Progress in disruption prediction at JET using neural networks

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Abstract

In this paper a neural network is trained to recognize a forthcoming disruption on the JET Tokamak to avoid plasma disruption or mitigate its effects.

The network has been trained using several plasma diagnostic signals as inputs, collected from successfully terminated and disruption terminated pulses performed during three years of recent JET Tokamak experiments.

INTRODUCTION

Disruptions are dramatic events, in which the plasma energy is lost within a time span of few milliseconds. They present serious problems for the operation of a Tokamak. Firstly, they put a limit on operational parameters, such as the plasma density and the current rise rate. Secondly, major disruptions, taking place at high plasma current, expose the tokamak to high temperature and severe mechanical stress. For this reason, disruption prediction is an important area to study.

Disruptions have different physical causes mostly of which have been identified but whose dynamics is not well known in detail. Therefore, present experimental operation frequently relies on using human experience, and often the disruption cannot be avoided or predicted and mitigated at all. Thus, a black box approach seems to be particularly suitable to extract the knowledge from past history. Literature reports several applications of neural networks to disruption prediction in different tokamaks [1 - 4].

In this paper, a Neural Network approach has been adopted to predict the risk of disruption at JET (Joint European Torus). The model uses as input signals a large number of plasma diagnostics selected from the JET database.

In particular, this study focuses on flat-top disruptions. During the flat-top scenarios the plasma is controlled in order to obtain a quasi-stationary plasma current, and steady equilibrium position and shape. Such sustained flat-top scenarios are of importance because they will be the normal operating conditions in next step Tokamaks such as the InternationalThermonuclear Experimental Reactor (ITER).

DIAGNOSTIC SIGNALS AND INPUT DATA

Pulses for training, validation and test sets were selected in the pulse interval 47830-57346, produced at JET between March 1999 and October 2002. The selected disrupted pulses belong to several disruption classes, e.g., Density Limit, Mode Lock, high Radiated Power, Internal Transport Barrier, etc.. Disruptions following a vertical instability were excluded because are unusual, and can be only identified few ms before the disruption event.

The criteria used to select the discharges for the network database were: I_{pla}>1.5 MA, X-point configuration and flat-top plasma current profile [5]. Plasma current below 1.5 MA were discarded because generally have little impact on subsequent conditioning and operation of the device. The wide database used by the authors in [5], although satisfying the above criteria, could not be used due to a change in the algorithms to evaluate four of the nine chosen signals (i.e. signals from 5 to 9 in Table 1). Thus, the selection of a new dataset has been necessary.

The selected inputs consist of nine signals describing the plasma regime in the discharge flat-top. The choice of the variables takes into account physical considerations and the availability of real-time data. Moreover, previous experiences on disruption prediction confirm the appropriateness of chosen input variables [5 - 6].

Table 1 shows the diagnostic signals used as input to the network.

The new database contains 92 disrupted pulses and 102 safe pulses, automatically selected from JET database between pulses satisfying the requirements on I_{pla}, X-point and flat-top.

Different temporal sequences have been selected for each pulse. Each sequence consists of 40 samples, with a sampling time of 20 ms. This sampling time allows the synchronization among different systems. Indeed, the neural predictor works by gathering signals from not synchronized sources; therefore, it has to wait for the slower system before the computation.

In order to avoid the selection of samples belonging to the thermal quench phase, not useful for precursors identification, the last 40 ms before the time of disruption (t_D) have been omitted. Therefore, the 40 selected samples for a disrupted pulse belong to the time window [t_D-840ms; t_D-40ms].

For the successful pulses the inputs are 40 samples randomly chosen during the flat top phase.

Signal name		Units
1.	Plasma current	[A]
2.	Locked Mode	[T/A]
3.	Radiated power	[W]
4.	Plasma Density	[1/m^3]
5.	Input Power	[W]
6.	Internal Inductance	[AU]
7.	Safety factor	[AU]
8.	Poloidal Beta	[AU]
9.	Plasma centroid vertical position	[m]

Table 1. Diagnostic signals (AU: adimensional units).

THE NEURAL MODEL

The Artificial Neural Network (ANN) is a traditional Multi Layer Perceptron [7]. It takes as input the 9 values of the chosen signals at time instant *t*. The single output is a real number between 0 and 1 representing the risk of disruption.

In fact the network target for each disrupted pulse, *y(t)*, is a sigmoid in the time window of 800 ms in order to represent a greater risk near the disruption:

$$y(t) = \frac{1}{1+e^{-[t-(t_D-t_\alpha)]/\tau}}.$$

t_D is the disruption time instant, t is the sampling time (20 ms) and t_α is such that $y(t_\alpha) = 0.5$.

The choice of t_α depends on the disruption class. In particular, since symptoms of Density Limit disruptions appear well in advance, the alarm can be anticipated. Thus, for Density Limit disruptions t_α is set equal to 320 ms, whereas for the other classes t_α = 280 ms.

The network target for the safe pulse is zero in every time instant.

The training set consists of 66 disrupted pulses and 71 successful pulses, while the validation set consists of 11 disrupted pulses and 15 successful pulses.

The test set consists of 15 disrupted pulses and 16 successful pulses.

Input data have been scaled in the interval [0;1].
For any pulse the ANN gives as output a time series representing the disruption risk.
Network performances have been quantified in terms of false and missed alarms.
For a successfully terminated pulse, the diagnostic system triggers a False Alarm (FA) if the maximum value of the series is greater than a predetermined threshold.
Conversely, the pulse is correctly classified.
For a disrupted pulse if the maximum value of the output series is less than the threshold, the diagnostic system misses the alarm (MA).
Conversely, if this value is greater than the threshold at least 100 ms before the disruption, the diagnostic system correctly triggers the alarm.

The choice of the threshold *th* is done by minimizing the detection error expressed as:
$E(th) = PFA(th)\, w_{FA} + PMA(th)$
where *PFA(th)* is the Percentage of False Alarms, *PMA(th)* is the Percentage of Missed Alarms, and w_{FA} is a false alarms weight factor.
PFA is defined as the number of successfully terminated pulses detected as disruption divided by the number of successfully terminated pulses.
PMA is defined as the number of disrupted pulses detected as successfully terminated pulses divided by the number of disrupted pulses.
The misclassification of good pulses has been penalized by a weight factor $w_{FA} = 4$. It is worth noting that, in order to minimize the missed alarms, as it will be crucial in future fusion reactors, it will be sufficient to use a different network threshold modifying w_{FA}.

RESULTS
The best network configuration is composed of 9 inputs, 1 hidden layers with 14 hidden neurons and 1 output, resulting in 155 network parameters.
Table 2 shows the results for the training, validation and test set .

	Training set	Validation Set	Test Set
MA	7/66	0/11	1/15
FA	2/71	1/15	1/16

Table 2. Performance results: FA=False Alarms, MA=Missed Alarms.

To into account possible delays in diagnostic signals, the analyzed time interval [t_D –40 ms; t_D –100 ms] has been swept in the range [t_D – 40 ms; t_D - 200ms]. As shown in Table 3, the number of missed alarms increases when the prediction is requested in advance.

Time to disruption (ms)	100	120	140	160	180	200
MA	1	2	3	4	4	4
FA	1	1	1	1	1	1

Table 3. Performance results for the test set, from 100ms to 200ms before the disruption
FA=False Alarms, MA=Missed Alarms.

To analyze 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.
For the predicted disruptions in the test, the neural predictor gives the alarm at least 80 ms before the mode lock indicator. Regarding the only MA, also the mode lock signal did not detect the imminent disruption.
Figure 1 shows the network performance for the disrupted pulse 50874.
The horizontal line indicates the network threshold, while the vertical line indicates the Soft stop time.
In this case, the network alarm occurred more than 360 ms before t_D and 80 ms before the mode lock alarm.

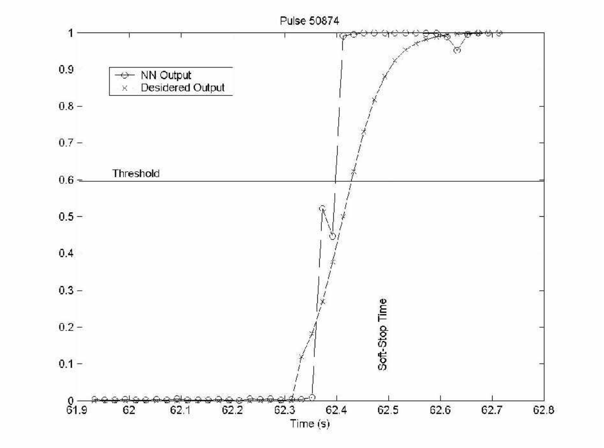

Figure 1. Correct Alarm on disrupted pulse 50874

CONCLUSIONS

A Multi Layer Perceptron has been trained to predict a forthcoming disruption at JET, 100ms before the disruption time.

The dataset, including disruptions from five different classes, assures the reliability and the generalization capabilities of the ANN predictor.

Pulses samples have been selected in a temporal window of 800 ms; for disrupted pulses the window consists the last 800 ms of the discharge, for successfully pulses consists of randomly chosen samples.

For the successfully predicted disruptions in the test, the neural predictor gives the alarm at least 80 ms before the mode lock indicator, which is presently used in the on-line disruption protection system.

For the predicted disruptions in the test, encouraging results have been obtained also when the ANN predictor triggered the alarm 200 ms before the disruption.

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