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Applied study of feature extraction using exhaustive search on high-beta disruption in JT-60U

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Likelihood of high-beta disruption has been discussed from feature extraction using exhaustive search. A support vector machine (SVM) [1] has been used to construct a disruption predictor model.

Establishment of prediction and avoidance of disruption is inevitable for realization of a tokamak fusion reactor. Since disruption physical mechanism has not been clearly identified yet, there have been studies trying to predict occurrence of disruptions based on experiment data using machine learning. Here, it should be noted that input parameters for machine learning have been given by empirical presumption in these studies to date.

In our previous study [2], the concept called "sparse modeling" was introduced to establish the method to select optimal input parameters. The sparse modeling exploits the inherent sparseness in all high-dimensional data to extract the maximum amount of information from the data [3]. It was shown that the performance of disruption prediction was improved by selecting appropriate input parameters.

In the present study, a model of disruption predictor has been constructed based on high-beta plasma experiment data in JT-60U where the beta value was close or above the no-wall beta limit [4]. A linear SVM is used as a two-class classifier here. The dataset consists of 23 candidate plasma parameters, that is, 10 macro plasma parameters (plasma current I_p, normalized beta β_N, poloidal beta β_P, internal inductance l_i, safety factor at 95% poloidal flux q_{95}, plasma triangularity δ, plasma elongation κ, amplitude of magnetic perturbation ($n=1$) $|B_\mathrm{r}^{n=1}|$, the ratio of plasma density to the Greenwald density limit $f_\mathrm{GW}=\bar{n}_\mathrm{e}/n_\mathrm{GW}$, ratio of radiated power to total input power $f_\mathrm{rad}=P_\mathrm{rad}/P_\mathrm{input}$), time derivative values for seven of macro parameters, and six local parameters (velocity of plasma rotation V_t and its radial gradient $\mathrm{d}V_\mathrm{t}/\mathrm{d}\rho$, ion temperature T_i and its radial gradient $\mathrm{d}T_\mathrm{i}/\mathrm{d}\rho$, normalized radial location of $q=2$ rational surface ρ/a, magnetic shear s).

It is important here to consider not only individual distributions of each parameter but also combinational effect between parameters. Therefore, the sparse modeling method called exhaustive search (ES), which searches all possible combinations of the input parameters, has been used in order to select the optimal combination of input parameters.

As a result of ES, several parameters have been extracted as the key parameters of disruption prediction, those are, β_P, q_{95}, κ, f_GW, and T_i.

Then these five parameters are highlighted to express the linear decision boundary of the classifier, in an exponential function. The input of a linear SVM was modified to the logarithms of each parameter and the calculation was carried again. Consequently, exponential expression of the boundary has been obtained as

$$1=e^{7.45}\beta_\mathrm{P}^{5.39}q_{95}^{-8.28}\kappa^{7.40}f_\mathrm{GW}^{4.50}T_\mathrm{i}^{0.120}.$$

The likelihood of occurrence of disruption can be given by the obtained exponential expression of decision boundary. In Fig. 1, the likelihood is expressed as function of β_P and f_GW. The expression of likelihood of disruption provides a hint of physical hypothesis and is applicable for design and development of a control system of a fusion reactor.

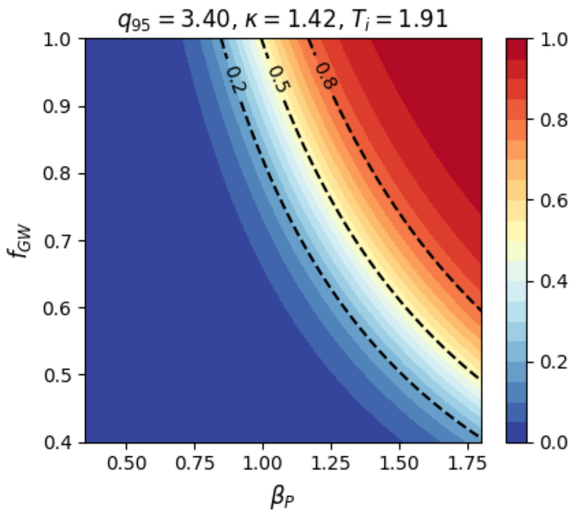

Figure 1: The contour plot of the likelihood of disruption against β_P and f_GW when q_{95}, κ, and T_i are fixed to their mean values in the dataset. Notations of the number on the contour lines are likelihood of disruption. For example, 0.8 means 80 % of likelihood.

References

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