LEARNED MODELS FOR INTEGRATED TOKAMAK SCRAPE-OFF LAYER MODELLING AND DESIGN

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ABSTRACT
The development of predictive tokamak scrape-off layer simulation capability is crucial for future fusion power plants. This work presents machine learning-based surrogate models to replicate the EDGE2D code, widely used for tokamak modelling. These models offer significant computational advantages, providing predictions much faster than traditional methods, enabling high-throughput experiment analysis, rapid design optimisation, and their use in integrated tokamak modelling systems and digital twins.

1. INTRODUCTION

Future tokamak devices will rely heavily on advanced predictive computer models for design, optimisation, and operation. A key goal is to develop a tokamak "digital twin", which accurately predicts the system's future state by coupling with live sensory information. Significant progress has been made, but a full fusion power plant digital twin requires further development.

Once crucial element to model is the scrape-off layer (SOL), where magnetic field lines intersect with material components. Energetic particles from the plasma core stream along the field lines towards the divertor region, impacting divertor target plates. Devices like ITER and STEP will require mitigation of energy flux to avoid damage. Plasma detachment is a promising approach to reduce divertor power load.

SOL plasma and neutral species modelling spans several fidelity levels. High-fidelity models like SOLPS, EDGE2D, and UEDGE solve dynamic equations for plasma and neutral species but are computationally intensive. Machine learning-based surrogate models of these codes offer significant speedup, encapsulating the full physics present in the training data. These models hold promise for tokamak design optimisation and as digital twin components.

This work describes the development of machine learning-based surrogate models of EDGE2D, running significantly faster than conventional methods. They can be used for simulating quantities of interest, replacing expensive SOL simulation components, and reconstructing full 2D fields within the SOL.

2. DATASET

The EDGE2D SOL simulation code has been used for decades for interpretative and predictive simulations. We use over 20,000 EDGE2D simulations of the JET tokamak and additional simulations of the MAST-U tokamak, categorised by run date and plasma configuration. This dataset provides a rich variety of physics and operational regimes for training models. Data mining and curation were essential for preparing the data for machine learning algorithms.

3. SURROGATE MODELS

We present several learned emulators of EDGE2D, categorised into three classes:

1. Emulators of 0D and 1D quantities of interest relating downstream conditions to upstream parameters.
2. Emulators of scalar quantities used as core-edge boundary conditions for integrated modelling systems.
3. Full-field emulators of 2D quantities.

These models provide output values many orders of magnitude faster than EDGE2D simulations. Category 1 models are relevant for rapid design optimisation and parameter scans. Category 2 models can replace EDGE2D in the JINTRAC integrated modelling suite, moving towards real-time tokamak integrated modelling and digital twin capability. Full 2D information is required for advanced divertor studies, providing enhanced interpretability and better initial conditions for SOL transport models.

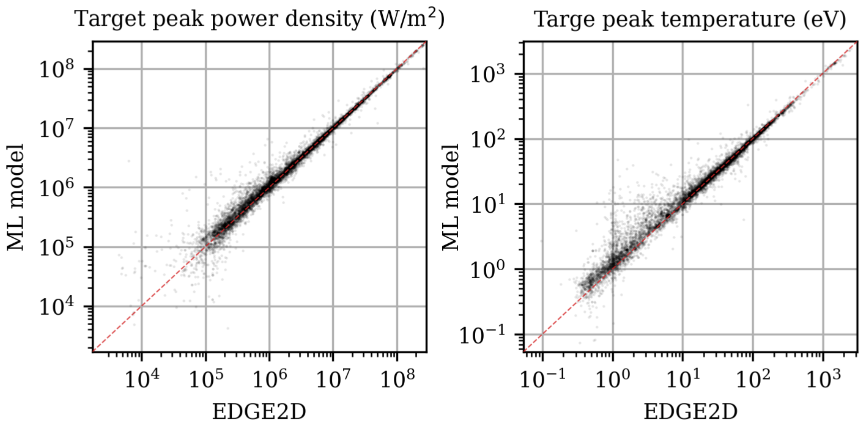

Figure 1. Calibration plots of outer divertor target peak power density and electron temperature. Learned model predicted values are presented as points against the value simulated by EDGE2D, with the dashed line representing perfect agreement.

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REFERENCES

[1] M. GRIEVES, J. VICKERS, Transdisciplinary Perspectives on Complex Systems: New Findings and Approaches, Springer (2017).

[2] M. TINDALL, et al., Towards a fusion component digital twin – virtual test and monitoring of components in CHIMERA by systems simulation, Fusion Eng. Des. **191** (2023) 113773.

[3] R. A. PITTS, et al., Status and physics basis of the ITER divertor, Phys. Scripta **2009** T138 (2009) 014001.

[4] R. P. WENNINGER, et al., DEMO divertor limitations during and in between ELMs, Nucl. Fusion **54** 11 (2014) 114003.

[5] R. WENNINGER, et al., The DEMO wall load challenge, Nucl. Fusion **57** 4 (2017) 046002.

[6] S. S. HENDERSON et al., An overview of the STEP divertor design and the simple models driving the plasma exhaust scenario, Nucl. Fusion **65** 1 (2024) 016033.

[7] A. LOARTE, et al. Power and particle control, Nucl. Fusion **47** 6 (2007) S203.

[8] P. C. STANGEBY, The Plasma Boundary of Magnetic Fusion Devices, CRC Press (2000).

[9] P. C. STANGEBY, Basic physical processes and reduced models for plasma detachment, Plasma Phys. Contr. F. **60** 4 (2018) 044022.

[10] S. WIESEN, et al., The new SOLPS-ITER code package, J. Nucl. Mater. **463** (2015) 480.

[11] R. SIMONINI, et al., Models and numerics in the multi-fluid 2-D edge plasma code EDGE2D/U, Contrib. Plasm. Phys. **34** 2-3 (1994) 368.

[12] D. REITER, et al., The EIRENE and B2-EIRENE codes, Fusion Sci. Technol. **47** 2 (2005) 172.

[13] T. D. ROGNLIEN, et al., A fully implicit, time dependent 2-D fluid code for modeling tokamak edge plasmas, J. Nucl. Mater. **196-198** (1992) 347.

[14] B. D. DUDSON, et al., Hermes-3: Multi-component plasma simulations with BOUT++, Comput. Phys. Commun. **296** (2024) 108991.

[15] B. D. DUDSON, et al., The role of particle, energy and momentum losses in 1D simulations of divertor detachment, Plasma Phys. Contr. F. **61** 6 (2019) 065008.

[16] V. GOPAKUMAR, D. SAMADDAR, Image mapping the temporal evolution of edge characteristics in tokamaks using neural networks, Mach. Learn. Sci. Tech. **1** 1 (2020) 015006.

[17] M. BRENZKE, et al., Divertor power load predictions based on machine learning, Nucl. Fusion **61** 4 (2021) 046023.

[18] B. ZHU, et al., Data-driven model for divertor plasma detachment prediction, J. Plasma Phys. **88** 5 (2022) 895880504.

[19] S. DASBACH, S. WIESEN, Towards fast surrogate models for interpolation of tokamak edge plasmas, Nucl. Mater. Energy **34** (2023) 101396.

[20] G. K. HOLT, et al., Tokamak divertor plasma emulation with machine learning, Nucl. Fusion **64** 8 (2024) 086009.

[21] M. ROMANELLI, et al., JINTRAC: A system of codes for integrated simulation of tokamak scenarios, Plasma Fusion Res. **9** (2014) 3403023.