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Feature extraction and prediction of radiative collapse in Large Helical Device using sparse modeling

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The feature of radiative collapse has been extracted from high-density plasma experiments in Large Helical Device (LHD) with a sparse modeling technique. The extracted features have been used to explore the underlying physics of the radiative collapse and to develop a machine learning predictor of the collapse.

In stellarator-heliotron plasma, radiative collapse is one of the most critical issues that limits the operational density. The Sudo scaling is known well as the scaling law of density limit, which suggests that the balance between heating power and radiative power loss is a key together with robust confinement capability such as plasma volume and magnetic field[1]. However, contribution of other operational conditions to the occurrence of radiative collapse are hidden behind the expression of the Sudo scaling, such as impurity contamination and wall conditions.

In the present study, machine-learning classifier that distinguishes plasmas in the close-to-collapse state in which the radiation collapse is likely to occur and in the stable state has been constructed based on experiment data in LHD. In the experiment, the hydrogen and deuterium gas-puff and was used as fueling and the magnetic configuration was fixed at the magnetic axis position R_{ax} of 3.6 m with B=1.375 T or 2.75 T. The surveyed line averaged density and heating power range up to $1.5 \times 10^{20}\ \mathrm{m}^{-3}$ and 15 MW, respectively. The data was labeled into stable and close-to-collapse states according to the density exponent $x = (\dot{P}_{\mathrm{rad}}/P_{\mathrm{rad}})/(\dot{\bar{n}}_{\mathrm{e}}/\bar{n}_{\mathrm{e}})$, which is a criterion of thermal instability[2]. Here, the dots mean time derivatives.

Using the constructed classifier, feature of radiative collapse has been extracted using exhaustive search (ES), which is one of the sparse modeling techniques. The sparse modeling is one of the frameworks of data-driven science and it exploits the inherent sparseness in all high-dimensional data to extract the maximum amount of information from the data[2]. In ES, all possible combinations of input parameters are compared each other to find out the optimal one.

As a result of feature extraction, line averaged electron density $\bar{n}_{\mathrm{e}}$, line emissions of CIV and OV, and electron temperature at plasma edge $T_{\mathrm{e,edge}}$ have been selected as key parameters of radiative collapse. Using those parameters, collapse likelihood has been calculated corresponding to distance from the boundary between stable and close-to-collapse states obtained by machine learning. Figure 1 shows a typical discharge with radiative collapse in LHD. In this discharge, the collapse likelihood increased and reached one before the plasma collapsed.

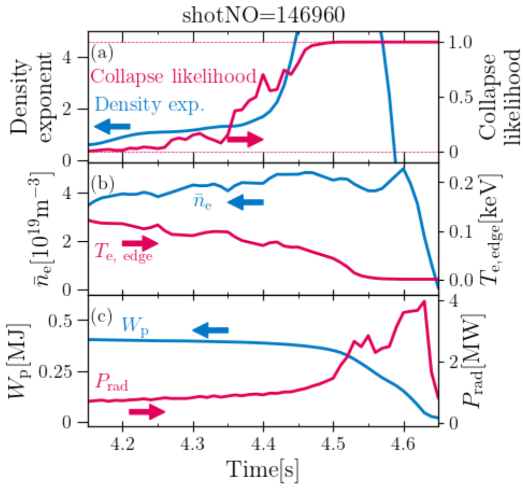

Fig.1 An example of collapsed discharge in LHD. (a) Density exponent and collapse likelihood, (b) line averaged electron density and electron temperature at plasma edge, (c) diamagnetic energy and radiated power are shown.

The likelihood has been verified with about 500 discharges in LHD and over 85% of radiative collapses have been predicted successfully at least 30 ms before occurrence. Also, using those extracted parameters, mechanisms of occurrence of radiation collapse have been discussed focusing on radiation loss of light impurities at plasma edge, especially outside the last closed flux surface.

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