

Shadow Masks Predictions in SPARC Tokamak Plasma-Facing Components Using HEAT code and Machine Learning Methods

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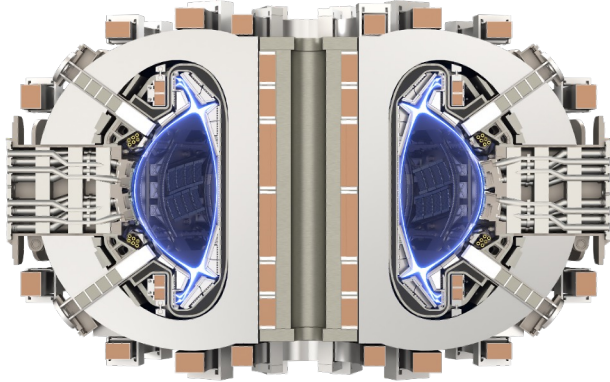
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Overview

- **SPARC tokamak**
- **HEAT code**
- **Database for the SPARC divertor**
- **Machine Learning for Shadow Mask predictions**
- **Integration of AI-Shadow Mask into HEAT**
- **Results and Future work**

This material is based upon work supported by the US Department of Energy, Office of Science, Office of Fusion Energy Sciences, under Awards DE-AC02-09CH11466 . This work is partially supported by Commonwealth Fusion Systems.

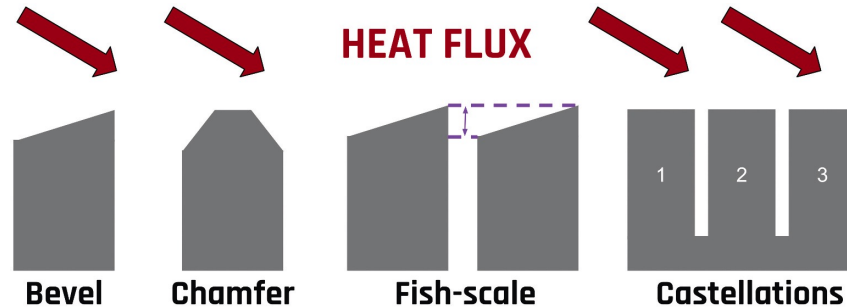
SPARC tokamak



| SPARC Primary Reference Discharge | | |
|---|------|----------------------------------|
| R | 1.85 | m |
| a | 0.57 | m |
| B₀ | 12.2 | T |
| I_p | 8.7 | MA |
| q* | 3.05 | (q ₉₅ = 3.4) |
| κ_{sep} | 1.98 | |
| <T_e> | 7.33 | keV |
| <n_e> | 3.13 | 10 ²⁰ m ⁻³ |
| τ_E | 0.77 | s |
| f_g | 0.37 | |
| P_{ohmic} | 1.7 | MW |
| P_{rf,coupled,operating} | 11.1 | MW |
| P_{fus} | 141 | MW |
| Q | 11.0 | (h-mode) |

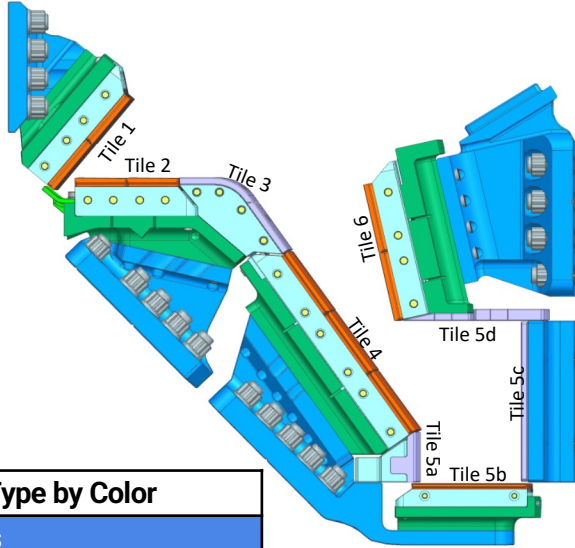
Kuang, A., et al. *Divertor heat flux challenge and mitigation in SPARC*. N. p., 2020. doi:10.1017/s0022377820001117.

SPARC divertor and PFCs (the importance of 3D PFC shaping)



- Beveling, chamfering, fish scaling, and castellations are 3-D PFC shaping techniques that reduce the risk of sublimation or melting by changing the incident angle of heat flux and protecting vulnerable edges.
- 3-D features like bevels and fish scales help protect leading edges, enabling operation under higher heat fluxes and expanding the machine's operational window while requiring careful plasma shaping control.

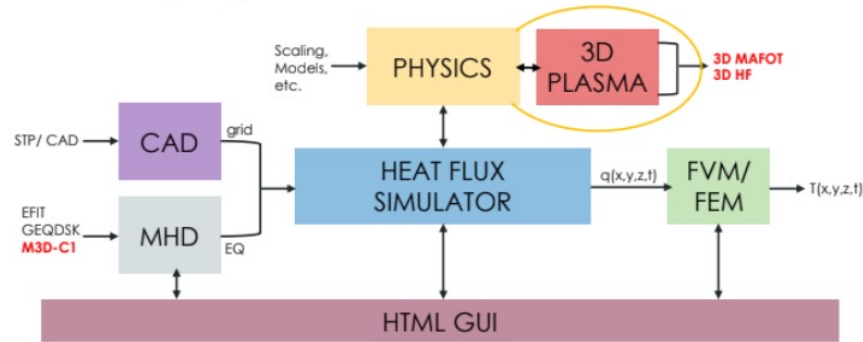
SPARC divertor and PFCs



| Type by Color |
|------------------|
| Pedestals |
| Support Plates |
| Carriers |
| HHF Slices (W) |
| LHF Slices (WHA) |
| Pins |
| Fasteners |

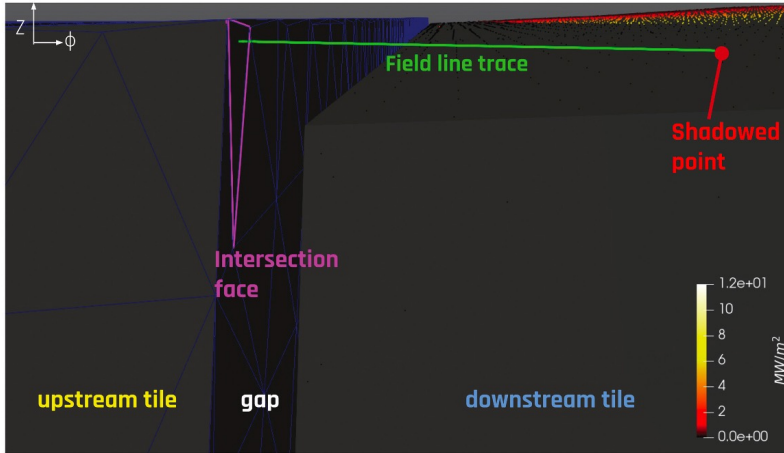
- Due to its high magnetic field and compact size, the SPARC tungsten-based divertor will operate with conditions at or above those expected in other tokamaks.
- The study of the SPARC divertor focuses on the critical challenge of managing heat flux during operation.
- Experimental results on SPARC will be crucial to reducing risk for other devices divertors.

HEAT Code



- HEAT code predicts heat loads on plasma-facing components (PFCs).
- Shadow mask refers to areas on the PFCs shielded from plasma magnetic field lines interaction.
- Field line tracing is used to assigned shadowed regions, as the trace progresses, the algorithm checks for intersections with other PFC faces along the trajectory, if and intersection is detected, the face is considered **shadowed** and no heat flux is assigned.

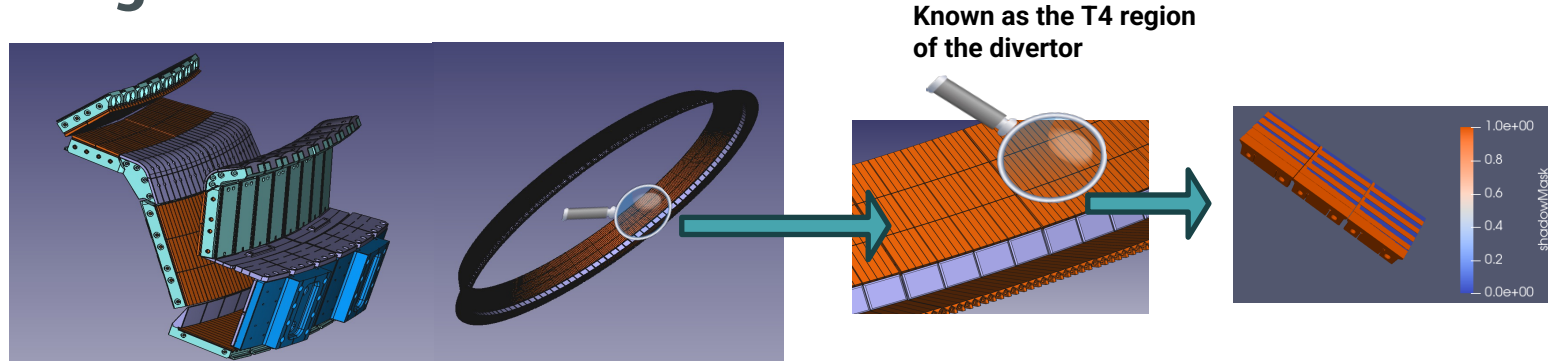
SPARC divertor and HEAT Code



NSTX-U close-up view of poloidal running gap between two PFC tiles.

- HEAT uses the MAFOT code, which can trace magnetic field lines for both 2D (axisymmetric) and 3D plasmas.
- HEAT parallelizes the field line tracing and intersection checking across multiple cores, enhancing computational efficiency.

Creating a Data Base

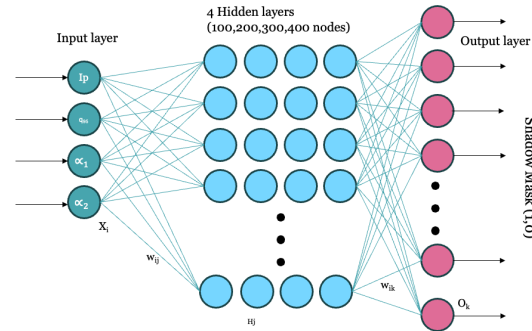


- Approximately 1000 diverted equilibrium files were used.
- 1 divertor carrier (15 tiles) with a 1 mm mesh resolution was selected for creating the database, more than 70,000 points.
- 4 equilibrium parameters were used as inputs to a NN. ORNL-FUSION EFIT toolkit code was used to read, provide and visualize EFIT g-file data for retrieve equilibrium parameters used as inputs (I_p , q_{95} and two incident line angles $B\theta/B\varphi$ at the top and bottom of the carrier)

Shadow Mask Predictions

Binary Classification to Predict Shadow Mask: Shadow detection involves binary classification where the goal is to predict a shadow mask that identifies shadow regions ('1') and non-shadow regions ('0').

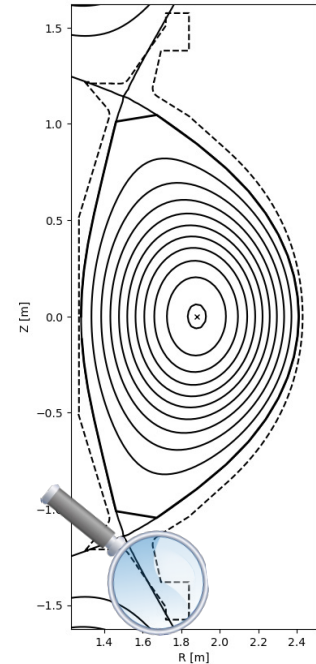
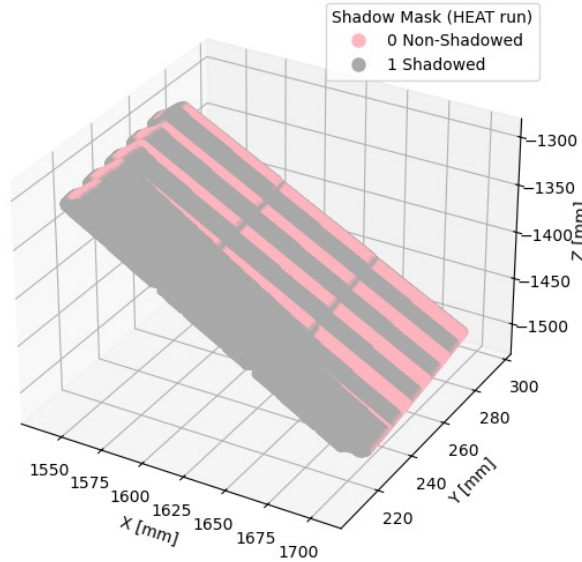
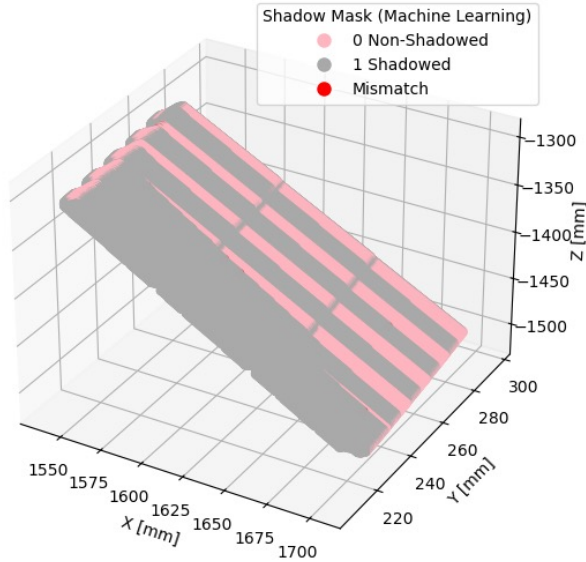
ML Architecture: Implemented a feedforward neural network with four hidden layers consisting of 100, 200, 300, and 400 nodes.



Tools Used: The model was implemented using a combination of PyTorch and Skorch to leverage the strengths of both frameworks in model training. MPI was used to parallelize and expedite the training using GPU resources (time reduction from 25 minutes to 30 seconds).

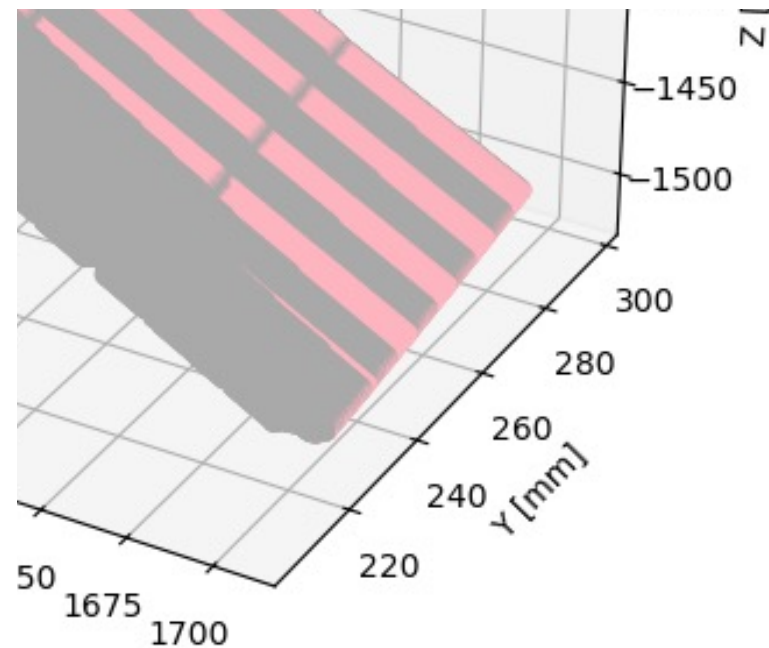
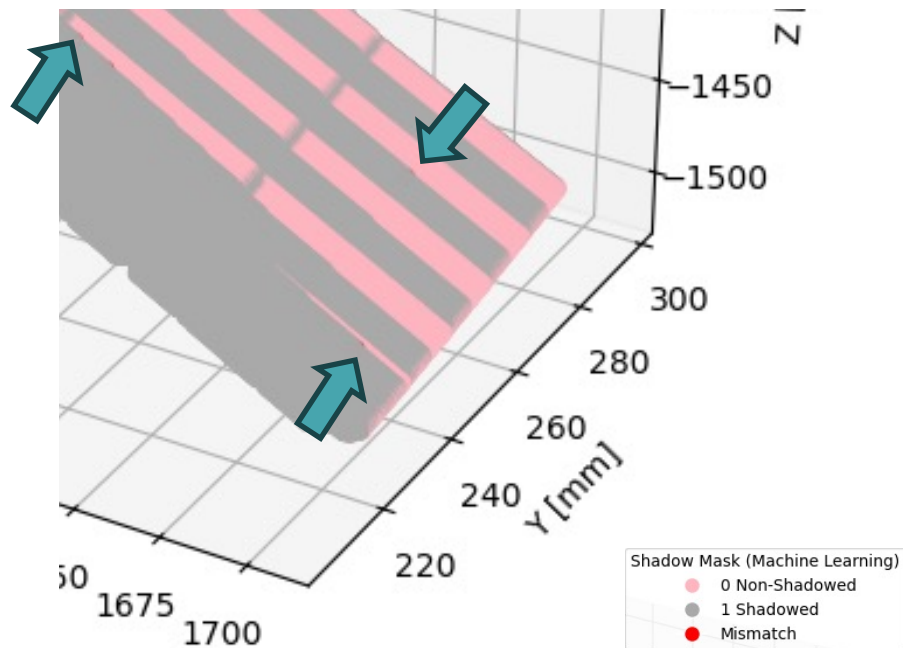
Shadow Mask predictions, good case

Equilibrium # 92 , $R^2 = 0.9992$



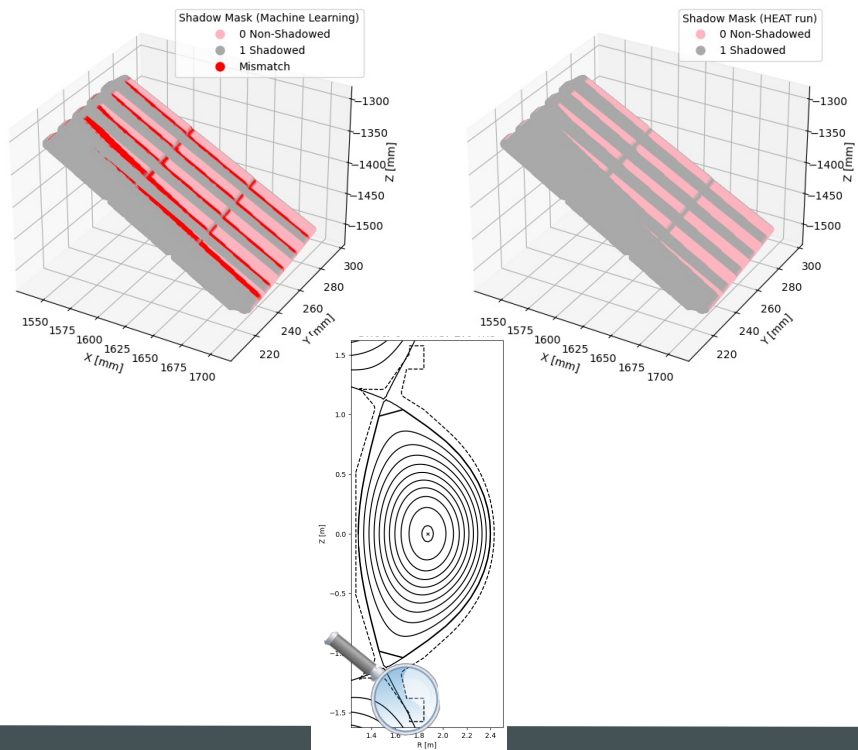
Improving training time using GPU's, from 25 minutes to 30 seconds !!! Overall $R^2=0.899$, where R^2 is the coefficient of determination and measured how well the predicted outputs fit the actual data.

Shadow Mask predictions, good case

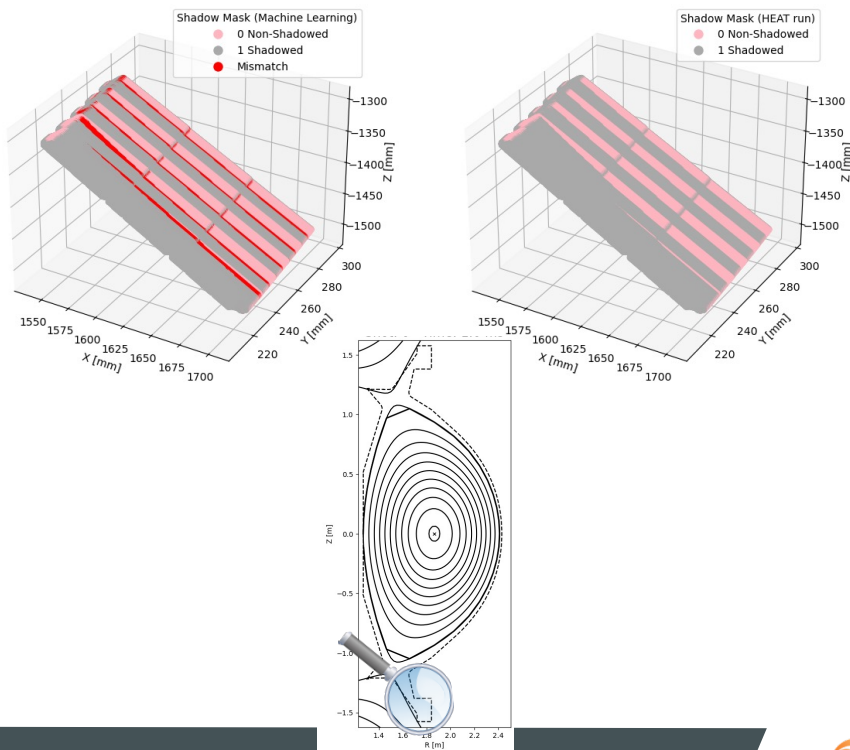


Shadow Mask predictions, not so good cases

Equilibrium # 213 , $R^2 = 0.5295$



Equilibrium # 44 , $R^2 = 0.6653$



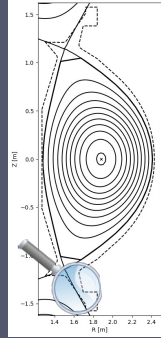
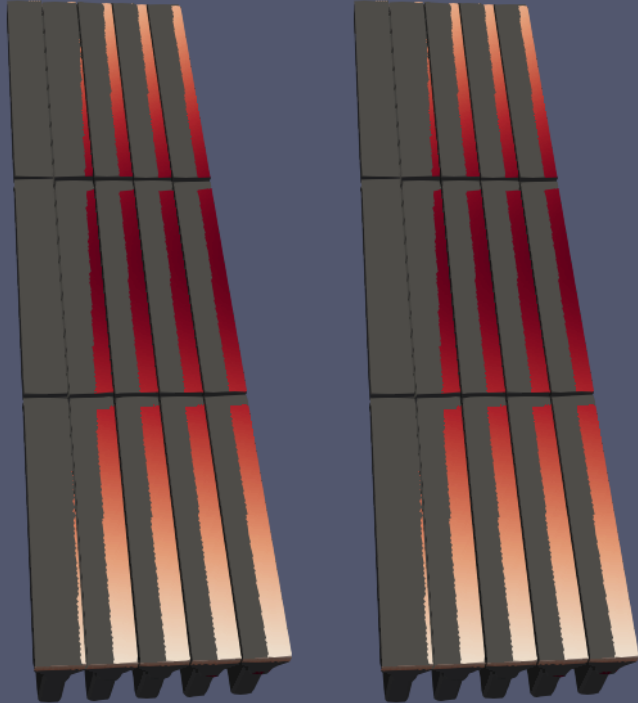
Heat Flux predictions

- Machine Learning version of the Shadow Mask calculation was substituted into the HEAT code which uses it to calculate the heat flux (MW/m^2) distribution based on the magnetic field configuration.
- General $R^2 = 0.955$, each run of HEAT code reduced its time from **45 minutes to 90 seconds** using as input **only 4** equilibrium parameters.
 - $R^2 > 0.75$, 95.7% of the cases (178 cases)
 - $R^2 < 0.75$, 4.3% of the cases (8 cases)
- The Heat run time of 90 seconds is mainly due to the overhead and file I/O, the NN predictions itself takes some milliseconds.

Heat Flux Predictions

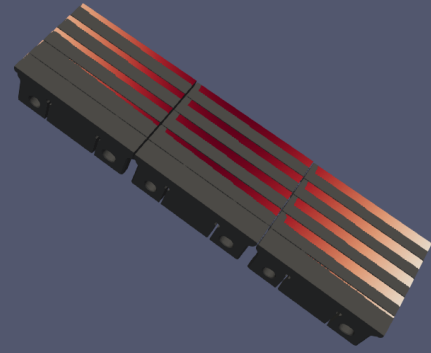
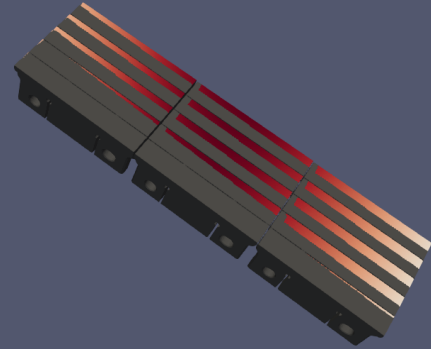
HEAT

ML-HEAT



HEAT

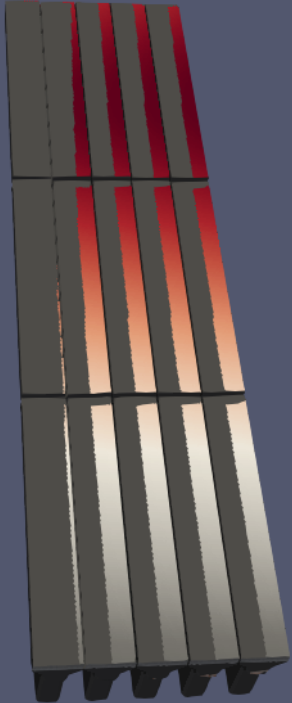
ML-HEAT



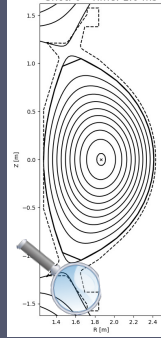
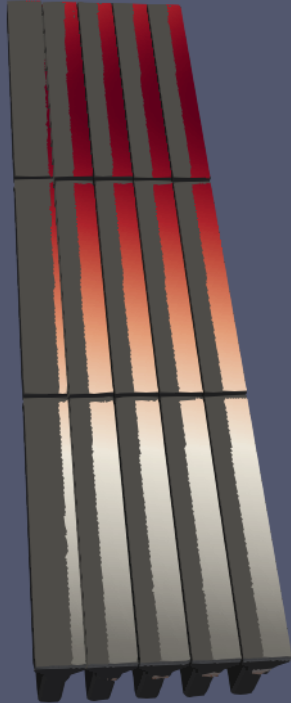
Best case, $R^2=0.9992$

Heat Flux Predictions

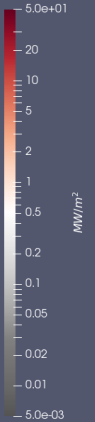
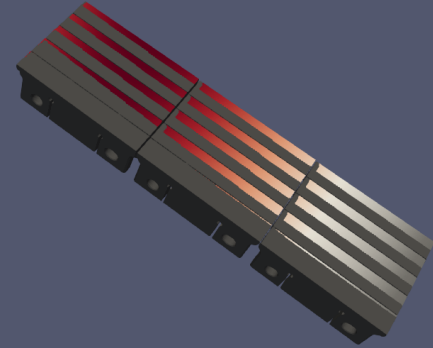
HEAT



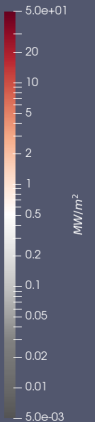
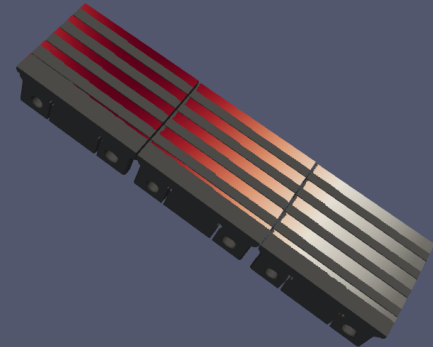
ML-HEAT



HEAT



ML-HEAT

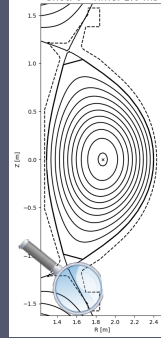
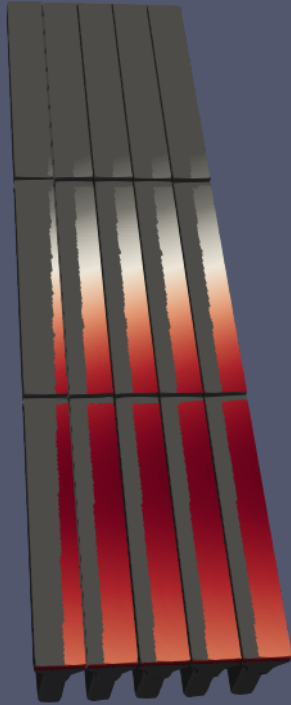
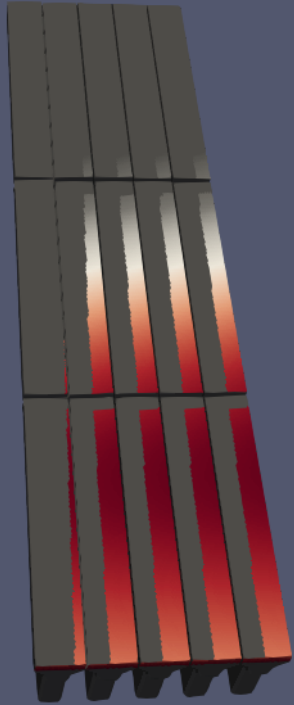


Not so good case, $R^2=0.6653$

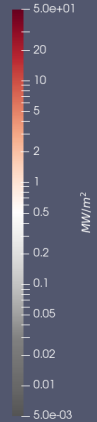
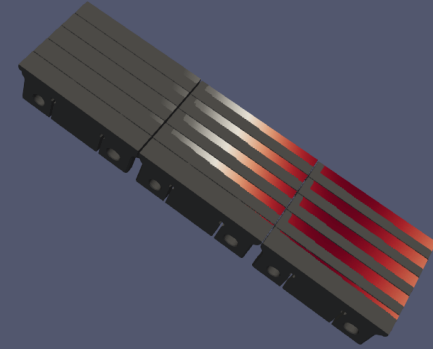
Heat Flux Predictions

HEAT

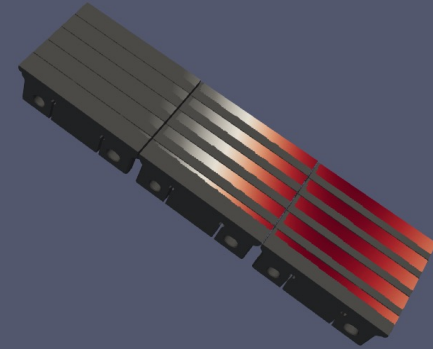
ML-HEAT



HEAT



ML-HEAT



Not so good case, $R^2=0.5295$

Future work

- Analysis of how these ML generated Shadow Mask patterns can be expanded to more regions of the divertor.
- Integration of AI-Shadow Mask calculation inside the Plasma Control System framework.
- Analyze SHAP values to provide detailed insights into how each input variable impacts the predictions of the shadow mask on PFCs.
- Integration of ML to predict the 3D Heat fluxes.

Where can you find more? APS!

- Munaretto S.: NP12.00115 [Impact of error field and error field correction on heat fluxes in SPARC](#)
- Scotto d'Abusco S. : NP12.00119 [3D heat flux modelling of rotating error field correction applied to the SPARC tokamak with the HEAT code](#)
- Corona D. : NP12.00120 [Shadow Masks Predictions in SPARC Tokamak Plasma-Facing Components Using HEAT code and Machine Learning Methods](#)
- All the posters will be Wednesday, October 9, 2024 [9:30 AM - 12:30 PM](#)
- Wingen A. (Thursday at 12.18pm): TO06.00015 [Development and validation of non-axisymmetric heat flux simulations with 3D fields using the HEAT code.](#)

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