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Scenario planning in tokamaks using machine learning accelerated models and genetic optimization

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Model-based between-shots and real-time actuator trajectory planning will be critical to achieving high performance and disruption-free operation in present-day tokamaks, ITER, and future fusion reactors. Such tools require models that are accurate enough to facilitate useful decision making and fast enough to enable optimization algorithms to meet between-shots and real-time deadlines. Since state-of-the-art integrated modeling codes are too computationally intensive, an accelerated simulation capability has been developed for NSTX-U by applying machine learning techniques to both empirical data and TRANSP simulations, enabling profile and equilibrium predictions at real-time relevant time scales. The approach includes machine learning surrogates for high-fidelity TRANSP modules to accelerate calculations by orders of magnitude while maintaining high fidelity. For quantities not well modeled by TRANSP modules, machine learning is applied to an experimental database. Results provide a glimpse of the potential impact of accelerated modeling on scenario optimization and control, motivating further development of models and applications.

Surrogate models for TRANSP calculations: In TRANSP, the influence of neutral beam injection on plasma heating, current drive, and torque is calculated by the Monte Carlo code NUBEAM. An accelerated surrogate model for NUBEAM was developed in [1] from a database of results for plasma conditions relevant to the NSTX-U operating space. Figure 1 shows good agreement between NUBEAM heating profiles and those predicted by the neural network. Importantly, the neural network only takes ~100 microseconds to evaluate compared to seconds or minutes for the original code. Surrogate models have also been trained for parameters used in the magnetic and momentum diffusion equations.

Empirically identified models: Rather than accelerating calculation of transport coefficients through the use of neural networks as done in [2,3], we explore an empirically driven approach to predicting profile evolution. Since the shape of the temperature and density profiles are typically observed to be `stiff', i.e., insensitive to the detailed distribution of sources, a neural network is

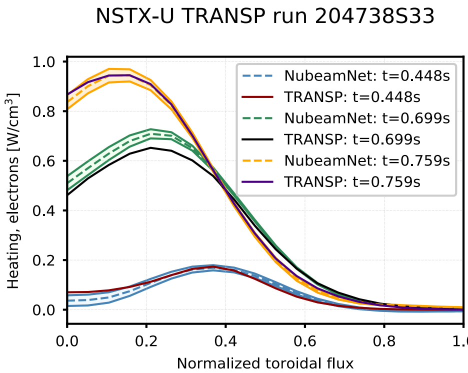

Figure 1: TRANSP calculated profiles of beam heating to electrons compared with the results of the NubeamNet neural network model.

trained on empirical data to predict the electron temperature and pressure profile shapes as a function of plasma current, plasma boundary shaping parameters, volume-averaged electron density and pressure as input. Volume averaged stored energy and density are then predicted from empirical confinement scaling expressions.

Actuator trajectory optimization: The fast execution time of the machine learning accelerated scenario model is exploited to enable rapid optimization of actuator trajectories. A combination of genetic optimization and sequential quadratic programming is used to obtain solutions [4]. Example results of applying the optimization approach to track target trajectories for fast ion pressure and electron pressure are shown in Figure 2. Future work will include further development of optimization techniques, and real-time applications.

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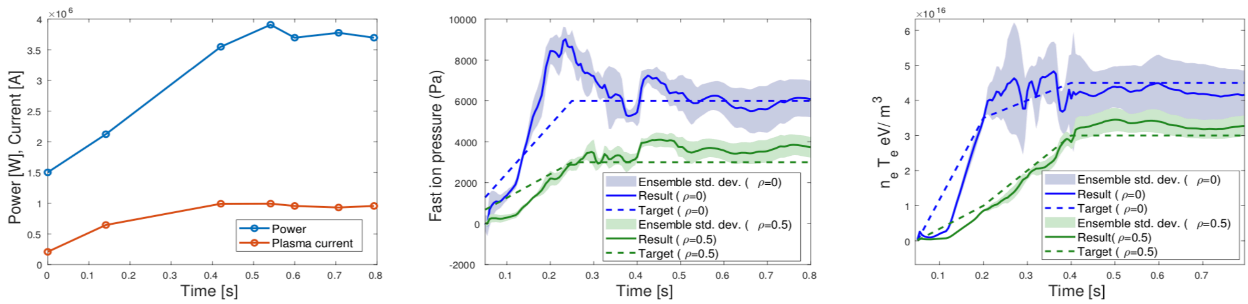

Figure 2: Optimized beam power and plasma current (left) for tracking fast ion (center) and electron pressure (right)