Characterization and sparse modeling of radiation collapse and density limit in LHD

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Abstract

- Likelihood of occurrence of radiative collapse has been estimated in Large Helical Device (LHD) by machine learning techniques.
- The likelihood has been estimated with four feature parameters selected by sparse modeling: $\bar{n}_{\rm e}$, $\rm CIV$, $\rm OV$, and $T_{\rm e,edge}$.
- Radiation collapse avoidance control system has been developed based on the collapse likelihood.
- Radiative collapse has been avoided in high-density hydrogen plasma by the control system successfully.

Background

Prediction and avoidance of radiative collapse

- Radiative collapse is one of the major cause of plasma termination in stellarator-heliotron plasma and limits plasma density.
- Prediction and avoidance of radiative collapse are important to improve operational density limit[1].

Purpose of this study

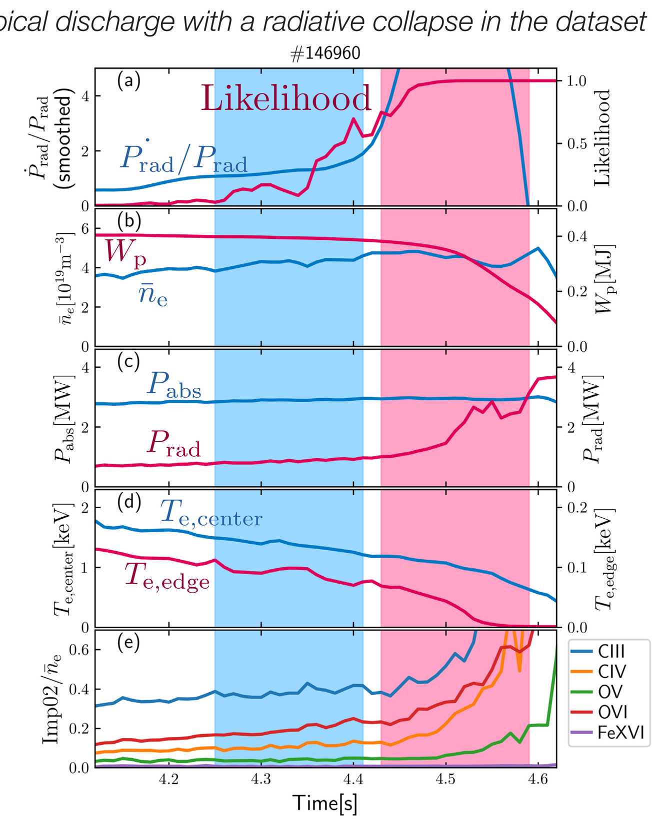
- Development of the predictor of radiative collapse
  - Classify "close-to-collapse" state and "stable" state by support vector machine (SVM), which is one of machine learning models.
  - The classifier model is trained based on high-density experiment data in LHD.
- Optimization of the input plasma parameters by sparse modeling[2]
- Development of a control system to avoid radiative collapse
  - The control system is applied to the LHD experiment.

Method

Training SVM classifier

- SVM has been used as binary classifier.
- Dataset has been constructed based on high-density experiment in LHD.
  - Gas-puff fueling and NBI heating has been used in these experiments
  - The data has been labeled as either "stable" or "close-to-collapse".
- Pre-processing of training:
  - Taking logarithms of dataset
  - Min-max normalization

Typical discharge with a radiative collapse in the dataset



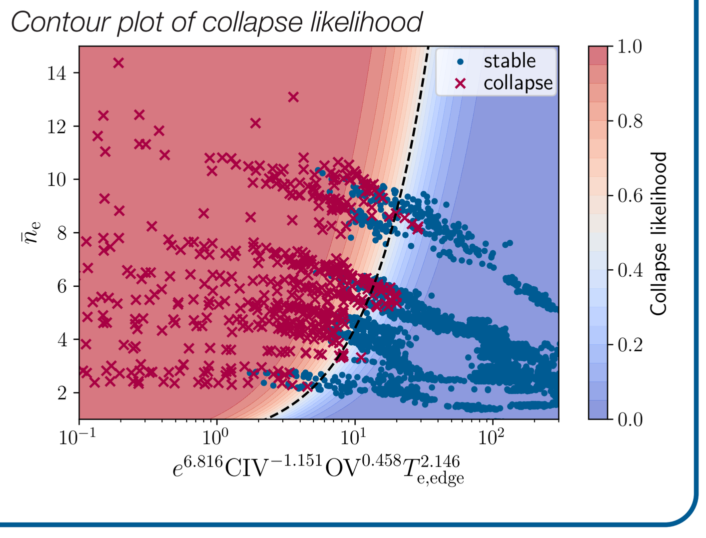
Parameters used in the dataset

Expression	Explanation
$\bar{n}_{\rm e}$	Line averaged electron density
$B_{\rm t}$	Troidal magnetic field at axis
$D/(D+H)$	Ratio of D ion to the sum of H and D ions
$P_{\rm abs}$	Absobed input power
$P_{\rm rad}/P_{\rm abs}$	Normalized radiation power
$\beta_{\rm dia}$	Beta estimated from diamagnetic energy
$\Delta_{\rm sh}$, a_{99}	Plasma shape parameters
CIII, CIV, OV, OVI, FeXVI	Impurity line intensity normalized by $\bar{n}_{\rm e}$
$I_{\rm sat}^{\rm 7L}$	Ion saturation current
$T_{\rm e,edge}$	Electron temperature at LCFS at vacuum

Quantification of collapse likelihood

- Feature of radiative collapse has been extracted by sparse modeling
  - Sparse modeling enables us to extract information from high-dimensional data by taking advantage of the inherent sparseness.
  - Extracted parameters: $\bar{n}_{\rm e}$, $\rm CIV$, $\rm OV$, and $T_{\rm e,edge}$
- Collapse likelihood has been quantified as the distance from boundray between "stable" or "close-to-collapse" classes.

Contour plot of collapse likelihood



Collapse avoidance in LHD

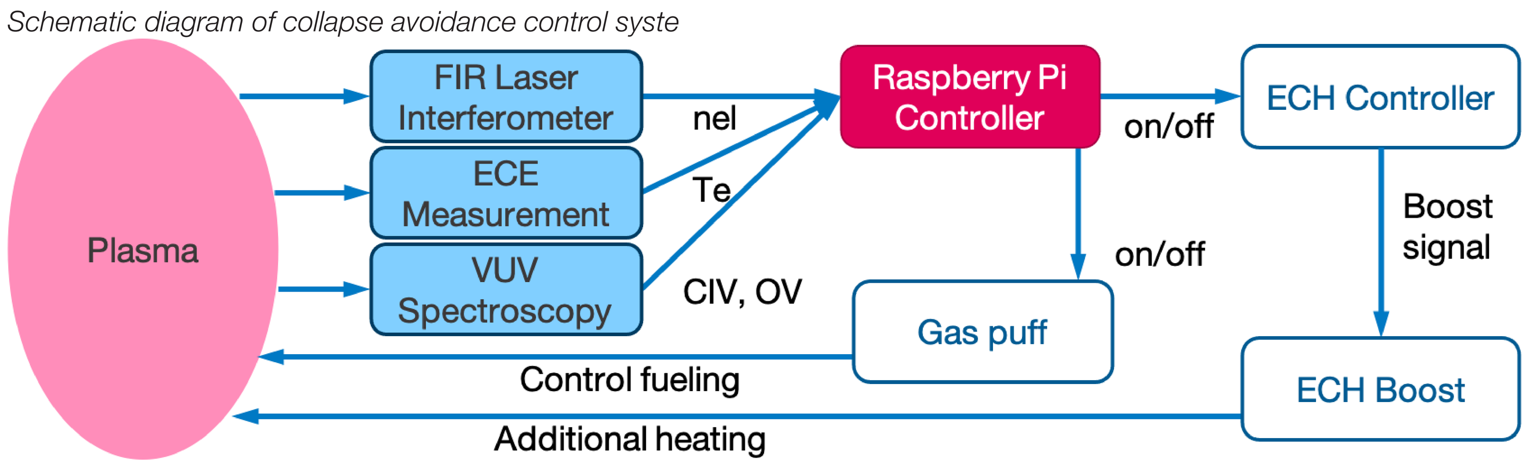
Validation of predictor model based on collapse likelihood[3]

- The predictor model has been validated with 535 discharges in LHD other than included in the dataset.
- In about 85% of collapse discharges, collapses has been predicted over 30 ms before they occur.
- False alarms are 5-10% of stable discharges.

Collapse avoidance control system

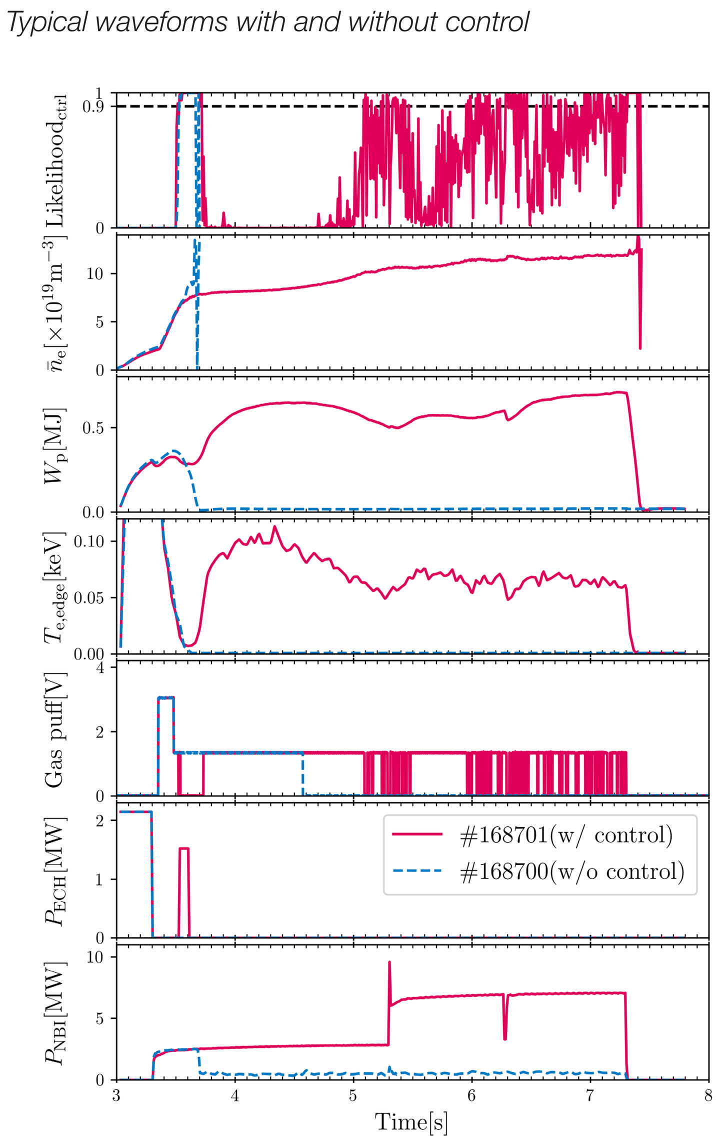
- A real-time control system to avoid radiative collapse has been developed based on the predictor model.
- When the likelihood exceeds threshold, gas puff is turned off and/or the electron cyclotron resonance heating (ECRH)[4] is turned on.
  - A single board computer (Raspberry Pi) calculates has been used to calculate the collapse likelihood in real-time.
  - For real-time control, $T_{\rm e,edge}$ has been replaced by $T_{\rm e}$ measured by electron cyclotron emission (ECE) measurement.

Schematic diagram of collapse avoidance control syste



Collapse avoidance control system

Typical waveforms with and without control



- The control system was applied to density ramp-up experiment with NBI heated hydrogen plasma in LHD.
- W/O control :
  - Radiative collapse occurred in the early phase of ramp up.
- With control :
  - Collapse in early phase was avoided.
  - $\bar{n}_{\rm e}$ was developed without collapse up to $\bar{n}_{\rm e} \sim 1.3 \times 10^{20} [{\rm m}^3]$.
  - The control system was turned on about 60 ms before the early phase collapse occurred.
  - In latter phase, collapse was avoided only by turning gas puff on/off.
- The control system was also applied to long-pulse (about 30 s) helium discharges in LHD.
  - The system detected the collapses, but it was too late to avoid it.
  - Control of fueling rate in helium plasma is generally difficult due to high recycling of helium.

Conclusion

- The result of data-driven approach to radiative collapse has been applied to plasma experiment in LHD.
- Radiative collapse was successfully avoided by the control system.
- The likelihood will be updated with data in helium discharges.
- Understanding of physical background of radiative collapse based on the likelihood is in progress[5].

Acknowledgements

This work is supported by the National Institute for Fusion Science grant administrative budgets NIFS18KLPP051, and JSPS KAKENHI Grant Numbers JP19J20641 and JP19H05498.

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