Physics informed fast Grad-Shafranov surrogates

E. Lewis[12], S. Pamela[1], Y. Andreopoulos[2]

[1] *Culham Centre for Fusion Energy, Oxfordshire, UK*

[2] *University College London, London, UK*

The calculation of ideal magnetohydrodynamic (MHD) equilibria is vital to understanding and controlling the behaviour of magnetically confined plasmas. These equilibria provide important integrated tokamak characteristics such as stored energy and edge safety factor in addition to serving as input for subsequent simulation codes. Equilibrium reconstruction is normally performed with numerical solvers. However such methods are computationally costly and inappropriate for real-time plasma control which typically requires calculation times below 100μs. In this work we present neural surrogate models that are able to rapidly reconstruct JET-ILW plasma equilibria. The models were developed to reproduce the poloidal flux function ψ(R,Z) calculated by EFIT, an equilibrium solver used on JET [1]. The surrogate inputs consisted of magnetic signals measured by diagnostic pick-up probes and flux loops. The training and validation dataset was created from 955 experimental JET-ILW pulses, and contained 311914 data points of individual 0.03s timesteps. Both multilayer perceptron (MLP) and convolutional neural network (CNN) architectures were tested [2]. It was found that the latter performed better in terms of Mean Squared Error (MSE) and Mean Structural Similarity (MSSIM) with the true flux geometry. The surrogate loss function was modified to incorporate the Grad-Shafranov equation, introducing a physical understanding of the problem to the network [3]. Figure 1 shows ψ predicted by the surrogate as a series of flux surfaces within the tokamak cross-section, compared to the EFIT ground truth. Model inference time is of the order of milliseconds, demonstrating the viability of surrogate EFIT models for real-time control scenarios.

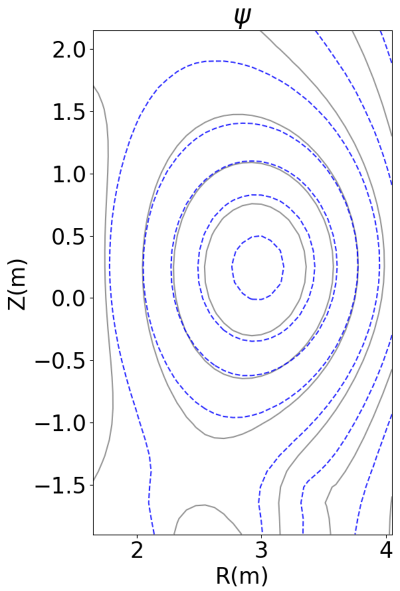

Figure 1: *EFIT (grey) and surrogate (blue) flux surfaces for JET-ILW shot #94257, MSE=0.003 MSSIM=0.967*

References

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