Reconstructing the Plasma Boundary with a Reduced Set of Diagnostics

M.S. Stokolesov[1], M.R. Nurgaliev[1], I. Kharitonov[1], E. Adishchev[1], D. Sorokin[1]

[1] *Next Step Fusion, Luxembourg, Mondorf-les-Bains, 56A Avenue François Clément, L-5612*

e-mail: ms@nextfusion.org

This study investigates the feasibility of reconstructing the last closed flux surface (LCFS) in the DIII-D tokamak using neural network (NN) models trained with broader or reduced input feature sets, ranging from well-posed tasks with extensive diagnostics (coil currents, plasma current, pressure and toroidal flux gradients) to ill-posed tasks relying on minimal data. The model trained exclusively on coil currents achieved a mean point displacement of 4.5×10^{-2} m on a held-out test set. The goal is to demonstrate the capability of machine learning algorithms to operate effectively in weak data environments, such as those anticipated in Fusion Power Plants (FPP) due to the presence of blankets and shielding.

This work employs neural network (NN) models based on Multi-Layer Perceptron (MLP), trained on historical EFIT [1] data. The training dataset comprised approximately 42,000 DIII-D discharges (2004-2024) including both positive (PT) and negative (NT) triangularities. The dataset was filtered to exclude shots with missing EFIT signals, durations under 1500 ms, or large time gaps (>100 ms). Additionally, ~30% of the dataset, identified as duplicates, was removed using a developed clustering approach based on state sequence similarity to ensure unbiased evaluation.

For robust model evaluation, a shape-based cross-validation scheme was employed. Plasma states were grouped into 16 regions based on top and bottom triangularity. Validation was performed on shapes unseen during training, with an example shown in Figure 1, demonstrating that even out-of-distribution shapes can be reconstructed with reasonable accuracy.

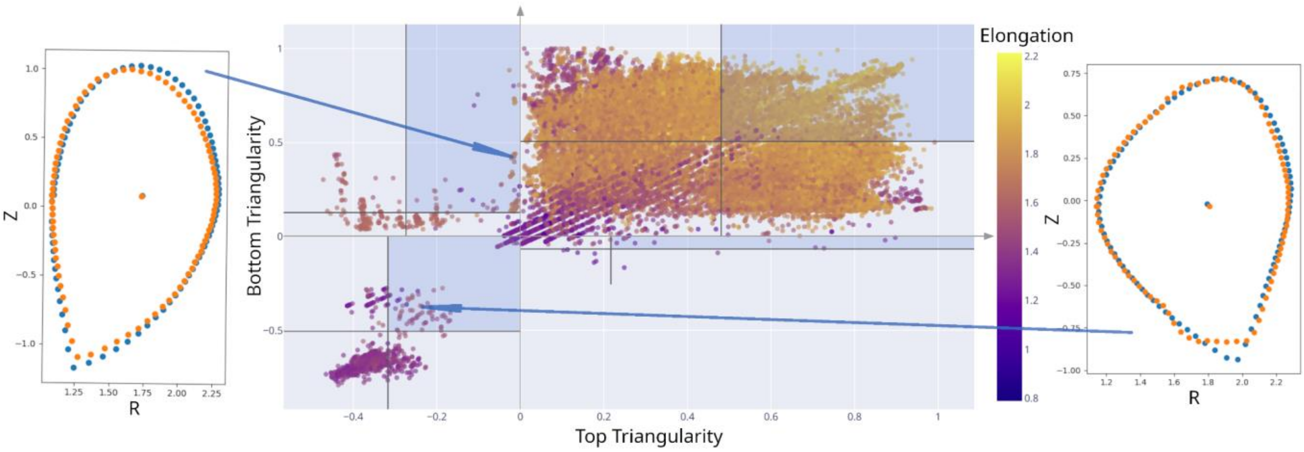

Fig. 1. Distribution of plasma states in the DIII-D database based on top and bottom triangularity. Each quadrant is divided into four parts, resulting in 16 groups for cross-validation. At each cross-validation step, the validation set was composed of data from 4 groups (one possible set is highlighted in blue), while the remaining 12 groups were used for training. Examples of plasma shapes are shown for PT and NT cases, demonstrating the accuracy of NN model #6 on cases not seen during training (blue – ground truth shape, orange – model reconstruction).

A total of six neural network models trained on various input feature sets were considered:

1. $[I_{coils}]$, I_p, $dp\ /\ \psi$, $F\ dF\ /\ \psi$;
2. $[I_{coils}]$, I_p, Flux loops, Magnetic probes;
3. $[I_{coils}]$, I_p, Magnetic probes;
4. $[I_{coils}]$, I_p, Flux loops;

5. $[I_{coils}]$, I_p, V_{loop};
6. $[I_{coils}]$.

All NN models achieved accuracy with mean point displacements of a few centimeters. Model #6, which used only coil currents as input, achieved a mean point displacement of 4.5×10^{-2} m on the test set, demonstrating the feasibility of LCFS reconstruction with minimal diagnostics. Standard DIII-D equilibrium reconstruction techniques and the plasma control system achieve an accuracy of 1-2 $\times$ 10^{-2} m. When using a model trained on the reduced set of diagnostics, the error increases by only a factor of two, which is a promising result for FPP applications. These applications require validation on data from larger devices with coil shielding, which can be achieved by generating purely synthetic datasets.

Testing on out-of-distribution negative triangularity shots resulted in reduced accuracy, consistent with findings from the study [2], where the coil-current-only model also struggled with data outside their training distribution.

Additionally, when tested on discharges controlled by RL-based plasma shape and position control algorithms, the coil-current-only model exhibited slightly reduced accuracy (6.3×10^{-2} m), likely due to the distinct plasma states generated by the RL agent.

This study demonstrates the feasibility of reconstructing the plasma boundary using only coil currents as input. The results also emphasize the importance of representative training data and careful consideration of control strategies for machine learning applications in fusion research. Notably, in general, there cannot be a one-to-one correspondence between coil currents and plasma shape. The coil-current-only models appear to have learned to reconstruct plasma shapes based on currents generated by specific control algorithms.

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References

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