Automated ICRF heating surrogate modeling via machine learning

Alvaro Sanchez-Villar (asvillar@pppl.gov)
Princeton Plasma Physics Laboratory
in collaboration with
N. Bertelli, S. Shiraiwa (PU PPPL), J. Miller (UCLA), Z. Bai, T. Perciano (LBNL), J. Hillairet (CEA-IRFM),
E. W. Bethel (SFSU), G. M. Wallace and J. C. Wright (MIT PSFC)

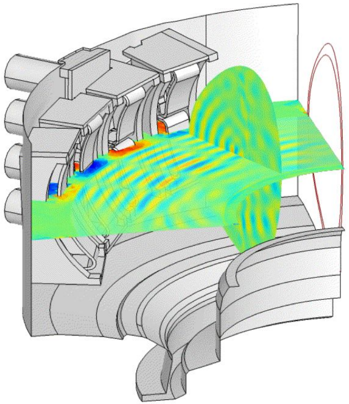
Hohenkammer, Germany, May 22, 2025

25th Topical Conference in Radio-Frequency Power in Plasmas

Full-wave codes unfeasible for applications as real-time control

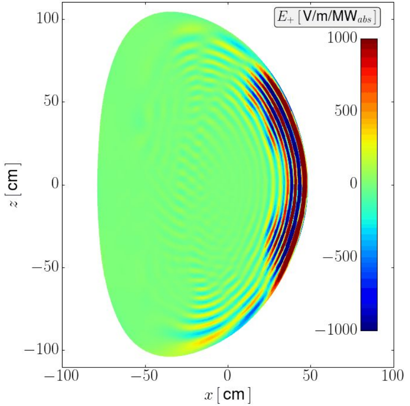
- Ion cyclotron range of frequencies (ICRF) actuator modeling
  - Antenna impact on plasma response
- Full-wave codes codes:
  - **computationally expensive**
  - even using HPC
- Unfeasible simulation times for:
  - **Specific scenario optimization**
  - **Inter-shot predictive modeling**
  - **Real-time control**

PETRA-M



S. Shiraiwa et al (2017) EPJ Web Conf. ***157*** *03048*

TORIC

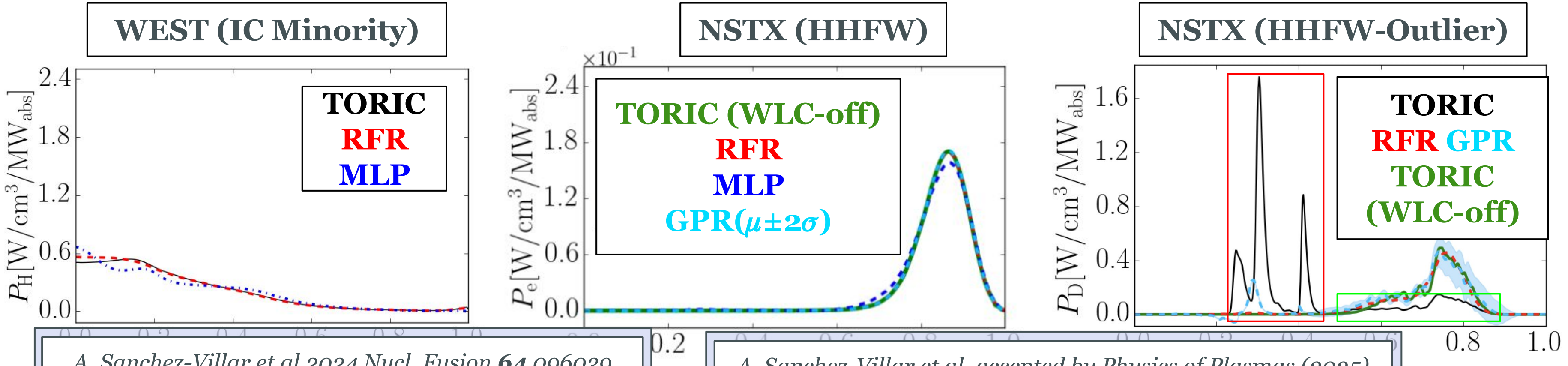


M. Brambilla (1999) PPCF ***41****, 1*

- Machine Learning (ML) models ⇨ Simplify and **accelerate computation**
- **Is there an effective ML surrogate design for the ICRF heating problem?**

Full-wave + ML enables robust real-time ICRF heating models

- **Real-time capable** ➪ Inference time: O(μs-ms)
- **High-fidelity** ➪ Regression accuracy: NSTX $R^2 > 0.9$ | WEST $R^2 > 0.7$
- **Uncertainty quantification** ➪ GPR (mean & standard deviation)
- **Robust:** can overcome challenging scenarios (incl. faulty-data/outliers)
- **Automated:** streamlined implementation and optimization



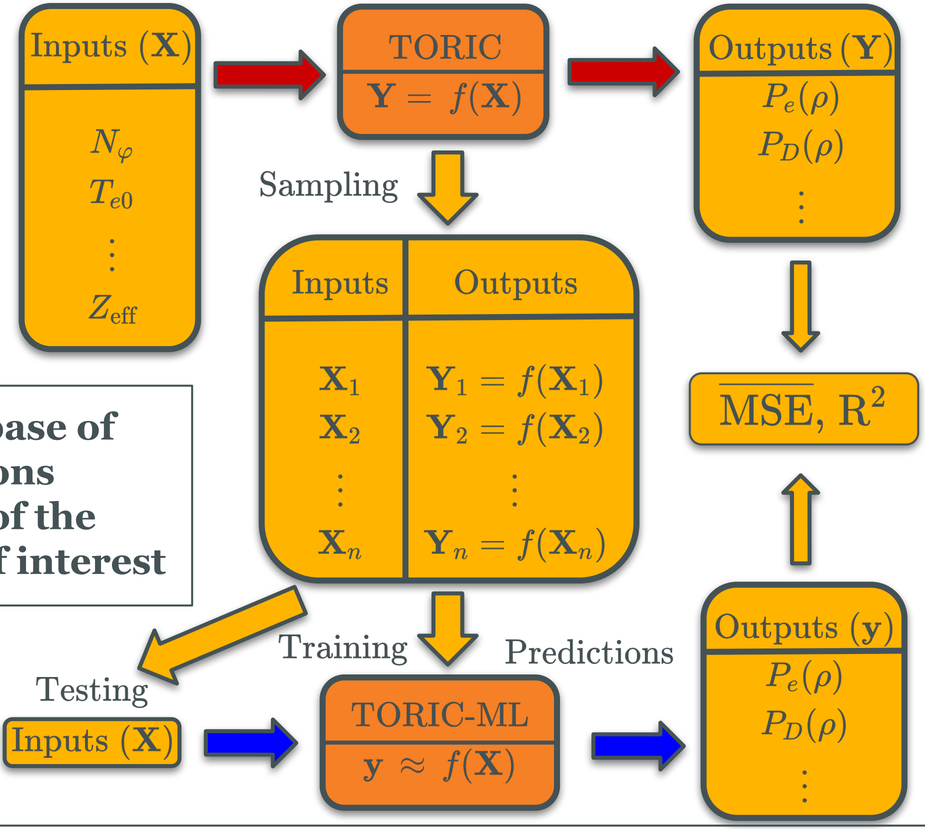
*A. Sanchez-Villar et al 2024 Nucl. Fusion **64** 096039*

A. Sanchez-Villar et al. accepted by Physics of Plasmas (2025)

Methodology

TORIC ICRF SPECTRUM SOLVER: O(min)

M. Brambilla (1999) PPCF ***41***
M. Brambilla (2002) PPCF ***44***



"Ground truths" are TORIC electron and ion power absorption 1D profiles

Generate a database of TORIC solutions representative of the parametric space of interest

Regression accuracy measured by:
1. Mean squared error (MSE)
2. Coefficient of determination(R^2)

$$\mathrm{MSE} = \frac{1}{N_y}\sum_{j=1}^{N_y}\frac{1}{N}\sum_{i=1}^{N}(y_{ij}-\hat{y}_{ij})^2\,,$$

$$\mathrm{R}^2 = \frac{1}{N_y}\sum_{j=1}^{N_y}\left(1-\frac{\sum_{i=1}^{N}(y_{ij}-\hat{y}_{ij})^2}{\sum_{i=1}^{N}(y_{ij}-\bar{y}_j)^2}\right)$$

SURROGATE MODEL FOR THE FORWARD PROBLEM: O(μs)

Two databases for flat-top operation of NSTX and WEST

- Heating schemes:
  - HHFW: $\omega > \Omega_{ci}$
  - IC minority: $\omega \sim \Omega_{ci}$
- Plasma species: D (D-H).
- Equilibriums are assumed to be fixed to:

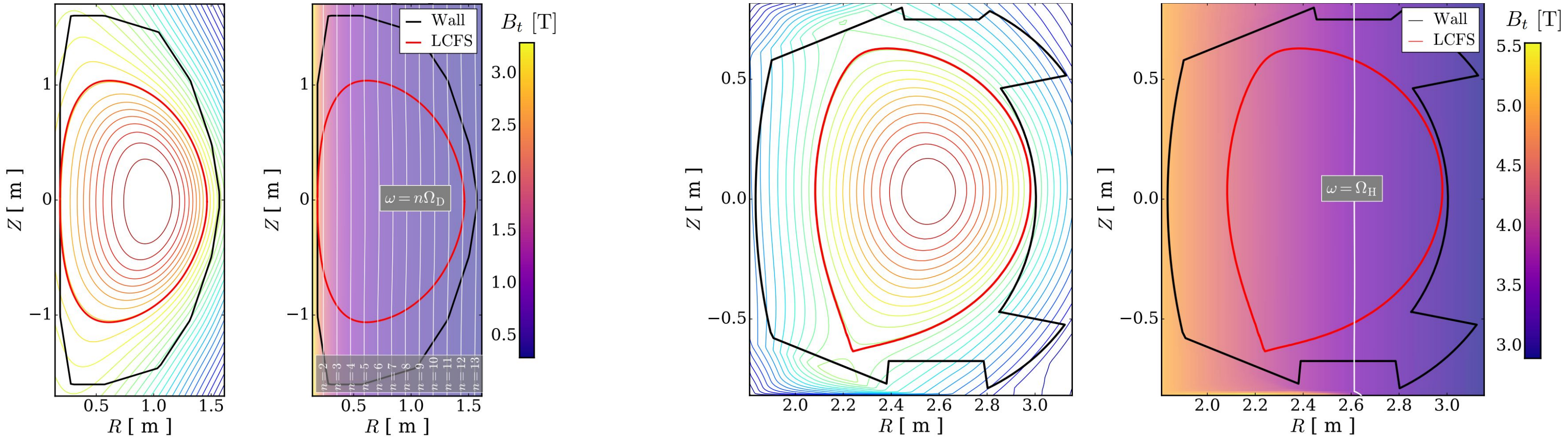
- **Flat-top** scenario plasma properties (e.g. temperature, density, etc) as :

$$T_e = (T_{e0} - T_{e1})(1 - \rho^{\alpha})^{\beta} + T_{e1}$$

  - 0/1 -> core/edge
  - α and β : profile shape exponents

*G. Taylor et al. (2012) PoP **19***
*J. Bucalossi et al. (2022) NF **62***

NSTX - Shot 138506 **WEST - Shot 56898**



Database generated to cover regimes measured experimentally

- Input parametric spaces investigated:

G. Taylor et al. (2012) PoP **19**

J. Bucalossi et al. (2022) NF **62**
V. Maquet et al. (2023) arXiv

NSTX

Inputs	Value
$N_\varphi[-]$	$[5-21]$
$n_{e0}\,[\mathrm{cm}^{-3}]$	$[5-20\times10^{13}]$
$T_{e0}[\mathrm{keV}]$	$[1-5]$
$\alpha[-]$	$[2-10]$

WEST

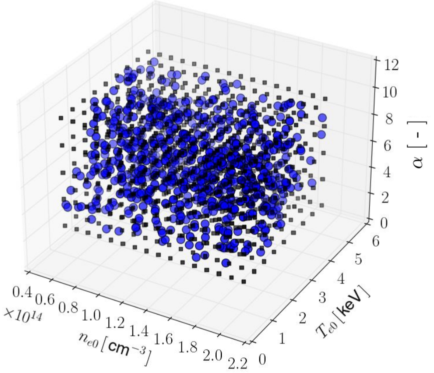
Inputs	Value
$N_\varphi[-]$	$[0-60]$
$n_{e0}\,[\mathrm{cm}^{-3}]$	$[4-8\times10^{13}]$
$n_{e1}\,[\mathrm{cm}^{-3}]$	$[1-3\times10^{12}]$
$T_{e0}[\mathrm{keV}]$	$[1-1.5]$
$T_{i0}[\mathrm{keV}]$	$[1-1.5]$
$\alpha[-]$	$[2-10]$
$X_{\mathrm{H}}[-]$	$[0.01-0.1]$

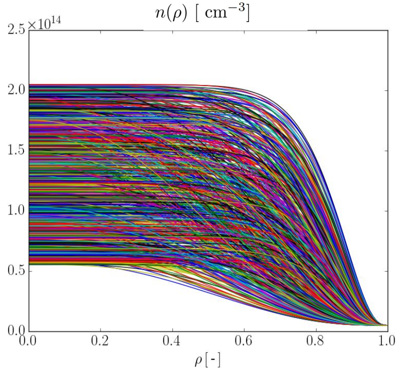
Increased complexity in the WEST database

M. W. Gardner (1999) Atmospheric Env.

- Data sampling (~10^4 cases each):
  - Latin Hypercube Sampling (**LHS**) method.

$$T_e = (T_{e0}-T_{e1})(1-\rho^\alpha)^\beta + T_{e1}$$

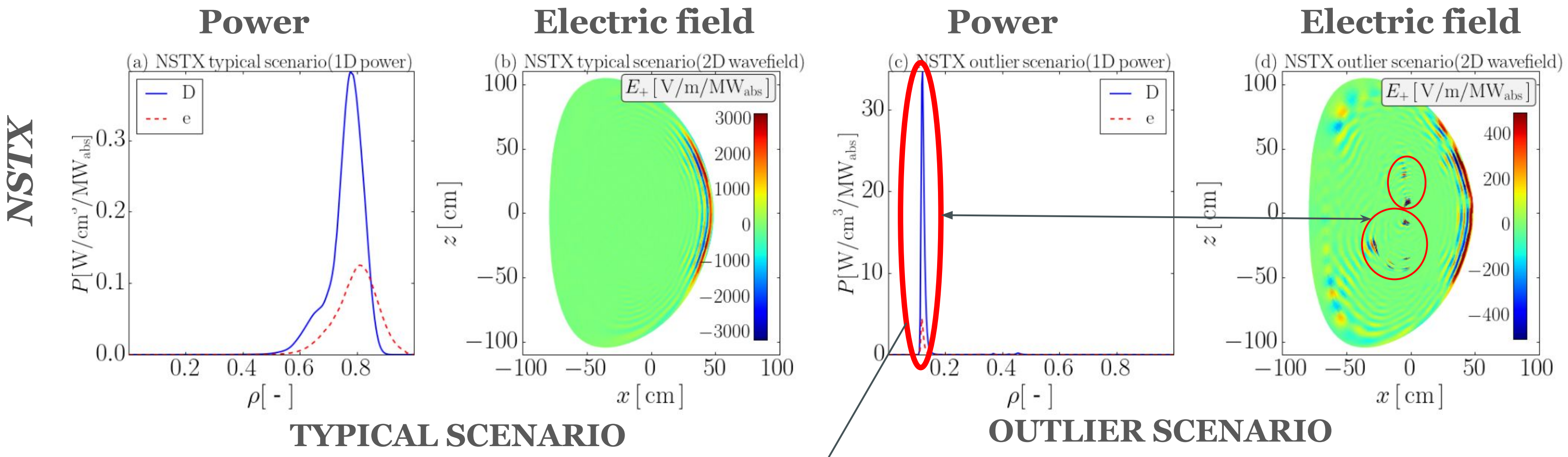




LHS provides a pseudorandom distribution across parameter space eliminating sampling statistical bias while ensuring high variance

Data is standardized, then analyzed, and curated

- **Standardization** of data using training data, and **principal component analysis** on WEST outputs → dimensionality reduction, improved profile inference time and accuracy.
- Exploratory analysis resulted in outlier identification in the NSTX database:



22% outliers understood to be numerical.

ML-algorithms selected to optimize performance

- ML-algorithms selected:
  - Random forest regressor (**RFR**).
  - Multi-layer perceptron regressor (**MLP**).

G. Wallace et al JPP 88.4 (2022): 895880401.
Experience in the group on ML for GENRAY/CQL3D

L. Breiman (2001) Machine Learning **45**

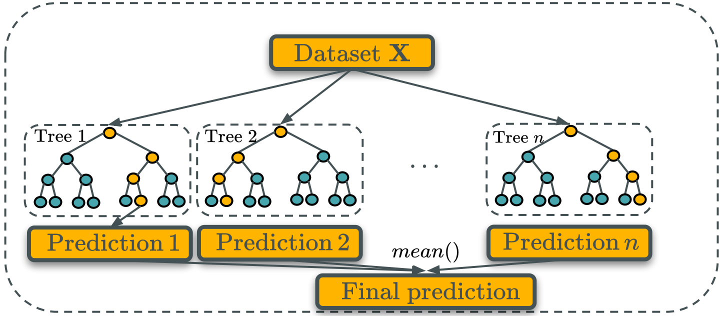
M. Stein (1987) Technometrics **29**

- Simplified & robust implementation: **scikit-learn**

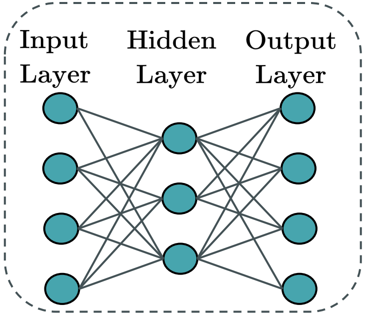
- Hyperparameters tuning:
  - Gridsearch.
  - Methodical scanning.

- 5-fold cross-validation.

Random Forest Regressors



Multilayer Perceptron



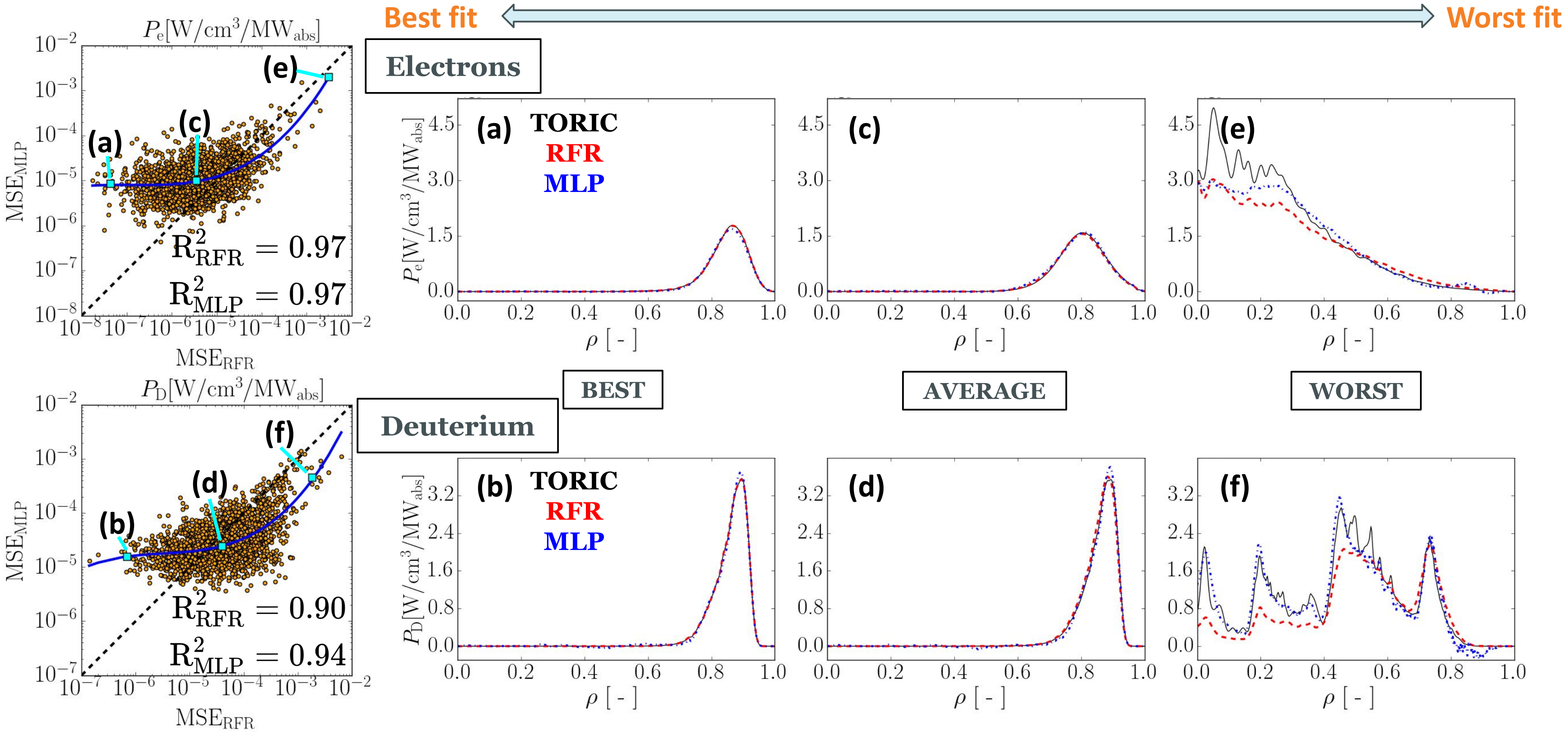
Summary of surrogates' performance metrics (NSTX)

- HHFW scenario **regression accuracy** increases from **R^2 = 0.51-0.75** to **R^2 = 0.94-0.97**.
- **Training times** in the order of a minute.
- Average profile **inference times** $\mathcal{O}(\mu s)$ compared to $\mathcal{O}(min)$ featured by TORIC.

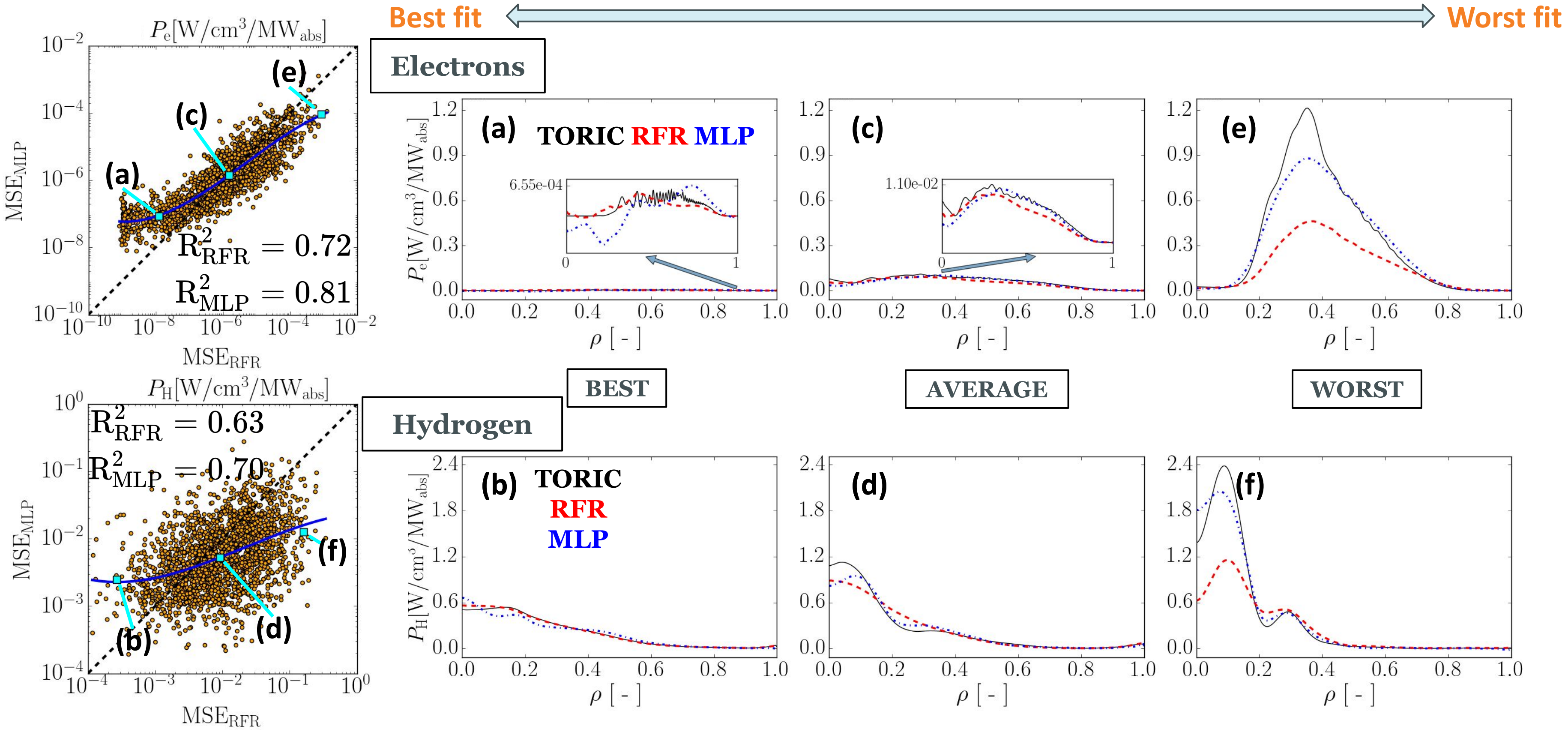
Target	Dataset	Method	R^2_{tr}	$\overline{MSE}_{tr}$	$\bar{t}_{tr}$ [s]	R^2	$\overline{MSE}$	$\bar{t}_I$ [μs]
P_e	NSTX (Original)	RFR	0.96	1.4×10^{-3}	40	0.62	2.6×10^{-3}	52
P_e	NSTX (Filtered)	RFR	0.99	3.3×10^{-6}	29	0.97	1.8×10^{-5}	49
P_e	NSTX (Original)	MLP	0.75	8.2×10^{-3}	106	0.75	2.1×10^{-3}	1
P_e	NSTX (Filtered)	MLP	0.97	2.1×10^{-5}	23	0.97	2.1×10^{-5}	2
P_D	NSTX (Original)	RFR	0.94	6.9×10^{-3}	42	0.51	6.1×10^{-2}	51
P_D	NSTX (Filtered)	RFR	0.99	1.5×10^{-5}	29	0.90	1.1×10^{-4}	54
P_D	NSTX (Original)	MLP	0.54	5.6×10^{-2}	84	0.51	7.1×10^{-2}	3
P_D	NSTX (Filtered)	MLP	0.96	4.7×10^{-5}	48	0.94	5.2×10^{-5}	4

- *Original: training and testing using NSTX database with outliers.*
- *Filtered: training and testing using NSTX database without outliers.*

NSTX surrogates predict HHFW heating

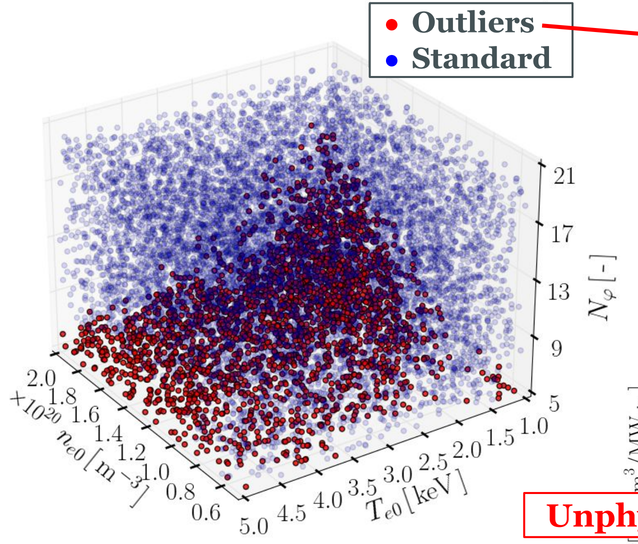


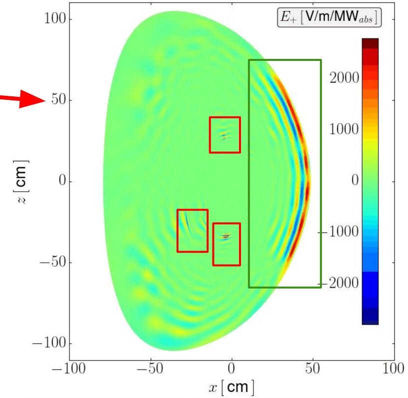
WEST surrogates predict IC minority heating

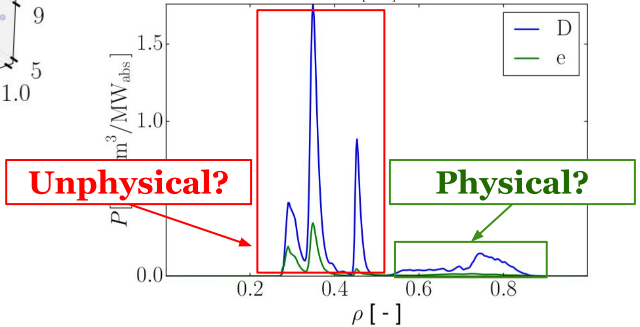


Outliers identified: how to solve heating in outlier scenarios?

Outliers appearing in specific regions of HHFW parametric regime → **Unphysical wavefields and power deposition profiles** → **Revisit the HHFW numerical and physical model implemented in TORIC**







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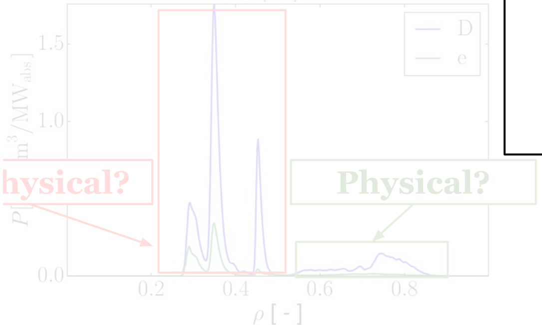


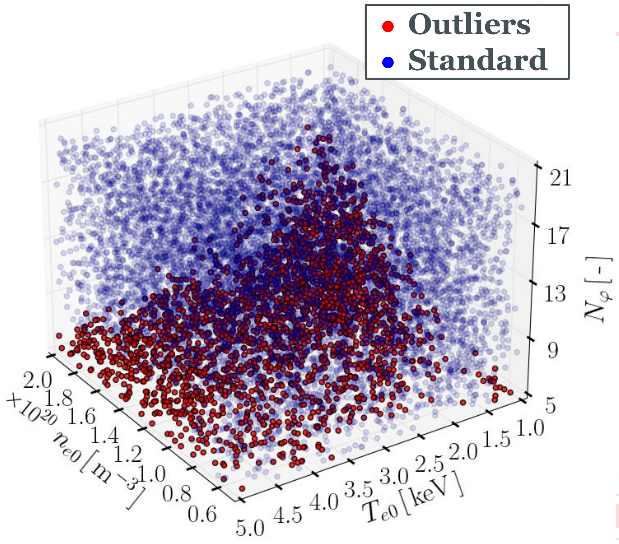
In the meantime, can we use ML to provide an alternative solution to overcome this issue?

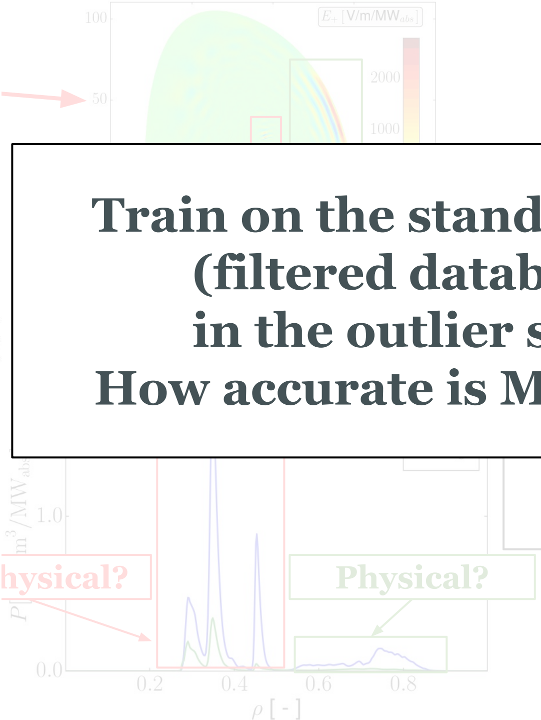
Proposed approach: ML extrapolation

Outliers appearing in specific regions of HHFW parametric regime

Unphysical wavefields and power deposition profiles

Revisit the HHFW numerical and physical model implemented in TORIC





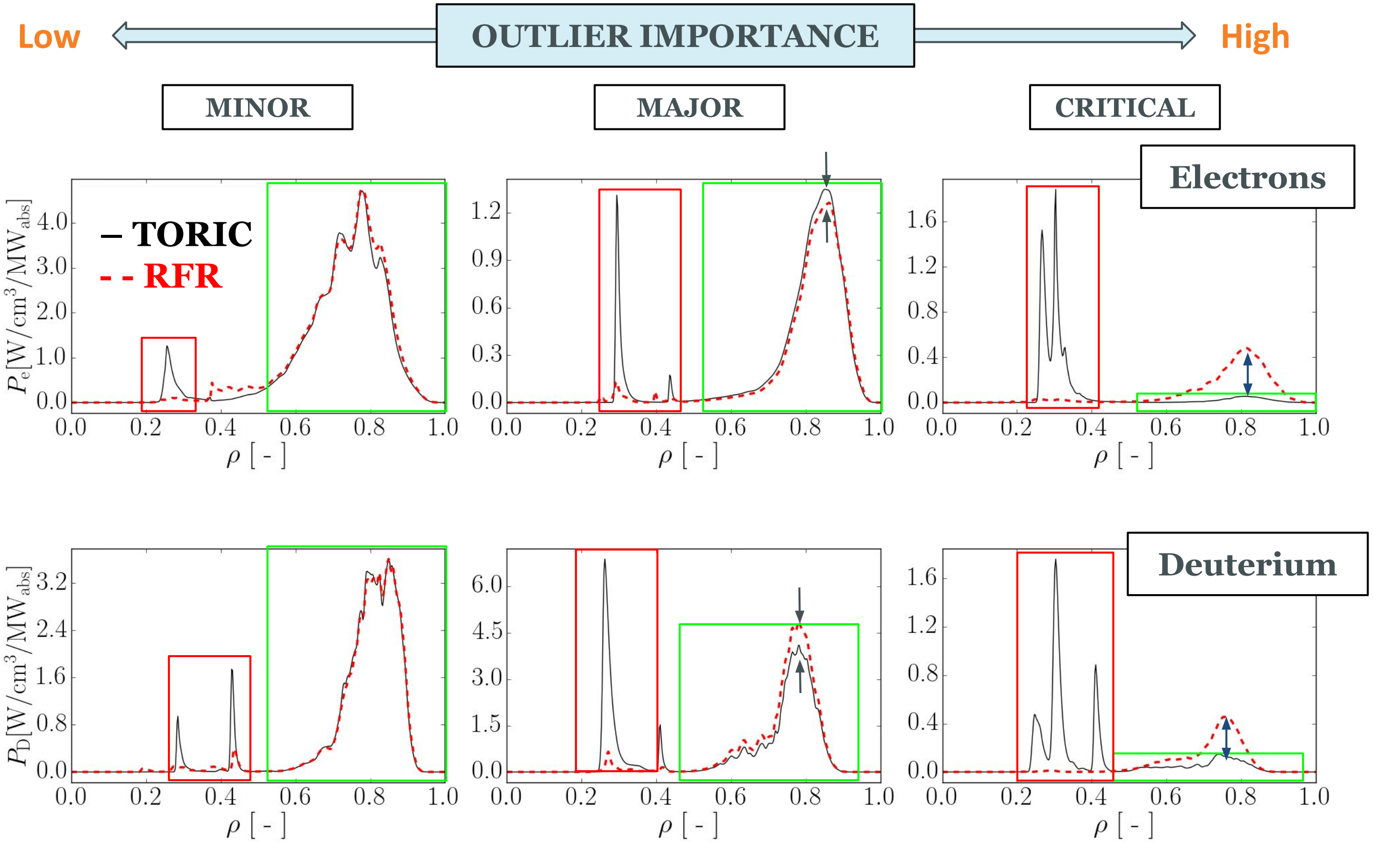
Train on the standard scenarios (●) (filtered database) and test in the outlier scenarios (●). How accurate is ML extrapolation?

to overcome this issue?

Proposed using RFR surrogates to overcome HHFW outliers

Extrapolated HHFW heating predictions:

- **Outlier free signals.**
- **Preserve key HHFW heating physics.**
- Predict **higher heating** than the reference model in major & critical outliers.



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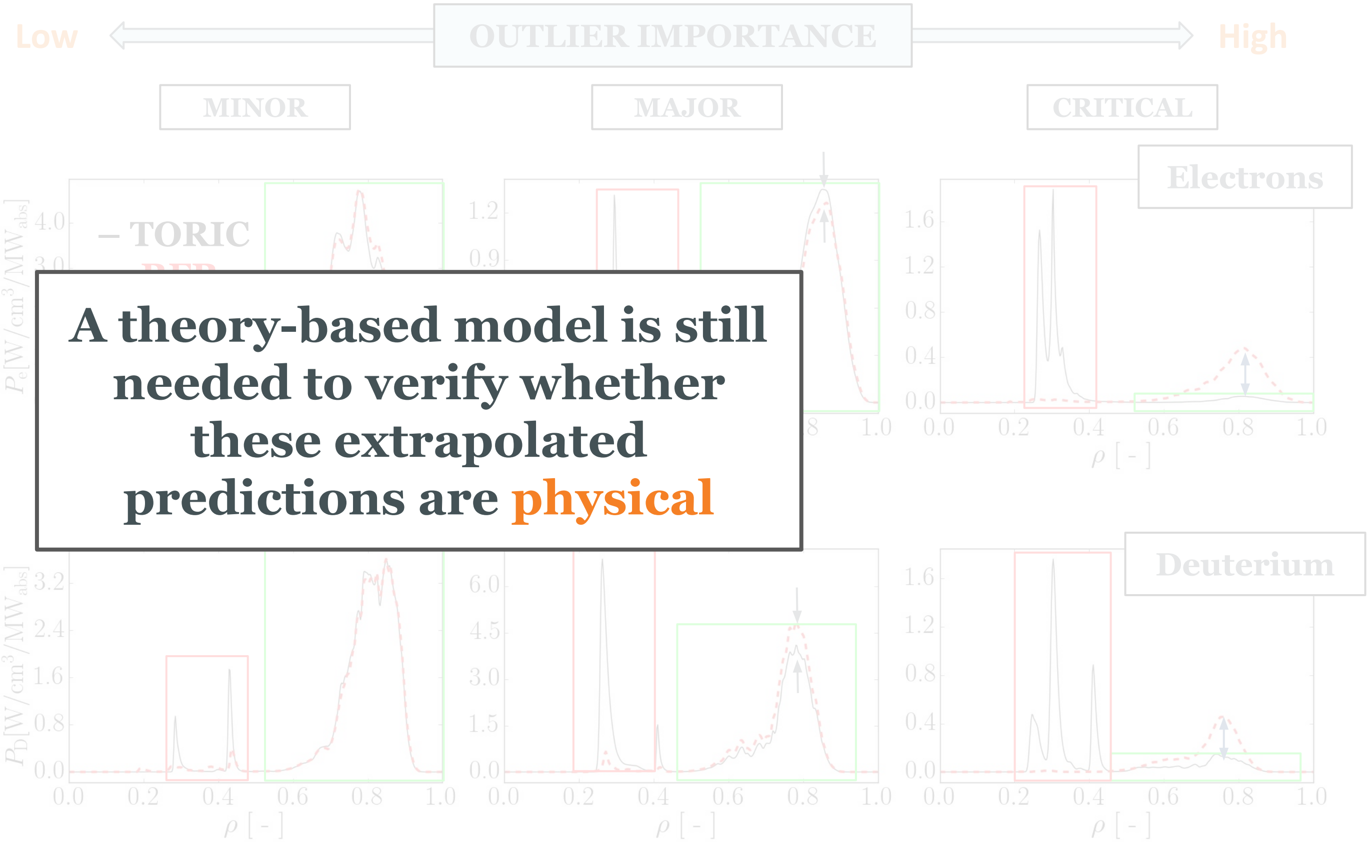
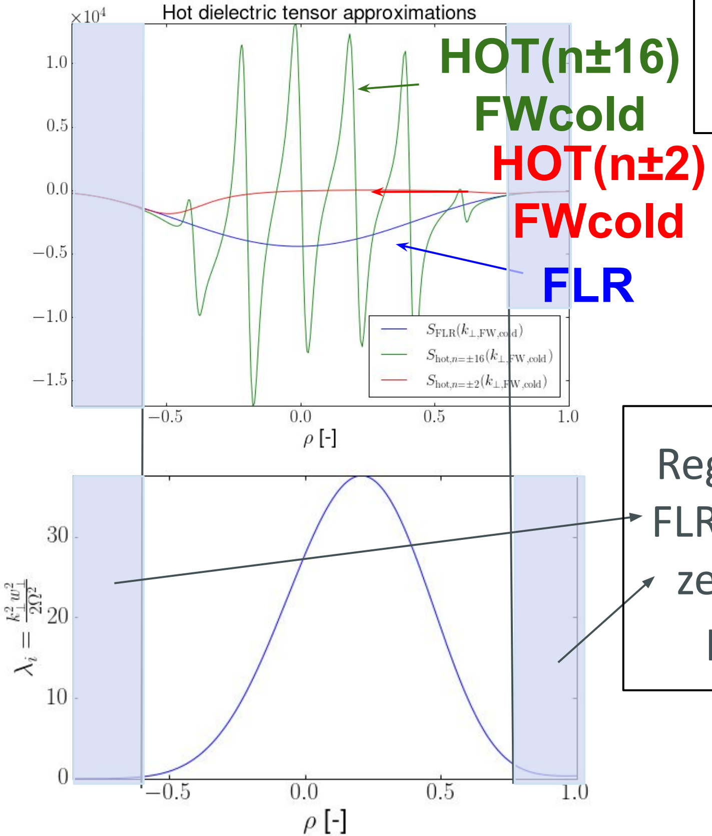


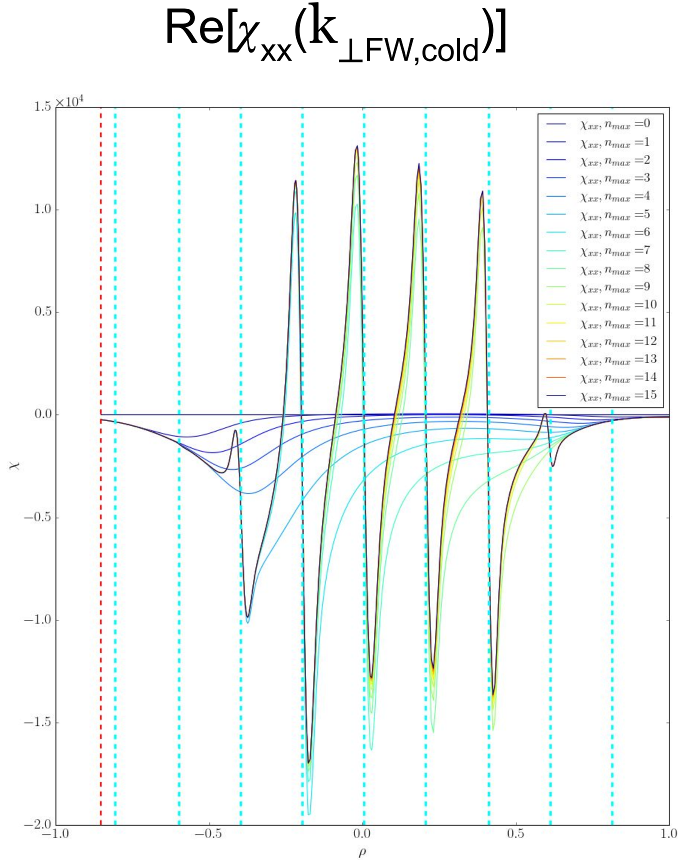
A theory-based model is still needed to verify whether these extrapolated predictions are physical

FLR effects in local hot dielectric tensor shown as superimposed modulation over the FLR approx. coefficient



Dielectric properties in the midplane

Regions of validity of FLR approximation of zero Larmor radius plasma current.

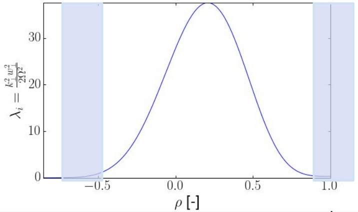


Verified outliers feature such sign reversal in WLC FLR correction

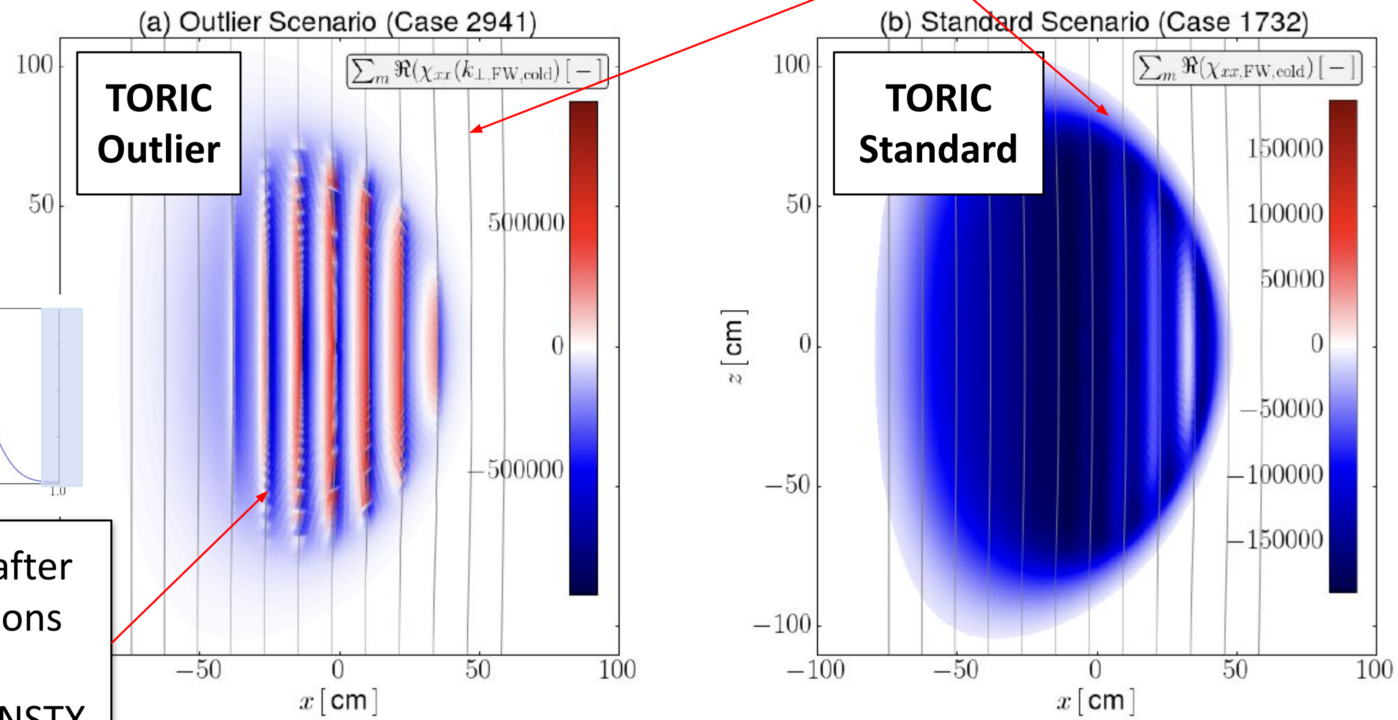
$$\sigma^* = \delta\sigma\left(\chi_{xx}(k_{\perp,\mathrm{FW,cold}}), d\psi, m\right) \propto -|m|\chi_{xx}(k_{\perp,\mathrm{FW,cold}})$$

Wavelength Control Algorithm (WLC)

Forced IBW evanescence in HHFW



Sign reversal after high $k_\perp \rho_i$ regions harmonic resonances in NSTX



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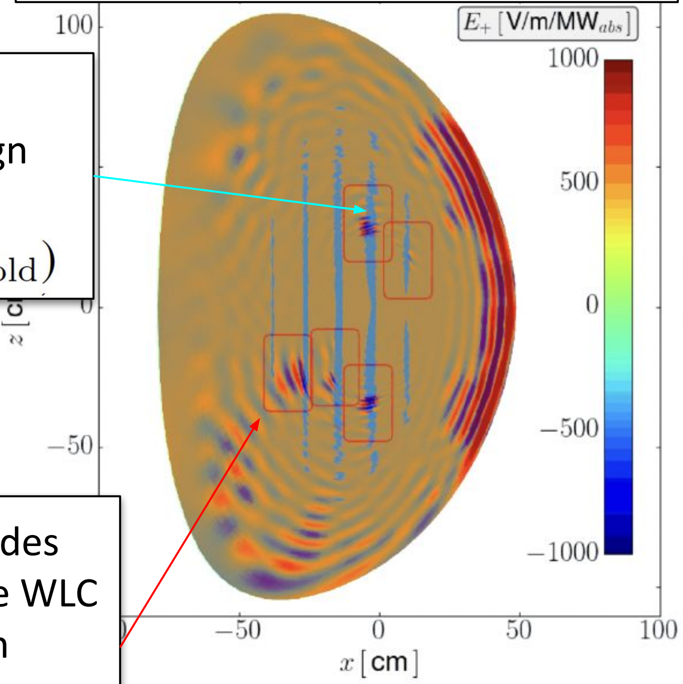
Numerical artifact related to the treatment of IBW in TORIC-HHFW

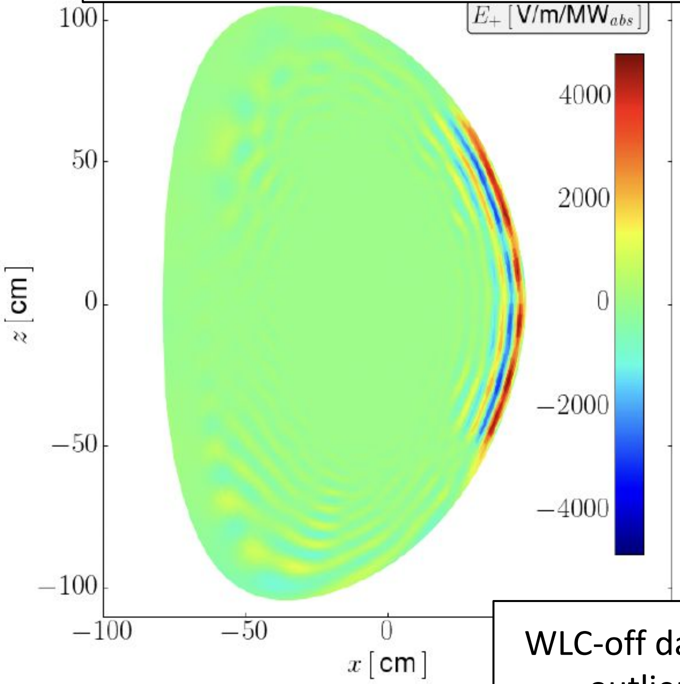
Outlier - WLC Active (Case 2941)



Regions of sign reversal in $\chi_{xx}(k_{\perp,\mathrm{FW,cold}})$

IBW-like modes induced by the WLC algorithm

Outlier - WLC Inactive (Case 2941)



WLC-off database is outlier-free
no IBW-like modes

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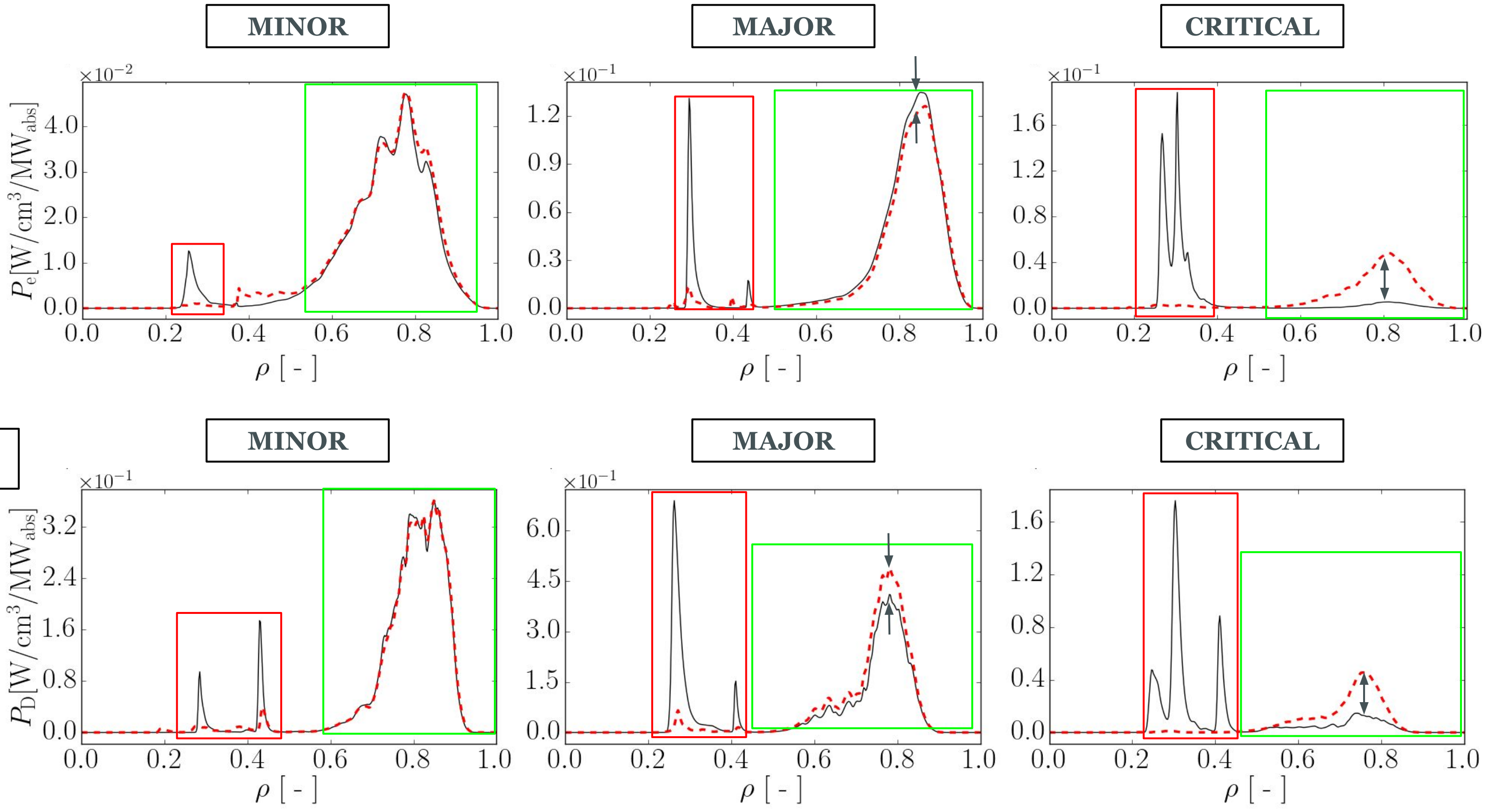
Proposed using RFR surrogates to overcome HHFW outliers

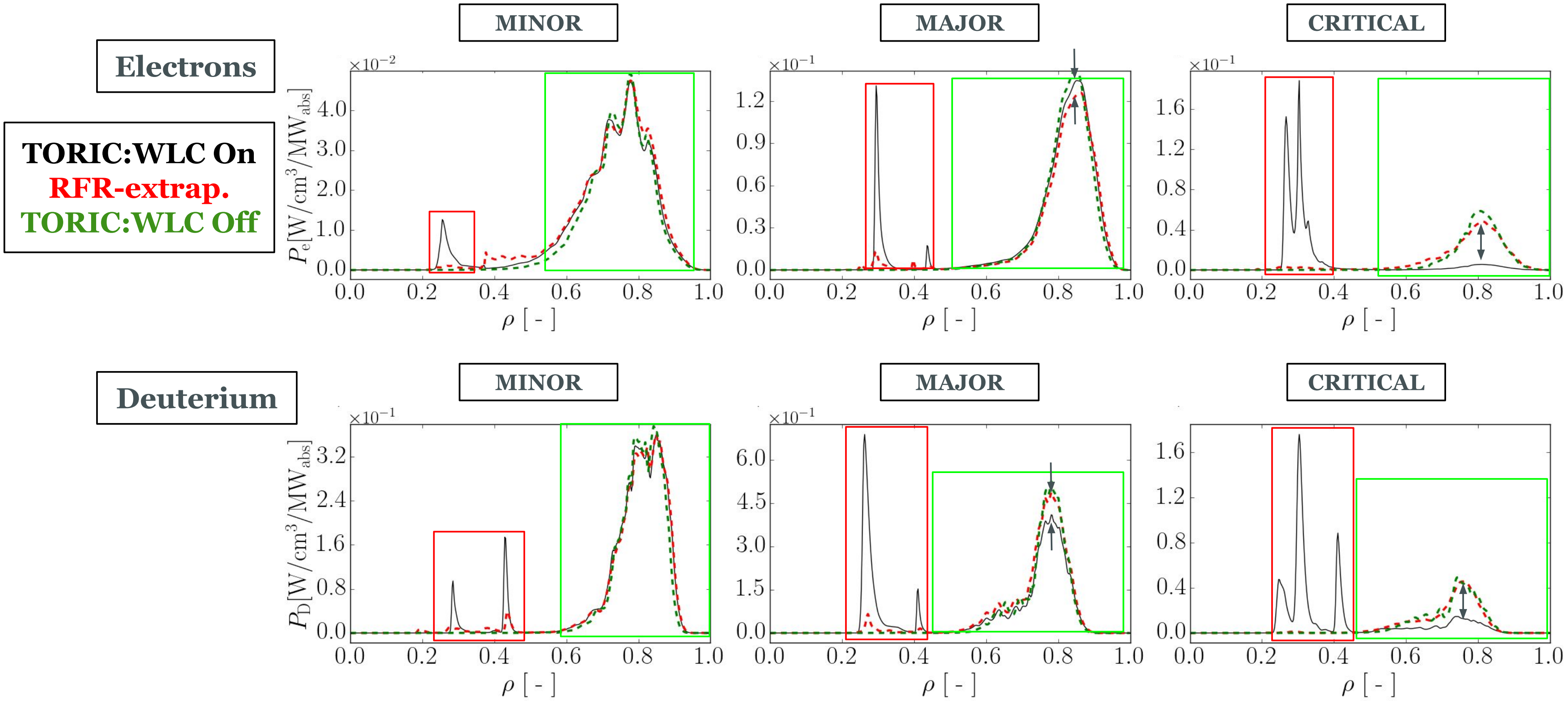
Electrons

TORIC:WLC On
RFR-extrap.

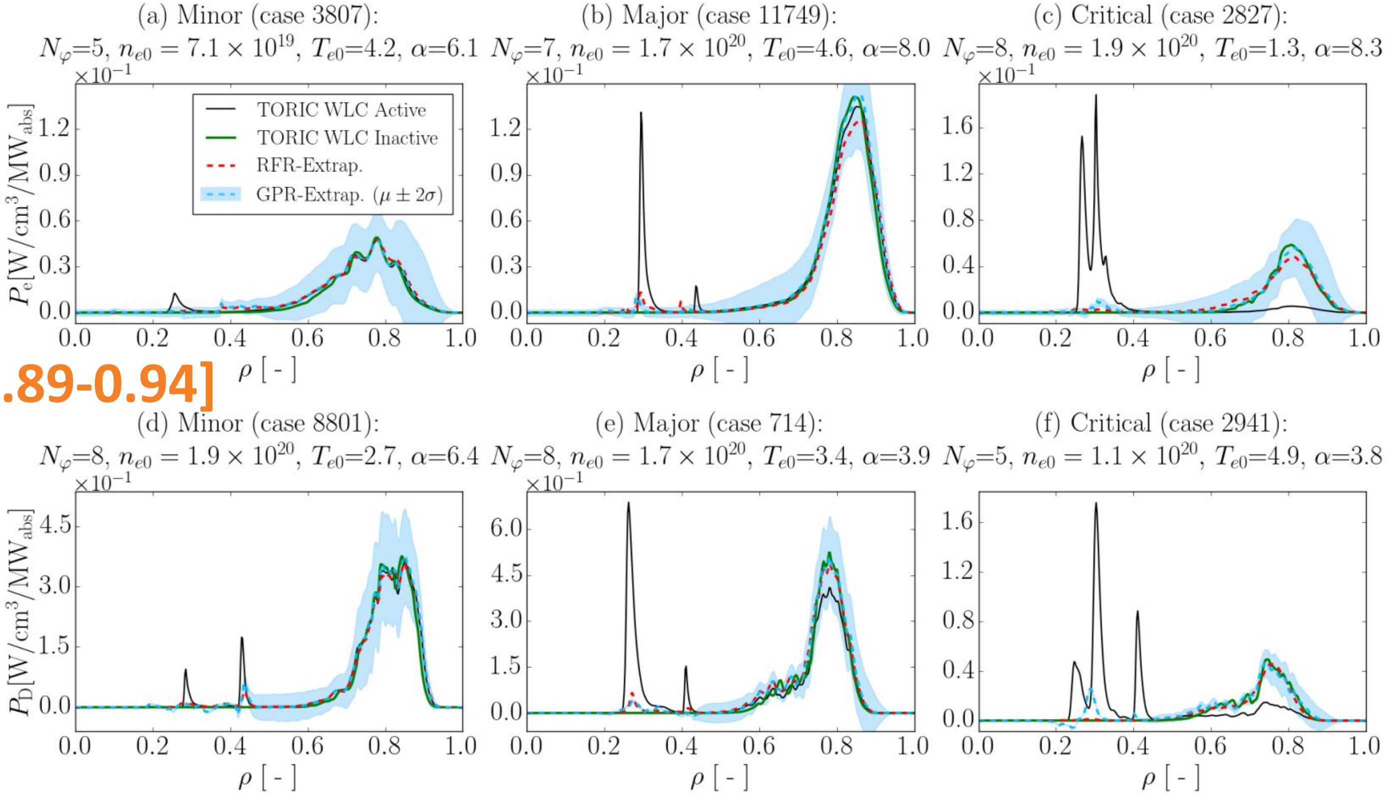
Deuterium



Surrogates closely predict HHFW heating in outlier regime



GPR models can also extend to the HHFW outlier regime



GPR R^2=[0.89-0.94]

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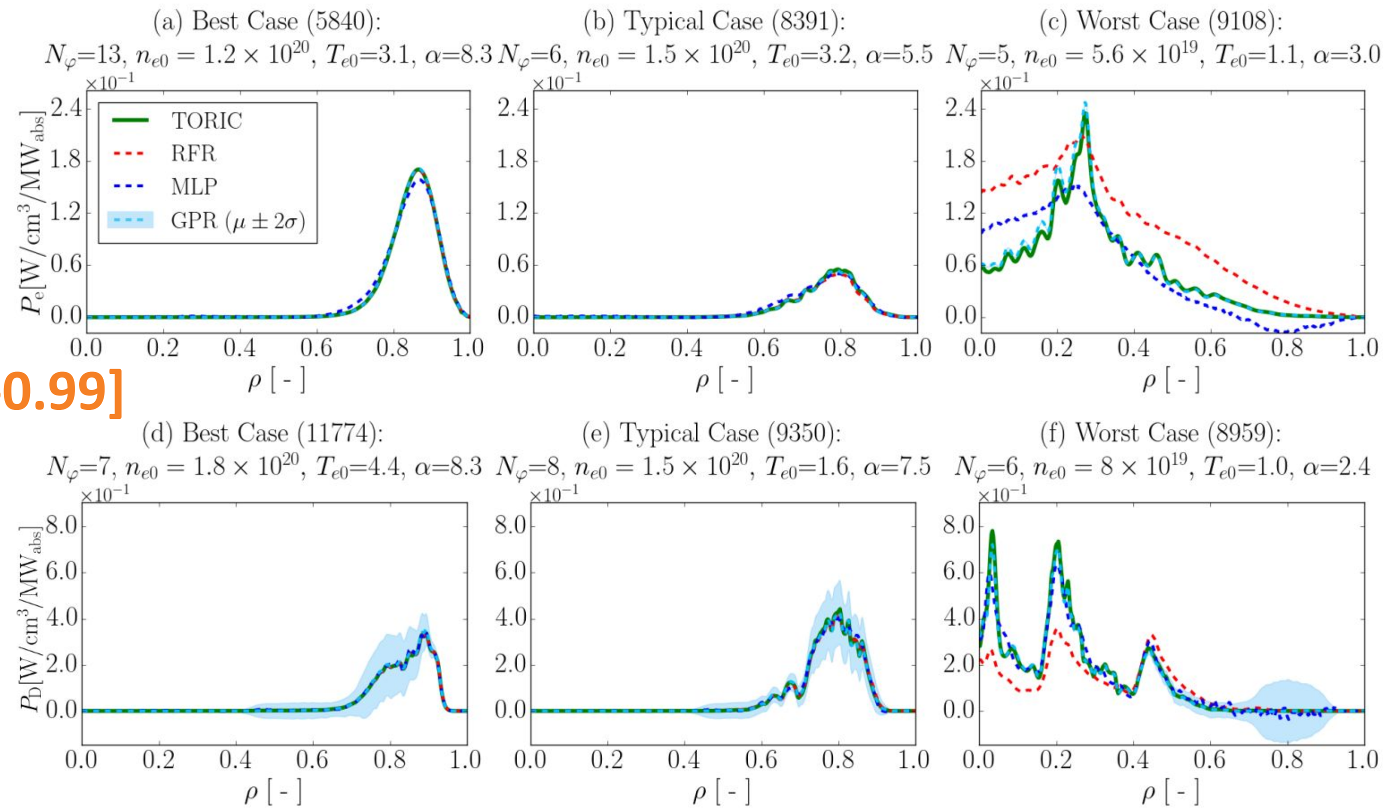
Final models for HHFW at NSTX (including GPR)



R^2= [0.93-0.99]

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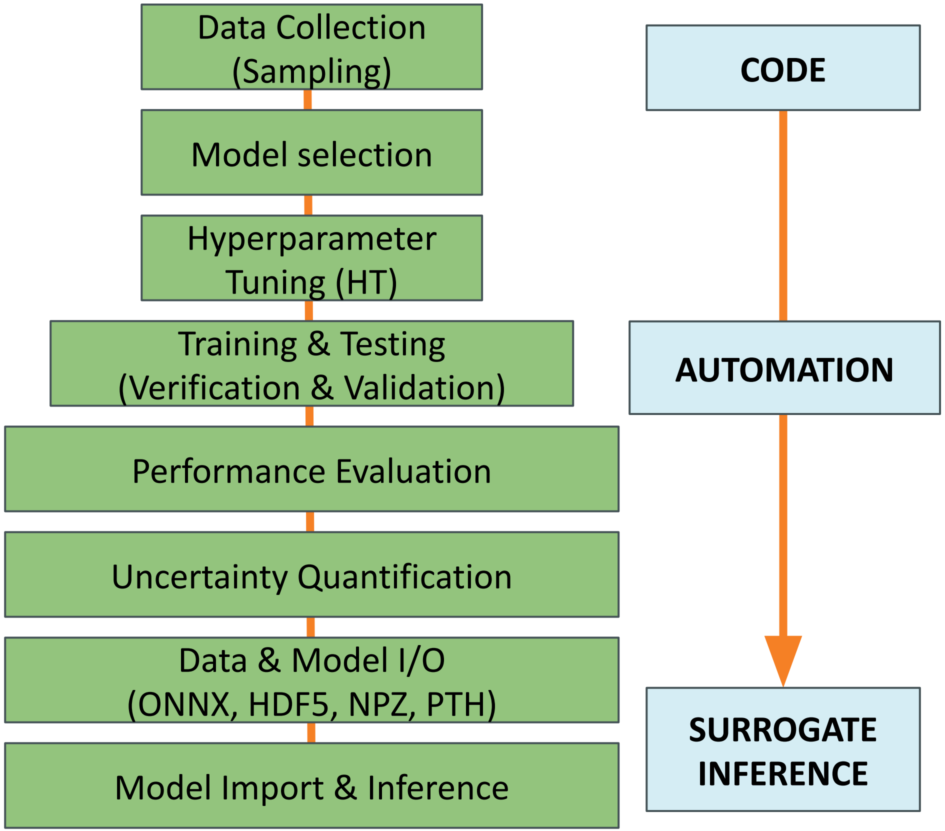
Automated Surrogate Modeling Generator Suite

- Streamlining end-to-end surrogate implementation
- Improved methodologies via AI/ML OS-software including:

PyTorch TensorFlow GPflow scikit learn

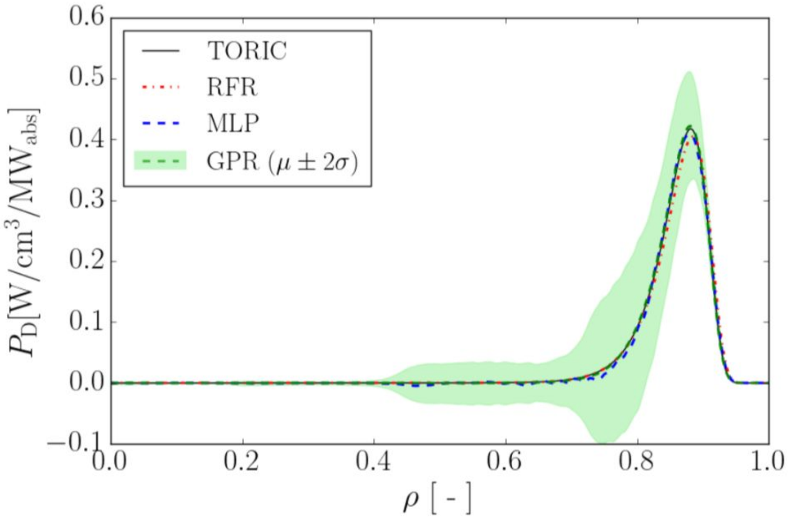
- Automation of hyperparameter optimization (e.g. Bayesian)

```
Best trial: FrozenTrial(number=29, state=1,
values=[3.0448241069484372e-05],
params={'num_layers': 3, 'hidden_size': 256,
'dropout_rate': 0.0, 'learning_rate':
0.0007918069636416778, 'batch_size': 30,
'activation_fn': 'LeakyReLU'},
```

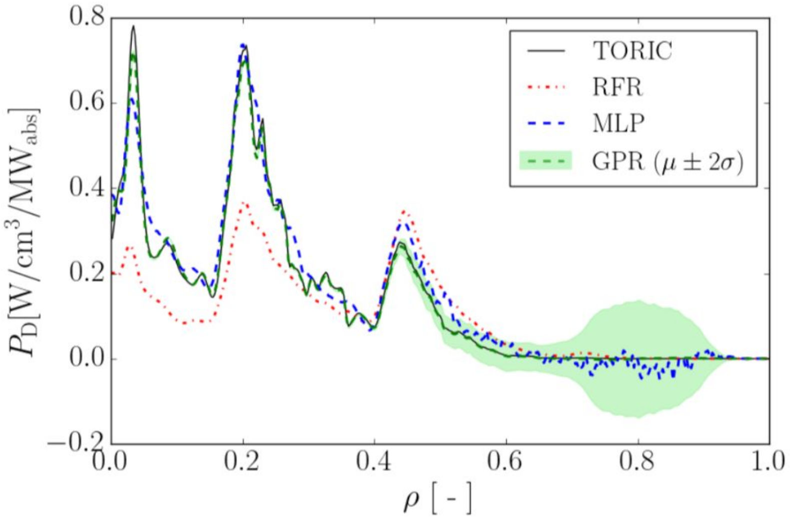


Automated surrogates for HHFW at NSTX

- Demonstrated the workflow to automatically optimize and train the surrogates



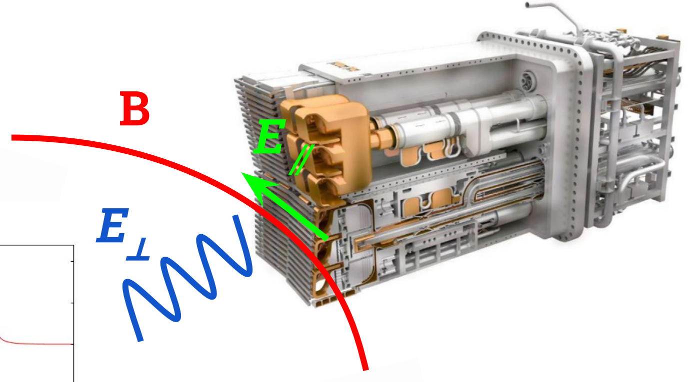
(a) Single-pass absorption

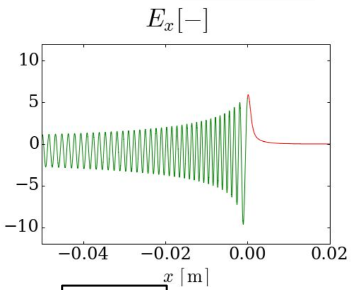


(b) Multi-pass absorption

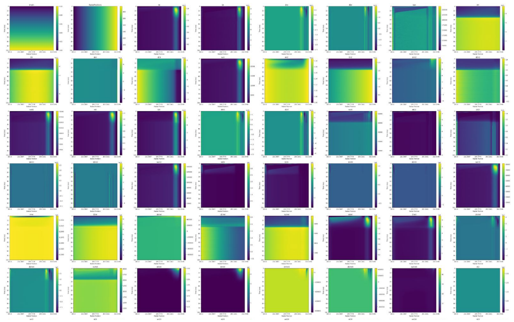
ML surrogates for Ion Cyclotron Wall Conditioning at ITER

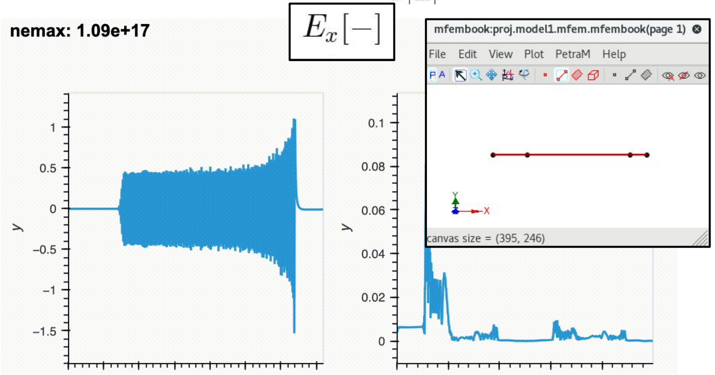
- Implementing ICWC surrogates for ITER
  - Work in progress
- PetraM 1D full-hot (R3 S. Shiraiwa)
  - LHR, SW/FW/**IBW**-> <u>high resolution</u>
  - Automated database generation
- TOMATOR1D refactoring (J. Miller-UCLA)
  - Refactoring and profiling
    1. Improvement of 40% in run-time

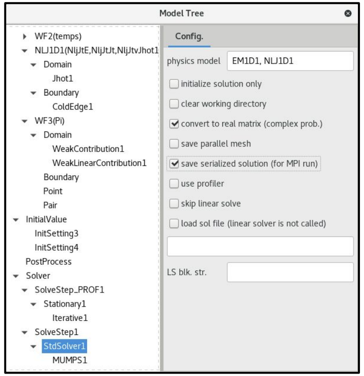




Visualization of TOMATOR1D runs





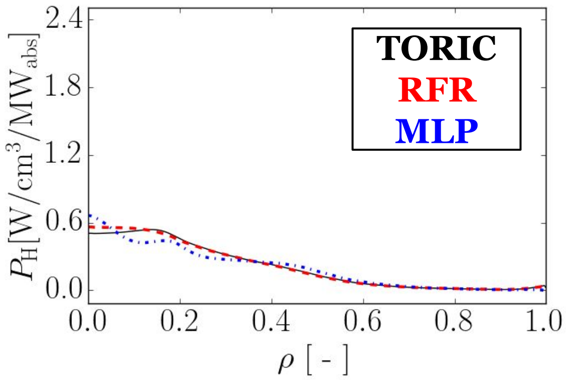


Summary

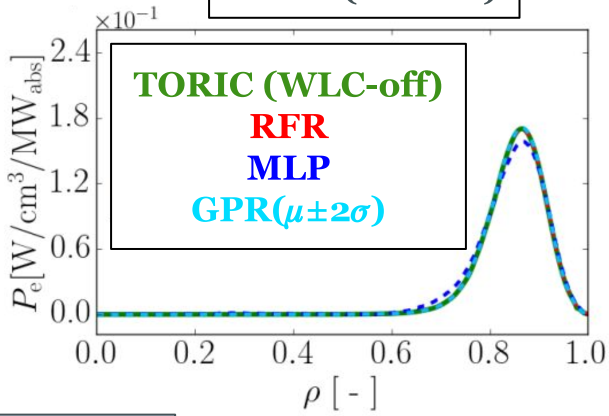
Full-wave + ML enables robust real-time ICRF heating models

- Real-time capable **O(µs-ms)** & High-fidelity **R^2> 0.9**
- Uncertainty quantification⇨ GPR (mean & standard deviation)
- Robust: can overcome challenging scenarios (incl. faulty-data/outliers)
- Automated: streamlined implementation and optimization

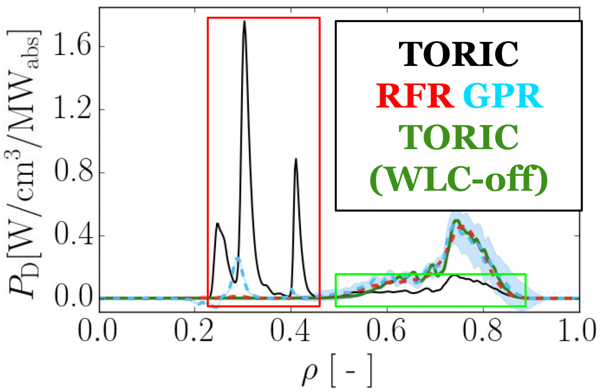
WEST (IC Minority)



NSTX (HHFW)



NSTX (HHFW-Outlier)



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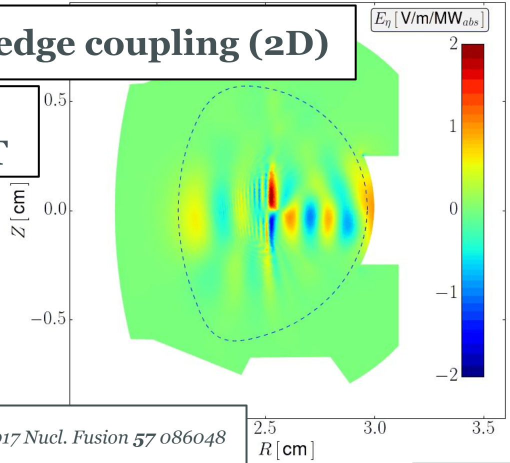
Future directions

- Our models are limited to specific scenarios; need to increase complexity further: impact of impurities, three-ion and other heating schemes, machines, equilibria, etc.
- Further modeling of HHFW scenarios relevant to NSTX/NSTX-U.
- Methodology being adapted to other Petra-M models (in particular ICWC):

Core-edge coupling (2D)

ICRF WEST

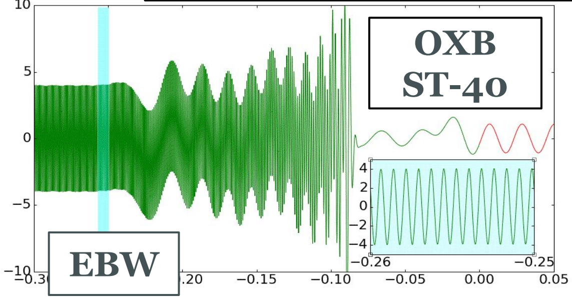


S. Shiraiwa et al 2017 Nucl. Fusion 57 086048

Hot plasma full-wave FEM

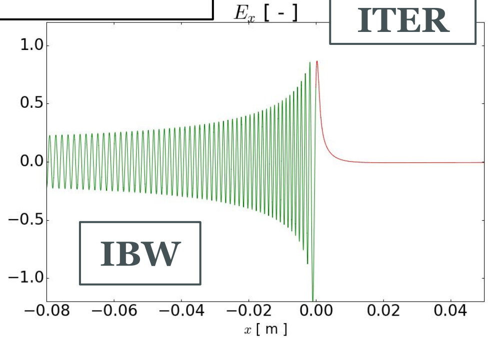
OXB ST-40

EBW



ICWC ITER

IBW



- Other ML at RFPPC2025 GENRAY/CQL3D *G. Pyeon Tue-4* TORIC-ASDEX *M. Sieben Mon-10*

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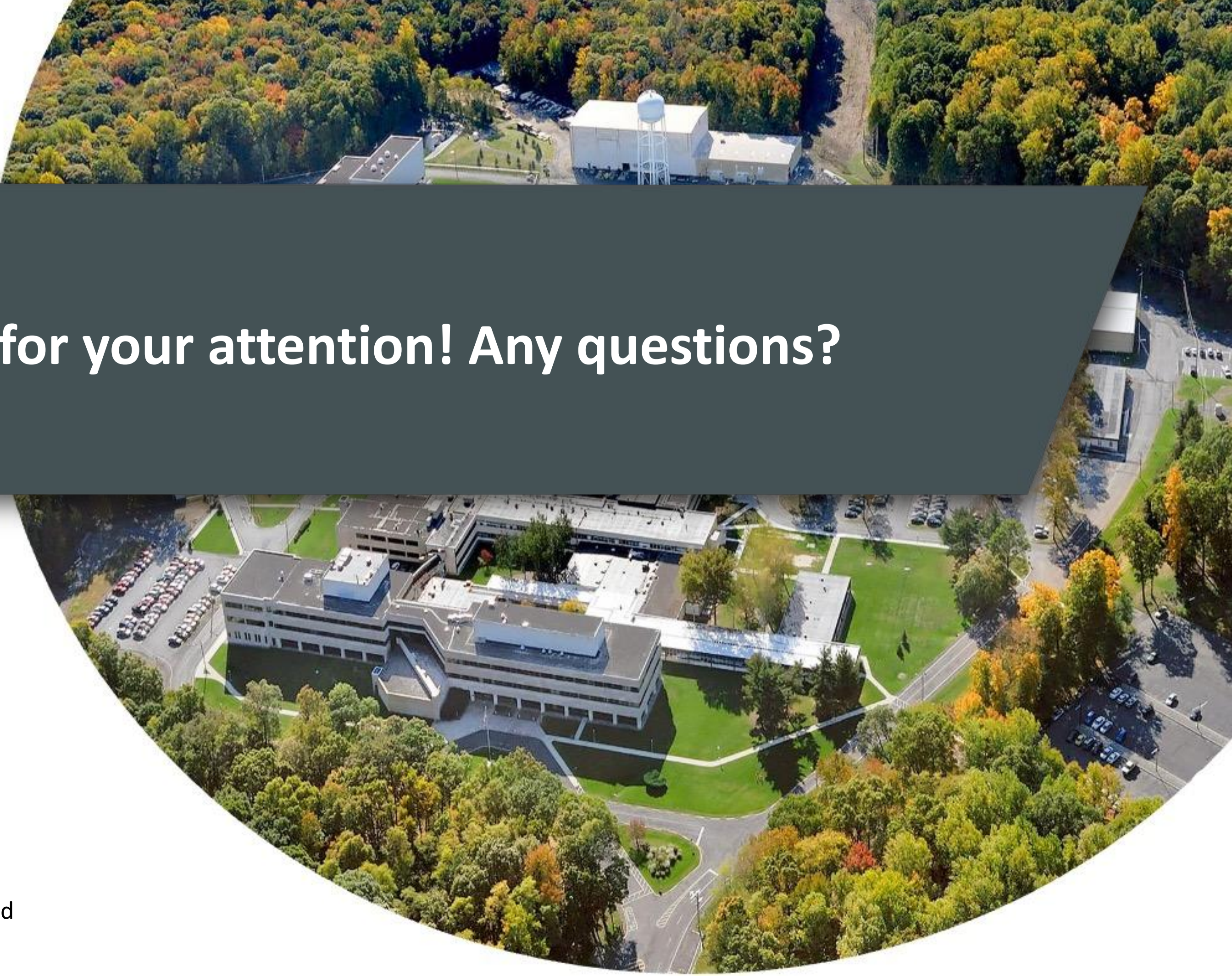
Thank you for your attention! Any questions?



Contact: asvillar@pppl.gov

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