

## 5<sup>th</sup> Asia-Pacific Conference on Plasma Physics, 26 Sept-1Oct, 2021, Remote e-conference Massive GTC global simulations of internal kink instability in DIII-D experiments for development and training of surrogate GTC model (SGTC) based on deep learning methods

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In real-time toroidal plasma experiments, accurate physics-based information of plasma instabilities can provide important guidance for successful plasma control. First-principles based simulations of plasma instabilities can improve the accurate understanding and prediction of the dynamics and transport at the plasma core and edge in future fusion devices, it can be expensive computationally to conduct these simulations. For example, simulation time for physical instabilities using gyrokinetic particle-in-cell codes is often on the order of hours on modern GPUs, making the direct application of these codes in real-time experiments infeasible. On the other hand, statistical methods including machine learning models have been applied in the Plasma Control System (PCS) to predict plasma behaviors. Recently deeplearning-based models have achieved promising results in disruption predictions [1] and the prediction of perturbed magnetic signals [2,3]. Here we present the first results on building a deep-learning based surrogate model (as shown in Fig. 1) as a physics-based instability simulator, trained based on data from global gyrokinetic toroidal code (GTC)[4], which has performed thousands of electromagnetic simulations on kink instability in the fluid limit by suppressing all kinetic effects and using the DIII-D experimental equilibria.

GTC first-principles simulation data are generated and used for training, validation and testing of SGTC. we ran GTC electromagnetic linear simulations of the non-tearing n=1 instabilities in the ideal MHD limit with equilibrium current and compressible magnetic perturbations [5], where n is the toroidal mode number, for 5758 equilibriums selected from DIII-D experiments. we then performed supervised training of SGTC models with these DIII-D equilibria and GTC output data. In most of the GTC simulations finding unstable modes, the mode structures resemble those of the internal kink modes with dominant m=1 component in electrostatic potential near the q = 1 rational surface. As the first study, a hand-tuned Convolutional Neural Network (CNN) was trained to predict the stability, i.e., classification between stable and unstable cases. The accuracy of the prediction on test cases is 89%, outperforming the non-DL methods like a random forest (with the accuracy 85%). Then an ensemble of CNNs is trained to predict the growth rate of the kink mode. The models are generated by automatic hyperparameter tunning. 10 best performing models are used for the prediction. The results shown in Figure 2 suggests good prediction for low growth rate cases where we have more training data. Another ensemble of CNNs

is trained to predict the mode structure. The result is shown in Figure 3. The key features of kink modes such as m=1 structure and large mode amplitude inside q=1surface are successfully captured by the deep learning model. These predictions are done within 1ms and fit the requirement of DIII-D PCS



Figure 1 SGTC prediction of the growth rate of the kink mode



Figure 2 SGTC prediction of kink mode structure

In summary, The SGTC internal kink simulators demonstrate strong predictive capabilities and shortens the simulation time by at least six orders of magnitude, and presents for the first time the possibility of bringing physics-based instability information from the first-principles based massively parallel simulations into the PCS of modern tokamak

References

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