Implementation of AI/Deep Learning Disruption Prediction into a Plasma Control System

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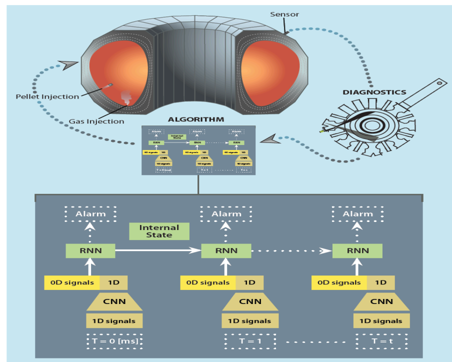
Introduction & Motivation:

• FRNN produces accurate "disruption score" for probability of "when" imminent disruption will occur + a sensitivity analysis in real time for underlying reasons as to "why? "

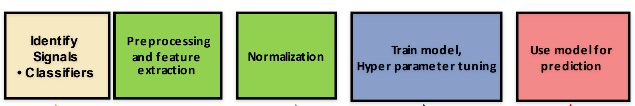
• Integration of AI/DL FRNN predictor into DIII-D plasma control system(PCS)

→ D3D's "start-up" phase involving over 200 shots in May/June 2020 showed "FRNN inference engine" can be readily functional (~ 1.7 ms) during real-time operations;

→ Motivates systematic studies of *actuator engagement* to possibly modify the plasma state to avoid or delay onset of disruptions



Machine Learning Workflow



Princeton/PPPL DL predictions now advancing to *multi-D time trace signals* (*beyond zero-D*)

Measured sequential data arranged in patches of equal length for training

All data placed on appropriate numerical scale ~ O(1)
e.g., Data-based with all signals divided by their standard deviation

• All available data analyzed;
• Train LSTM (Long Short Term Memory Network) iteratively;
• Evaluate using ROC (Receiver Operating Characteristics) and cross-validation loss for every epoch (equivalent of entire data set for each iteration)

Apply ML/DL software on new data

FRNN with Physics-based inputs: HPC Training & Prediction for disruption with enhanced accuracy and advanced alarm time

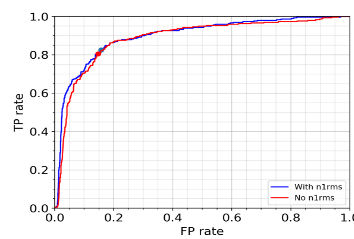


FIG. 1. Comparison of the ROC curves with and without the n=1 finite frequency mode amplitude ("n1rms")

Distinguishing disruptive and non-disruptive tearing modes

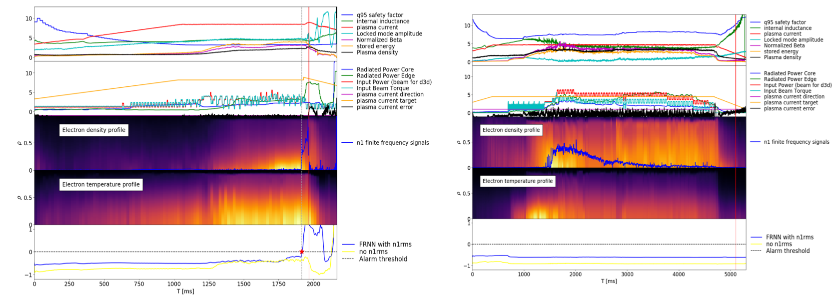


FIG. 2. DIII-D shot number 161362 in the left panel and DIII- shot number 170239 in the right panel. In each panel, the upper 4 sub-panels show measured signals as FRNN input, and the bottom sub-panel show FRNN model outputs

Studying contributions of physics-based signals to disruption score

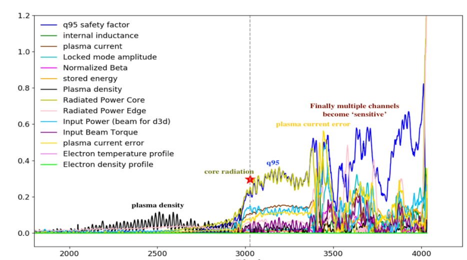


FIG 3. Evolution of the sensitivity score of the shot #164582

Summary & Future Studies:

• Integration of AI/DL FRNN predictor into DIII-D plasma control system(PCS) + Interpretation via statistical sensitivity studies with real-time actionable integration into PCS

• When more signals are included in training database, better predictive capability can be achieved:

→ Exciting neural network to discriminate between disruptive and non-disruptive tearing modes.

→ FRNN "inference engine" demonstrably functional (~ 1.7 ms) on time-scales needed for real-time actuator engagement.

→ Motivates ongoing & future efforts to interconnect new features of present studies to enable DL sensitivity output in real time into the proximity control architecture designed for handling major disruption causes in the DIII-D PCS.