Development of Model-based Divertor Detachment Prediction

Ben Zhu*, Menglong Zhao, Harsh Bhatia, Bill Meyer, Tom Rognlien, Timo Bremer, Xue-qiao Xu

Lawrence Livermore National Laboratory

Divertor power exhaust handling is a key component of the success for future tokamak reactors. So far, the most successful power reduction is achieved by *detachment*. Nevertheless, establishing a proper degree of detachment without compromising pedestal and core plasma performance is not trivial.

We have developed a physics model-based detachment prediction with machine learning techniques by finding robust and accurate projections among three distinct descriptions of steady-state plasma states — model inputs (i.e., engineering parameters such as heating power, puffing rate/upstream density), omniscient diagnostics (ODs, such as synthetic Langmuir probe, Thomson scattering, radiation measurements), and *latent space* that identified by an autoencoder when compressing the ODs.

As a starting point, we use highly efficient 1D UEDGE model which contains the crucial physics ingredients of detachment (e.g., ionization and recombination of plasma and neutrals) to simulate the plasma and neutrals along the open magnetic field lines in the Scrape-Off Layer. Over 300,000 simulations with varying model inputs (e.g., different upstream density, power, carbon fraction and divertor leg, or, magnetic connection length) are performed to generate the training database; and we find that a 6-dimensional bottleneck layer (6D) in latent space is good enough to closely yield a match for our true system in configuration space (i.e., the ODs such as upstream temperature, divertor target density, temperature and saturation current, as well as radiation profile). Based on this finding, forward surrogate models are trained to make predictions into the bottleneck layer from model inputs; then the trained decoder is used to reconstruct back the ODs to the configuration space. Current proof-of-principle model performs similarly to the analytical two-point model but with local flux-limited thermal transport and features additional detachment front prediction. Moreover, this approach can be easily extended to incorporate richer physics in a more realistic experiment setting once trained upon a higher fidelity dataset.

Most importantly, our study demonstrates that the complicated divertor plasma state has a low-dimensional representation in latent space. Therefore, this new latent space description of plasma state not only can be used to construct a fast and robust surrogate model for steady-state detachment prediction, but also has the potential to be used for dynamical control once the critical plasma nonlinear dynamics (in latent space) was successfully identified.

This work was performed for US DOE by LLNL under DE-AC52-07NA27344. LLNL-ABS-832653

*zhu12@llnl.gov