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Avoidance control of high-density collapse based on data-driven prediction in Large Helical Device

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Contents

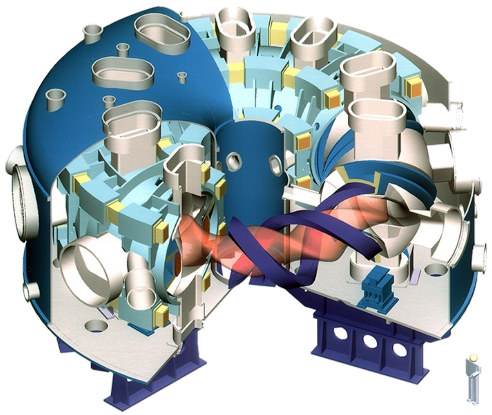
Introduction: collapses in stellarator-heliotron plasmas

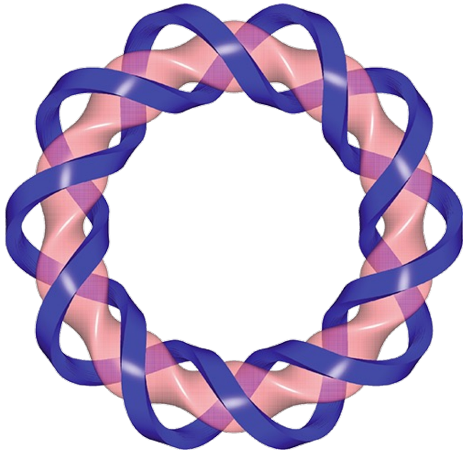
Radiative collapse and density limit in stellarator-heliotron plasmas

- Improvement of density limit is necessary to realize fusion reactor.
- Radiative collapse is the major termination event that limit operational density in stellarator-heliotron plasmas.
  - Sudo scaling is one of the best-known scaling laws of density limit. [Sudo et al., 1990]
  - Theoretical analyses show the impurity radiation loss is important in radiative collapse.
    [K.Itoh et al., JPSJ(2001) and Zanca et al., NF(2019)]
- Prediction and avoidance of radiative collapse are necessary for high-density operation.

Large Helical Device (LHD)

- LHD is the largest superconducting helical device which started operation in 1998 in Toki (Japan).
- In this study, radiative collapses in density ramp-up experiment in LHD have been considered.



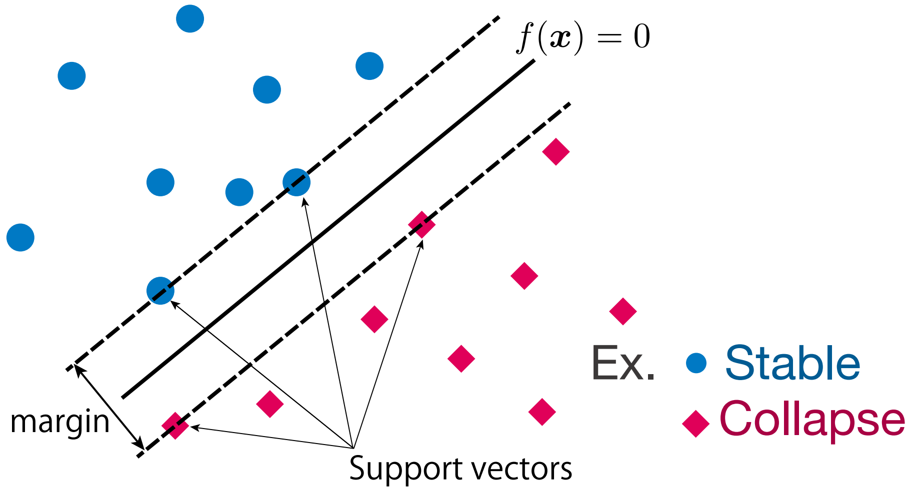


[https://www-lhd.nifs.ac.jp/]

Introduction: data-driven study on radiative collapse

Radiative collapse predictor using machine learning

- Aim to give a criteria to avoid radiative collapse.
- Classify stable and close-to-collapse data using support vector machine (SVM) based on high density experiment data in LHD.



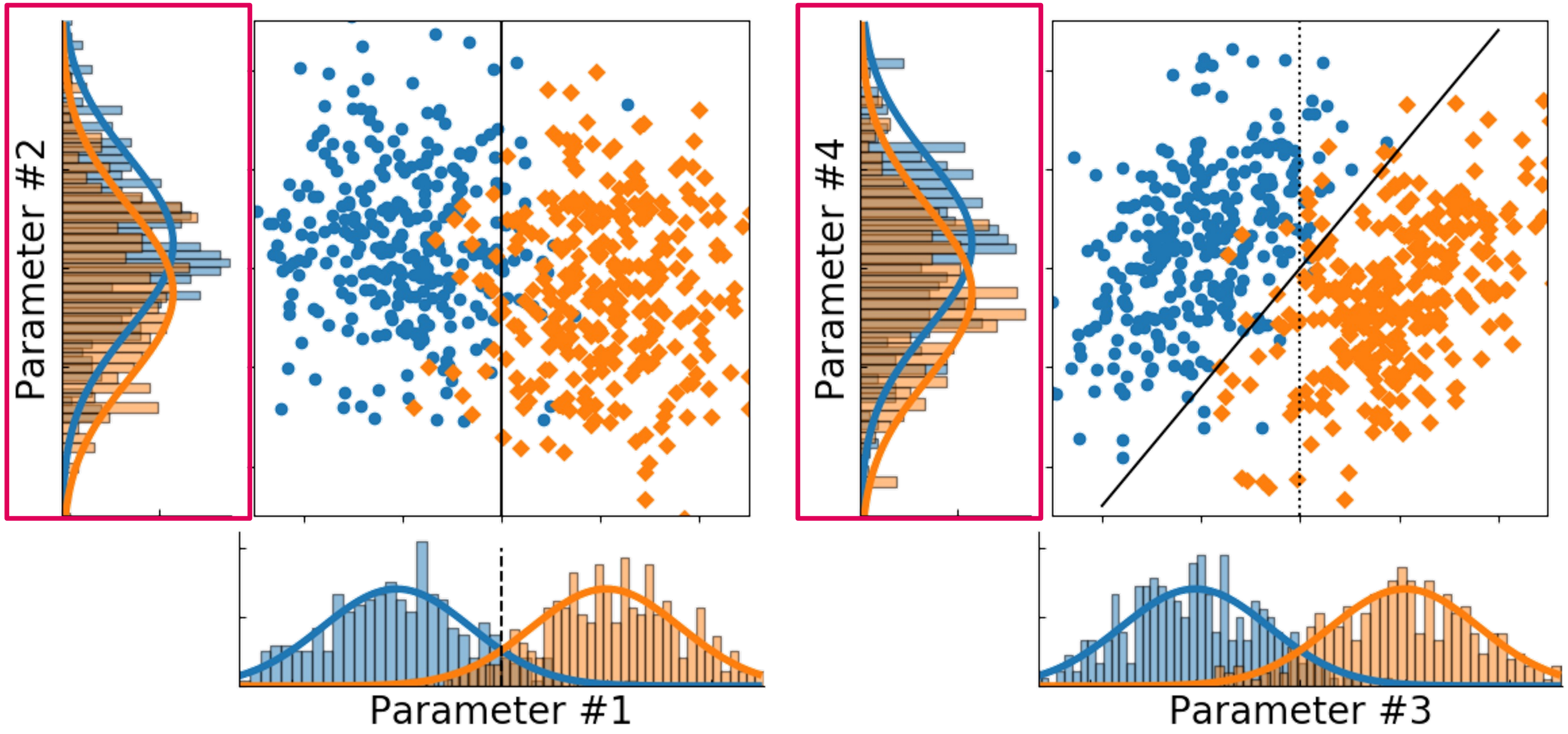
Feature extraction of radiative collapse

- Aim to develop new density limit scaling and understand physical background of occurrence of radiative collapse.
- Exhaustive search, which is one of sparse modeling techniques, has been used to select optimal combination of input parameters.
  - It was shown that selecting optimal input parameter can improve performance of classifier in disruption prediction. [Yokoyama et al., FED(2019)]

Introduction of sparse modeling #1

A framework of data-driven science

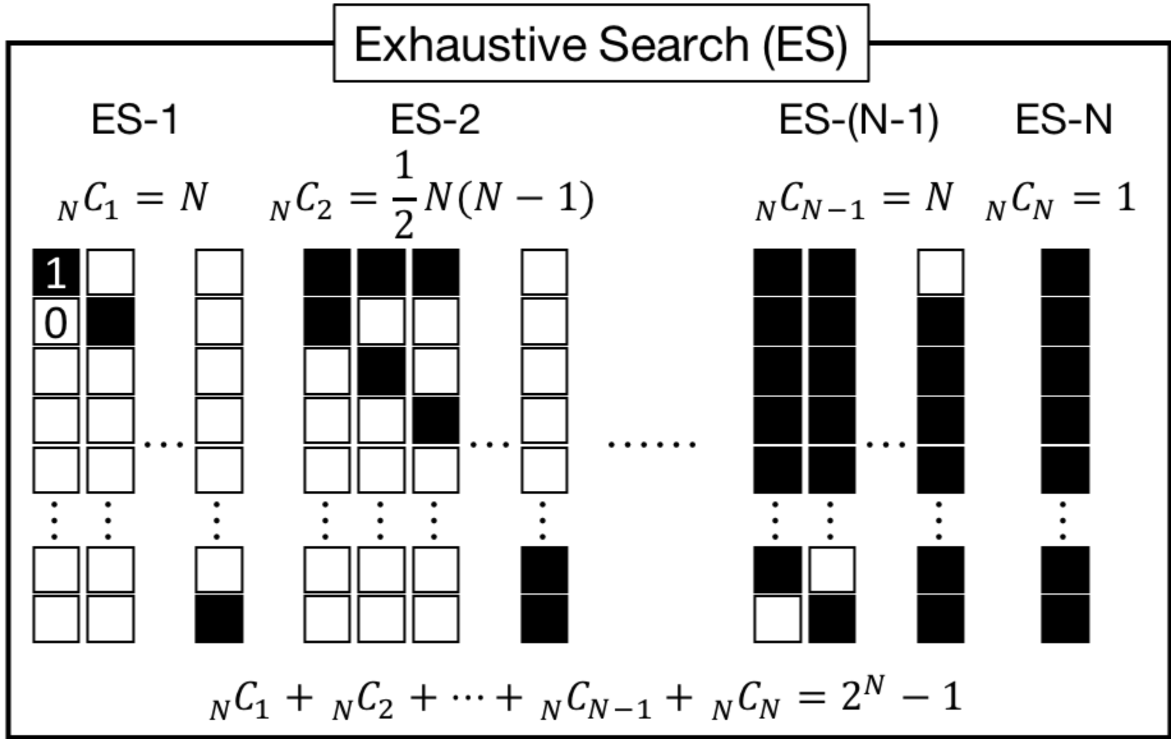
- Exploits the inherent sparseness in high-dimensional data.
- Extracts the maximum information from data effectively.



Introduction of sparse modeling #2

Parameter selection in classification problem

- Consideration of not only individual distributions but also the effect of parameter combinations is necessary.
- Exhaustive Search (ES) has been used.
  - In ES, all possible combinations of parameters are compared to find out the optimal combination.
  - Parameters are selected considering the effect of parameter combinations.



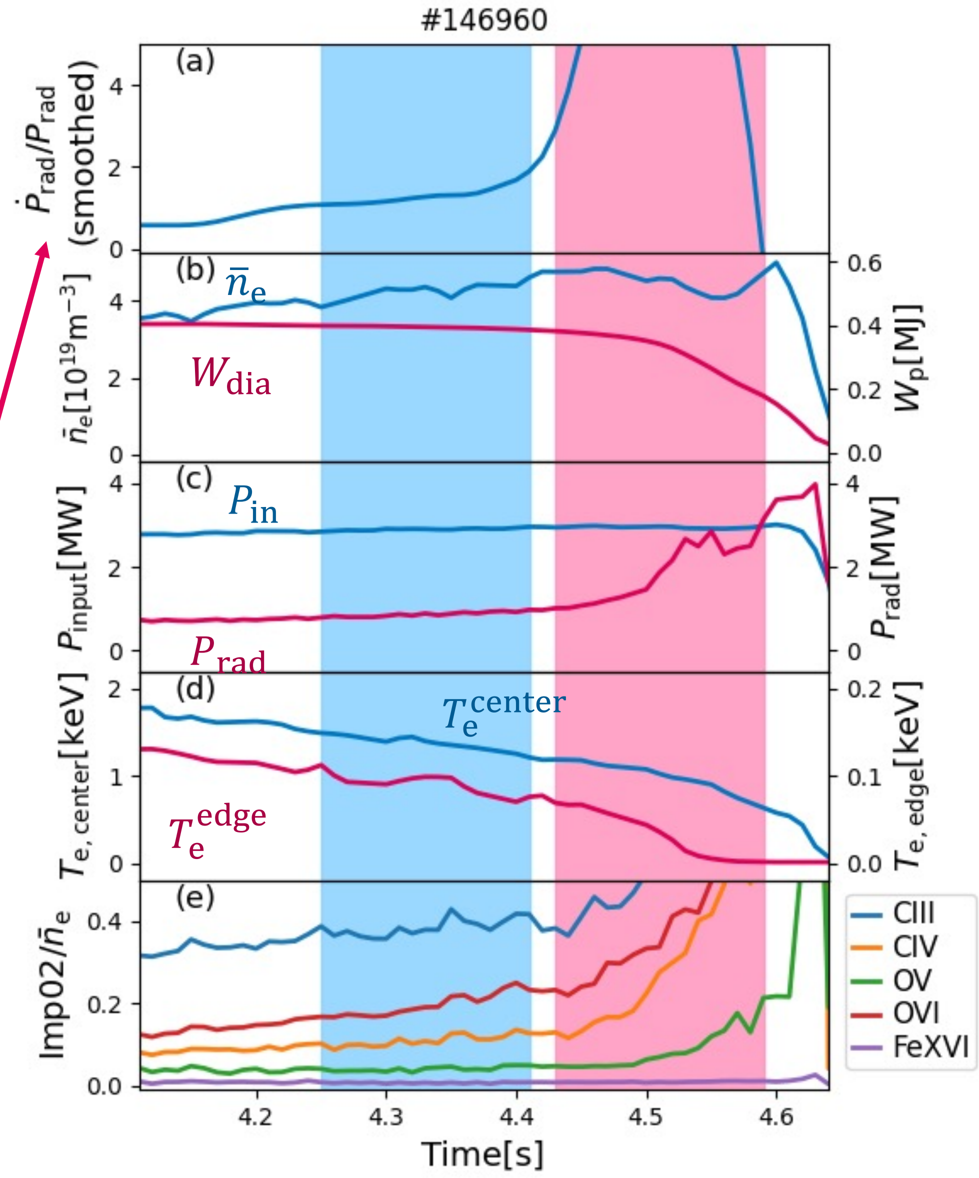
Construction of dataset

Radiative collapse data

- High density experiment in LHD
- Experiment conditions
  - Hydrogen and deuterium plasma
  - Density ramp-up by gas puff fueling
  - High and low magnetic field
  - Changing NBI heating power

Preprocessing

- Labeling according to $\dot{P}_{\mathrm{rad}}/P_{\mathrm{rad}}$
  - Close-to-collapse: $\dot{P}_{\mathrm{rad}}/P_{\mathrm{rad}} > 2.5$
  - Stable (far from collapse): $\dot{P}_{\mathrm{rad}}/P_{\mathrm{rad}} < 2$
- Min-max normalization
- Taking logarithms of the dataset



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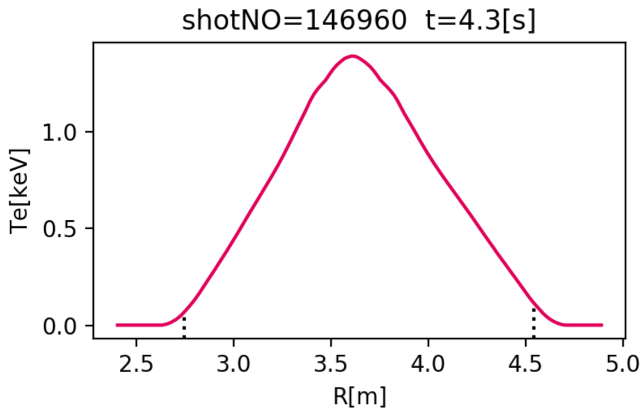
Candidate parameters

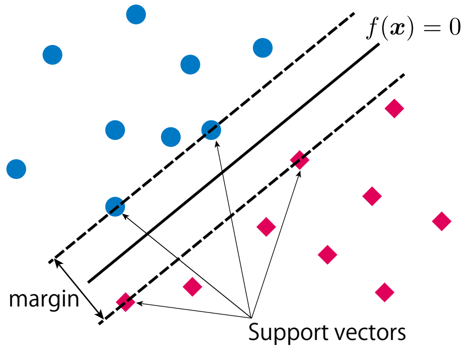
- Global parameters
  - $\bar{n}_{\mathrm{e}}$, B_{t}, β_{dia}, a_{99}, Δ_{sh}, and $\mathrm{D/(D+H)}$
- Input and radiation power
  - Absorbed heating power P_{abs}
  - P_{rad} normalized by P_{abs}
- Ion saturation current at divertor $I_{\mathrm{sat}}^{\mathrm{7L}}$
- Impurity line emissions normalized by $\bar{n}_{\mathrm{e}}$
  - CIII, CIV, OV, OVI, and FeXVI
- Electron temperature at last closed flux surface (LCFS) at vacuum $T_{\mathrm{e,edge}}$



Results of feature extraction

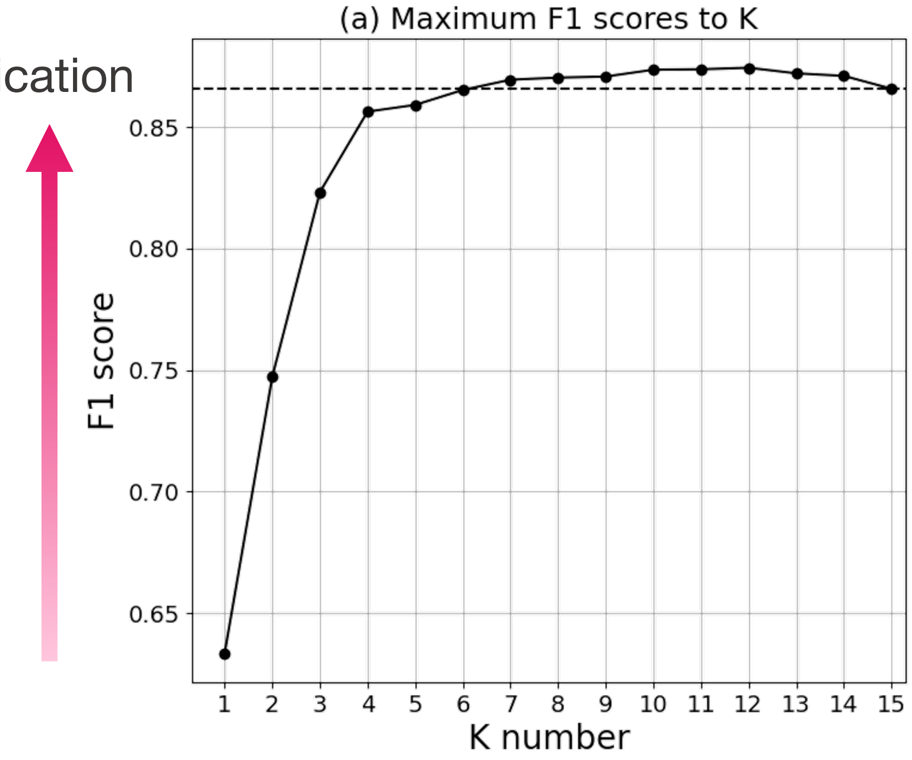
Summary of ES results

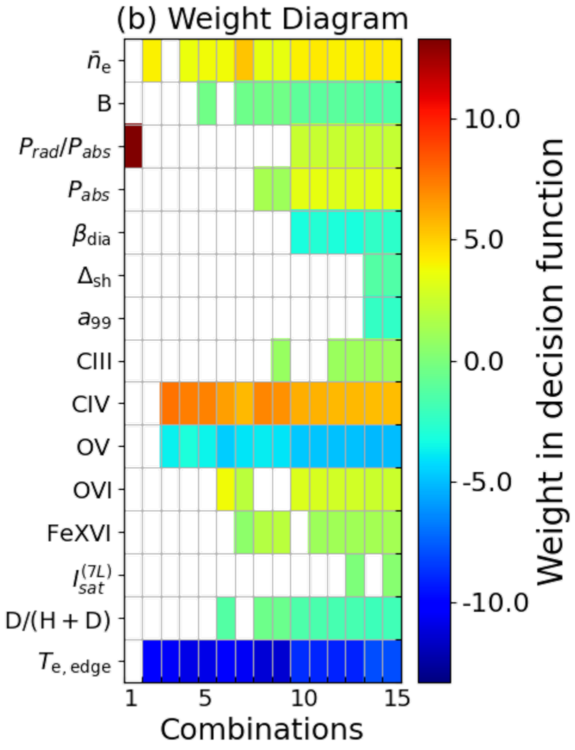
- The performance of classification was maximized with few parameters
- Some parameters are included in common around K=6



$f(\boldsymbol{x}) = \boldsymbol{w} \cdot \boldsymbol{x} + b$

Better classification

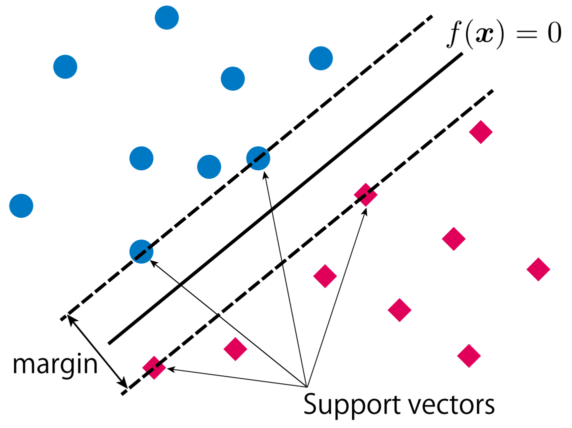




Results of feature extraction

Result of ES-5-SVM

- Extracted parameters: $\bar{n}_{\mathrm{e}}$, CIV, OV, and $T_{\mathrm{e,edge}}$
  - Combination of those parameters is important to predict collapse
- Decision boundary: $1 = \exp(-5.89)\, \bar{n}_{\mathrm{e}}^{0.864} \mathrm{CIV}^{0.995} \mathrm{OV}^{-0.395} T_{\mathrm{e,edge}}^{-1.85}$



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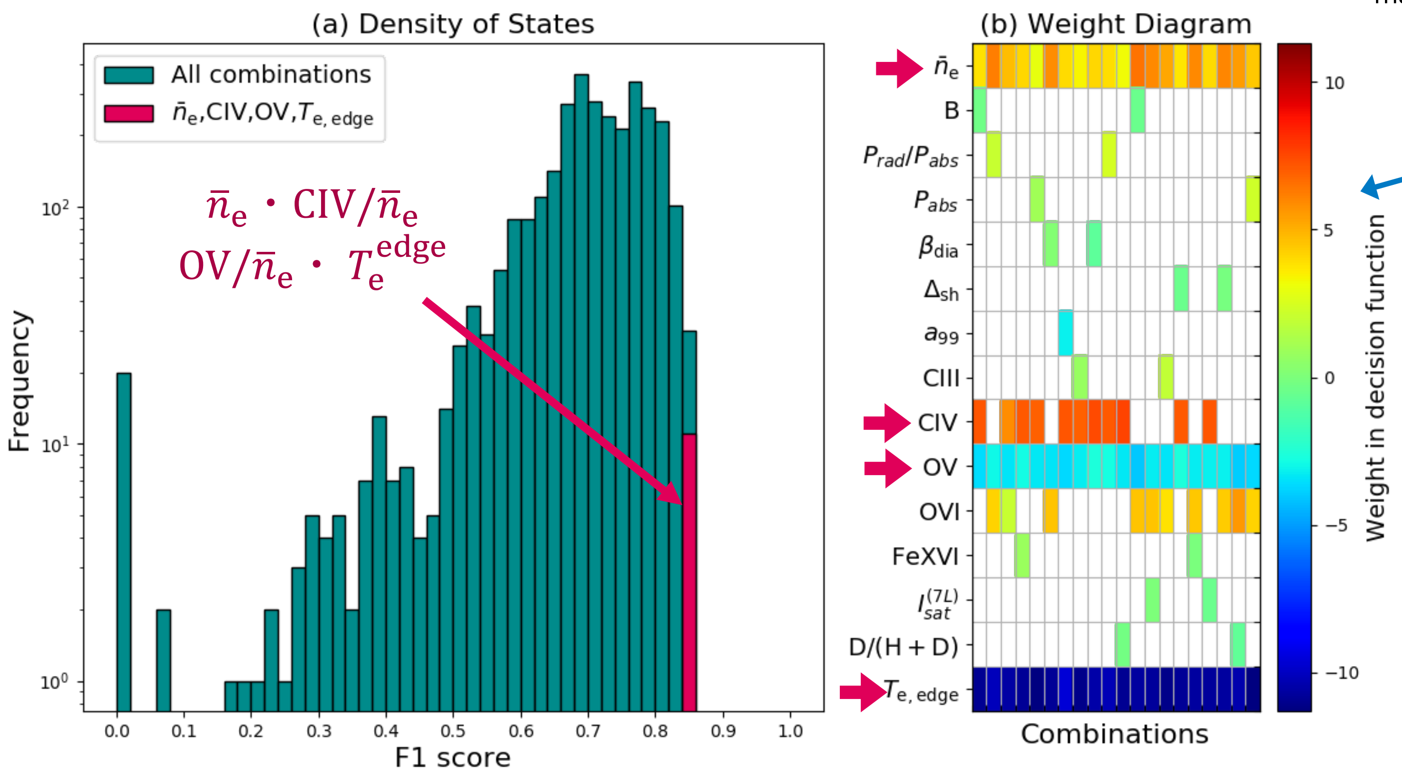
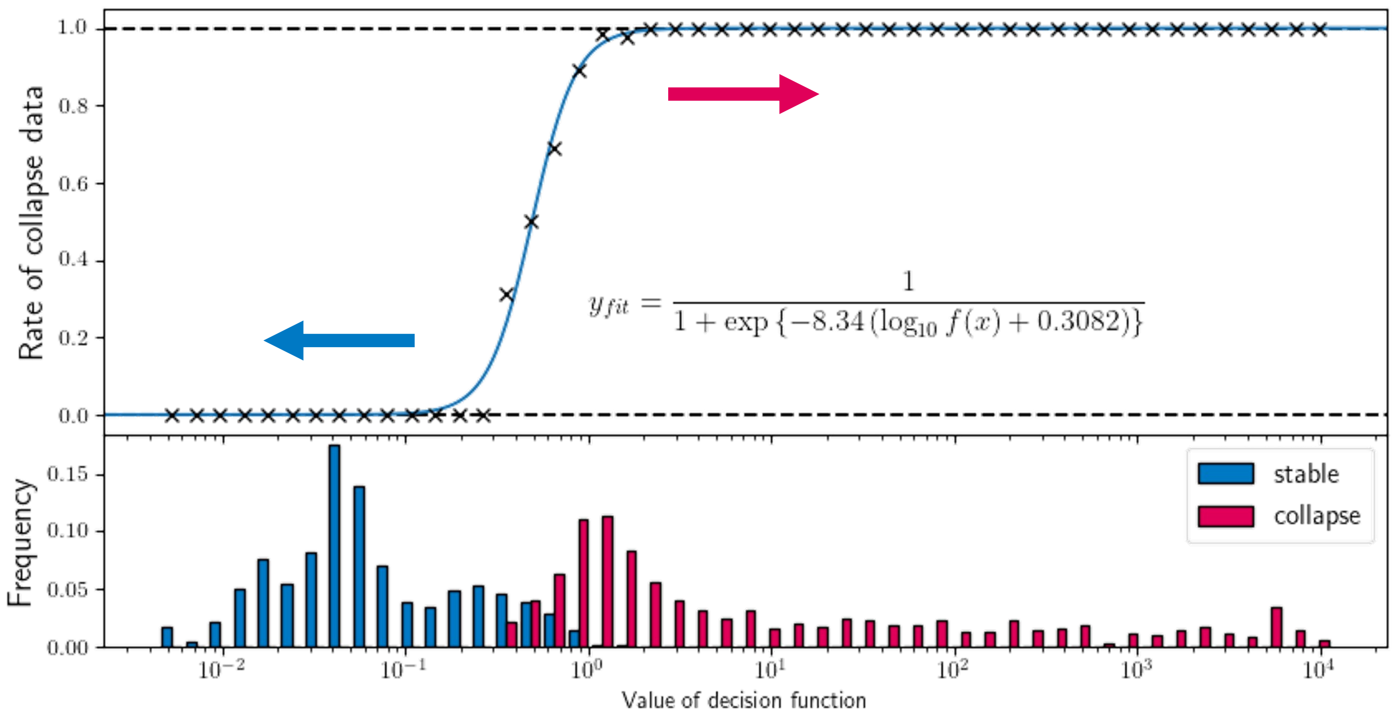


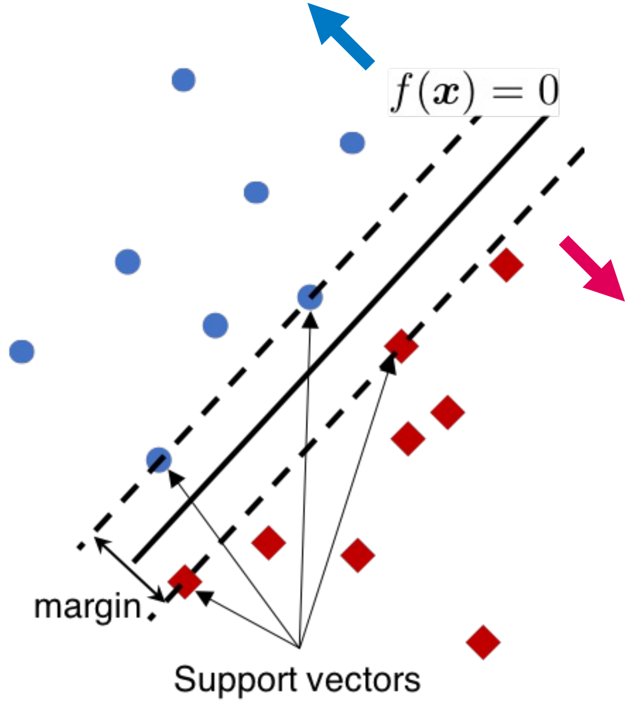
Collapse likelihood #1

Calculation of collapse likelihood

- Calculated using extracted parameters ($\bar{n}_\mathrm{e}$, CIV, OV, and T_e@edge).
- Corresponding to the distance from the boundary.

$$1 = \exp(-5.89)\ \bar{n}_\mathrm{e}^{0.864}\mathrm{CIV}^{0.995}\mathrm{OV}^{-0.395}T_{\mathrm{e,edge}}^{-1.85}$$





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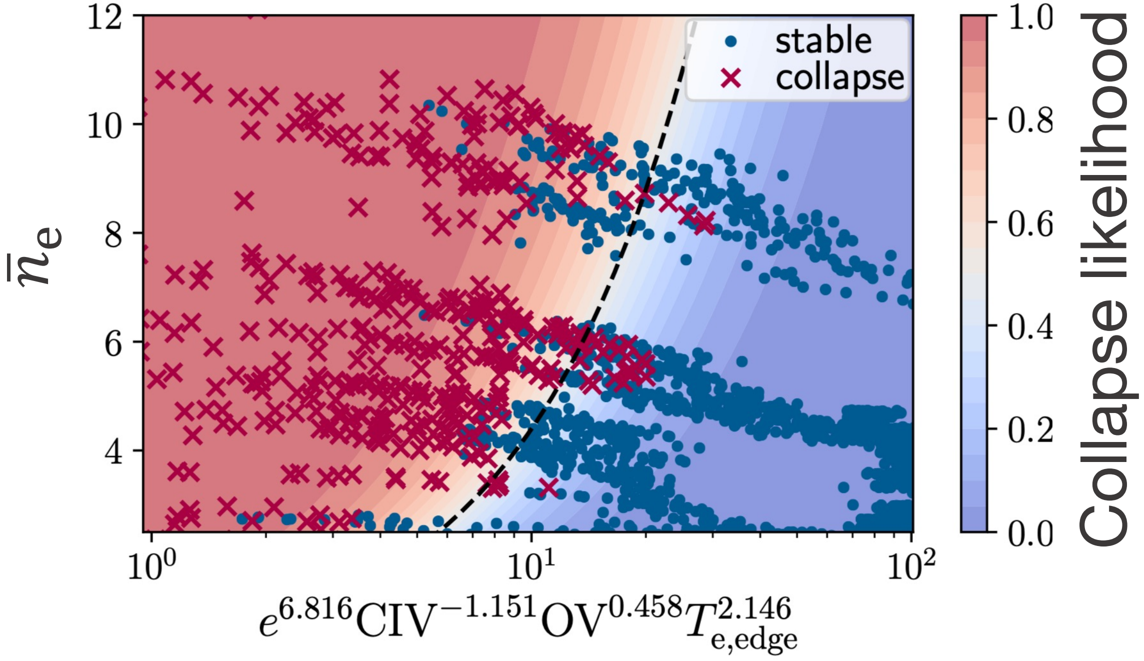
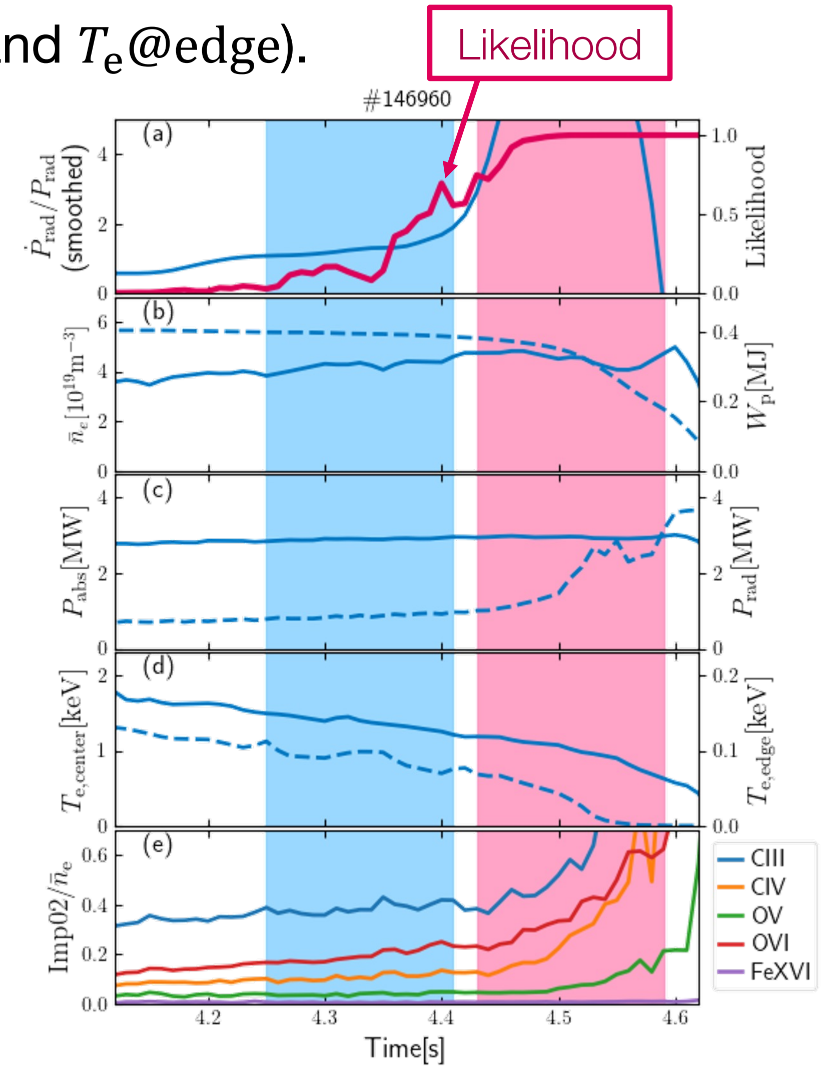
- Operational region has been expressed using collapse likelihood





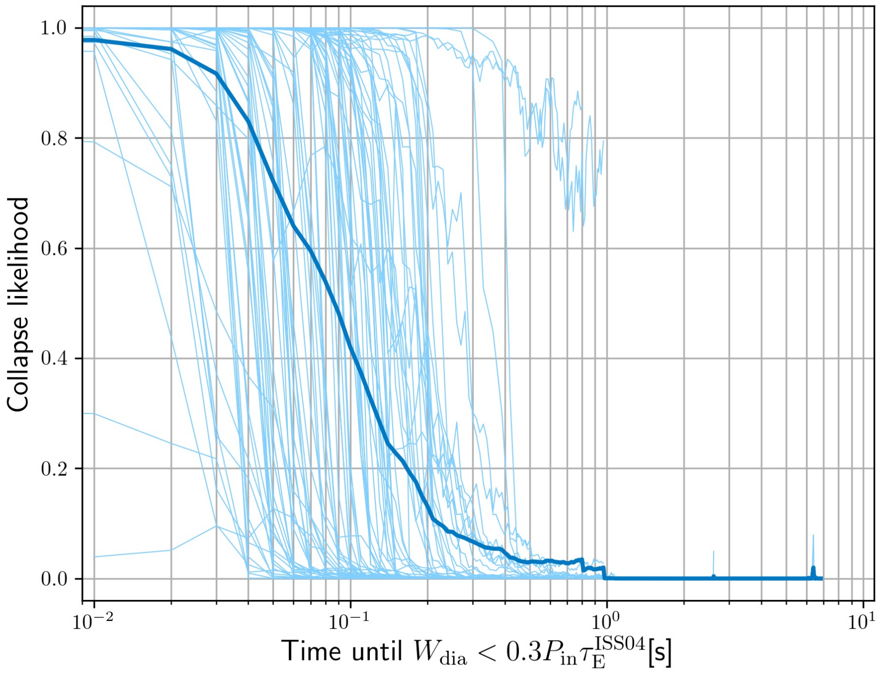
Predictor model using collapse likelihood

Validation of predictor model

- The model has been validated using discharges outside the training dataset.
  - Magnetic configuration is the same as the dataset.
  - No impurity pellet is injected during the discharge.
- 91 collapse discharges and 444 stable discharges has been considered.

Result of validation

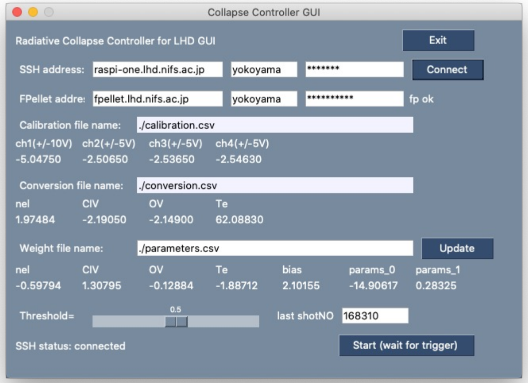
- In most collapse discharges, collapse likelihood was raised by time and reached about 0.9 just before the collapse
- About over 85% of collapses are predicted before occurrence (> 30ms) successfully.
- False alarms are 5-10% of stable discharges.

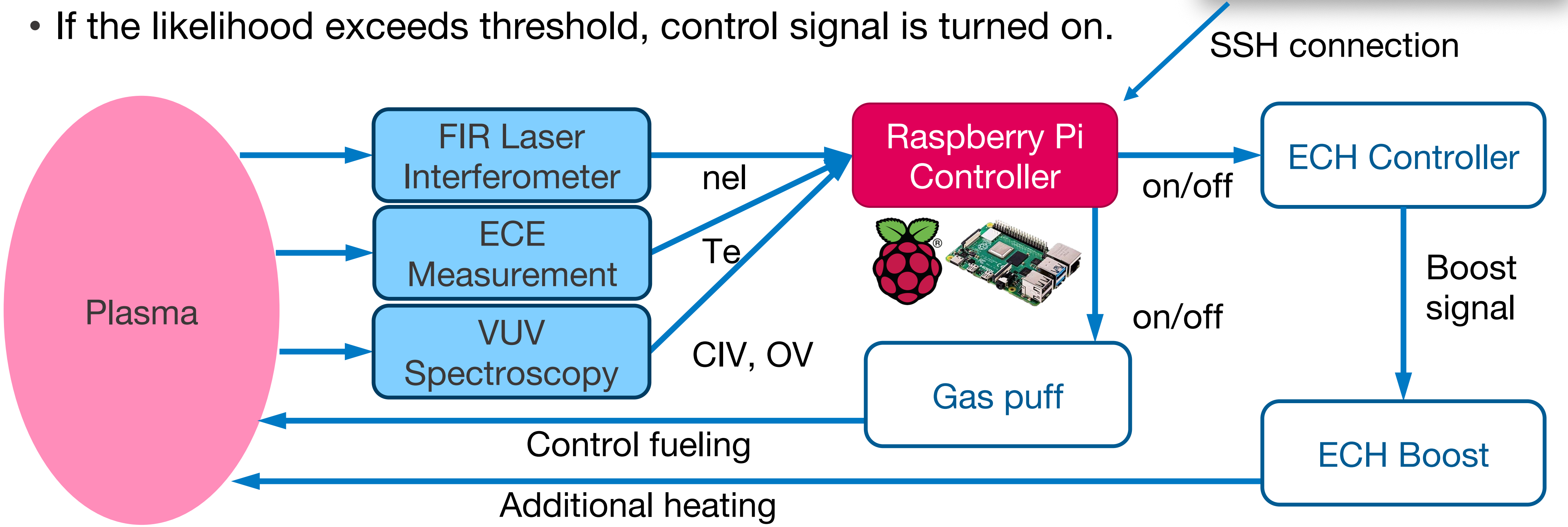


Feedback control experiment to avoid collapse #1

Overview of feedback control system

- Input: $n_e L$ (FIR), T_e (ECE), CIV and OV (VUV spectroscopy)
- Actuators: 1. Electron cyclotron heating (ECH) boost injection
  2. Turning off gas-puff fueling
- Collapse likelihood is calculated in real time by Raspberry Pi.
- If the likelihood exceeds threshold, control signal is turned on.

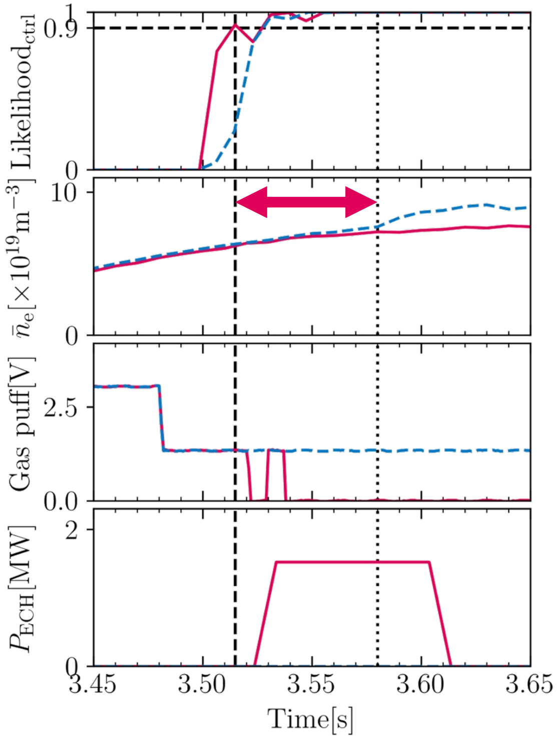


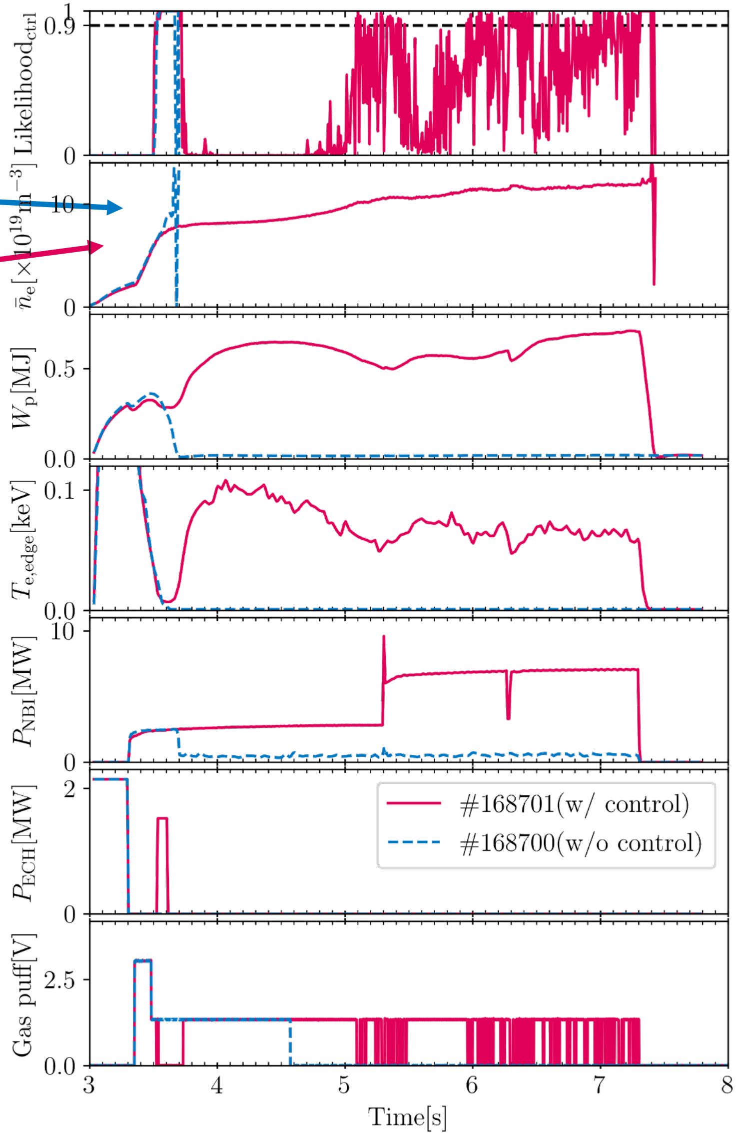


Feedback control experiment to avoid collapse #2

Density ramp-up in H plasma

- Discharge without control
  - Radiative collapse occurred in the early phase of ramp up.
- Discharge with control
  - Collapse in early phase was avoided.
  - The collapse was detected about 65ms before occurrence.
  - Density developed without collapse up to $\bar{n}_e > 1.2\times10^{20}[\mathrm{m}^{-3}]$.

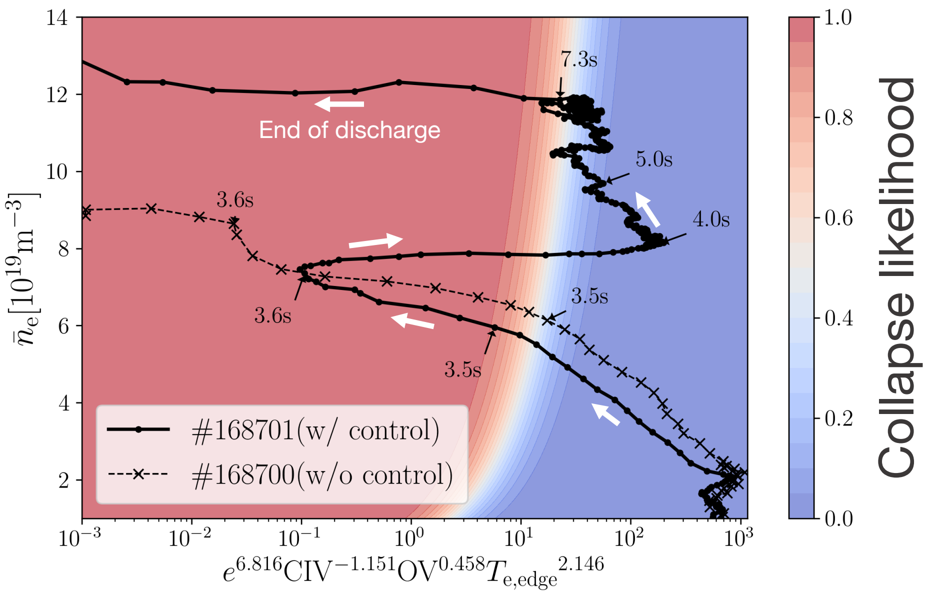


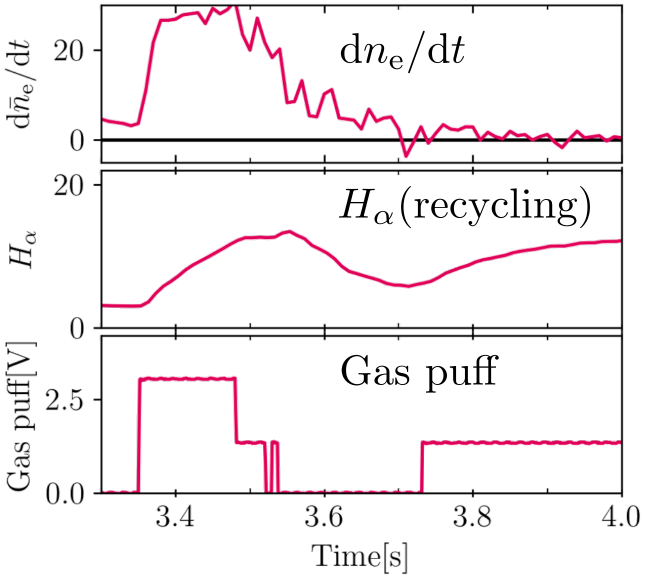


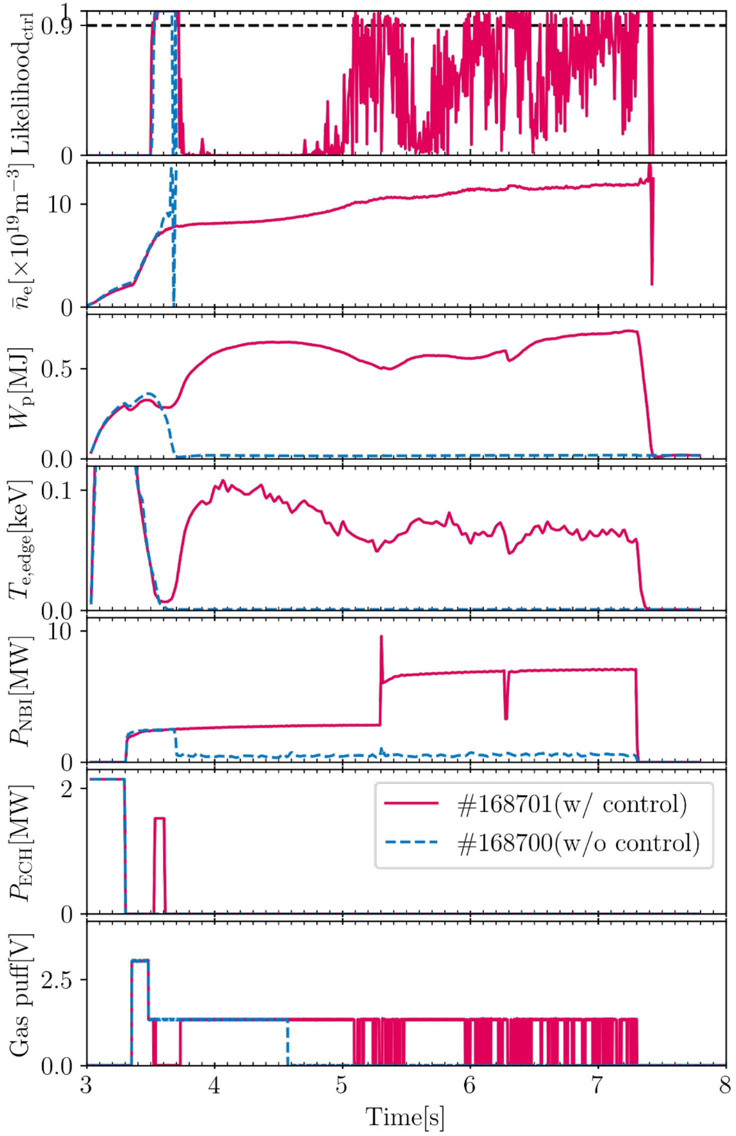
Feedback control experiment to avoid collapse #3

Plasma state and operational region

- When avoiding the collapse,
  it was observed that the plasma returned
  from the unstable region to stable region.
- While recovering from unstable state,
  plasma density kept increasing since the recycling existed.







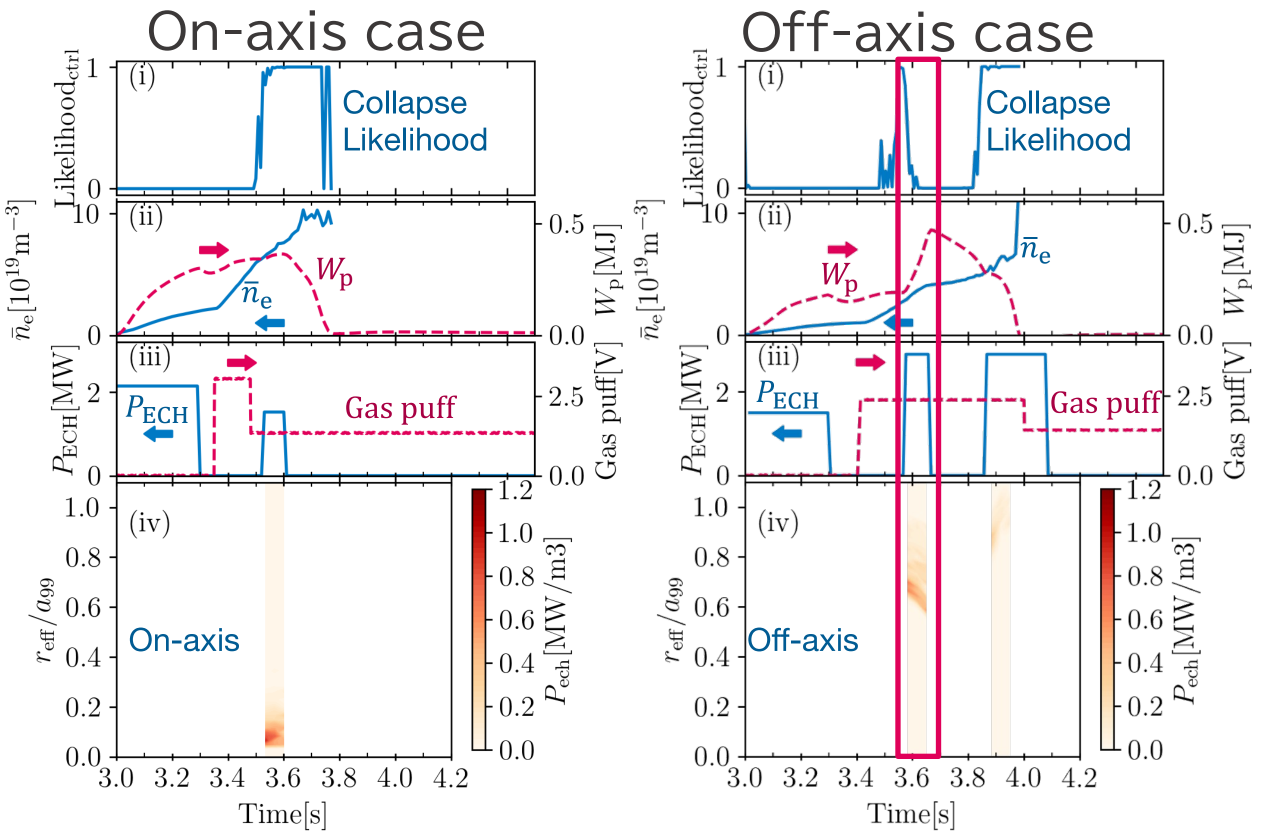
Collapse avoidance with only ECH boost

Motivation

- Collapse could not be avoided only with on-axis boost ECH
- According to the extracted feature (CIV, OV), the power balance at plasma edge may be important
- Off axis ECH has been used to heat edge region effectively

Off-axis ECH experiment

- In low-density case, collapse was avoided only with off-axis boost ECH
- After density became higher, collapse was not avoided
- Possibility to avoid collapse only with off-axis ECH was shown.



Conclusion

Data-driven approach on collapses in fusion plasma

- In high-performance plasma, collapses are likely to occur and limit plasma performance.
- Data-driven prediction and avoidance of collapses are necessary.

Data-driven control to avoid radiative collapse in LHD

- Collapse likelihood has been estimated quantitatively by means of data-driven method.
  - The feature parameters used to estimate the likelihood has been extracted by sparse modeling
  - When the plasma approaches collapse, the likelihood increases.
- The real-time collapse avoidance control system has been developed and applied to avoid density ramp-up experiment in LHD.
  - If the likelihood exceeds the threshold, fueling is regulated and additional heating is injected.
  - The plasma behavior while avoiding the collapse has been discussed and the attenuation of inward pinch effect has been observed.
  - Possibility to avoid radiative collapse by off-axis ECH was shown.