Cross-Machine Modeling of Machine-Learning based Helium Line Intensities

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While the helium line intensity ratio method has been used to measure electron, n_e, and temperature, T_e, by combining measured line intensities with a collisional radiative model (CRM) [1], one of its difficulties is to include the photon transport and metastable atom transport. A machine learning (ML) approach has been considered as an alternative method to measure n_e/T_e from the line ratios. If training data is sufficiently available, it can be a useful diagnostic tool. The challenging issue in this approach is developing a global model that can be applied to other devices. In this study, we collected an OES dataset and n_e/T_e data from four linear divertor simulators, and we investigated the cross-machine validation of a developed ML model.
Data from the following four linear devices are used: Magnum-PSI, NAGDIS-II, and PISCES-A, and Lotus-I. Line intensities at 447.1 nm (4^3D-2^3P), 492.2 nm (4^1D-2^1P), 501.6 nm (3^1P-2^1S) + 504.8 nm (4^1S-2^1P), 667.8 nm (3^1D-2^1P), 706.5 nm (3^3S-2^3P), and 728.1 nm (3^1S-2^1P) are considered. The dataset includes 24, 64, 6, and 3 discharges (radial profiles) and 960, 417, 342, and 70 data points from Magnum-PSI, NAGDIS-II, PISCES-A, and Lotus-I, respectively. Laser Thomson scattering was used in Magnum-PSI and a Langmuir probe was used in the other devices to obtain n_e/T_e. In addition to a deep neural network (DNN) model, physics-informed ML approach [2] was also tested, where a pre-trained NN with a CRM tuned with experimental data [3].

It was shown that a DNN model trained with the dataset from three devices leads to an error of ~100%, when applying it to a remaining unseen fourth device for both n_e and T_e, which is significantly higher than the model applied to the seen devices. This is primarily due to device-specific parameters such as plasma radius and different ranges of n_e and T_e, which hinder the model's generalizability across devices. To address this, we additionally performed fine-tuning using data from the target device itself. It was found that errors significantly decreased except for Magnum-PSI, where n_e is higher and T_e is lower than in the other devices. Furthermore, the reduction in the errors was more significant for physics-informed models. The results suggested that the physics-informed model has an advantage when using fine-tuning with a limited dataset.

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