Digital Twins for the Material Plasma Exposure eXperiment (MPEX)

G. Staebler[1], R. Juneja[1], A. Kumar[1], V. Reshniak[1], R. Archibald[1], C. Hauck[1], R. Barnett[1], M. Cianciosa[1], W. Tierens[1], M. Yang[1], P. Seleson[1], S. Reeve, [1] G. Watson [1], J. Duggan [1], B. Dudson[2], V. Geyko[2]

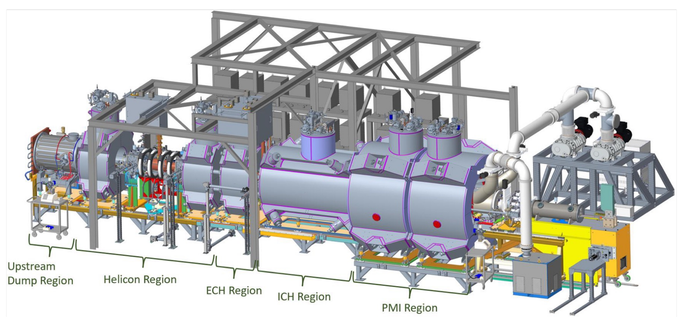
[1]Oak Ridge National Laboratory, [2]Lawrence Livermore National Laboratory
staeblergm@ornl.gov

MPEX target parameters

pulse length = $10^6 sec$

power to target = $20\ MW/m^2$

ion fluence = $10^{31}/m^2$



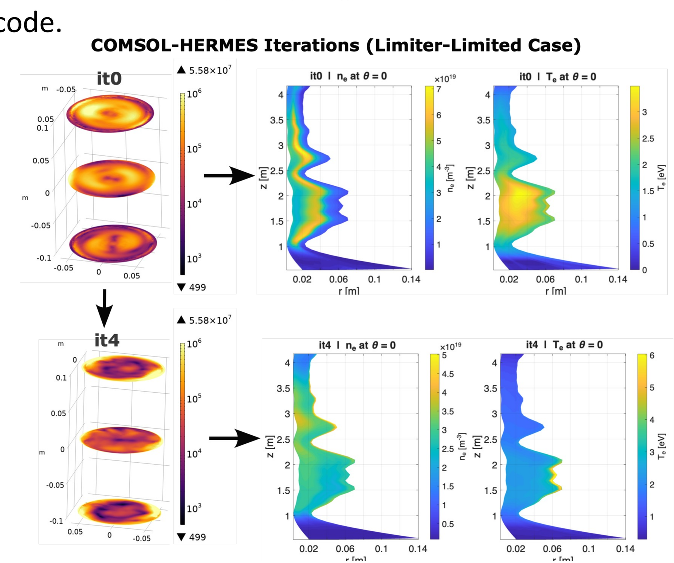
The MPEX device under construction at ORNL

Abstract

The Materials Plasma Exposure eXperiment (MPEX) device [1], under construction at Oak Ridge National Laboratory, will start its operations in December 2026. The goal of MPEX is to provide plasma fluence and heat flux, at fusion reactor levels, for continuous pulses lasting up to two weeks, to assess the damage to divertor target materials. The design of MPEX was guided by an integrated physics modeling workflow [2] that has continued to be improved during construction. A proto-type, namely proto-MPEX, was built to verify the Helicon plasma source, ion cyclotron heating (ICH), and electron cyclotron heating (ECH) plasma heating designs. Over 14,000 discharges were run in proto-MPEX. To help achieve the design goals of MPEX an **MPEX-AI-Hot-Spot Controller** is being trained with experimental data from proto-MPEX, and physics model simulations. The controller consists of a machine learning (ML) map of the control actuators (magnetic field coil currents, fueling gas puff, RF heating) to the distribution of plasma heat on the target and on the Helicon window, or other unwanted locations. Once this ML map is learned, an artificial intelligence (AI) AI-agent finds the optimum control settings to maximize the plasma directed to the target while minimizing hot spots elsewhere. A trained proto-MPEX-AI Hot-Spot Controller will be verified on proto-MPEX with only Helicon heating. A second goal is to build an **MPEX-AI Damage Assessment Digital Twin**. Training this model will require physics model simulation, and experimental data, of the full range of material damage from the plasma and heat fluxes in MPEX. As a first step, an E-BEAM AI Damage Assessment Digital Twin is being trained using experimental data from the JUDITH1 E-BEAM facility at Forschungszentrum Juelich IFN and simulated data using the CabanaPD code [3]. First a ML model is trained that maps between the damage assessment (cracking patterns due to high heat flux) and the microstructure grain boundary characteristics of the different grades of tungsten targets. An AI-agent then finds the optimum tungsten characteristics for a weighted damage assessment. This report is on work performed for the MPEX-AI Digital Twins project [4]. Details are given in the progress report. [5]

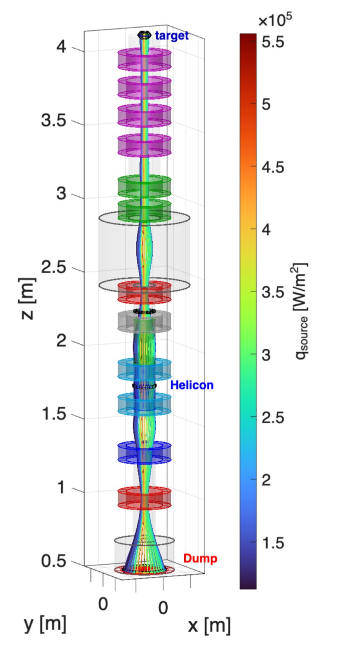
High Fidelity Plasma + Helicon Modeling

- The highest physics fidelity modeling of the helicon generation of the plasma is carried out by coupling the COMSOL 3D helicon heating code with the HERMES-3 3D collisional plasma turbulence code.
- 3D COMSOL simulations calculate the spatial helicon RF power deposition profile in the source region.
- The RF power deposition is imported into Hermes-3D as a volumetric electron heat source.
- Hermes self-consistently evolves plasma density, temperature, pressure, and parallel flows using the RF heating input.
- Iterative COMSOL–Hermes coupling captures the interaction between RF power absorption and plasma transport.
- The evolving plasma modifies the RF heating distribution, driving convergence toward a self-consistent solution.
- This workflow provides high fidelity predictions that will be validated with the InfraRed TeleVision (IRTV) heat flux and plasma profile measurements from probes and Thompson scattering on MPEX.



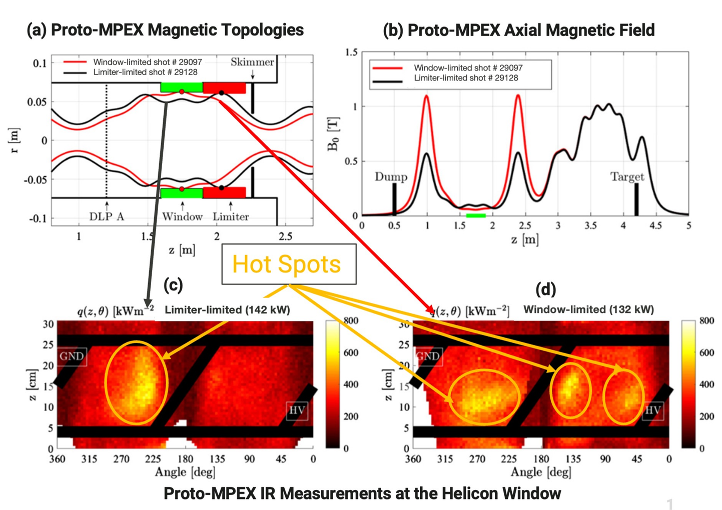
Collisional Flux Tube Reduced Fidelity Plasma Model for Training

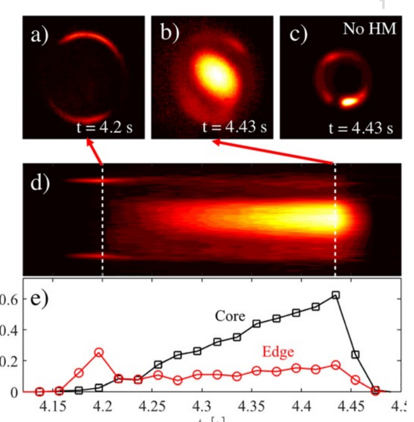
- IRTV heat-flux measurements at the target, dump and window are converted into a flux tube resolved quantity $Q_{\parallel}(l,m)$
  $q_{IRTV}(l,m) = Q_{\parallel}(l,m)\sin[\alpha_W(l,m)]$ where
  q_{IRTV} = measured IRTV heat flux
  $Q_{\parallel}$ = parallel energy flux carried by a flux tube
  α_W = magnetic field incidence angle at the surface
- The 1-D flux-tube model assumes the heat transport is dominated by collisional conduction along the magnetic field (the fast C1 code is used with fluid neutrals)
- Uncertainty quantification of the 1-D flux tube model is made by comparing with selected 3-D Hermes-3 simulations that include cross-field turbulent transport, and with measurements of the plasma in MPEX (probes and Thompson scattering at fixed locations near the target).
- The 1-D flux tubes will be run in parallel on GPUs to complete the 3-D plasma profile for each case to build a surrogate model training set
- The variation of the flux tube plasma predictions with neutral recycling coefficients is included in the training data so that the surrogate can quickly determine the plasma that best fits the measured IRTV heat fluxes and plasma profiles.



MPEX-AI Surrogate Model for Magnetic Fields

- Solving the Biot-Savart law for the magnetic field generated by the currents in the coils of MPEX with a MatLab code produces the range of magnetic fields that the power supplies and coils can produce.
- A machine learning model trained on a database of these simulations provides a fast surrogate.
- An AI-Agent uses the surrogate to determine the coil currents that will produce the magnetic field configuration subject to the constraints of the helicon, ICH and ECH heating and reduction of heating on the helicon window and vacuum vessel.
- The **hot spots on the helicon window** can be reduced in strength and stretched out axially by making sure the window is not directly connected by field lines to the target (limiter-limited, black lines).
- The azimuthal window hot spots are caused by the helicon heating asymmetries and can only be reduced by operating in the central heating regime at higher density and helicon power.
- For MPEX, maintaining the magnetic field in the ICH and ECH regions such that the resonant absorption is in the center of the plasma is critical.
- MPEX has 24 coils making operator adjustment of the coils to achieve the desired magnetic fields at various locations difficult without an AI-optimizer.





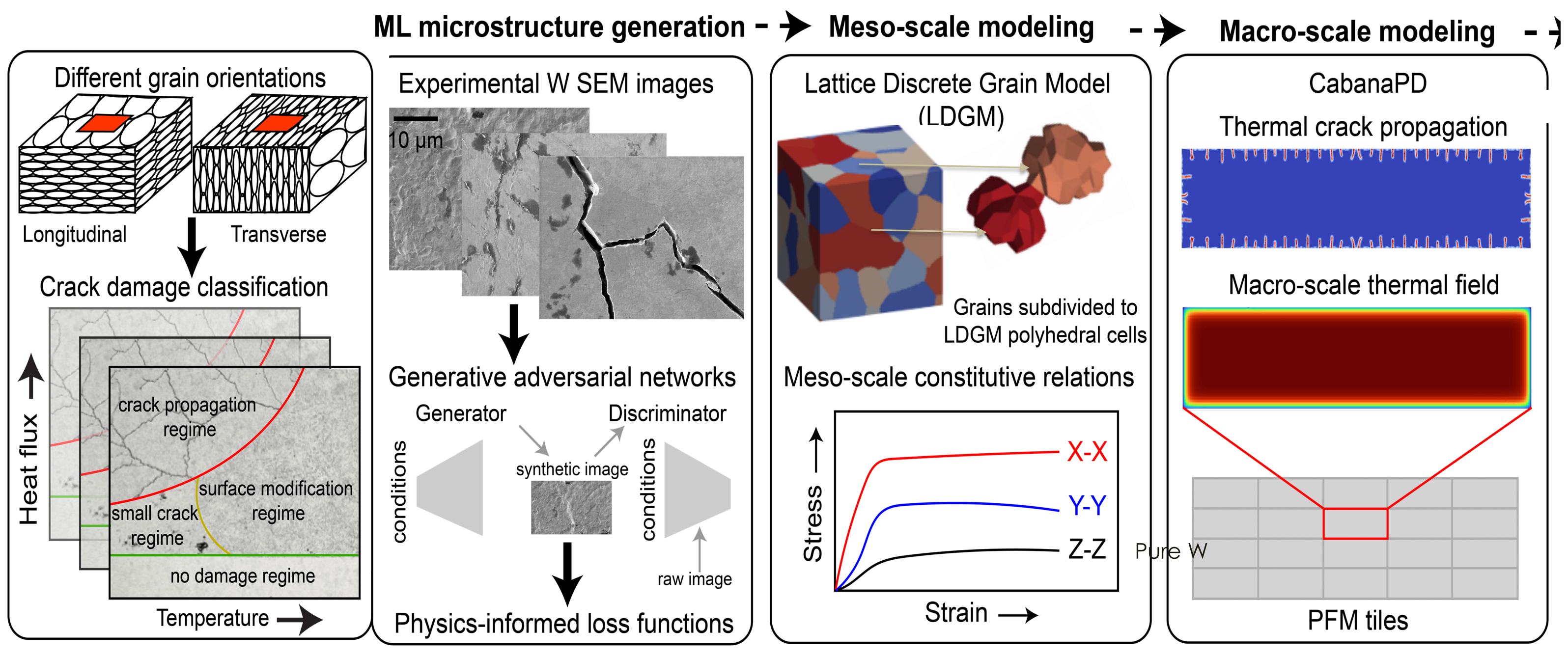
IRTV image of the proto-MPEX target showing the transition from edge heating to central heating at 4.22 sec as the plasma density and helicon power are increased.

MPEX-AI Hot Spot Controller

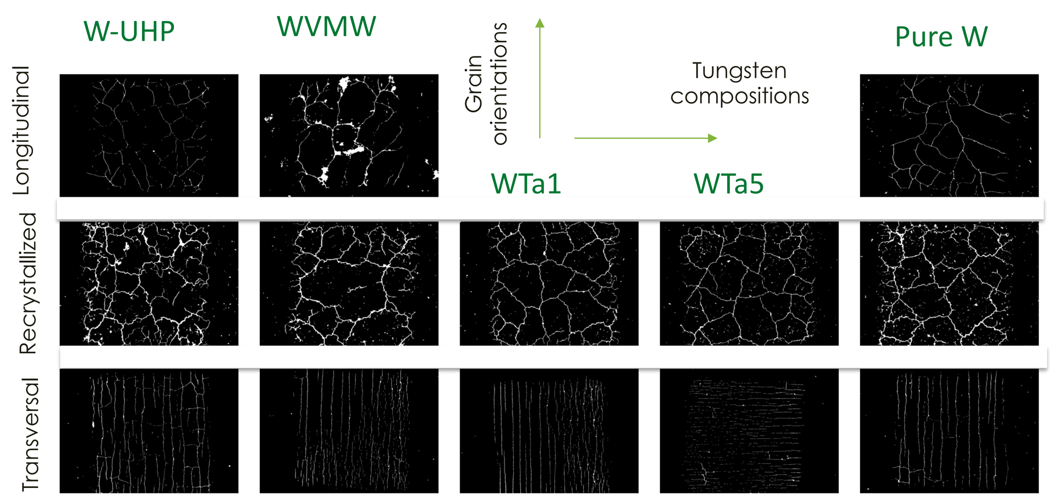
- The MPEX-AI Hot Spot Controller will be used in the operations control system to rapidly mitigate over-heating of surfaces that are off the target enabling MPEX to continue operation for up to 2-week long pulses.
- The magnetic field line surrogate determines where the field lines terminate on the material surfaces.
- The flux tube plasma surrogate informs the controller of the inferred plasma profiles in the helicon heating zone.
- A surrogate of the boundary between edge and central helicon heating regimes will be used by the controller to determine how to modify the gas puff, helicon power, magnetic fields, to avoid the edge heating regime.
- Surrogate models of the ICH, ECH/EBW heating on MPEX are planned for the next phase of the project.
- A proto-MPEX Hot Spot Controller will be tested in operations with only helicon heating before MPEX begins operations.

AI-Automated Experimental e-Beam Tungsten Damage Assessment

An initial proof-of-concept framework is established for pure tungsten PFC crack damage detection and prediction



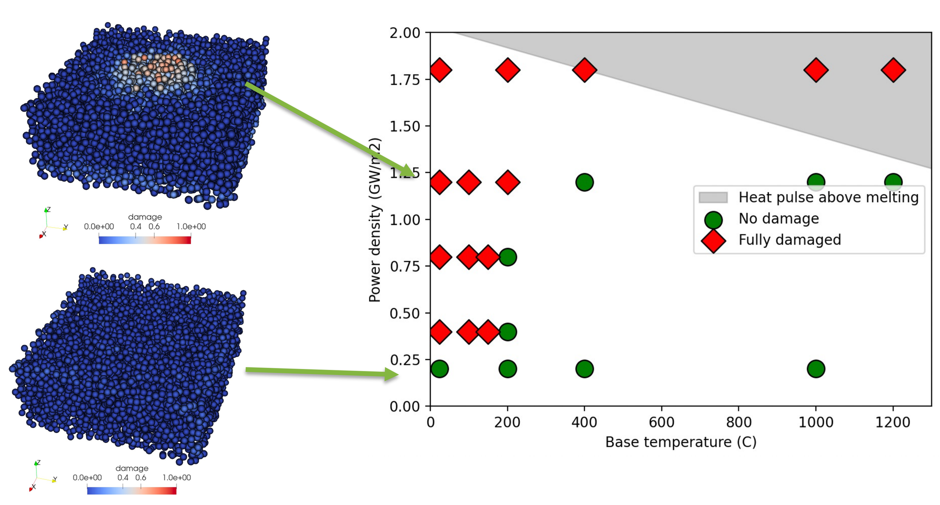
- **An automated crack detection tool is developed using AI SEM image processing**
- Crack patterns vary with grain orientation and tungsten composition
- The crack density can be projected to a latent space with a diffusion transformer and unmeasured cases interpolated with generative AI.
- The complete JUDITH-1 data set is too sparce for an accurate interpolation.
- High fidelity simulations, validated with the existing data, can be used to simulate cases not in the data to improve the interpolation and expand the range outside the experimental reach.



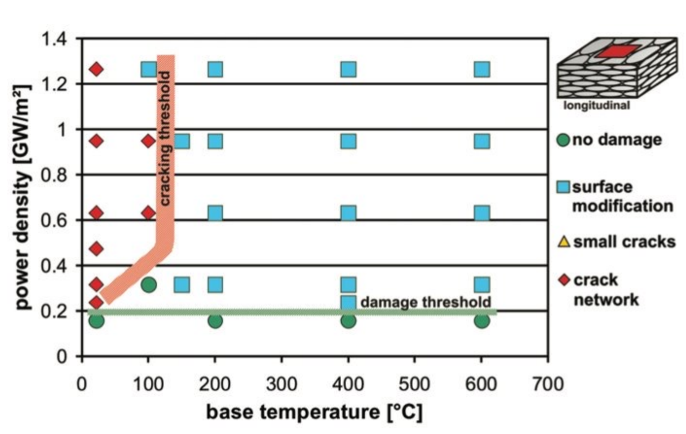
High Fidelity CabannaPD Simulation of e-Beam Tungsten Damage

- Validation of CabannaPD with JUDITH-1 data is determining the model fidelity and resolution required.
- An anisotropic stress model was needed to capture the observed difference with grain structure.
- CabannaPD predicts macroscopic damage but does produce cracking networks at this resolution.

100 cycles, pure W recrystallized test case with CabanaPD



JUDITH-1 e-Beam experimental data
Pure W longitudinal



MPEX-AI Damage Assessment Digital Twin

- The concept for the Damage Assessment Digital Twin is to train a machine learning surrogate map between the pre-exposure material metrics and the post-exposure damage assessment metrics. This surrogate is used by an AI-optimization agent to find the best performing material metrics for a weighted set of requirements. These materials are generatively interpolated from the training data and may represent new materials to test in MEPX or to simulate.
- The training set is composed of MPEX experimental damage assessments and simulated damage assessments using validated models. Simulations guided by the AI-agent will be performed automatically to refine the search for optimum materials. Simulations of materials with exposure outside the limits of MPEX will be included in the training to find bounds on material lifetimes.
- Data from the Fusions AI Digital Convergence Platform on other types of material damage (neutron, activation, radioactive decay ..) will be used to augment the AI Damage Assessment Digital Twin search for optimum fusion materials.
- A suite of computational models to simulate all types of plasma material interactions produced by MPEX will be developed by the MPEX Science Collaboration and added to the Damage Assessment Digital Twin.

Summary

The MPEX-AI Digital Twins project is a new paradigm for accelerating the development of fusion using AI-advantage. The project is building surrogate models and digital twins for operational control and damage assessment during the preparation for operations phase of MPEX. These resources will help resolve operational issues for MPEX, enable faster progression to full power, plasma fluence and pulse length targets, so that discovery science can commence. The scientific software stack required to analyze data, simulate results and conduct AI-guided searches for better performing plasma facing materials will be ready at the start of MPEX operations. The data, simulations, surrogates and digital twins will all be connected to each other and to the American Science Cloud using the Galaxy Framework [6]. AI-Automation of data analysis and AI-guided simulations will be orchestrated through Galaxy connections to high performance computing resources and the Fusion AI Digital Convergence Platform of the Genesis Mission. In a proposed second phase of the project, a digital twin of the engineering systems of MPEX using Omniverse will be built to enable a whole device aware AI-control system. A Large Language Model AI-instructor to guide research staff on the use of the Galaxy framework connected resources. Ion implantation from the plasma interactions will be added to material damage assessment modeling. Impurity ion generation at the target and tracking through the plasma will also be added. The kinetic effects on the parallel energy transport due to mirror physics and the generation of non-Maxwellian distributions by the ICH and ECH/EBW will be added to the high-fidelity plasma physics modeling capability.

Acknowledgements/References

Acknowledgement:

This work was supported by the U.S. Department of Energy under DE-AC05-00OR22725 and DE-AC52-07NA27344

References:

[1] J. Rapp et al. “Final Design of the Material Plasma Exposure eXperiment”. In: Fusion Science and Technology 79.8 (2023), pp. 1113–1123. doi: 10.1080/15361055.2023.2168443.

[2] A. Kumar and J. F. Caneses. “Kinetic simulations of collision-less plasmas in open magnetic geometries”. In: Plasma Physics and Controlled Fusion 64.3 (Jan. 2022), p. 035012. doi:https://doi.org/10.1088/1361-6587/ac3dee.

[3] Sam Reeve et al. CabanaPD. Version 0.4.0. Aug. 2025. url: https://doi.org/10.5281/zenodo.16997636

[4] Gary Staebler et al. MPEX AI Digital Twins. 2026. url: https://arxiv.org/abs/2605.09205.

[5] Gary Staebler et al. MPEX AI Digital Twins Milestone Report. 2026. url: https://arxiv.org/abs/2605.12116

[6] The Galaxy Community. “The Galaxy platform for accessible, reproducible, and collaborative data analyses: 2024 update”. In: Nucleic Acids Research 52.W1 (July 2024), W83–W94. doi:10.1093/nar/gkae410.

Oak Ridge National Laboratory

U.S. DEPARTMENT OF ENERGY