Exploring machine learning approaches to surrogate modelling of linear GENE simulation of tokamak edge

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The standard operational scenarios projected to provide reactor-relevant performance in tokamak plasmas require a self-organized transport barrier and formation of a pressure pedestal at the edge [1]. Simulations of the residual turbulence within this transport barrier is one of the most demanding components in high fidelity predictions of the edge plasma performance in tokamaks [2 – 7]. The transport fluxes driven by this residual turbulence can be simulated by solving a nonlinear, saturated turbulent state of the gyrokinetic (GK) Vlasov-Maxwell system of equations, which represents the most advanced theory for turbulence in strongly magnetized plasmas. However, such simulations are computationally extremely demanding, ruling out application in large scale reactor and scenario design or real-time prediction activities. Therefore, reduced transport models, such as the ballooning critical pedestal technique in the EPED model [8], are typically used in these applications. However, such a model reduction approach propagates the prediction uncertainty as an investment risk in the large reactor facilities. Development of machine learning algorithms for high-performance computers (HPC) has opened a pathway to bridge this gap between model fidelity and computational throughput, as demonstrated by related studies of accelerated core plasma turbulence simulations with surrogate models QLKNN and TGLFNN [9 – 11].

This contribution presents early results on machine learning approaches to surrogate local, linear pedestal GK simulations, conducted with the continuum GK code GENE [12]. The local linear GENE simulations take as input the initial plasma conditions as well as relevant features of the confining magnetic field and predict stability thresholds, turbulence drives, growth rates, mode frequencies, and eigenfunctions. Focusing on local, linear GK reduces the overall computational demand, such that generation of a sufficient training database is expected to be feasible. This conference contribution will present the first proof-of-principle work focused on a restricted, limited dimensionality input space, further reducing the demand on generating an extended training database. The plan of this project is then to explore active learning and physics-informed approaches to data efficiently expand the domain of applicability of the developed surrogate model [13].

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