*33rd EPS Conference on Plasma Phys. Rome, 19 - 23 June 2006 ECA Vol.**30I**, P-2.143 (2006)*

Disruption prediction at ASDEX Upgrade using neural networks

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Abstract - In this paper, a Multi Layer Perceptron is trained to act as disruptions predictor at ASDEX Upgrade. In particular, an optimization procedure is performed to identify a time instant that discriminate between disruptive and safe phases of disruptive discharges. The neural predictor has been trained, validated and tested using 149 disruptive pulses, selected from two years of ASDEX Upgrade experiments from 2002 to 2004. Non disruptive pulses has not been used to design the predictor, because the disruptive discharges at ASDEX Upgrade present a safe phase sufficiently long to well represent also the behavior of safe pulses. In order to limit the neural network size, for each disruptive shot, seven plasma diagnostic signals have been selected from numerous signals available in real time. A Self Organizing Map has been used to reduce the shot dimensionality in order to improve the training of the Multi Layer Perceptron, greatly increasing the prediction capability of the system. The results are quite good, with a prediction success rate greater than 90%.

INTRODUCTION

A disruption warning indicator is strongly recommended for real time tokamak control since it would allow appropriate actions to avoid disruptions or mitigate their consequences [1-3]. This paper deals with the design of a disruption prediction system based on neural networks [4]. The network is fed with seven diagnostic signals, suitably selected to describe the plasma regime during the current flat-top of the discharge, and it predicts the occurrence of a disruption. Data for this study were selected in the shots range 16000-20000, performed in ASDEX Upgrade between June 2002 and July 2004.

The system consists of two parts, a clustering block and a neural disruption predictor. During the training phase, a Self Organizing Map [5-6] (SOM) performs a data reduction, selecting a limited number of significant samples from a pulse, and it feeds a Multi Layer Perceptron [4] (MLP), trained to capture the relationship between the input plasma parameters and the disruptive or non disruptive (safe) states of the plasma itself. The correct identification of the two consecutive phases is crucial to efficiently train the MLP.

Defining as *precursor time* (t_{prec}) the time instant that discriminate between safe and disruptive phases, some disruption precursors are expected to appear after t_{prec}. Unfortunately, t_{prec} does not have a prefixed value, and the identification of the two different phases is often a very difficult task. In [1], the precursor time was defined as the transition time between L mode and H mode, which occurs before the disruption, or the starting time just before a MARFE, which will end with a disruption, for plasma that has been in L mode for longer than

0.8 s. These criteria not always apply, as, for example, an H/L transition may occur too much in advance with respect to the disruption time, to be considered as a disruption precursor.

In this paper, the time instant t_{prec} is identified by means of a heuristic optimization procedure. In particular, several training sessions of the MLP have been performed varying the time interval [t_{prec}÷ t_D], where t_D is the disruption time.

THE DATABASE

Seven plasma parameters have been selected to feed the neural predictor: the safety factor (q_{95}), the total input power (P_{inp}), the locked mode signal, the radiated power versus total input power (P_{frac}), the internal inductance (li), the poloidal beta (β_p), and the electron density (n_e). The sampling time is equal to 1 ms.

From the disruptive shots available at ASDEX Upgrade, the following disruptions have been discarded: disruptions occurring in the ramp-up phase; disruptions occurring after 100 ms from the beginning of the ramp-down phase; VDE disruptions; gas puffed disruptions. Moreover, some other shots have been excluded as they contain corrupted diagnostic signals, or as they do not contain all the prescribed signals. The resulting database consists of 149 disruptive pulses. In particular, the training, the validation and the test sets consist respectively of 100, 16, and 33 disruptive pulses.

THE NEURAL PREDICTION SYSTEM

The architecture adopted for the predictor training consists of the cascade of a SOM and of the MLP disruption predictor.

For each shot, the SOM block performs a clustering of the samples, preserving the input topology. Hence, each cluster is supposed to contain samples belonging to similar plasma states.

Note that, the majority of samples in a disrupted shot belongs to the safe phase, and then a data reduction is requires to avoid the imbalance between the large number of safe samples and the smaller number of disruptive samples in the training set.

Moreover, the correct identification of the time instant t_{prec} is crucial to efficiently train the MLP. As previously cited, t_{prec} is identified by means of a heuristic optimization procedure. Thirteen training sessions have been performed by varying t_{prec} in the temporal window [t_D – 80, t_D – 40] ms with a time step of 5ms, while in the time window [t_D – 160, t_D – 100] ms the time step is set equal to 20ms. The lower bound of the temporal window is chosen considering that the locked-mode appears within 160 ms before the disruption in 91.3% of the shots of the training and validation sets.

The samples belonging to the interval [0, t_{prec}] are considered safe while those corresponding to the subsequent time instants until t_D are considered disruptive.

For each value of t_{prec}, the training session consists of the following steps:

- A data reduction using the SOM: only one sample for each cluster containing safe samples is considered for the training phase. Conversely, all the disruptive samples are included in the training set.
- The predictor design: the MLP network topology has been selected by a trial-and error procedure. For this purpose several MLPs have been trained varying the number of the hidden layer nodes. In particular, the growing method has been adopted [4], which consists of progressively increasing the number of hidden neurons, until the performance of the network reaches the desired value. The network output has been set equal to 0 for the safe samples, while it has been set equal to 1 for the disruptive samples.

The time instant t_{prec} giving the best performance in the validation set is chosen to select the MLP disruption predictor.

RESULTS

The performance of the prediction system is evaluated in terms of percentage of prediction success rate, false alarms rate, and missed alarms rate. The false alarm rate is defined here as the ratio between the numbers of disruptive pulses predicted by the system 160 ms before the disruption, and the total number of disruptive pulses, in per cent. Note that, in the literature [1-3] a false alarm is triggered when a safe pulse is predicted as a disruptive pulse. In this paper, only disruptive pulses are considered, and a false alarm is predicted if the alarm is triggered too much in advance. The missed alarm rate is defined as the ratio between the number of disruptive pulses predicted less then 5 ms before the disruption, and the total number of disruptive pulses, in per cent. In fact, the disruption mitigation system in ASDEX Upgrade needs 5 ms to act. Therefore, a missed alarm is predicted if the predictive system detects it too late to allow the mitigation system to intervene. Hence, a disruption prediction is considered successful if the system is able to detect the incoming disruption in the time window [$t_D - 160$, $t_D - 5$] ms.

The choice of the threshold equal to 160 ms comes again from the analysis of the locked mode signal.

In order to find the best time instant to trigger the disruption alarm, two parameters have been optimized. The first parameter is the alarm threshold, which discriminates the safe plasma from the disruptive plasma. This threshold has been optimized in the range from 0.55 to 0.8, with step 0.05. The second parameter is indicated with k. The prediction system generates a trigger only when the neural network output remains above the threshold a “k” number of consecutive samples. The parameter k has been optimized in the range from 1 to 15. The optimization consists in minimizing the false alarm rate.

The best performance in terms of false and missed alarms correspond to t_{prec} equal to 50 ms, alarm threshold equal to 0.75, and k equal to 7 ms. The best network configuration is composed of 7 inputs, 1 hidden layer with 24 hidden neurons, and 1 output, resulting in 217 network parameters.

Table 1 shows the results for the training, validation and test sets. The errors on the test set have been calculated considering the whole sequences of the samples for each pulse.

	False alarm rate alarm time<t_D-160 ms	Prediction Success Rate t_D -160 ms<alarm time< t_D -5 ms	Missed alarm rate alarm time> t_D -5 ms
Training set	1%	89%	10 %
Validation set	0%	93.75%	6.25%
Test set	3.03%	90.91%	6.06%

Table 1: Network performance

CONCLUSIONS

In this paper a neural disruption predictor for ASDEX Upgrade has been designed, which is able to predict more than 90% of the disruptive shots considered in the test set. The precursor time is optimized by minimizing the number of false alarms.

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