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ABSTRACT.
This paper presents a neural network-based disruption predictor wherein multiple plasma diagnostic signals are combined to provide a composite impending disruption warning indicator. To take into account that disruption precursors appear in different time instants for different pulses, an off-line clustering procedure allows to automatically select the training set samples.

1. INTRODUCTION

In this paper, a neural network approach has been adopted to predict the risk of disruption at JET (Joint European Torus). Multiple plasma diagnostic signals are combined to provide a composite impending disruption warning indicator.

Literature reports several applications of neural networks to disruption prediction in different tokamaks [1 – 3]. In particular, in [4] an MLP has been successfully trained to forecast an impending disruption using as input good pulses or samples belonging to a temporal window of 400ms before the disruption time. Unfortunately, the percentage of false alarms produced by the neural network, when applied on-line to the whole length of a disrupted pulse, increases considerably. Training the neural network on the whole length of the pulse could be sufficient, but this could cause a difficult learning process.

To solve this problem, a clustering procedure based on Self Organising Maps [5]is adopted, which allows one to automatically select a limited number of significative samples to be used during the training phase, considering the whole length of the pulse. The trained network is now installed on line. It is currently in testing phase, and should be used to mitigate disruptive events.

2. DIAGNOSTIC SIGNALS AND INPUT -DATA

Pulses for the study were selected in the pulse interval Pulse No's 47830-57346, produced at JET between March 1999 and October 2002. The selected disrupted pulses belong to several disruption classes: Density Limit, Mode Lock, High Radiated Power, Internal Transport Barrier, and Transition H/L-mode. The criteria used to select the discharges for the network database are: I_{pla}>1.5 MA; X-point configuration; flat-top plasma current profile [3].

The selected inputs consist of nine signals describing the plasma regime i.e., Plasma Current, Locked Mode, Radiated Power, Plasma Density, Input Power, Internal Inductance, Safety Factor, Poloidal Beta, and Plasma Centroid Vertical Position [3 – 4].

The database consists contains 172 disrupted pulses and 102 safe pulses.

3. CLUSTERING AND PREDICTION TECHNIQUES

The predictive system structure consists of a cascade of a clustering block, and a neural disruption predictor.

The clustering procedure is carried out by a Self Organising Map (SOM) [5]. A SOM is an unsupervised neural network, commonly used to construct classifiers, since it provides a continuous topological mapping between a multidimensional feature space and a 2-D space. A key feature of SOMs is that the nodes in the output array are arranged such that neighbouring nodes represent similar patterns and nodes that are well separated represent different patterns.

The disruption predictor is a traditional MLP [6]. The MLP is the most widely used type of supervised neural networks. It is composed of layers of neurons in which the input layer is connected to the output layer through the hidden neurons. The training process is undertaken by changing the connection weights such that a desired input-output relationship is realised.

MLP with one hidden layer and nonlinear activation functions are universal approximators [7], i.e., they are capable of approximating any continue function to any desired degree of accuracy, provided that enough hidden units are available.

4. THE NEURAL PREDICTOR

For each *disrupted* pulse, the SOM network takes as input all the samples of the pulse except the last 40ms before the time to disruption belonging to the termal quench phase, with a sampling time of 20 ms, and gives, as output, clusters of similar data. The clusters are divided in three groups: *disrupted*, *good* and *uncertain* clusters.

The disrupted samples belong to the same cluster of the sample (t_d-40ms), which is for sure a disrupted sample. All the disrupted samples have been included in the training set.

The good and uncertain samples belong to the remaining clusters. In particular, the uncertain samples are the samples belonging to clusters between good and disrupted clusters and are excluded in the training phase. Only one sample for each good cluster is considered for the training phase.

With this procedure the amount of training data has been considerably reduced if compared to the whole length of the pulse, without losing any useful information. In fact, 86 disrupted pulses, composed of 36316 samples, resulted in 7070 samples after the clustering.

The MLP has as input the 9 values of the signals for the samples selected by the SOM. The training set consists of 69 disrupted pulses while the validation set consists of 17 disrupted pulses. The test set consists of 86 disrupted pulses and 102 successful pulses.

The diagnostic system triggers a False Alarm (FA) if either two consecutive outputs in a successfully terminated pulse are greater than a predetermined threshold or two consecutive outputs in a disrupted pulse, occurring more than 1 second before the disruption, are greater than the threshold. The system misses the alarm (MA) if at least two consecutive outputs are not greater than the threshold in time instants preceding the disruption at least 100 ms.

5. RESULTS

The best network configuration is composed of 9 inputs, 1 hidden layer with 15 hidden neurons and 1 output, resulting in 166 network parameters.

Table 1 shows the results for the training, validation and test set. It is worth noting that an alarm in a disrupted pulse, occurring more than 1 second before the disruption, is considered a

__Table 1__: Performance results: FA = False Alarms, MA = Missed Alarms.

	Training Set	Validation Set	Test Set
MA	0/69 (0%)	3/17 (17,6%)	28/86 (32,5%)
FA	3/69 (4,3%)	0/17 (0%)	11/188 (5,8%)

As can be noted, network performance are good in terms of FAs, whereas the network still present a quite high percentage of MAs. It has been noticed that 40 test pulses are about 15 months older than all the others. It has, as well, been noticed that special configurations (elmy h-mode), that are quite familiar in recent experimental campaigns whose data are used in the test, are not present in the training set.

To analyse the prediction capability, the network detection time and the Soft Stop time have been compared. The Soft Stop is a shut down procedure, triggered by the Mode Lock indicator, which is presently used in the on-line disruption protection system. Table 2 shows the percentage of MA for the network (MLP) and for the Mode Lock (ML).

__Table 2__. Comparison between MLP and ML

	MLP	ML
MA	28/86 (32%)	44/86 (51%)

It has to be noticed that the two systems have 21MAs in common. Moreover, a comparison of the prediction time for the 25 disruptions correctly predicted by both systems shows that the neural network triggers the alarm before the Mode Lock for 16 disruptions.

CONCLUSIONS

An MLP has been trained to predict a forthcoming disruption at JET 100ms before the disruption time. Due to author's previous experience on disruption prediction, an automatic procedure to select the training samples considering the whole length of the pulse has been adopted. As a result, the number of FAs produced by the network when considering only good pulses has been reduced. The network still presents a quite high percentage of MAs. Nevertheless, it shows better performance with respect to the procedure presently used in the on-line disruption protection system at JET.

Future work will focus on the training set update in order to include the missing configurations responsible of missed alarms. Moreover, a novelty detection technique will be applied in order to evaluate the reliability of the network output during the on-line application and update the network in case of plasma configurations not used during the training phase.

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