

Fast prediction of edge plasma parameters in W7-X based on EMC3-EIRENE modeling database using machine learning

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EMC3-EIRENE [1,2] is a powerful computational tool used for self-consistent 3D modeling of edge plasma transports, widely applied in the design and optimization of stellarator and tokamak configurations. However, a significant challenge is the substantial manual effort and computational resources required, which restrict the applicability of EMC3-EIRENE in many scenarios.

This work explores the feasibility of using machine learning to rapidly predict W7-X edge plasma parameters based on an EMC3-EIRENE simulation database. The current simulation database scans four variables: radiation fraction f_{rad} (0.2 to 0.8), separatrix density n_{es} (2 to $7 \cdot 10^{19} \text{m}^{-3}$), particle diffusivity D_{\perp} (0.3 to $1.1 \text{m}^2/\text{s}$) and energy diffusivity χ_{\perp} (0.6 to $1.5 \text{m}^2/\text{s}$), while keeping the heating power at 6 MW. The machine learning method aims to learn the physics relationships between the input parameters and EMC3-EIRENE results using a neural network model (NNM), and then predict the EMC3-EIRENE-AI simulations based on the provided input parameters. After building the neural network model, advanced algorithms like Bayesian Optimization with HyperBand are used to overcome the challenge of optimizing hyperparameters during the training process.

Figure 1 illustrates the best hyperparameters determined from 120 trials within the given hyperparameter space. The subsequent plasma parameter predictions using the neural network model are based on these optimized hyperparameters.

After optimization, the NNM model shows significantly better performance compared to the linear regression method. Figure 2 presents an example using a random EMC3-EIRENE test case. The difference in electron temperature between the traditional EMC3-EIRENE model and the NNM model prediction is generally within 5 eV, whereas the linear regression model shows a larger discrepancy, especially in the magnetic island regions.

It is worth mentioning that acquiring edge plasma parameters using the neural network model takes only a few minutes on a standard office computer, while conventional simulations typically require several thousand CPU core-hours. This potential enhancement not only saves significant computational resources, but also may enable EMC3-EIRENE to guide ongoing experiments directly from the control room, markedly enhancing experimental efficiency.

References

- [1] Y. Feng et al., J. Nucl. Mater. 266–269 812–8, 1999.
 [2] D. Reiter, et al., Fusion Sci. Technol. 47 172–86, 2005.

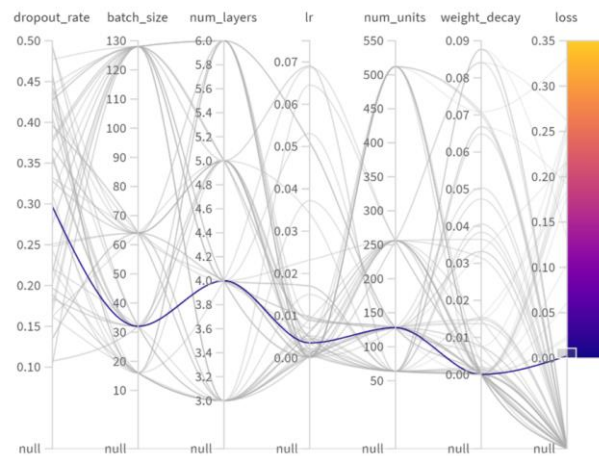


Figure 1. Scan of the hyperparameter space in machine learning.

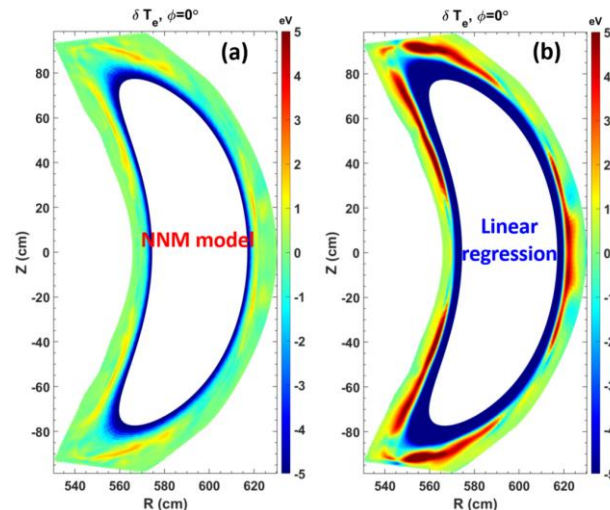


Figure 2. (a, b) the differences between a random EMC3-EIRENE test case from the database and the corresponding predicted electron temperature using NNM model and linear regression, respectively.