FORECAST OF TEXT PLASMA DISRUPTIONS USING SOFT X-RAYS AS INPUT SIGNAL IN A NEURAL NETWORK

A. Vannucci , K.A. Oliveira
Instituto de Fisica Universidade de Sao Paulo, SP, Brazil

T. Tajima
Institute for Fusion Studies - University of Texas, Austin, TX, USA

Y.J. Tajima
Department of Physics and Astronomy - Swarthmore College - Swarthmore, PA, USA

Abstract

A feed-forward neural network is used to forecast major and minor disruptions in TEXT tokamak discharges. Using the experimental data of soft X-ray signals as input data, the neural net is trained with one disruptive plasma discharge, while a different disruptive discharge is used for validation. After proper training, the networks with the same set of weights, it is then used to forecast disruptions in two other different plasma discharges. It is observed that the neural net is capable of predicting the onset of a disruption up to 3.12 ms in advance. From what we observe in the predictive behavior of our network, speculations are made whether the disruption triggering mechanism is associated with an increase in the m = 2 magnetic island, that disturbs the central part of the plasma column afterwards, or the initial perturbation has first occurred in the central part of the plasma column and then the m = 2 MHD mode is destabilized.

1. INTRODUCTION

Artificial neural networks are computer algorithms which simulate, in a very simplified form, the ability that brain neurons have to process information. Within each unit of the network, all the input weighted signals are summed and an excitatory or inhibitory signal is then fired to the next layer's units, depending whether the result of the sum has reached a certain threshold value or not. These weights are adjusted (or educated) to minimize errors in prediction (back propagation [1]).

Observing the time delayed vector of a physical quantity *X* at time *t*, of the tokamak data: $X_t = [x_t, x_{t-\tau}, x_{t-2\tau}, \ldots , x_{t-n\tau}]$ then it is reasonable to suppose that the future state of the system, at time $t+\tau$, could be predicted by a smooth non-linear function F: $x_{t+\tau} = F(X_t)$ where $\tau = 0.04$ ms corresponds, in this work, to the sampling rate of the CAMAC acquisition system.

However, since the function F is not known, the idea is to alternatively use a neural network to approximate F and, therefore, predict the future evolution of the system. This is done by training neural first, that is, by finding the correct set of weights for all connections.

In a single-step process the soft X-ray data points are predicted one time step ahead only ($\tau = 0.04$ ms), while in multi-steps predictions the predicted output at time $t + \tau$ is fed back into the input and is used to predict a new output at time $t + 2\tau$, which is fed back into the input together with the values previously predicted, in order to predict a new output at time $t + 3\tau$, and so on.

The neural net architecture used in this work had the configuration (15 - 9 - 3 - 1), that is, 15 neural units in the input layer, 9 units in the first hidden layer, 3 units in the second hidden layer and only one unit in the output layer. The activation functions were chosen to be g(x) = tanh(x) for all the hidden units and g(x) = x for the output unit. The training of the network and the disruption prediction was carried out over the last 200 ms of the plasma discharges.

2. DISRUPTION FORECAST

In order to find the adequate weights for all the connections between the neural units, two different disruptive plasma pulses have been used: the training set and the validation set. The single and multi-step forecasting processes are performed, afterwards, over two others disruptive pulses, distinct from the ones used for training and validation.

In Fig. 1 the basic experimental signals, related to the first one of the plasma disruptive discharges used for forecasting, are shown. This pulse corresponds to an $I_p \approx 170$ kA plasma discharge that disrupted at t ≈ 470 ms. About 18 ms before the major disruption a minor disruption occurred, as observed in the Mirnov magnetic signal (Fig. 1c), causing a significant drop on the average electron density (Fig. 1f) and electron temperature as observed through the X-ray emission signals (Fig. 1d). This same feature, that is, the major disruption being preceded by a minor disruption just before the plasma current collapse, is also observed on the plasma discharges used for validation and for training the net.

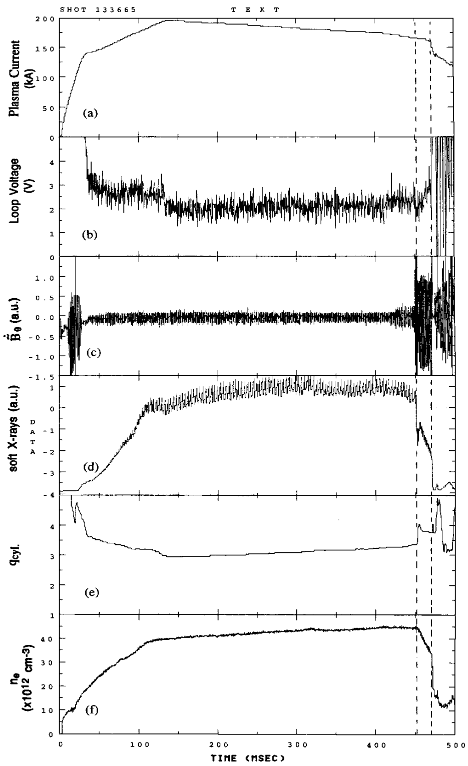

fig.1 -TEXT disruptive discharge used for forecasting. The major disruption was preceded by a minor disruption.

The result of the forecasting process for this plasma shot is shown in Fig. 2. As it can be observed, for one time step-prediction (Fig. 2a) the result obtained from the neural network agrees almost perfectly with the experimental signal. By increasing the forecast time interval, i. e., the number of time-steps, as showed in Fig. 2b for 25 time-steps, the shape of the sawteeth oscillations is observe to be somewhat deformed but the net is still capable of accurately predicting the instance of the minor disruption that takes place at t ≈ 452 ms. The longest forecasting time achieved is obtained for 63 time-steps (Fig. 2c) for which the net still accurately predicts the occurrence of the minor disruption. This corresponds to a forecasting of the disruptive instability 2.52 ms before it actually takes place for the medium sized TEXT tokamak. For time-steps longer than that, the net continues predicting the disruption but now with a time shift delay, as shown in Fig. 2d for a 90 time-steps forecasting.

Examining in detail the result obtained for the 63 time-steps forecast (Fig. 2c), it can be observed that in order to make this prediction, the net used 15 experimental data points that are positioned around t ≈ 449.5 ms. This particular time interval is located exactly in the oscillatory region of the last "typical" sawtooth oscillation, when our eyes are unable to perceive any peculiar occurring in the soft X-ray emission which would signal that an instability has started at that point (or before) and that a disruption in coming soon. Only after the crash of this sawtooth at t ≈ 450.0 ms, when an strong fluctuation starts to build up afterwards, one can say that a disruptive instability indeed has been triggered.

As another test for the neural network, exactly the same set of weights obtained and used above is now used to forecast the disruption that occurred in a second plasma discharge, with $I_p \approx 170$ kA, which disrupted at t ≈ 424 ms. Differently from the first discharge analyzed, however, in this particular plasma discharge the major disruption was not preceded by any minor disruption.

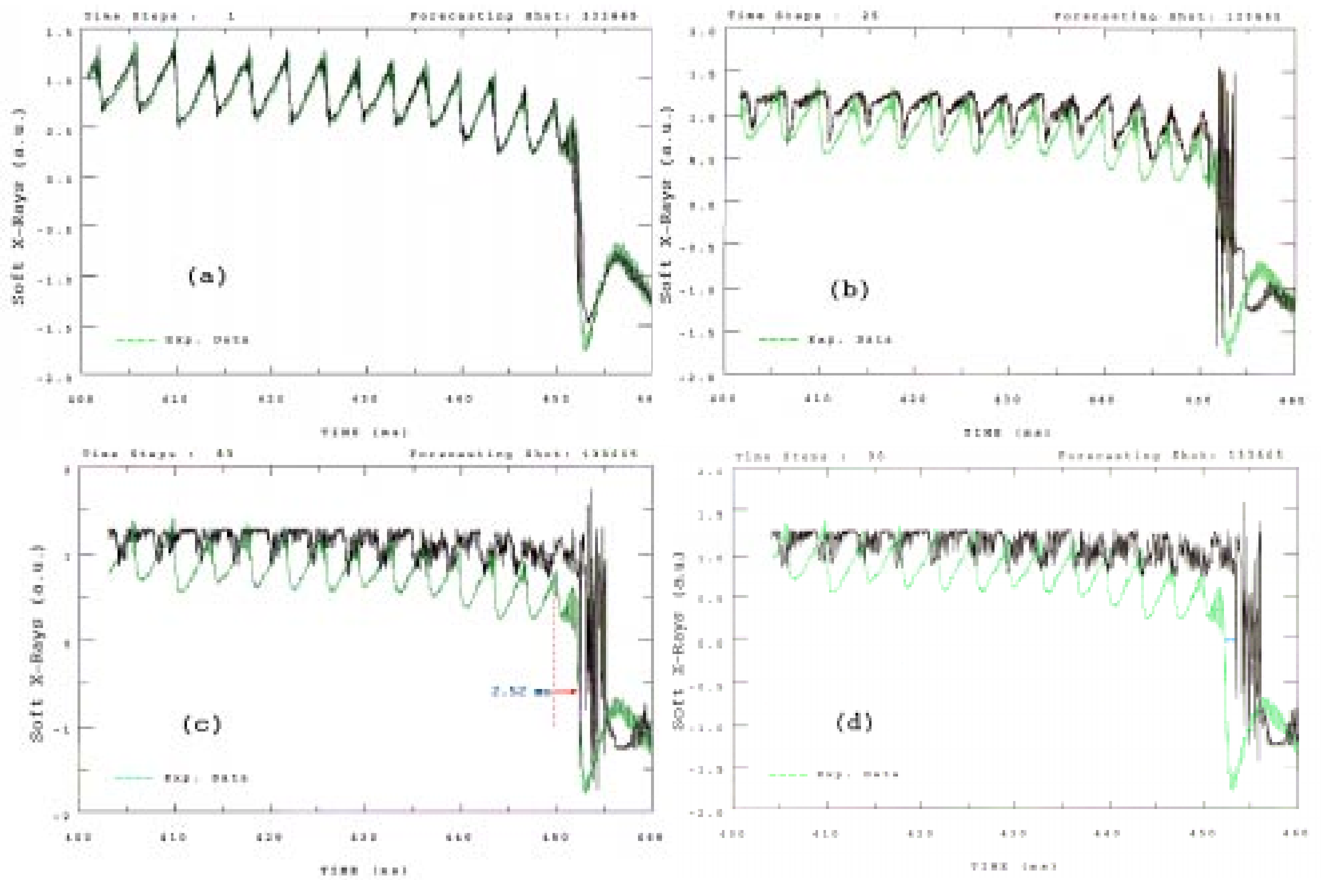

fig.2 -Comparation of the neural net results (in black) with the experimental data (in green) for several time-steps. The best prediction is obtained for 63 time-steps.

The results of the multi-step forecasting analysis done for this discharge show that the net is able to accurately predict the disruption time up to time-step 78 (Fig. 3). This corresponds to a forecast of the occurrence of the major disruption 3.12 ms in advance, value which is nearly triple the time that has been obtained previously using only magnetic data to feed the neural networks [2]. For larger time-steps, once again a time shift in prediction appears between the experimental signal and the result provided by the network.

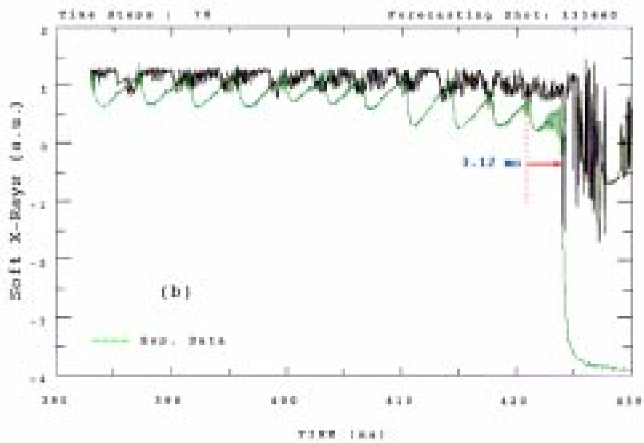

fig.3 - Neural net results for a second TEXT plasma. Now, the major disruption was not preceded by a minor disruption. The best result is obtained for the 78 time-steps prediction.

Interestingly, in both prediction cases the experimental data points used by the net to accurately forecast the minor and major disruption (Fig. 2c and Fig. 3) are located in time prior to the amplitude increase of the magnetic fluctuation signals, as can be seen in Fig. 4.

Since the neural networks was able to forecast disruptions using data points related to some particular instances of time before the observation of an increase in amplitude of the MHD activity,

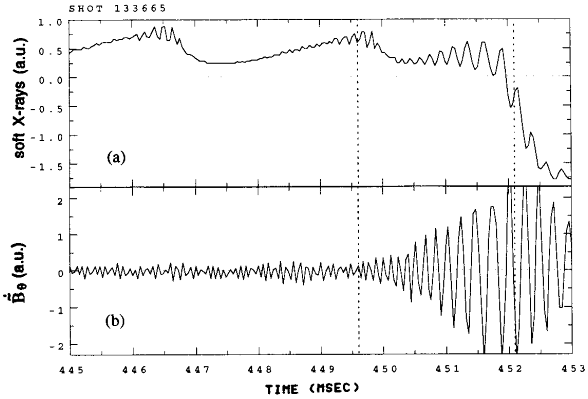

fig.4 - Soft X-ray intensity (a) and Mirnov magnetic signal (b) close to the disruption time. As can be observed, the experimental data used by the net in its best performance, for both cases analyzed, are located in time just before the MHD activity starts increasing in amplitude.

this observation might suggest that it is not the growing magnetic islands related to the q = 2 magnetic surface that would consequently disturb the inner island at q = 1 magnetic surface. The results obtained in this work suggest that it is probably the other way around, i. e., some disturbance phenomena would develop first around the central part of the plasma column (visualized by the soft X-rays central detector) and then the plasma region within the q = 2 magnetic surface would be affected, destabilizing the m = 2 MHD mode. This interpretation reminds us the works already done in tokamaks suggesting that the disruptive instabilities would be caused by a “cold bubble” moving towards the plasma center [3,4]. However, some more careful and further investigations must be done in order to give more confidence about the reality or not of this process.

Finally, as a continuation to this work, a recurrent Elman type of neural network is being used to forecast plasma disruptions, using soft X-ray as input signals. The preliminary results already obtained have shown a significant improvement, due to the network's recurrent feature, over the capability of the feed forward neural net in identifying the diruption precursor oscillations.

3. CONCLUSION

It has been shown that feed-forward neural networks can be effectively used to forecast both minor and major disruptive instabilities in tokamaks. Our forecasting time of minor or major disruptions is almost three times the one based on magnetic data [2]. We also note that the future larger tokamaks have longer plasma time scales than the medium size machines such as TEXT. This opens up a possibility of using feed-back controlled auxiliary systems to avoid the occurrence of the upcoming disruption or at least to minimize its harmful effects. Observing that the soft X-ray experimental data points used by the net in the best forecasting cases are located prior to the instance of the amplitude increase in the Mirnov magnetic signals, this might suggest that the perturbation which triggers the disruptions first initiates in the central part of the plasma column where the q = 1 magnetic surface is located and only afterwards this instability would reach the outer part of the plasma column, destabilizing the m = 2 MHD mode. The neural net may be employed in predicting and controlling plasma behavior in disruption and in perhaps more general dynamics as well.

References

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