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Real-time predictions of ICRF power absorption profiles via machine learning

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Significant acceleration of accurate radio-frequency (RF) power absorption profile predictions in the ion cyclotron range of frequencies (ICRF) was achieved using machine learning (ML)-based algorithms. A traditional approach for obtaining these predictions is to use the spectral based full wave solver TORIC [1,2]. However, the considerable computational expenses of these codes have impeded their application to real-time control, inter-shot predictive modeling or specific scenario optimization. The physics of ICRF heating features complex power absorption phenomenology as both electron and ion species are contributing [3]. As each plasma-wave interaction yields a power deposition with different shapes, the resultant RF absorption profile presents a significant challenge for training ML-algorithms. In this work we present the results of our ICRF wave surrogate modeling efforts to obtain accelerated predictions of the power absorption profiles of WEST [4] and NSTX [5] without losing physics fidelity. Two ML-methods are employed to develop the surrogate models: the Random Forest Regressor (RFR) [6] and the Multi-Layer Perceptron (MLP) [7]. The models are trained using databases generated with TORIC, which solves the wave equation in both minority and high-harmonic fast wave (HHFW) heating schemes, present in WEST and NSTX, respectively. Over 10^4 cases are sampled in each machine-specific parametric regime of interest via the Latin Hypercube Sampling method [8], which produces a pseudo-random sample optimally distributed over the multidimensional input parameter space. The accuracy (scoring) achieved by the surrogate models is measured in terms of average mean squared error (MSE) and coefficient of determination (R^2). Best scorings achieved vary within [$\sim 10^{-2}$,$\sim 10^{-5}$] MSE and [0.71-0.96], respectively. The surrogates implemented for the 1D RF power absorption of electrons and ion species (i.e. hydrogen and deuterium ions) reduce the inference time from O(~1-5min) to O(~30-50μs). While the MLP can achieve better performances, its scoring is strongly sensitive to the presence of outliers, which are found in the TORIC generated database, and result in decreased MLP scoring due to increased noise levels in the predictions. Further discussion on the nature of these outliers is provided. In the HHFW database, outlier filtering provides a significant boost to surrogate scoring, where, for instance, electron power predictions can improve R^2 from 0.62-0.70 to 0.95-0.96 and MSE from $2.1\text{-}2.6 \cdot 10^{-3}$ to $2.1\text{-}1.1 \cdot 10^{-5}$ for RFR-MLP respectively. Power absorption profile predictions of the outlier cases with filtered-dataset trained RFR preserve the main physical aspects of ICRF absorption while eliminating outlier features (see Figure 1). Although outliers are also present in the WEST database, its origin is shown to be correlated to underresolved small wavelength IBW modes in the high field side.

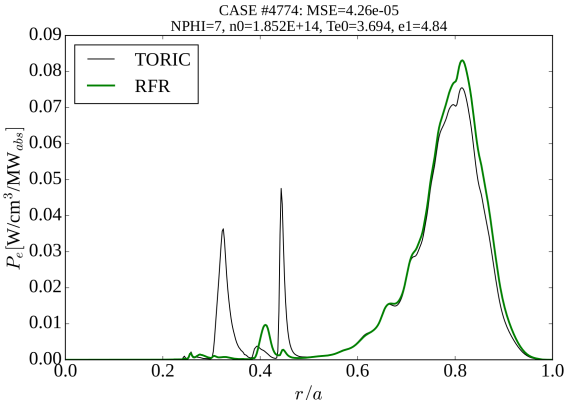

Figure 1: Prediction of electron power absorption profile for an outlier case in the HHFW database

Application of principal component analysis allowed to reduce the dimensionality of electron and hydrogen power absorption profiles for WEST database, from 300 point profiles to uniquely 5 and 7 components, respectively. Training MLP regressors on the projected data resulted in boosting both electron and hydrogen power predictions scoring from the R^2=0.57-0.64 obtained using the original data to R^2=0.85-0.85.

Finally, results of the application of both RFRs and MLPs to predict 2D RF variables such as the power deposition and the wave electric field will be discussed.

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References

[1] M. Brambilla, PPFC **41**, 1 (1999).
[2] M. Brambilla, PPFC **44**, 2423 (2002).
[3] J. R. Wilson, and P. T. Bonoli, Physics of Plasmas **22**(2), 021801 (2015)
[4] Hillairet et al., Nuclear Fusion **61**, 096030 (2021)
[5] Bertelli et al., Nuclear Fusion **62**, 126046 (2022)
[6] L. Breiman, Machine Learning **45**, 5-32 (2001)
[7] M. W. Gardner, and S. R. Dorling, Atmospheric environment **32**, 14-15 (1998)
[8] M. Stein, Technometrics **29**(2), 143-151 (1987)