Real-time disruption prediction in the PCS of EAST tokamak through a random forest model

W. Hu [a], C. Rea [b], Qiping Yuan [a], Erickson Keith [c], Dalong Chen [a], Biao Shen [a], Yao Huang [a], Jianyuan Xiao [d], Junjie Chen [d], Yanmin Duan [a], Yang Zhang [a], Huidong Zhuang [a], Long Zeng [a], Jinping Qian [a], Robert Granetz [b], Bingjia Xiao [a], Jiangang Li [a]

[a] Institute of plasma physics, Chinese academy of science [b] Plasma Science and Fusion Center, MIT [c] Princeton Plasma Physics Lab [d] School of Nuclear Science and Technology, University of Science and Technology of China

Email: huwh@ipp.ac.cn, crea@mit.edu

Introduction

In the quest for achieving nuclear fusion reactors, disruptions pose a serious risk and have to be avoided in tokamak plasma discharges. During a disruption, the plasma stored energy rapidly decays and the plasma resistance increases resulting in a thermal quench first, and then a current quench, where all the accumulated energy is released on the plasma-facing components on milliseconds time-scale. High energy particles may generate in this process and hit the inner wall leading to serious radiation damage to the materials. If a disruption can be predicted far in advance to allow control actions to mitigate or avoid its effects, not only the damage can be reduced, but also the plasma discharge parameters (including plasma current, density and temperature) can be optimized. For a fusion reactor, it is unbearable to have more than 1% disruptions [1]. Therefore, it is of great significance to design a disruption prediction system and send out warning signals to trigger the disruption mitigation system, such as MGI, SPI and fast ramp down of plasma current. In the EAST tokamak, we have implemented a real-time disruption prediction model in the Plasma Control System (PCS). The Disruption Prediction via Random Forest (DPRF) algorithm is based on a random forest [2] model trained using a database of about 1000 discharges, of which half are disruptive and half are non-disruptive discharges. A version of DPRF has already been implemented on DIII-D [3], and for its application on EAST, we focused on a set mostly dimensionless plasma signals, acting as input features of the algorithm. Among them, Ip, Greenwald density fraction, loop voltage (Vloop), the error on the current centroid position, an indication of the plasma vertical stability together with the elongation (kappa) are diagnostic measurements; li, β_N, W_{MHD}, kappa and q_{95} are modelling outputs of plasma equilibrium reconstruction code EFIT [4].

During a discharge, it is possible to switch between different random forests throughout the plasma discharge and it is a configurable parameter in the PCS.

Materials and methods

1. Data collection

① Plasma Greenwald density limit of different tokamak is $n_G = I_p/(2\pi a^2)$ [5]

② The EAST density operation range is GW_{frac}=ne/nG~0.2-0.8 [6].

③ Flattop phase of 486 disruptive discharges with density reaches 0.8nG and 480 non-disruptive discharges are selected as training shots. Samples are taken every 1 ms and they are divided into two kinds:

$$\begin{cases} \text{unstable: samples between } [\text{disruption}_{\text{time}} - 1.7\text{s} \text{ and } \text{disruption}_{\text{time}}] \text{ of disruptive shots} \\ \text{stable: all other samples except unstable samples} \end{cases}$$

④ Plasma signals used in training are shown in the right table.

Plasma parameter	Description
Ip_{error}	(Ip – Ip_programmed)/Ip_programmed, where Ip is the plasma current
β_N	Normalized beta (ratio of plasma pressure to magnetic pressure)
li	Plasma internal inductance
q_{95}	Safety factor at 95% flux surface
GW_{frac}	Ratio of plasma density to Greenwald density limit
W_{MHD}	Plasma energy storage
z_{error}	(z – z_programmed)/a, where z is the vertical position of plasma center, a is the minor radius of the tokamak
kappa	Plasma elongation
Vloop	Plasma loop voltage

2. Training with random forest

① Random forest, which is a decision tree based ensemble machine learning technique is applied to train the prediction model.

② Disruptivity is the output of DPRF represent probability of disruption.

③ Disruptivity is also divided into feature contributions of input signals:

$$\text{Disruptivity} = \text{bias} + \sum_{i=1}^{9} c_i$$

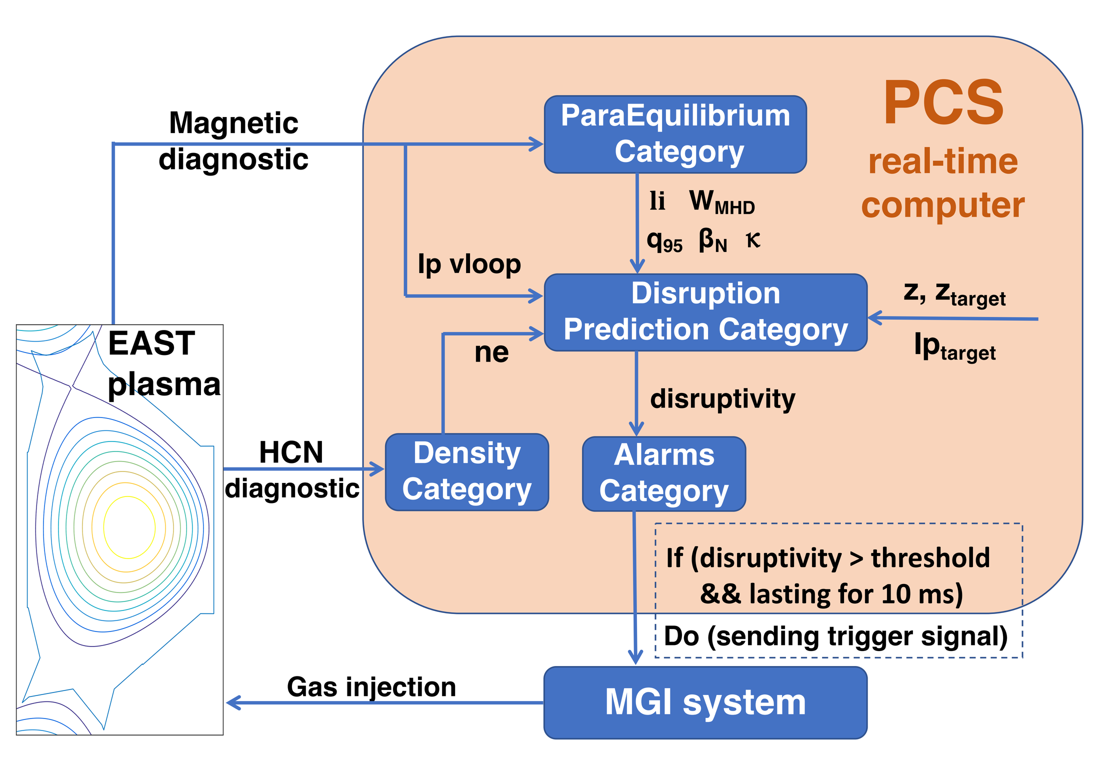
3. PCS implementation

① The trained DPRF algorithm is implemented into PCS system.

② The input signals used by DPRF calculation can be accessed in PCS in real-time with a frequency of 1 kHz

③ Plasma density and current measured by diagnostic and sent to PCS

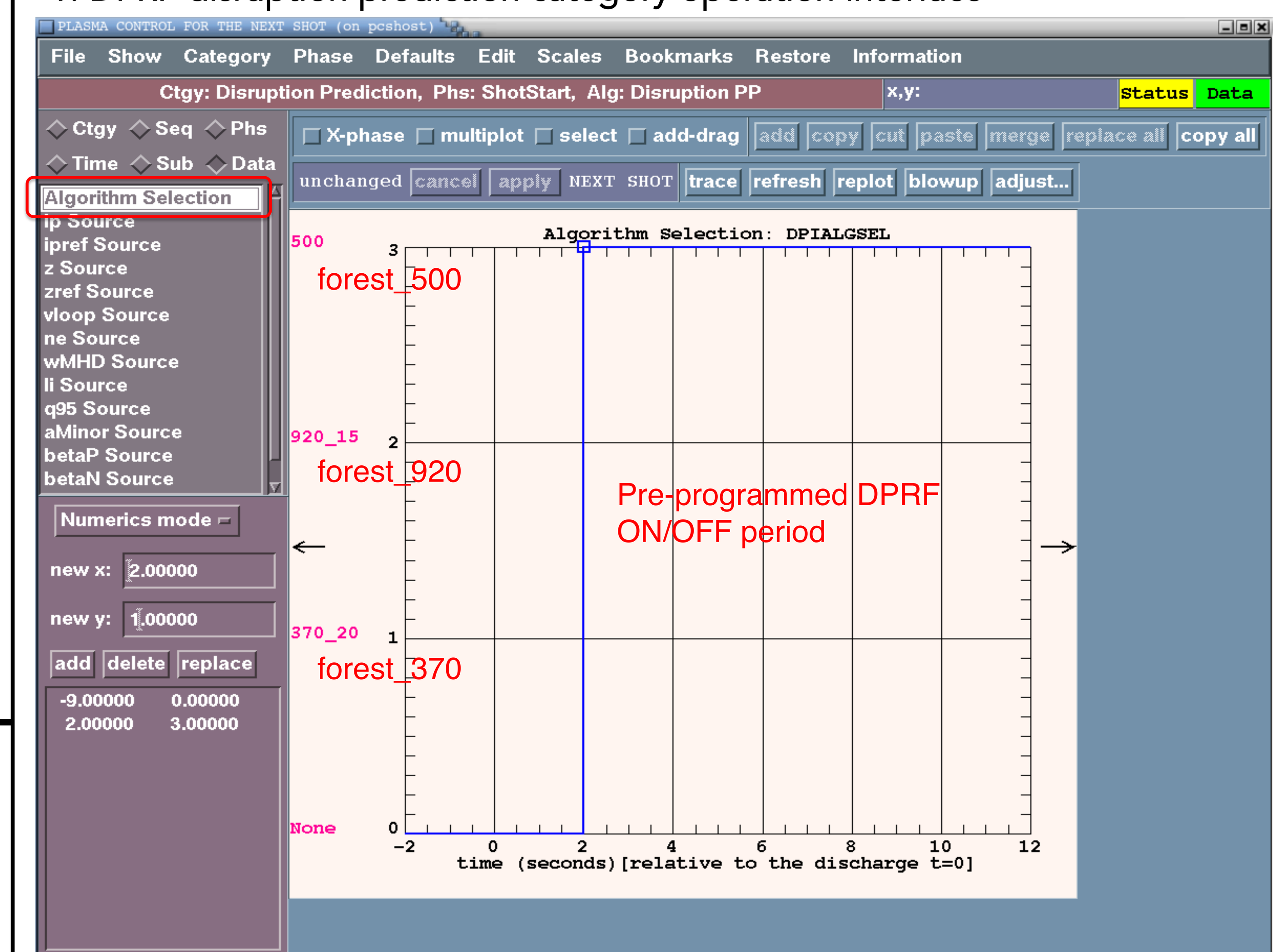
④ Plasma equilibrium parameters are calculated by real-time EFIT [7].



W. Hu, C. Rea et al., in preparation 2020

Results

1. DPRF disruption prediction category operation interface



Four parameters need to be set before DPRF running with plasma discharge for real-time disruption warning:

① Algorithm selection: 3 models are implemented in PCS at present. Before experiment, operator can choose one of them to run.

② Warning threshold setting

③ Alarming time setting. The lasting time of warning before trigger disruption mitigation system, such as MGI and fast ramp down system.

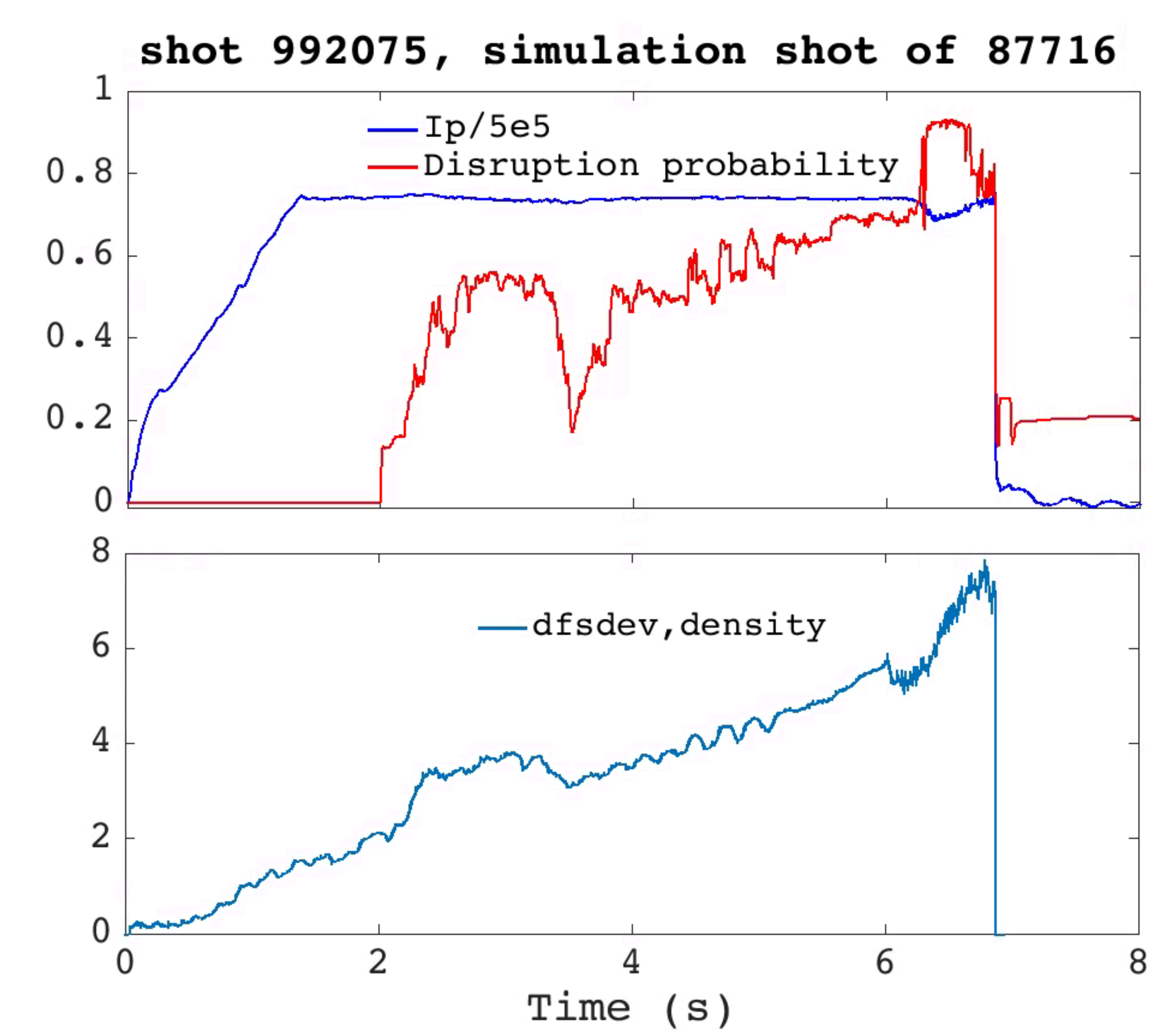
④ DPRF turning on time period.

Example: Algorithm = forest_500
threshold = 0.8
alarming time = 10 ms
turning on from 2 s to end of discharge.

2. Off-line testing

#992075 is a simulation shot that runs off-line before real-time experiments.

As plasma density ramps up, plasma disruption probability (disruptivity) increases and reaches above 0.8 before disruption happens. If setting threshold = 0.8 and warning time = 10 ms, the disruption mitigation system would have been triggered before disruption.



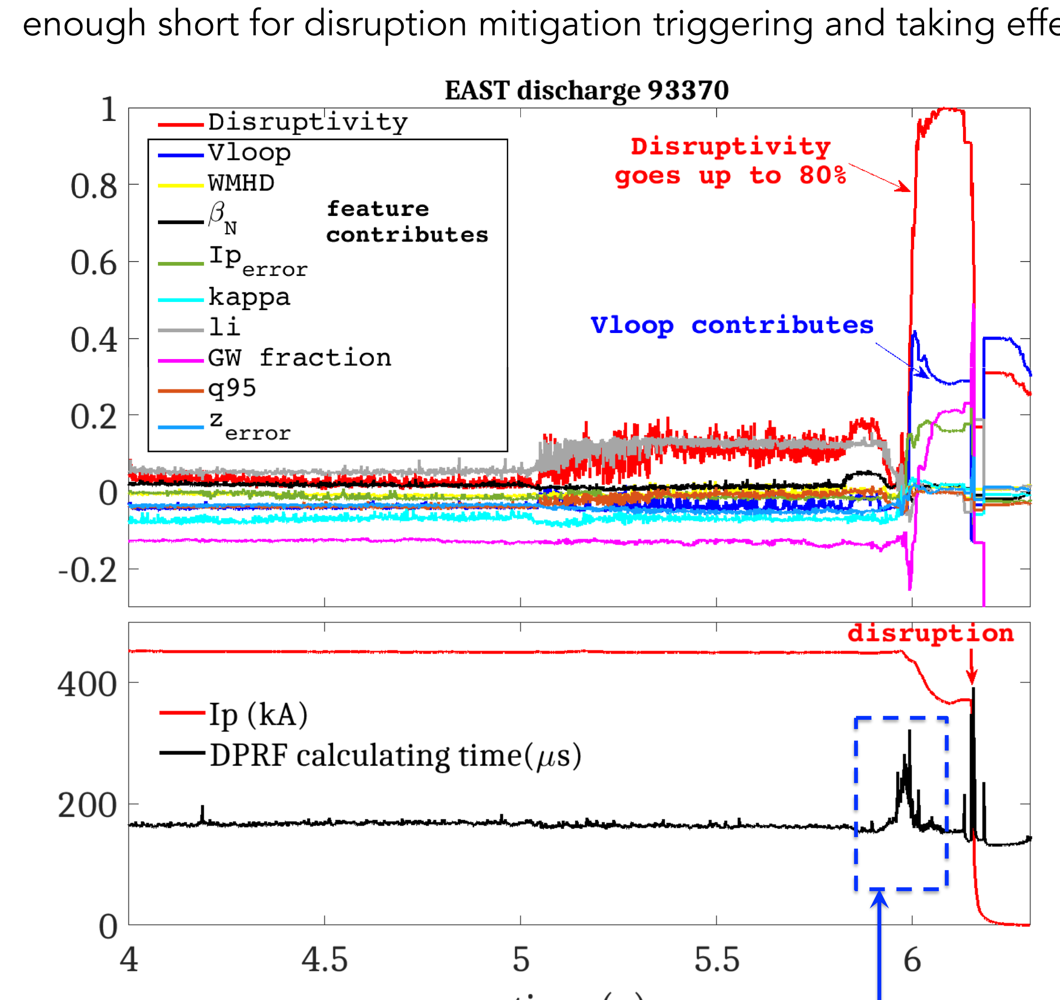
3. Real-time experiment

EAST discharge 93370 is a real time disruption prediction discharge example.

In this discharge, the plasma disrupts at around t = 6.15 s. Disruption probability (disruptivity) rises to 0.8 at around t = 6 s. If setting threshold = 0.8 and warning time = 10 ms, the disruption mitigation system would have been triggered 140 ms before disruption.

The features contributions show that it is the loop voltage (Vloop contributes) that mainly causes the disruptivity to increase.

Besides, DPRF's computing time to calculate the disruptivity, as well as the feature contributions is around $150-300\,\mu s$. This is enough short for disruption mitigation triggering and taking effects.



The spike in the computing time for shot 93370 at around 6 seconds is because the algorithm (DPRF) is non deterministic as it takes more time to navigate different decision paths across different trees in the forest. Usually longer decision paths and therefore spikes in computing time, are associated to more complex data behavior, like anomalous or disruptive behavior.

Conclusions

① A disruption predictor of EAST tokamak plasma is built using a random forest model trained with scalar plasma diagnostic measurement and plasma re-construction equilibrium parameters that can be accessed in real-time from the PCS system.

② The DPRF model is successfully implemented into the real-time plasma control system of EAST. Input signals can be accessed every 1 ms.

③ Successfully testing real-time disruption prediction on EAST PCS. DPRF calculation time after every set of input data is around $150-300\,\mu s$, which is much shorter than 1 ms. This calculation time satisfy the need of real-time disruption warning and mitigation.

Future plan

① Adding plasma density and radiation peaking factor to train the model.

② Test the model in real-time experiments to trigger the fast ramp down system in EAST.

③ Apply other machine learning technique to train disruption predictor.

Literature cited

[1] T. C. Hender *et al.*, "Chapter 3: MHD stability, operational limits and disruptions," *Nucl. Fusion*, vol. 47, no. 6, 2007.

[2] L. Breiman, "Random Forests," *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, 2001.

[3] C. Rea, K. J. Montes, K. G. Erickson, R. S. Granetz, and R. A. Tinguely, "A real-time machine learning-based disruption predictor in DIII-D," *Nucl. Fusion*, vol. 59, no. 9, 2019.

[4] L. L. Lao, H. S. John, R. D. Stambaugh, A. G. Kellman, and W. Pfeiffer, "Reconstruction of current profile parameters and plasma shapes in tokamaks," *Nucl. Fusion*, vol. 25, no. 11, pp. 1611–1622, 1985.

[5] Greenwald M. Density limits in toroidal plasmas[J]. Plasma Physics and Controlled Fusion, 2002, 44(8): R27.

[6] Zheng X, Li J, Hu J, et al. Density limits investigation and high density operation in EAST tokamak[J]. Plasma Physics and Controlled Fusion, 2016, 58(5): 055013.

[7] Huang Y, Xiao B J, Luo Z P, et al. Implementation of GPU parallel equilibrium reconstruction for plasma control in EAST[J]. Fusion Engineering and Design, 2016, 112: 1019-1024.

Acknowledgments

This work is supported by the National Key R&D Program of China (Grant No: 2018YFE0302100) and President Foundation of Hefei Institutes of Physical Science of Chinese Academy of Sciences (Grant No: YZJJ2020QN11) and the U.S. DOE Office of Science under Awards DE-FC02-04ER54698, DE-C0014264 and DE-AC02-09CH11466.