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Abstract. A surrogate model of the wave absorption in the ion cyclotron range of frequencies is presented. The model is trained to capture the physics of 1D electron and ion power absorption profiles for both the high harmonic fast wave scheme in NSTX, and the minority heating scheme in WEST. The surrogate models, based on both the random forest regressor and the multilayer perceptron algorithms, reduce inference time of 1D power absorption profiles from 1-5 minutes required by TORIC to ~50 μs with high accuracy (i.e. $R^2 = 0.71 - 0.96$).

Introduction and methodology. Radio-frequency wave heating systems in the ion cyclotron range of frequencies (ICRF) are widely used actuators in the operation of magnetic confinement fusion devices. Even with the use of high performance computing, available RF actuator modeling tools are still too computationally expensive, making their application unfeasible for specific scenario optimization, inter-shot predictive modeling, or real-time control. In this context Machine Learning (ML) has established as a clear candidate for bringing the physics underlying in these tools to the aforementioned applications. Recently, surrogate models of the lower hybrid current drive physics model using ray-tracing-Fokker/Planck simulations were obtained featuring significant decrease in inference time [1].

In this work we demonstrate surrogate models for the 1D ICRF wave absorption profiles. ICRF physics is rather complex, as not only it involves electron Landau damping but also ion cyclotron damping at the fundamental and harmonic resonances. Surrogate models are trained with databases generated using TORIC [2, 3], an ICRF full-wave simulation code for toroidal geometries. Two databases of ~10000 cases each are generated targeting flat top scenarios in two different regimes: the high harmonic fast wave (HHFW) in the National Spherical Torus Experiment (NSTX) [4], and the minority heating scheme in the W Environment in Steady-state Tokamak (WEST) [5]. Therefore both frequencies (ω) in the order and above the ion cyclotron frequency are covered by the surrogates developed. Radial plasma property profiles are assumed to follow the shape $n_e = (n_{e0} - n_{e1})(1-\rho^{e_1})^{e_2} + n_{e1}$, where subscripts 0 and 1 refer to core and edge, e/i to electron/ion, and ρ is the normalized radial coordinate. The input parametric spaces chosen cover the important physics for each scenario. For NSTX, the toroidal mode number N_φ is selected between [5-21], the core electron density $n_{e0} \in [0.5-2] \times 10^{14}$ cm^{-3} and temperature $T_{e0} \in [1-5]$ keV, and exponent $e_1 \in [2-10]$. In WEST database parameters scanned are $N_\varphi \in [0-60]$, $n_{e0} \in [4-8] \times 10^{13}$ cm^{-3}, $n_{e1} \in [1-3] \times 10^{12}$ cm^{-3}, $T_{e0} \in [1-1.5]$ keV, $T_{i0} \in [1-1.5]$ keV, $e_1 \in [2-10]$, and the minority fraction $X_H \in [0.01-0.1]$. Latin Hypercube Sampling is used to ensure an unbiased dataset while being representative of the variability of the parametric space covered. The 1D surrogate models selected are the Random Forest Regressor (RFR) [6] and the MultiLayer Perceptron (MLP). Surrogate training is carried out with 80% of the database, and the rest is used for testing. Five-fold cross validation is applied. Every predicted profile ($\boldsymbol{y}$) is compared to the ground truth ($\boldsymbol{Y}$) by standard scoring metrics as the average mean squared error $\overline{\mathrm{MSE}} = 1/N\sum_{i=1}^{N}(\boldsymbol{Y}_i - \boldsymbol{y}_i)^2$, and the coefficient of determination $R^2 = 1 - (\sum_{i=1}^{N}(\boldsymbol{Y}_i - \boldsymbol{y}_i)^2/(\boldsymbol{Y}_i - \bar{\boldsymbol{Y}})^2)$, N being the number of test samples, and $\bar{\boldsymbol{Y}}$ is the mean ground truth profile.

Scenario	Variable	Method	MSE[W/cm^3/MW$_{abs}$]	R^2[-]	$\bar{t}_i$ [μs]
HHFW	P_e	RFR	2.1×10^{-5}	0.95	54
	P_D	RFR	9.2×10^{-5}	0.93	49
Minority	P_e	PCA-MLP	9.1×10^{-6}	0.85	33
	P_H	PCA-MLP	6.8×10^{-3}	0.85	35
	P_D	PCA-MLP	4.1×10^{-4}	0.71	31

Table 1: *Summary of scoring results for TORIC-ML surrogate models*

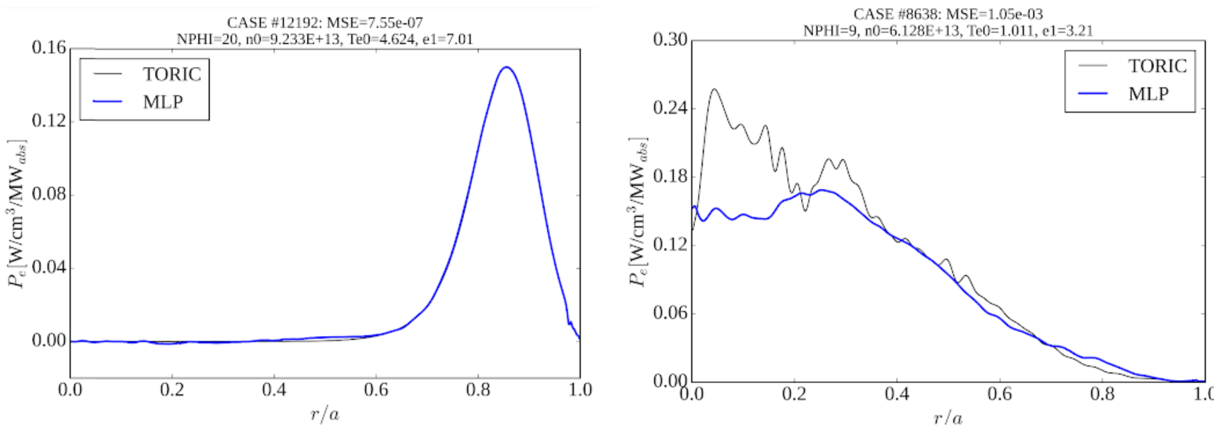

Figure 1: *MLP best (left) and worst (right) predictions of P_e in the filtered HHFW database for NSTX. Ground truth from TORIC simulations in black and MLP predictions in blue.*

HHFW regime (NSTX). Surrogate scoring results trained on the entire HHFW database results in poor surrogate scoring for 1D electron (P_e) and deuterium (P_D) absorption profile predictions (i.e. $R^2 = 0.62/0.51$). Analyzing the database, part of TORIC's electric field solutions present pronounced maxima at unexpected locations, which is denoted as outlier behavior. The nature of these cases is still under investigation, but it is observed that they are correlated with regions of parametric space which are more demanding for the simulation as low core temperature(i.e. low damping), high plasma density (i.e. small wavelengths) and low toroidal mode number. A non-MSE based metric is used to identify that outliers represent 23% of the HHFW database. Surrogate training with the filtered database shows a significant improvement in both predictions of electron/ion power profiles, from $R^2 = 0.62/0.51$ to 0.95/0.93 and from $\overline{\mathrm{MSE}} = 2.6\times10^{-3}/6.1\times10^{-2}$ to $2.1\times10^{-5}/9.2\times10^{-5}$. In HHFW scenarios the majority of power is absorbed by electron species through Landau damping [7]. Figure 1 shows the best and worst electron power absorption profile predictions in terms of MSE for the MLP surrogate model. Additionally, training the RFR on the filtered database shows the capability of providing predictions for outlier cases that preserve the main physical aspects of absorption while eliminating outlier features (see Fig. 2).

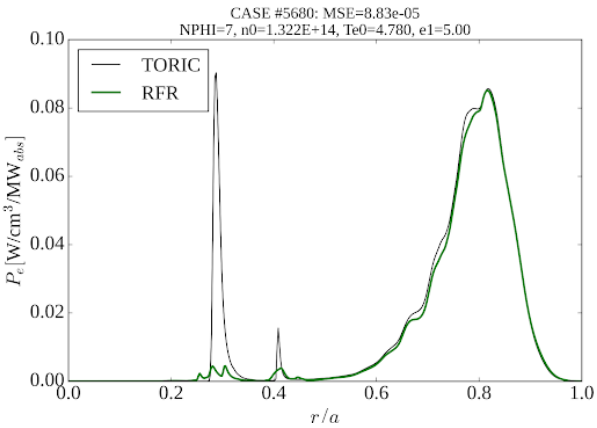

Figure 2: *Prediction of electron power absorption profile for an outlier case in the HHFW database.*

Minority regime (WEST). Minority heating scenario features increased complexity compared to HHFW due to the higher number of species and diversity of the absorption mechanisms [8], including the presence of significant mode conversion of the fast wave (FW) to the ion Bernstein wave (IBW) close to the ion-ion hybrid resonance. In this regime hydrogen absorption (P_H) by cyclotron damping at the fundamental resonance represents the major part of total power absorption and the rest is dominated by electron Landau damping of both FW and IBW. Additionally, the higher physics complexity also requires increasing the number of free input parameters including minority fraction and others, so that the database resolution per free parameter is significantly decreased. Nevertheless, fair performances are obtained by training surrogates on the entire minority database where RFR slightly outperformed the MLP (e.g. $R^2(P_H) = 0.59/0.57$). Outlier cases are also found in this database although of different nature, being correlated under-resolved IBW mode undamped in the high field side featuring extremely short wavelengths. In this scenario outlier elimination before training shows no significant effect in scoring so they are maintained in the dataset. Application of principal component analysis allows to reduce the complexity of P_e and P_H absorption training data from 300 components to 5 and 7 principal components, respectively, while maintaining 99% of the variance of the original dataset. A MLP is trained for each PCA projected database, and with the use of hyperparameter tuning on the batch size, number of hidden layers, learning rate value and method, activation function and solver, network scoring predicting P_{H}/P_e profiles is improved from $R^2 = 0.57/0.64$ to 0.85/0.85 and from $\overline{\mathrm{MSE}} = 1.7\times10^{-2}/1.7\times10^{-5}$ to $6.8\times10^{-3}/9.1\times10^{-6}$.

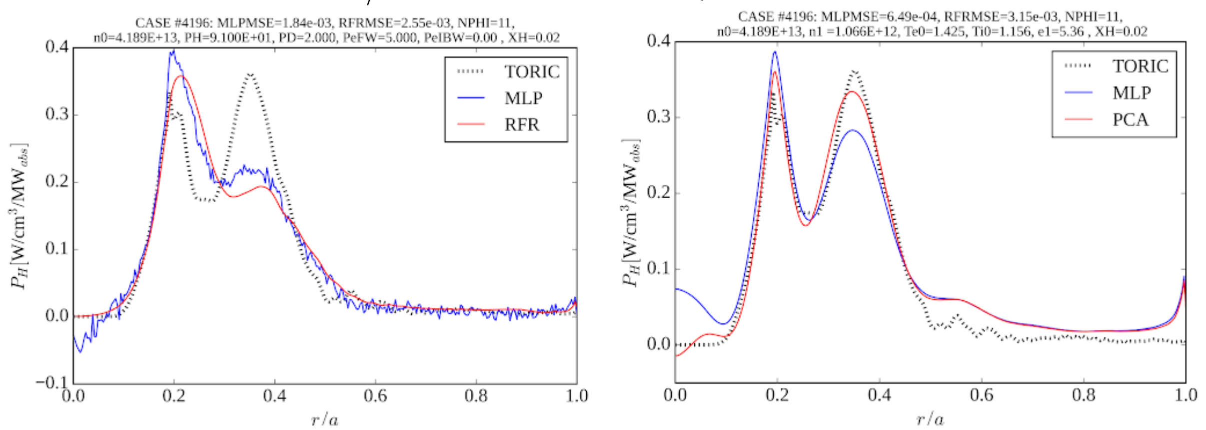

Figure 3: *Predictions of MLP surrogates (blue) trained on entire data (left) and PCA projected data (right) for the same case compared to the TORIC ground truth (black). RFR predictions for the same case shown on the left (red) and on the right (red) we show the PCA-projected ground truth.*

Concluding remarks. In this work we have demonstrated the development of fast ($\sim$50 μs compared to 1-5 min. TORIC simulation time) and accurate (i.e. $R^2 = [0.71-0.96]$) surrogate models of the ICRF 1D wave absorption in both HHFW and minority heating schemes, for NSTX and WEST, respectively. While some outliers are found in both databases, these affect more the performance of HHFW predictions and are correlated to regions input parametric space featuring small damping and expected short wavelengths. The predictions show to be robust even in outlier cases, where the key physical aspects of absorption are preserved while avoiding the outlier features. Overall, these aspects make TORIC-ML appealing for its incorporation into integrated modeling and control codes.

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