EXPLORATORY MACHINE LEARNING STUDIES FOR DISRUPTION PREDICTION USING LARGE DATABASES ON DIII-D

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ABSTRACT

Using data-driven methodology, we exploit the time series of relevant plasma parameters for a large set of disrupted and non-disrupted discharges from the DIII-D tokamak with the objective of developing a disruption classification algorithm. We focus on a subset of disruption predictors, most of which are non-dimensional and/or machine-independent parameters such as the plasma internal inductance li and the Greenwald density fraction n=nG, coming from both plasma diagnostics and equilibrium reconstructions. The utilization of dimensionless indicators will facilitate a more direct comparison between different tokamak devices.

In order to eventually develop a robust disruption warning algorithm, we leverage Machine Learning techniques and, in particular, we choose the Random Forests algorithm to explore the DIII-D database. We show the results coming from both binary (`disrupted' / `non-disrupted') and multi-class classification problems. In the latter, the time dependency is 2 introduced through the definition of class labels on the basis of the elapsed time before the disruption (i.e. `far from a disruption', `within 350 ms of disruption', etcetera). Depending on the formulation of the problem, overall disruption prediction accuracy up to 90% is demonstrated, approaching 97% when identifying a `stable' and `disruptive' phase for disrupted discharges. The performances of the different Random Forest classifiers are discussed in terms of accuracy, by showing the percentages of successfully detected samples, together with the false positives and false negatives rates.