Development of AI Framework for Plasma Equilibrium Parameters Generation for Virtual Tokamak Environment

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Abstract

Tokamak simulators are increasingly being utilized for visualizing, analyzing, optimizing, and controlling Tokamak plasma scenarios by integrating experimental data with physics-based models and AI-driven approaches. The traditional approach for solving the Grad–Shafranov (GS) equation poses a significant challenge for real-time plasma equilibrium prediction, as it requires finding an optimal solution involving both experimental measurement and physical solutions [1]. Joung et al. [2], has developed supervised neural network scheme for predicting a quasi-periodic disruptive eruption of the edge plasmas based on BES measurement. J. Seo et al. [3] in their work have developed and validated a deep neural network-based multimodal prediction system that estimates the future tearing instability likelihood from multi-diagnostics signals in the DIII-D tokamak. In this study, we develop data driven AI models to accelerate equilibrium prediction while maintaining high accuracy. A synthetic dataset is generated using a forward GS solver [4] which takes input from plasma currents, pressure profiles, and coil currents and generates magnetic flux distribution and equilibrium shape for a medium sized tokamak device. We train two AI models (Fig. 1) using the synthetic data set wherein the first classifies whether a given input set are convergent or not and the second predicts equilibrium parameters. The AI models demonstrate reasonable predictive capabilities, reconstructing the separatrix region (Fig. 2) and key equilibrium parameters for a particular tokamak configuration and data sets. It achieves significantly faster computation, reducing the average runtime by 35X on Intel(R) Xeon(R) Silver 4314 CPU machine.

Comparative analysis of AI-generated flux profiles (Fig. 3) with numerical solutions as well as analytical methods shows a close match, with minor deviations attributed to data resolution limitations. Additionally, ψ values predicted at various (R, Z) coordinate aligns well with numerical results, with error margins remaining minimal across different cases. The AI-based RXD predictions also exhibit good agreement with both published literature [5] and numerical solvers [4] (Table 1), confirming the robustness of the approach. These findings highlight the potential of AI-driven models as efficient alternatives to traditional solvers, offering real-time plasma equilibrium prediction capabilities.

Table 1: AI Predicted RXD Comparison with Numerical Solver

AI Predicted RXD	Numerical Solver RXD	Error (%)	AI Predicted RXD	Numerical Solver RXD	Error (%)	AI Predicted RXD	Numerical Solver RXD	Error (%)
4.16	4.1	1.46	4.21	4.16	1.20	4.42	4.13	7.02
3.77	3.86	2.33	4.73	5.05	6.33	6.05	5.86	3.24
1.73	1.67	3.59	4.53	4.86	6.79	2.9	3.01	3.60
1.68	1.8	6.66	4.63	4.98	7.02	6.02	6.2	2.90

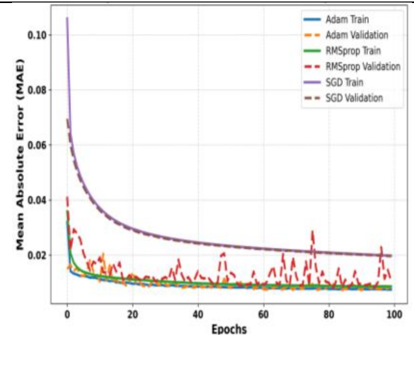

Fig. 1: AI model Training loss with multiple optimizers (Root Mean Square (RMS), Stochastic gradient descent (SGD), Adaptive Moment Estimation (ADAM))

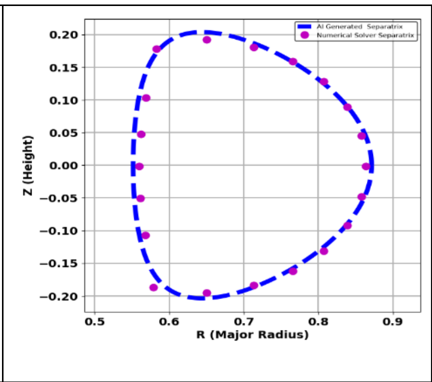

Fig. 2: AI generated Separatrix vs Numerical Solver (BV1 = -136 kAt, BV2 = -50 kAt, D1 = 150 kAt, D2 = 0, D3 =0, Ip = 100 kA, Beta = 0.02)

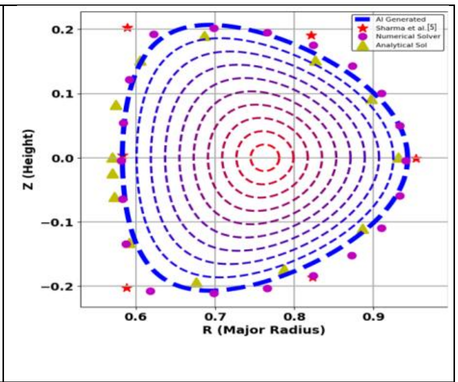

Fig. 3: AI generated flux lines as compared to analytical soln./published results/numerical solver (BV1 = -136 kAt, BV2 = -50 kAt, D1 = 150 kAt, D2 = 4 kAt, D3 =0, Ip = 100 kA, Beta = 0.29)

References:

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