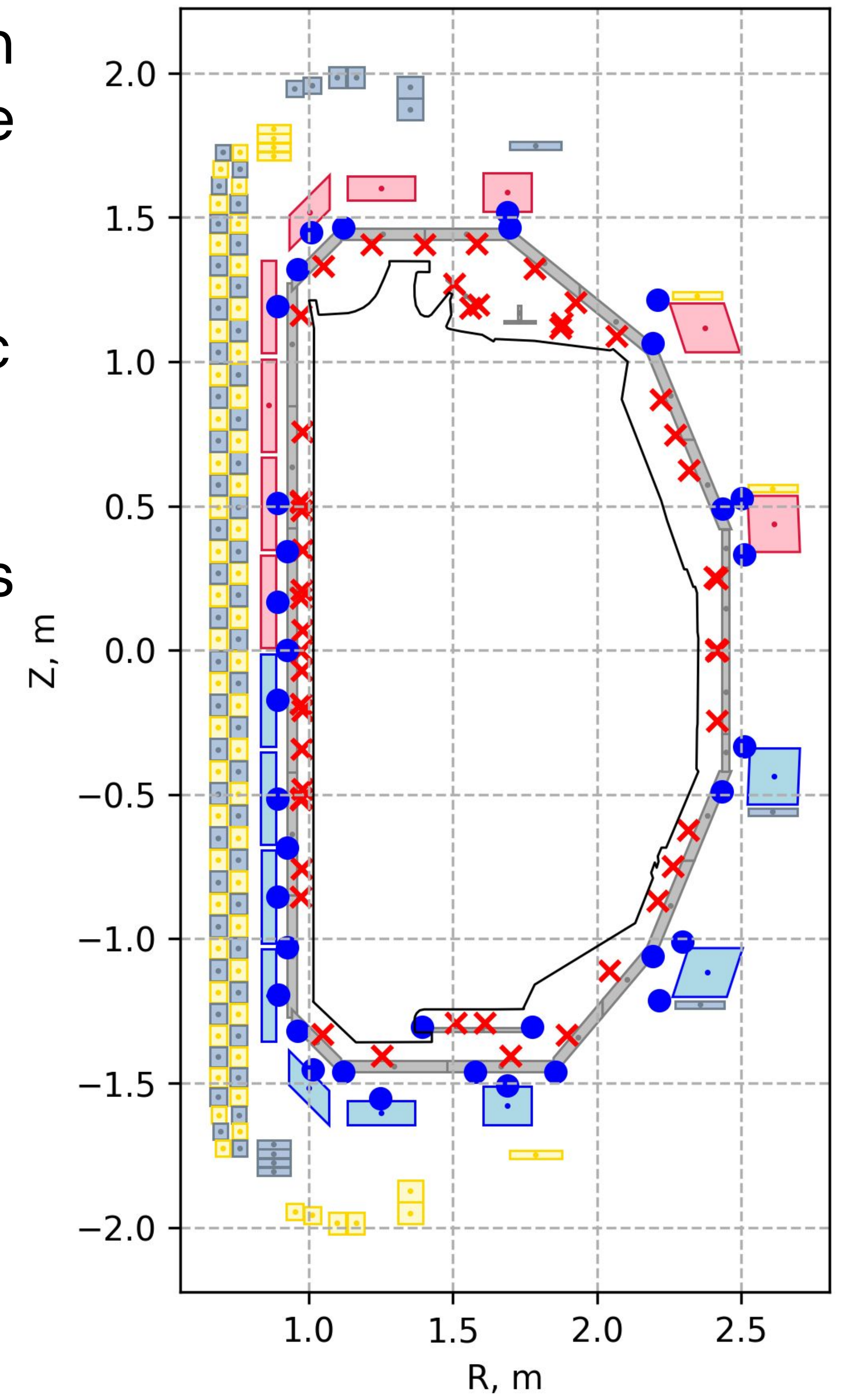
Historical DIII-D EFIT data from 2020-2025 includes shots with pulse length >2 seconds

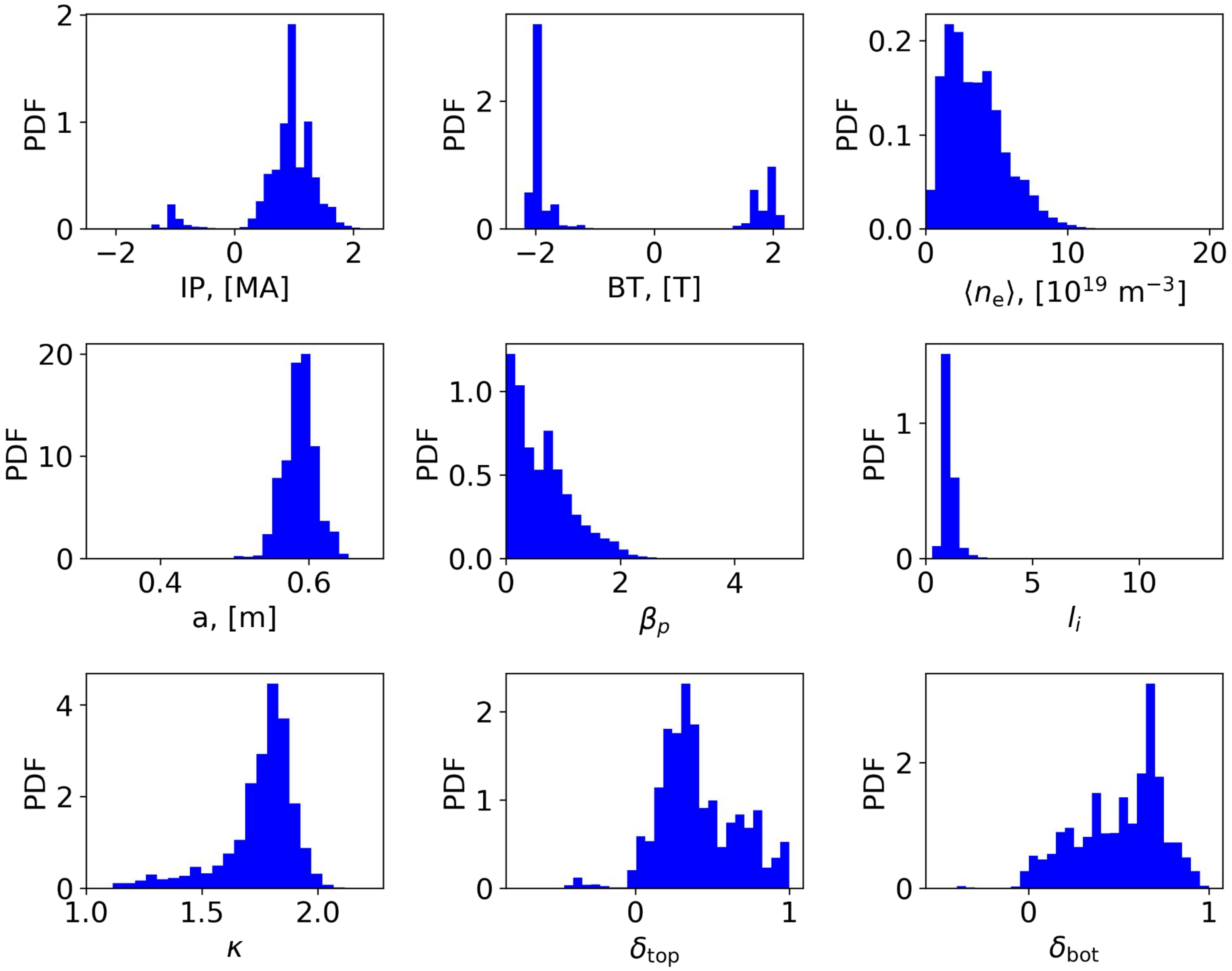
Shots filtered to have common magnetic diagnostics across whole dataset

Rampup, flattop, and rampdown phases are included with 20 ms timestep.

NT and PT cases included

Results in >7000 shots and >1.8 million timesteps in total



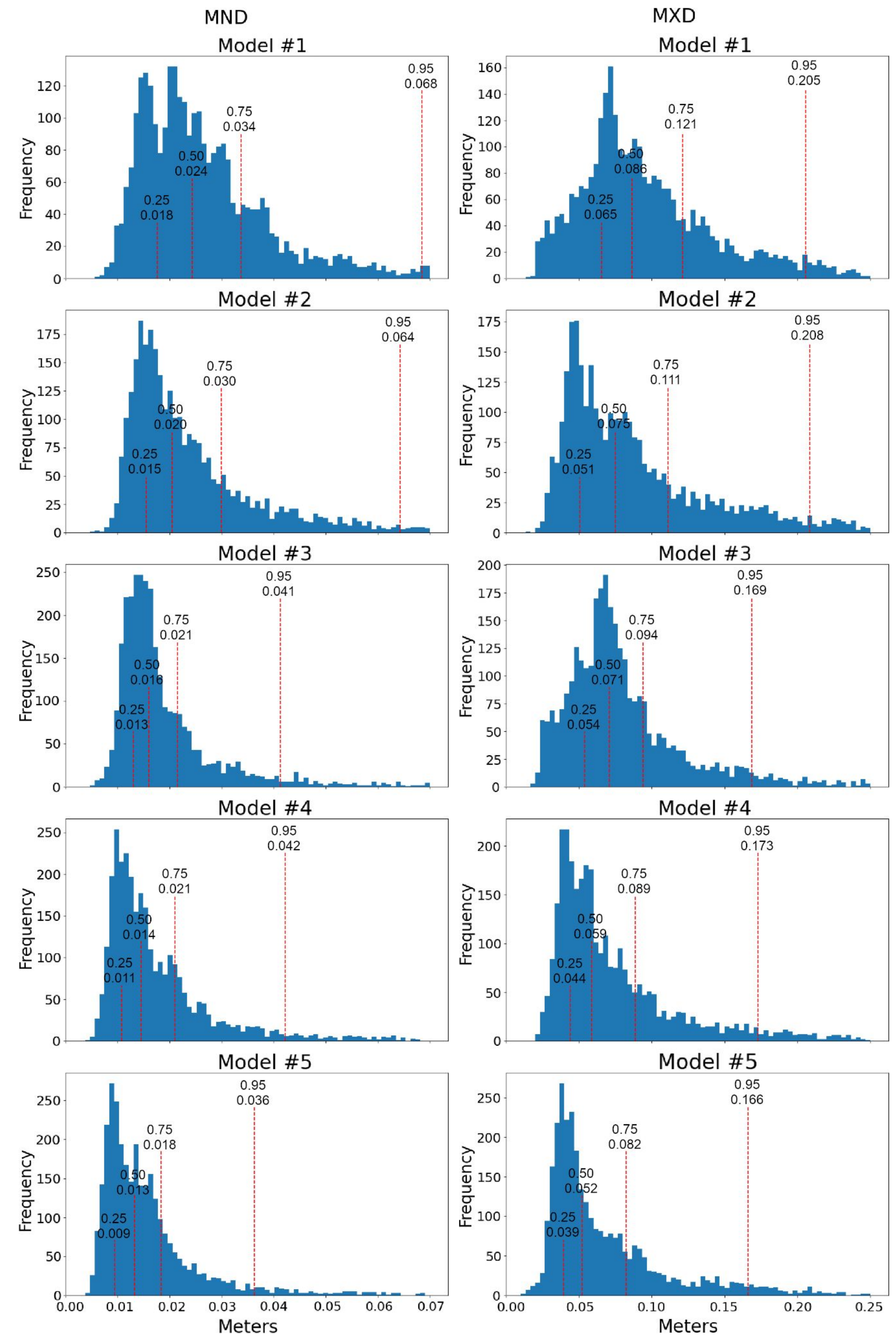


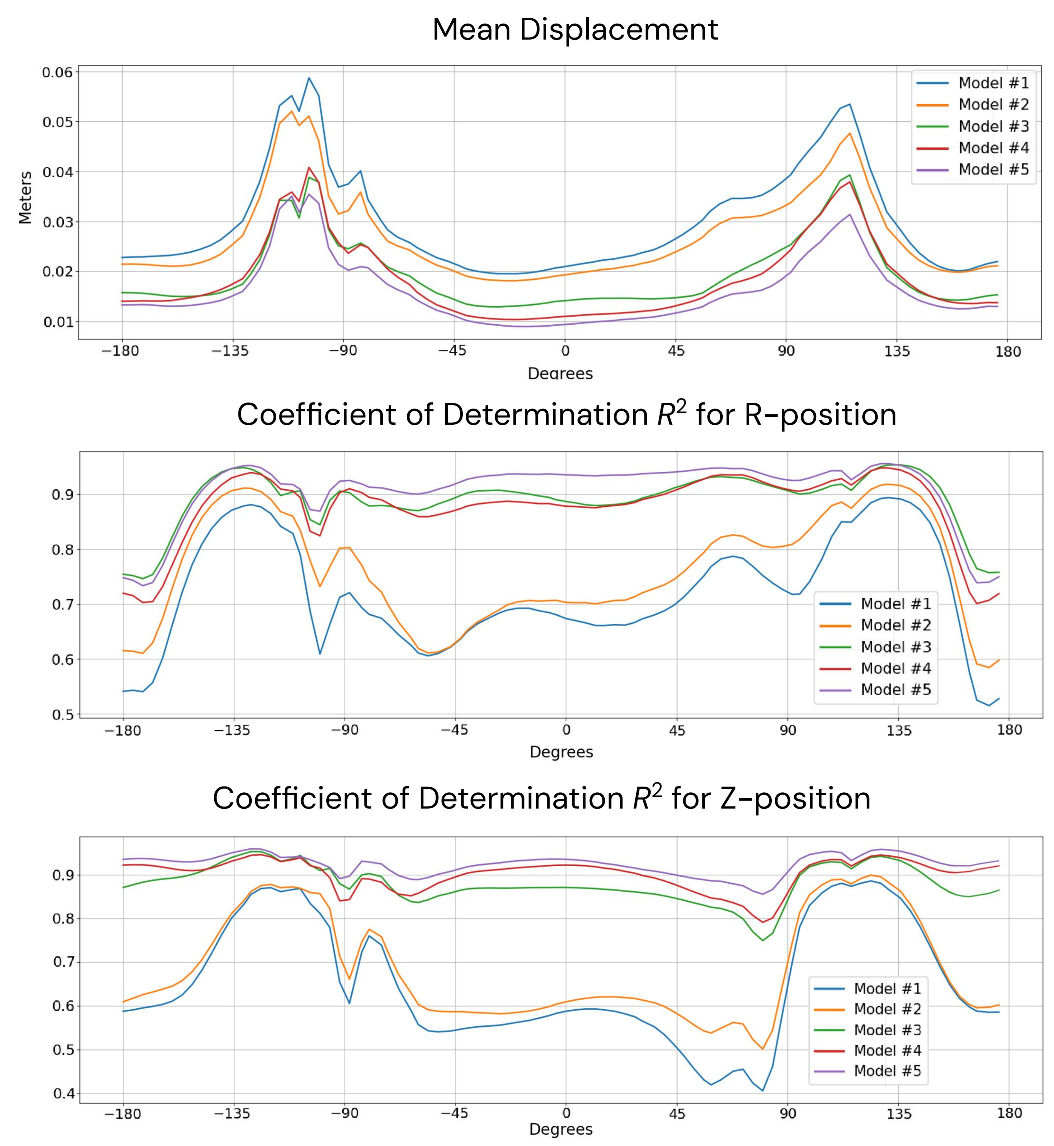
ML models comparison

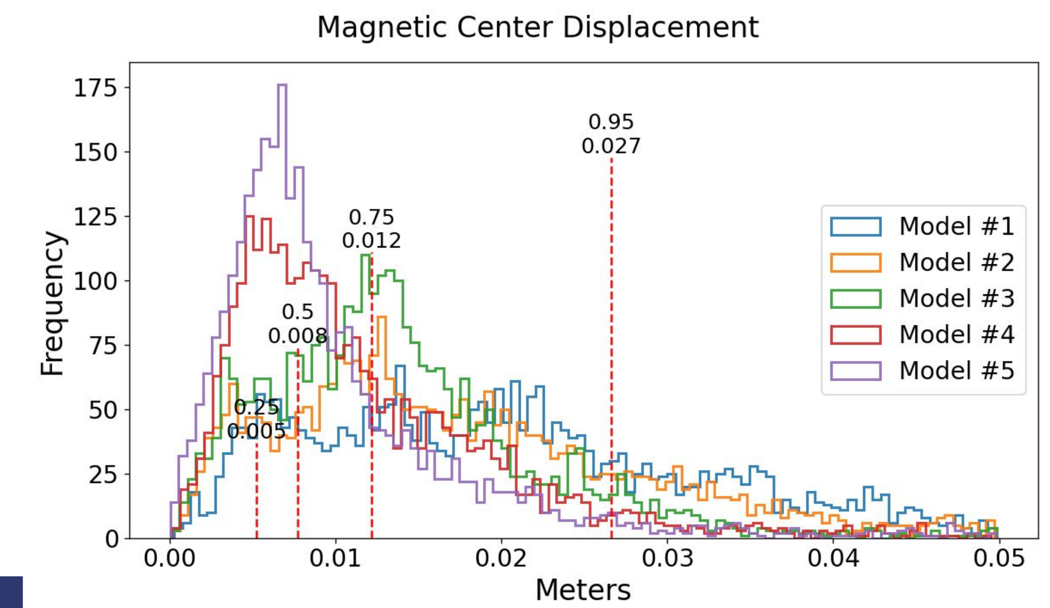
More information is better. The most pronounced deviations are located in X-point regions.

Adding more information improves MND more than MXD

~6cm/~20cm (MND/MXD) is achievable in the least informed model #1







Model	Cross validation			Test		
	MND	MXD	mean R^2	MND	MXD	mean R^2
1	0.026	0.095	0.384	0.030	0.099	0.785
2	0.024	0.095	0.441	0.027	0.091	0.816
3	0.018	0.087	0.647	0.019	0.081	0.910
4	0.018	0.089	0.633	0.018	0.074	0.910
5	0.017	0.086	0.689	0.016	0.069	0.930

Conclusion

Surrogate ML models allow achieving good accuracy in plasma position and tolerable performance in plasma boundary reconstruction in midplane area while operating with fewer diagnostic inputs. The most difficult zone for applied methods are X-point areas. Beyond serving as lightweight surrogates for equilibrium solvers, these models can also play a supporting role in plasma control by providing early warnings of off-normal behavior.

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