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Data-driven study of high-beta disruption prediction in JT-60U using exhaustive search

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A disruption predictor model has been developed by using a support vector machine (SVM) [1] based on high-beta experiment data in JT-60U. Optimal input parameters have been extracted by exhaustive search (ES). Performance of a disruption predictor has been evaluated by input small numbers of parameters such as beta, plasma elongation, and ion temperature.

Disruption in tokamak plasmas is a serious threat for a tokamak fusion reactor. Disruption physical mechanism has not been clearly identified yet although prediction of disruption is inevitable for realization of a tokamak fusion reactor. Therefore, 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.

A model of disruption predictor has been developed based on high-beta plasma experiment data in JT-60U where the beta value was close or above the no-wall beta limit [2] in this study. A linear SVM is used as a two-class classifier here. The model has been evaluated by treating each discharge data as time series data. 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 of ES, which searches all possible combinations of the input parameters, has been used in order to select the optimal combination of input parameters. Here, the sparse modeling exploits the inherent sparseness in all high-dimensional data to extract the maximum amount of information from the data [3]. For the N variables, 2^N-1 combinations are possible, and the same number of repetitive calculations are required in ES. In order to remove the combination explosion risk, K-Sparse exhaustive search (ES-K) has been applied. This method assumes that the optimal combination of explanatory variables is K-sparse, i.e., a combination of K out of N parameters is optimal.

In Fig. 1, the best performance of predictor is shown against each K number in ES-K. The performance of disruption predictor is closest to the ideal performance (perfect prediction of all disruptions and no false alarm) when K=7 (i.e., the combination of seven parameters), and does not show significant difference in $K=6$ to 10. Common key parameters such as β_{P}, q_{95}, κ, f_{GW}, and T_{i} have been extracted from combinations in cases of $K=$ 6 to 8.

The equation of the decision boundary which divides the disruptive region from the non-disruptive region has been obtained by the combination of these key parameters. This expression is used to evaluate likelihood of disruption occurrence. This result will be useful to design a secure operational regime and develop control systems of fusion reactors.

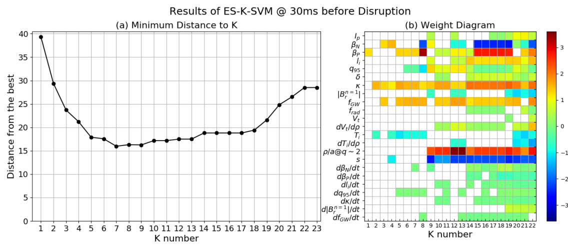

Figure 1: (a) Minimum distance from the ideal predictor performance as a function of K number, and (b) the corresponding weight diagram representing the combination at each point. The color bar in (b) represents the weight of each parameter in decision function obtained by SVM.

References

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