Disruption prediction with sparse modeling by exhaustive search

T. Yokoyama[1], T. Sueyoshi[1], Y. Miyoshi[2], R. Hiwatari[2], A. Isayama[3],
G. Matsunaga[3], N. Oyama[3], Y. Igarashi[4], M. Okada[1], and Y. Ogawa[1]
[1] *Graduate School of Frontier Science, The University of Tokyo, Kashiwa, Japan*
[2] *Rokkasho Fusion Institute, QST, Rokkasho, Japan*
[3] *Naka Fusion Institute, QST, Naka, Japan*
[4] *Japan Science and Technology Agency, PRESTO, Saitama, Japan*

Introduction

Plasma disruption is one of the crucial phenomena in a tokamak fusion reactor. Because the disruption causes serious impact to the reactor, it is necessary to elucidate and control the disruption to realize nuclear fusion reactor. However, its physical mechanism is not clearly identified yet, so there are some studies trying to predict the occurrence of disruptions using experimental data [1, 2, 3]. Those approaches are called data-driven science, and many of them use machine learning method to extract information from data.

Now we focused on the importance of selection of input parameters and introduced "sparse modeling" idea to select the optimal input parameters. The present research is conducted as follows: first, a dataset using experimental data in JT-60U is prepared. Second, a disruption predictor is constructed using linear SVM as a 2-class classifier. Finally, the optimal combination of input parameters is searched using "K-sparse exhaustive search", which is a kind of sparse modeling.

Construction of dataset

In the present research, the machine learning model was trained and tested using high-beta plasma experimental data in JT-60U. The data was separated into 2 cases, i.e., non-disruptive and disruptive. The dataset includes 69 non-disruptive and 54 disruptive cases. In Table 1, 17 parameters used in the present research are shown. We selected 10 plasma parameters considered to be related to disruption, and not only instantaneous values but also time derivative values are used for 7 parameters. And for each discharge, the base time was defined: For the non-disruptive cases, we chose the base time to be the moment when the normalized beta is the highest while for the disruptive cases, we selected the moment when the current quench started. The values of these plasma parameters are sampled in the intervals of 5 ms before the base time, as shown in Fig. 1.

Table 1: List of the plasma parameters obtained from each shot.

Name of parameter	Expression
Plasma Current [MA]	I_p
Normalized beta	β_N
Poloidal beta	β_P
Plasma internal inductance	l_i
Safety factor at 95% of poloidal flux	q_{95}
Plasma triangularity	δ
Plasma elongation	κ
Mode lock amplitude ($n=1$) [mT]	$\lvert B_\mathrm{r}^{n=1}\rvert$
The ratio of the plasma density to the Greenwald density limit	$f_\mathrm{GW} = \bar{n}_\mathrm{e}/n_\mathrm{GW}$
The ratio of the radiated power to the total input power	$f_\mathrm{rad} = P_\mathrm{rad}/P_\mathrm{input}$
Normalized beta time derivative	$\mathrm{d}\beta_\mathrm{N}/\mathrm{d}t$
Poloidal beta time derivative	$\mathrm{d}\beta_\mathrm{P}/\mathrm{d}t$
Plasma internal inductance time derivative	$\mathrm{d}l_\mathrm{i}/\mathrm{d}t$
Safety factor at 95% of poloidal flux time derivative	$\mathrm{d}q_{95}/\mathrm{d}t$
Plasma elongation time derivative	$\mathrm{d}\kappa/\mathrm{d}t$
Mode lock amplitude ($n=1$) time derivative	$\mathrm{d}\lvert B_\mathrm{r}^{n=1}\rvert/\mathrm{d}t$
The ratio of the plasma density to the Greenwald density limit time derivative	$\mathrm{d}f_\mathrm{GW}/\mathrm{d}t$

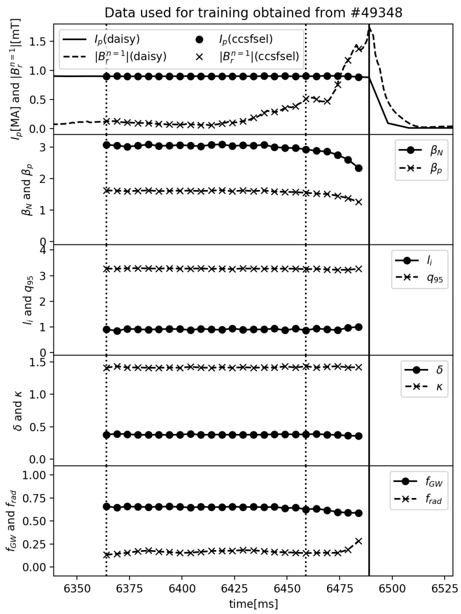

Figure 1: Example of experimental data used for training and testing the model. The solid line shows the moment at which the current quench occurred. The data was sampled every 5 ms and 20 points in the range indicated by the dotted line were used for training.

Support vector machine

Support vector machine (SVM) is one of machine learning methods, and it works with labeled data $\boldsymbol{x} \in \mathbb{R}^d$ and its label $y \in \{-1, 1\}$. In the present research, linear SVM was used as 2-class classifier to divide discharges into 2 classes, that is, non-disruptive and disruptive, respectively. The conceptual basis of the SVM is to find a hyperplane that divides data distributed in a multidimensional space into labeled sub-spaces. In the linear SVM, the hyperplane is represented as $f(\boldsymbol{x}) = \boldsymbol{w} \cdot \boldsymbol{x} + b$.

Sparse modeling by K-sparse exhaustive search

In order to select the optimal combination of input parameters, the concept called "sparse modeling" was introduced using "K-sparse exhaustive search" (ES-K) [4]. In ES-K, all possible combinations of parameters are exhaustively searched assuming that the optimal combination consists of K parameters, that is, ${}_NC_K$ combination to take the K from the N parameters are compared each other for each K.

To compare combinations, all combinations must be scored according to the accuracy of the separation using the combination of parameters. However, there is only finite data we could use, so we conducted cross validation (CV). In CV, the dataset was separated into 2 parts, training data and testing data. Based on training data, the separation of data according to the labels is established and it is evaluated using testing data in order to estimate the separation of actual data using finite data.

Calculation

In the training procedure, all training data is treated as a set of instantaneous values while in the testing procedure, each discharge is judged disruptive or not in chronological order and once the discharge is judged to be disruptive, all remaining data is treated as judged to be disruptive. With those procedures, the predictor is evaluated for each time before the disruption occurs for each combination of input parameters. The predictor is evaluated based on the following two indices, PSR and FAR.

$$\textit{Prediction Success Rate (PSR)} = \frac{\textit{Number of shots correctly judged as disruptive}}{\textit{Total number of disruptive shots}}, \quad (1)$$

$$\textit{False Alarm Rate (FAR)} = \frac{\textit{Number of shots incorrectly judged as disruptive}}{\textit{Total number of non-disruptive shots}}. \quad (2)$$

In order to compare combinations, the distance from the point where PSR = 100% and FAR = 0% which is the most ideal performance is calculated. Small distance indicates better performance of the predictor.

$$\text{distance} = \sqrt{(100 - \text{PSR})^2 + \text{FAR}^2} \quad (3)$$

Results and discussion

Figure 2 shows the results of ES-K. For each result of ES-K at 30 ms before the disruption occurs, the minimum distance is shown in the left figure, and the combinations corresponding to each result of ES-K are shown in the right figure. The minimum distance takes the minimum value at $K = 6$, the parameters used here were $|B_\mathrm{r}^{n=1}|$, f_GW, $\mathrm{d}l_\mathrm{i}/\mathrm{d}t$, $\mathrm{d}\kappa/\mathrm{d}t$, $\mathrm{d}|B_\mathrm{r}^{n=1}|/\mathrm{d}t$, $\mathrm{d}f_\mathrm{GW}/\mathrm{d}t$. Also, the minimum distance changes little from $K = 3$ to 8. The optimal combinations of $K = 3, \ldots, 8$ contain the common parameters, that is,

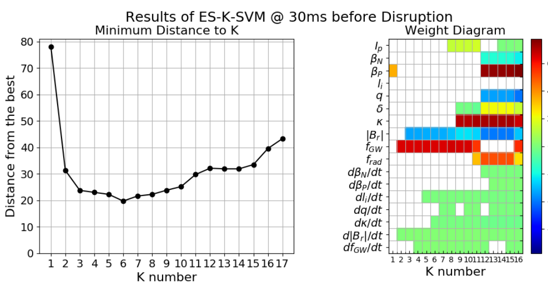

Figure 2: The minimum distance at 30 ms before disruption occurs for each K and the combinations corresponding to the results. The colors in the right diagram show the weight of each parameters in the equations of separating hyperplane obtained by SVM.

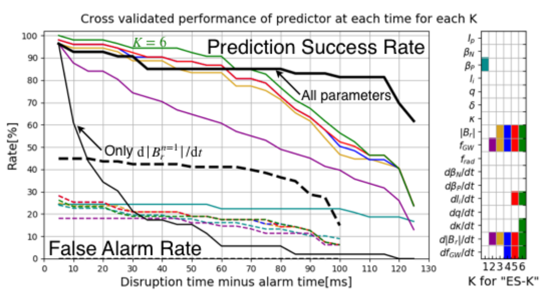

Figure 3: Comparison of PSR (solid lines) and FAR (dashed lines) at each time for $K = 1, \ldots, 6$. The bold black lines show the result obtained using all 17 parameters. The right diagram shows the combinations corresponding to the same colors in the left graph.

$|B_\mathrm{r}^{n=1}|, f_\mathrm{GW}, \mathrm{d}|B_\mathrm{r}^{n=1}|/\mathrm{d}t$.

The PSR and FAR for each time for the optimal combinations in ES-K for $K = 1, \ldots, 6$ are shown in Fig. 3. The PSR of $K = 6$ is higher than others at around 50 ms before the occurrence of the disruption, while the FARs of $K = 1, \ldots, 6$ are almost same, but the FAR obtained by all parameters is much higher than others.

In Fig. 3, the PSR using only $\mathrm{d}|B_\mathrm{r}^{n=1}|/\mathrm{d}t$ to predict is shown. It grows quickly just before the occurrence of the disruption, less than 20 ms. On the other hand, the PSR using $\mathrm{d}|B_\mathrm{r}^{n=1}|/\mathrm{d}t$ and other parameters grows earlier than it. This result means that the relationships between $\mathrm{d}|B_\mathrm{r}^{n=1}|/\mathrm{d}t$ and other parameters have important information to predict the disruption.

The two examples of discharges truly and falsely judged as disruptive are shown in Fig. 4. In the right figure, $\mathrm{d}\kappa/\mathrm{d}t$ and $\mathrm{d}|B_\mathrm{r}^{n=1}|/\mathrm{d}t$ at the moment when the predictor judged as disruptive are similar to the left one. This may be the reason why the discharge was judged as disruptive. However, $|B_\mathrm{r}^{n=1}|$ in this discharge does not grow after the moment, and finally, the discharge does not disrupt. This result suggests that the model that deals with time series data may be able to prevent this type of false alarm.

Conclusions

In the present research, the disruption predictor based on linear SVM is constructed using experimental data in JT-60U and the optimal combination of input parameters is searched by K-sparse exhaustive search. As a result, the performance of the predictor is improved by selecting input parameters, and three parameters, $|B_\mathrm{r}^{n=1}|, f_\mathrm{GW}, \mathrm{d}|B_\mathrm{r}^{n=1}|/\mathrm{d}t$, are extracted as key parameters of disruption prediction with the present dataset. In particular, the relationships between $\mathrm{d}|B_\mathrm{r}^{n=1}|/\mathrm{d}t$ and other parameters seemed to be important.

References

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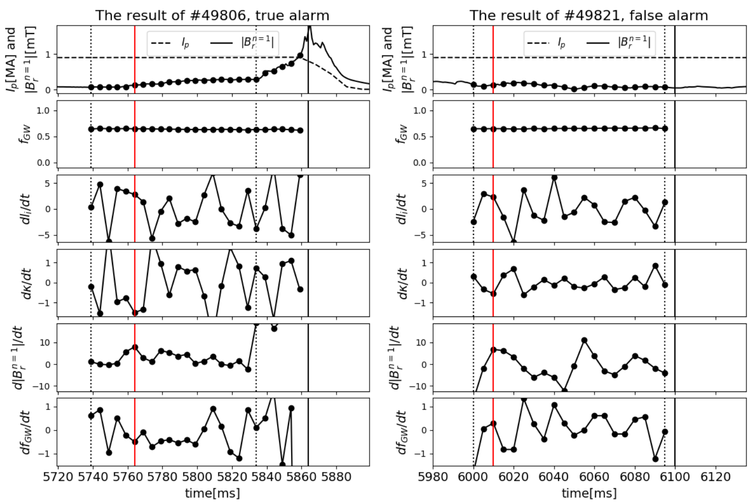

Figure 4: The examples of discharges truly and falsely judged as disruptive. The moment when the predictor judged as disruptive is shown by red lines.