全状態探索によるデータ駆動アプローチを用いた JT-60Uの高ベータディスラプション予知と物理背景の抽出

Data-driven approach on high-beta disruption in JT-60U using exhaustive search

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1 Introduction

Disruption is an event that suddenly shuts down the plasma current in a tokamak reactor. To realize tokamak fusion reactor, continuous studies of control and elucidation of disruption have been carried out [1, 2]. Since the physical mechanism of occurrence of disruptions is not clearly identified yet, recently many researchers have made an attempt at data-driven science to predict the disruptions.

Although it was recognized that appropriate selection of the input plasma parameters would be quite important to improve the prediction performance, the methodology on the appropriate choice of plasma parameters remains unclear. To solve this issue, we introduced sparse modeling, which exploits the inherent sparseness in all high-dimensional data to extract the maximum amount of information from the data [3]. In our previous research, it was shown that the performance of disruption prediction is improved by selecting input parameters using sparse modeling. In the present research, we modified both the dataset and predictor model to improve the performance of predictor and extract key parameters for disruption.

2 Modification of dataset

The disruption predictor used in this research is trained and evaluated based on high-beta plasma experimental data in JT-60U, where the beta value was close or above the no-wall beta limit [4]. Because most of the disruptions in those discharges are expected to be results from resistive wall mode, we added some parameters that related to plasma rotation and gradient of plasma pressure, e.g., plasma velocity $V_{\rm t}$ and ion temperature $T_{\rm i}$. Those values are obtained from magnetic equilibrium calculation in JT-60U.

3 Results

The results obtained from calculations using previous and modified dataset are shown in fig. 1 as blue and orange lines, respectively. In the early time before disruption, the prediction success rate using new dataset is much better than that using the old one. Also, the false alarm rate is smaller using new dataset than using the old one.

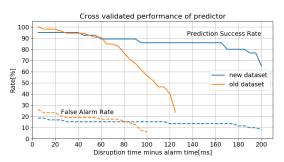


Fig. 1: The comparison of predictor performance at each time.

References

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