Scenario adaptive disruption prediction study for next generation burning-plasma tokamaks

J. Zhu[1], C. Rea[1], R.S. Granetz[1], E. S. Marmar[1], K. J. Montes[1], R. Sweeney[1], R.A. Tinguely[1], D. L. Chen[2], B. Shen[2], B. J. Xiao[2], D. Humphreys[3], J. Barr[3], O. Meneghini[3]

[1] Plasma Science and Fusion Center, Massachusetts Institute of Technology, Cambridge, MA, USA

[2] Institute of Plasma Physics, Chinese Academy of Sciences, Hefei, Anhui, China

[3] General Atomics, San Diego, CA, USA

Scenario adaptive strategy provide possible solution for ITER DMS trigger development

- Developing a reliable DMS trigger for ITER's high performance operation using limited high performance data from itself is a key for the success of ITER [1-3].
- Data-driven disruption predictors trained on abundant low performance discharges work poorly on the high performance regime of the same tokamak, which is a consequence of the distinct distributions of the **tightly correlated** signals related to disruptions in these two regimes.
- Matching operational parameters among devices can greatly improve cross machine accuracy.
  - ➢ Highlight the importance of developing ITER baseline scenario on existing tokamaks.
- Combining **low performance data from the target** with **high performance data from other machines** gives good performance on the **high performance regime** of the target machine.
  - ➢ A possible strategy for ITER DMS trigger development.

[1] De Vries P.C. *et al* 2016 *Fusion Sci. Technol.* **69** 471–84

[2] J.X. Zhu *et al* 2021 *Nucl. Fusion* **61** 026007

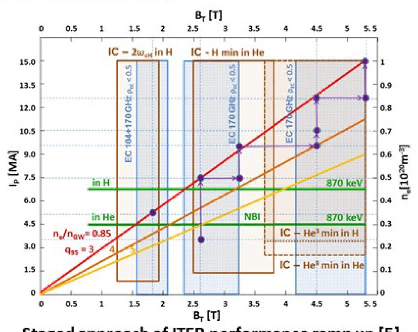
[3] Kates-Harbeck J. *et al.* 2019 *Nature* **568**, 526–531

Using data from existing machines to simulate the low/high performance phases on ITER

- Select three operational parameters: β_p, q_{95} and **input power (P_{in})** that are important to tokamak operation but less significant to our disruption predictor and calculate their flattop averaged values[1] for each shot in our databases (C-Mod, DIII-D and EAST) [2, 4].
- Choose performance cutoff thresholds for all three parameters (averaged values) and select various high/low performance (high/low P_{in}, high/low β_p, low/high q_{95}) datasets on three machines.

Performance cutoff threshold of β_p, P_{in} and q_{95} on three devices

	β_p low/high cutoff		P_{in} low/high cutoff (MW)		q_{95} low/high cutoff	
C-Mod	<0.15	>0.25	<1.0	>3.0	<4.0	>4.6
DIII-D	<0.60	>0.80	<3.5	>7.5	<4.5	>5.0
EAST	<0.55	>0.75	<0.6	>3.0	<5.0	>6.0



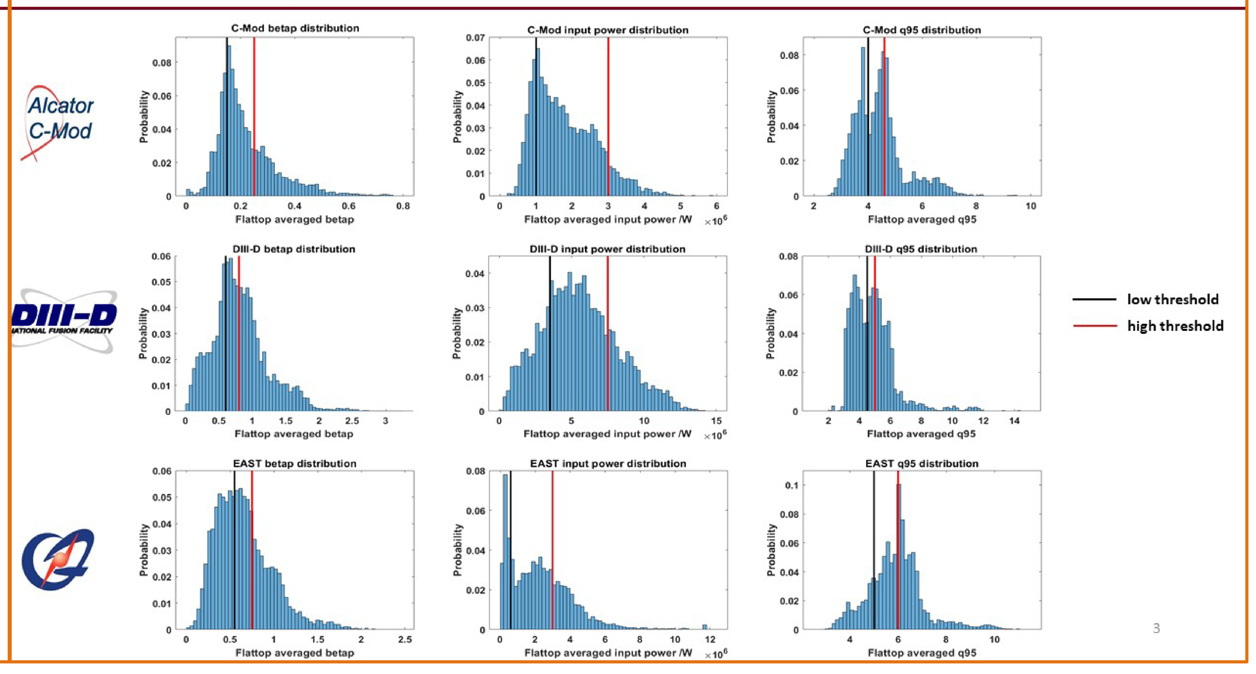
Staged approach of ITER performance ramp up [5]

[4] Montes K. J. *et al.* 2019 *Nucl. Fusion* **59** 096015

[5] ITER Organization 2018 *ITER Research Plan within the Staged Approach (Level III–Provisional Version)* Report ITR-18-003 (www.iter.org/technical-reports)

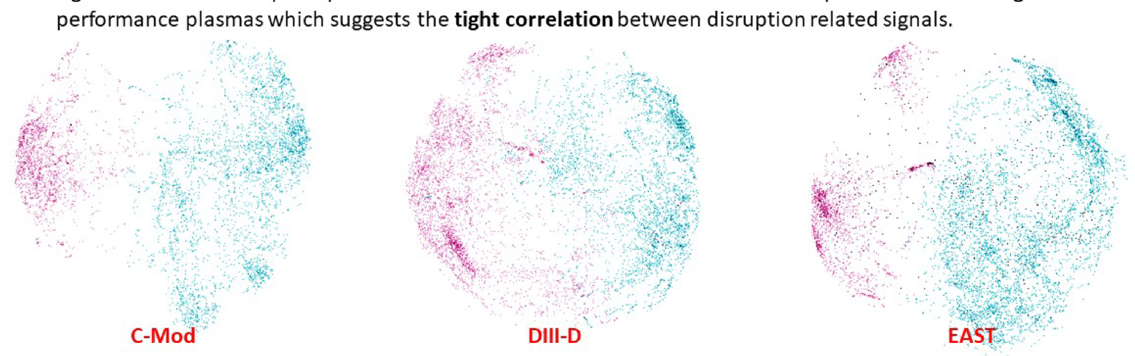
[1]For β_p and P_{in}, average is only taken over the flattop period when the heating is on.

Distribution of three parameters on each device



Unsupervised clustering reveals clear separation between low/high performance regime

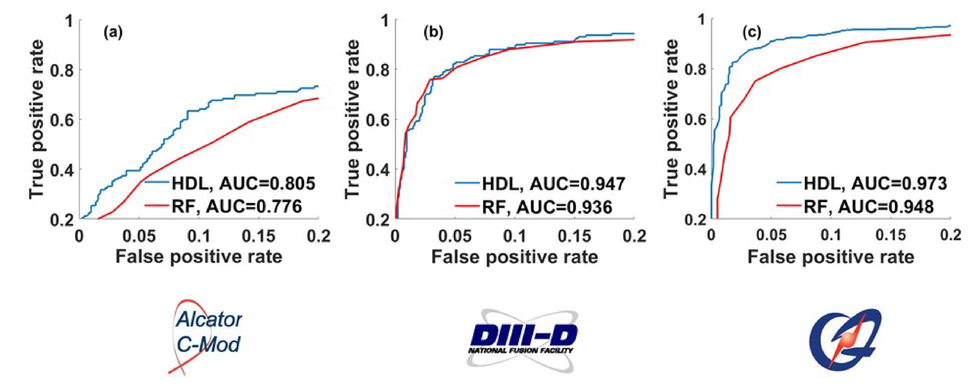
- An orthogonal linear transformation called **Principal Component Analysis** (PCA) [6] is applied to all three databases to facilitate the visualization of plasma data in a 2-D plane
- In all clustering plots, both x and y axes are linear combinations of 12 training features. Each magenta point represent a 10-step plasma sequence randomly sampled from the flattop of a high performance shot while each cyan point represent a 10-step sequence randomly sampled from the flattop of a low performance shot. The coloring is done a *posteriori*.
- PCA clustering plots show limiting the ranges of a few parameters can greatly change distributions of other signals related to disruption prediction and makes clear distinction between low performance and high performance plasmas which suggests the **tight correlation** between disruption related signals.



[6] Pearson K. 1901 *Philosophical Magazine.* **2** (11): 559–572

Hybrid Deep Learning (HDL) Predictor [2]: a fast, powerful and general model for disruption prediction

- Consist of an advanced deep neural net converts an input plasma sequence to a predicted label and a shot-by-shot testing scheme to simulate alarms triggered in the Plasma Control System (PCS) [2].
- Achieve state of the art performance (benchmark against optimized Random Forest (RF) predictor) on all three devices with limited hyperparameter tuning, suitable for cross machine study.



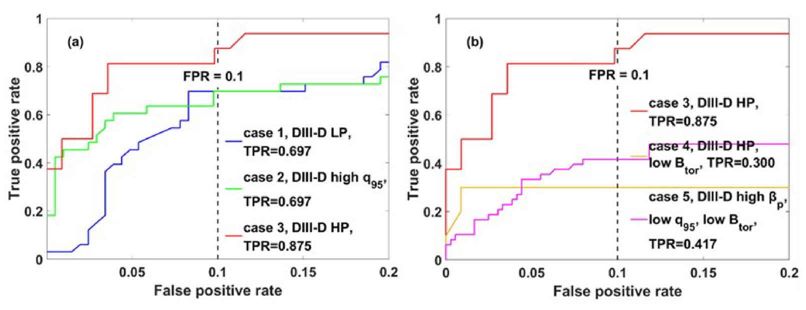
Cross-machine study: explore data-efficient disruption prediction on new devices.

- Develop a reliable predictor that work on high-performance operational regime using low performance operational data is strongly desirable for ITER [5].
- A "*train-on-LP-data*" strategy is to train a predictor using low performance data from our target machine and hope it works for high performance operation.
- We have designed numerical experiments to investigate whether this strategy works. If not, how to improve this using data from other devices.
- Setup: two machines as '***existing/other machines***', with the third one chosen as a '***new/target device***'.
- Performance metric: success rate vs. false alarm curves [7] at 50ms before the current quench.
- All following qualitative conclusions are **machine-independent** (only show the DIII-D case which means **DIII-D** is the ***new device*** while **C-Mod and EAST** are ***existing machines***. In addition, the test set is always DIII-D high β_p, high P_{in} and low q_{95} dataset unless otherwise stated.).

[7] Bradley A. P. 1997 *Pattern Recognition*, **30**, 1145–1159

Only using low performance shot doesn't work on high performance regime

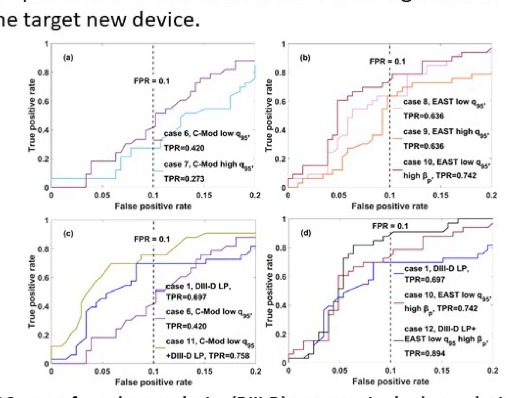
- Train on few hundreds **low performance** *new device* shots works **badly** on *new device* **high performance** regime.
- Although P_{in} and B_{tor} are not training features, predictors trained on high performance (with/out P_{in} constraint) low B_{tor} discharges perform poorly for the high performance high B_{tor} discharges.
- Signals related to disruption prediction are closely correlated. Although the chosen physics-based signals (β_p, P_{in}, q_{95}) do not directly contribute much to the power of model, limiting their range can deeply affect the distributions of more important signals and hence change the prediction results.



ROC curves from the new device (DIII-D) test set using only new device data.

Improve the "*train-on-LP-data*" strategy by adding data from other machines

- Training on "matched" data from existing machines greatly outperforms the unmatched data, and progressively matching more parameters continuously improves the target performance. Therefore, developing ITER baseline scenario discharges on existing tokamaks, and training predictors on these, should greatly improve disruption prediction on ITER itself.
- In the absence of high performance data from the new device, combining "matched" high performance data from existing machines with low performance data from the new device gives the best prediction accuracy for the high performance regime of the target new device.



ROC curves from the new device (DIII-D) test set using both new device and existing machines (C-Mod, EAST) data.

Summary

1. Preliminary data exploration on three datasets finds limiting the ranges of three chosen parameters clearly separates the resulting low/high performance plasmas which suggests the close correlation between disruption related parameters.
2. Data-driven disruption predictors trained on abundant low performance discharges work poorly on the high performance regime of the same tokamak, which is a consequence of the distinct distributions of the tightly correlated signals related to disruptions in these two regimes.
3. Matching operational parameters among tokamaks strongly improves cross-machine accuracy which implies our model learns from the dimensionless physics scalings of these parameters and confirms the validity of these scalings for disruption prediction from the data-driven perspective.
4. Suitable predictivity of the high performance regime for the target machine can be achieved by combining low performance data from the target with high performance data from other machines.
5. Possible strategy for ITER data-driven DMS trigger: combine low performance ITER data with ITER baseline discharges from existing machines to meet the initial requirement. Add high performance ITER data and further boost the performance to achieve long term requirement.