Generalizing Shadow Mask Predictions for SPARC Plasma-Facing Components Using Machine Learning

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Plasma-facing components (PFCs) play a vital role in ensuring the stability and safety of tokamak operations. In the SPARC tokamak, understanding and predicting heat load distributions on these components is critical due to their complex 3-D geometries and the extreme operational conditions [1]. Shadow masks, regions of PFCs shielded from heat flux due to geometric effects, are particularly important to model accurately, as errors in predictions can lead to component failures, including melting, or compromised operational performance. The HEAT code (Heat flux Engineering Analysis Toolkit) has been instrumental in enabling precise 3-D heat flux analyses, but its computational intensity limits its applicability in scenarios requiring rapid or real-time predictions [2].

To address these challenges, was integrated machine learning (ML) techniques with HEAT to develop surrogate models for fast and accurate shadow mask predictions. Using a feedforward neural network (FNN), trained on a diverse database of SPARC equilibriums encompassing variations in plasma current, safety factor and incident magnetic field angles, it successfully replicated HEAT's predictions for specific PFC geometries [3]. This approach achieved a substantial reduction in computation time, down to the millisecond range, enabling feasibility for between-shot analysis and fast design iterations. The FNN-based model exhibited strong predictive accuracy across the training set and validation cases, demonstrating the capability of ML-enhanced methods to complement computationally intensive physics-based models.

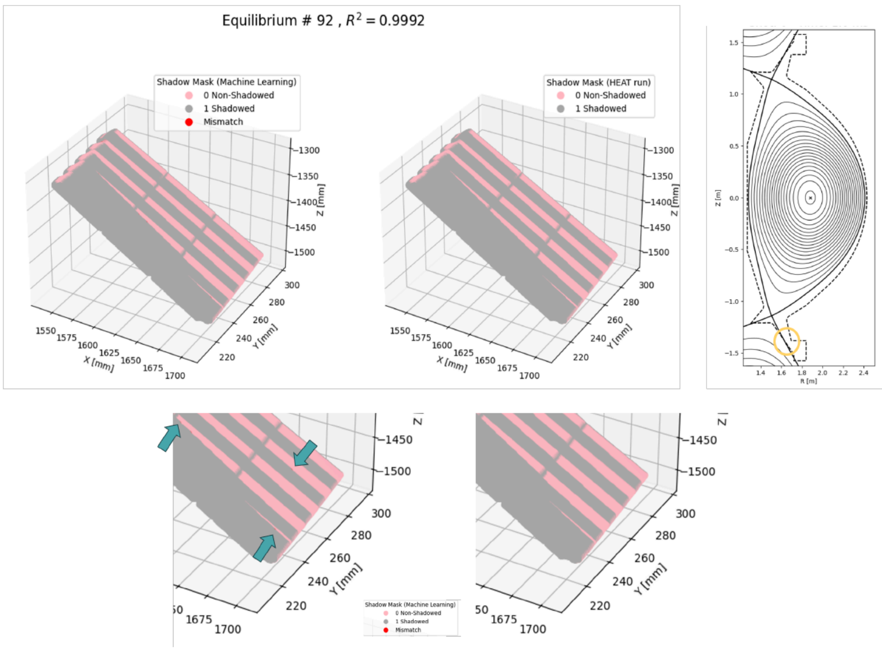

Figure 1. Combined view of the shadow mask prediction and a zoomed-in detail for a certain equilibrium. The blue arrows in the bottom image indicate the small regions where the prediction algorithm made incorrect predictions.

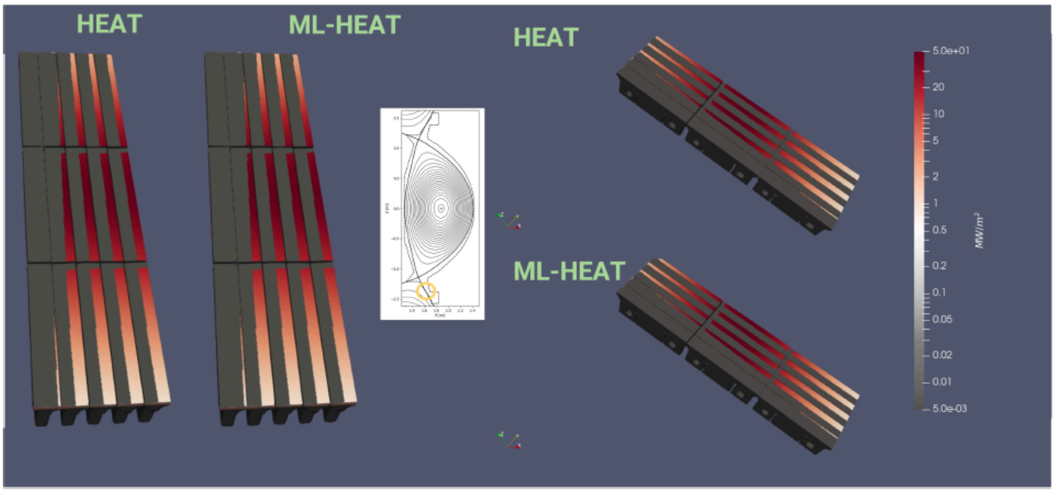

Figure 2. Comparison of the heat flux prediction using the regular and ML versions of the Shadow Mask calculation in the HEAT code for a given equilibrium. $R^2 = 0.9992$ and RMSE = 0.45 MW/m^2

The implementation of these FNN-based surrogate models with HEAT also facilitated a deeper understanding of the intricate interplay between 3-D PFC geometry and plasma parameters. The incorporation of diverse training data ensured robustness to typical operational conditions. This step forward not only enhances the ability to predict shadow masks but also could optimize the iterative process of PFC design and testing. While the FNN-based surrogate model represents a significant step forward, its applicability remains limited to the specific PFC elements and geometries included in the training database. To address this limitation, we focus on generalizing the surrogate model to extend its applicability across a broader set of PFC configurations. This generalization effort involves leveraging advanced ML architectures, particularly graph-based, which are well-suited for capturing spatial and topological relationships inherent in 3-D geometries [4]. By transitioning to a generalized model, this work aims to advance the state of surrogate modeling for tokamak divertor heat flux analysis. The final goal is to make use of the fast prediction of shadow masks for operational porpoises , where they can be used during or in between plasma discharges.

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