Overview of real-time disruption prediction in JET: applicability to ITER

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1.- INTRODUCTION

Avoidance and mitigation of disruptions are crucial problems in ITER and are becoming increasingly relevant at JET with the installation of the new ITER-Like Wall (ILW). But it should be emphasised that a disruption prediction is a pre-requisite to put into operation any avoidance or mitigation method. This work summarizes the *evolution of our research lines regarding disruption prediction on JET* during the last years and discusses their *potential applicability to ITER*.

Disruption predictors are typically based on binary classification techniques. Given a dataset of N examples represented by pairs $(\mathbf{x}_i, y_i), i = 1,...N$, (where $\mathbf{x}_i \in \mathbb{R}^m$ is a vector of dimension m that represents features of distinctive nature among the N examples and $y_i \in \{+1, -1\}$ is the label about the plasma behaviour, *i.e.* disruptive or non-disruptive), a training process determines a mathematical function to split the feature space into two regions. After completing the training, new feature vectors $\mathbf{x}_{new} \in \mathbb{R}^m$ are classified as disruptive or non-disruptive depending on the parameter space region where they are located.

We have tackled three main research topics about disruption prediction in JET from 2008: advanced predictors, advanced predictors from scratch and disruption time predictors. All of them are based on the fulfilment of four important requirements. Firstly, they use multidimensional data. Secondly, they are based on discovering relations between signals to identify a forthcoming disruption. Thirdly, they have been programmed to provide deterministic responses. Last but not least, they were designed to use only real-time signals.

2.- PREDICTOR REQUIREMENTS

These requirements establish useful characteristics to be met by disruption predictors and they summarize the experience of years in fusion on the development of predictors.

- The requirement of using *multidimensional data* comes from the fact that a single signal is not able to provide predictions of any type of disruption. In addition, it is important to note that the term "multidimensional data" is not only related to the use of several signals but also to the use of different signal domains (typically, time and frequency, but other domains are possible) [1].

- Existing theoretical models and simulation tools have performances far from those that are needed [2]. Some related problems are: incomplete models, strong assumptions and unphysical boundary conditions. An alternative to this is to find out data-driven models with quantities not necessarily physics based.
- *Determinism* is the guarantee that two consecutive predictions will never exceed a certain time interval. This time interval is the minimum time needed to perform avoidance and mitigation actions after the recognition of an incoming disruption.
- Some predictors, which were tested with processed signals, showed degraded results when the data were changed for the *real-time signals* [3]. Therefore, only signals from real-time diagnostics have to be considered.

3.- ADVANCED PREDICTORS IN JET

Our first Advanced Predictor Of DISruptions (APODIS) in JET was trained/tested with the JET database between years 2000 and 2007 [4]. The main differences with previous predictors (either in JET or in other tokamaks) are: a) APODIS is based on a multi-layer architecture of Support Vector Machines (SVM) classifiers. b) The complete evolution of the discharges (from plasma breakdown to extinction) is considered for training/test purposes. c) The training/test database (2124 discharges) was the biggest one used in JET at that time. d) No bias was introduced in the types of disruptions considered.

Based on the above APODIS version, a new one was developed [5] that differs in six aspects: a) installation in the JET real-time network, b) the amount of shots considered for training/test (8360 discharges between years 2006-2009), c) a different signal dataset, d) the signal representations (both time and frequency domain), e) an exhaustive data pre-processing to remove discharges with outlier signals and, finally, f) the use of high performance computing for training purposes. This second version of APODIS was used in ILW experiments. After 991 discharges corresponding to the three first JET ILW campaigns and without any retraining, the success rate of the predictor is 98.36% (alarms are triggered, on average, 426 ms before the disruptions, time to be compared with about 30 ms that is the minimum time in JET to take mitigation actions). The false alarm and missed alarm rates are 0.92% and 1.64% respectively.

To finish this section, it should be emphasised that APODIS is being used not only as a disruption predictor but also to investigate the physics of disruptions. As a first step, APODIS has been used in off-line mode to determine the point of no return (PNR) for JET disruptions. We define the PNR as the time instant from which the disruption has been unavoidable. By analysing the PNR of 191 JET disruptions with C wall of six experimental campaigns (between 2008 and 2009), the PNR times until the disruption follow an exponential distribution with parameter $\lambda = 4.17\ s^{-1}$. Therefore, the probability that the PNR is 30 ms or less (this is the minimum time in JET to take mitigation actions) is 0.12. Additional research from the PNR is being carried out.

4.- ADVANCED PREDICTORS FROM SCRATCH IN JET

This section is devoted to discussing the need of developing adaptive disruption predictors with very limited data for training. This is necessary because ITER cannot wait for hundreds of disruptions to train a predictor. Therefore, in order to address this issue, two different types of predictors from scratch [6, 7] were developed with 1237 JET discharges (of which, 201 were disruptive) from the three first ILW campaigns (years 2011 – 2012). In both adaptive cases, the discharges are used in chronological order to create predictors from scratch as the discharges are produced.

In predictions from scratch, the first training process, to distinguish between disruptive and non-disruptive behaviours, is carried out after the availability of at least 1 example of each class. In the two JET predictors [6, 7], a new retraining is performed after each missed alarm.

Reference [6] describes a predictor from scratch based on APODIS. The results with the 1237 JET discharges mentioned above (and used in chronological order) show that a high success rate (93.5%) and a low false alarm rate (2.3%) can be achieved after including in the training process about 40 disruptive discharges. However, 40 disruptive discharges could be too large for the ITER needs and higher learning rate classifiers from scratch are necessary.

Reference [7] develops a probabilistic predictor based on the conformal prediction theory (in particular, a Venn predictor is used) [8]. An important characteristic of this type of predictor is that it qualifies each prediction not only with a probability but also with the corresponding error bar. The results after the chronological processing of 1237 JET discharges from the ILW campaigns show a good success rate (94%) and a low false alarm rate (4.2%), starting from the first disruption. The average probability interval about the reliability and accuracy of all the individual predictions is 0.811 ± 0.189 and the average anticipation time to the disruption is 654 ms. Therefore, this predictor does not need to wait for tens of disruptions but it shows a false alarm rate that is twice the one obtained with the APODIS from scratch predictor.

5.- DISRUPTION TIME PREDICTORS IN JET

Three different works that deal with the problem of predicting the time-to-disruption (TTD) are [3, 9, 10]. The first one, [3], is based on a two-layer artificial neural network and was applied to the ASDEX Upgrade tokamak. The predictor generates a temporal evolution signal about the TTD on a periodic basis. An alarm is triggered when the TTD is below a certain time threshold that is empirically determined after the training process. The second work, [9], uses a fuzzy framework to achieve a suitable clustering of the input space and a complex structure of neural networks. The output is also a temporal evolution signal that gives the TTD on a periodic basis. Again, an alarm is triggered when the TTD is below a certain threshold that is empirically established. Reference [10] was applied to the JET database and was also based on artificial neural networks. The neural network output is obtained periodically and it is a real number between 0 and 1 that represents the risk of disruption. An alarm is triggered when the neural network output is above a certain threshold that is chosen minimizing a detection error function. The three above TTD predictors share the common policy that when the TTD estimation is below a certain threshold, an alarm is raised. Also, it is important to note that, firstly, they were tested with a limited number of discharges and, secondly, not all types of disruptions were considered.

A very recent work [11] tackles the development of disruption time predictors under a new approach. Instead of generating a temporal evolution signal to predict the time to disruption and to trigger the alarm when special conditions are met, the objective is to predict a disruptive behaviour and when the prediction is positive to simultaneously provide the time to disruption. To accomplish this, a special combination of individual predictors (based on SVM classifiers) is performed. The respective outputs (disruptive or non-disruptive behaviours) are combined into a single one and when the combined prediction is ‘disruptive’, the TTD is also provided.

1237 JET discharges (1036 safe and 201 disruptive) corresponding to the three first ILW experimental campaigns have been considered for the analysis. By randomly chosen

60% disruptive and 60% non-disruptive discharges for training, the remaining ones have been used for test. The results include a success rate of 100% in the recognition of disruptive behaviours and a false alarm rate of 0.2%. All disruptions are predicted with a TTD of 160±3 ms, which reflects a high precision in the estimation. The exact time interval between the identification of the disruptive behaviour and the disruption itself was 160 ms, which means that the disruption time predictor is also very accurate. These results are independent of the initial dataset of random discharges for training.

6.- FUTURE WORK IN THE VIEW OF ITER

The outcomes of the predictors from scratch are very promising. At present, two different predictors have been tested with all discharges of the three first ILW campaigns of JET. The first one requires tens of disruptions to be trained, but provide a lower false alarm rate. More research about these methods and even a combined version of them is necessary.

With regard to time to disruption predictors, it is important to note that they can be essential methods to activate optimal avoidance or mitigation actions, whose automatic selection can depend on the time to disruption predicted. Results in JET are very encouraging. Finally, it should be noted that the disruption time predictors analyzed do not follow a '*from scratch approach*'. Versions of disruption time predictors from scratch would be very desirable for ITER.

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