Initial Results of a Machine Learning-based Real Time Disruption Predictor on DIII-D

C. Rea[1], R.S. Granetz[1], N. Eidietis[2], K. Erickson[3], M.D. Boyer[3], R. Johnson[2]

[1]*MIT Plasma Science & Fusion Center, Cambridge, MA, US*

[2]*General Atomics, San Diego, CA, US*

[3]*Princeton Plasma Physics Laboratory, Princeton, NJ, US*

A disruption prediction algorithm, developed using machine learning, runs in real time in the DIII-D plasma control system (PCS), and accurately predicts impending major disruptions with several hundred milliseconds warning time, while also having a very low rate of false alarms. The algorithm is based on the Random Forests machine learning method, and has been developed starting from an extensive database of more than 10000 DIII-D discharges, both disruptive and non-disruptive ones. The algorithm uses 9 plasma parameters that are derived from several real time diagnostic signals and real time EFIT equilibrium reconstructions, which are provided by the PCS on a cycle time of 250 μs. Most of the parameters are dimensionless (e.g. l_i, β_p, …) or cast in a dimensionless form (e.g. n/n_G, $B_p^{n=1}/B_{tor}$ …), which facilitates multi-machine analyses. The prediction algorithm was trained on all types of major disruptions occurring during the flattop phase, without differentiation by cause, and the initial results do indeed show good success at recognizing multiple types of major disruptions during the flattop, and even during the rampdown phase of discharges.

A reliable prediction warning time of several hundred milliseconds allows, at least conceptually, for the possibility of actively avoiding an impending disruption, *if* the specific cause(s) of the disruption can be identified, and if control 'knobs' exist to modify the identified cause(s). However, although Artificial Intelligence (AI) methods can accurately make predictions, it is not well-understood how to determine which input features are responsible for the output prediction. Determining how to do this is currently a high-priority topic of AI research, which we are now pursuing in order to effectively close the disruption avoidance control loop.

This work was supported by the U.S. Department of Energy under DE-FC02-04ER54698, DE-SC0014264 and DE-AC02-09CH11466.