Predicting the Onset of Plasma Disruptions in Tokamaks Using Artificial Neural Networks

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I - Introduction

Artificial neural networks are computer algorithms that simulate, in a very simplified form, the ability of brain neurons to process information. Basically, 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 (Fig. 1). The training of the neural net is performed by adjusting the weights between each connection as to minimize the error during the prediction processes ("*back propagation*") [1,2].

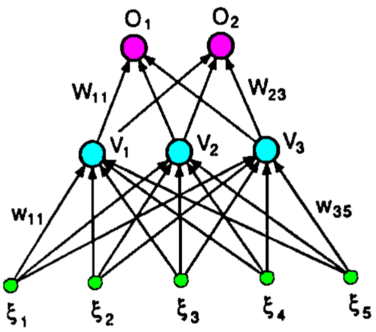

Fig. 1 – Feed-forward neural network showing the weighted connections between all the neurons units.

II - Basic Idea

Considering the tokamak a low dimensional dynamic system and supposing the time delayed vector:

$$X_t = [x_t, x_{t-\tau}, x_{t-2\tau}, \dots , x_{t-n\tau}], \tag{1}$$

then it is reasonable suppose that the future state of he system at time could be predicted by a smooth non-linear function ***F***:

$$x\ (t + \tau) = F\ (X_t) \tag{2}$$

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. To do this, the neural net must be properly trained first, that is, the correct set of weights for all connections must be found. This process consists basically in feeding the neural net repeatedly with experimental data, and in comparing the output signal Ô (forecasted) with the real (experimental) signal O (Fig. 2):

$$\varepsilon\ \{W\} = 1/M\ \sum (O_j - \hat{O}_j\ \{W\})^2 \tag{3}$$

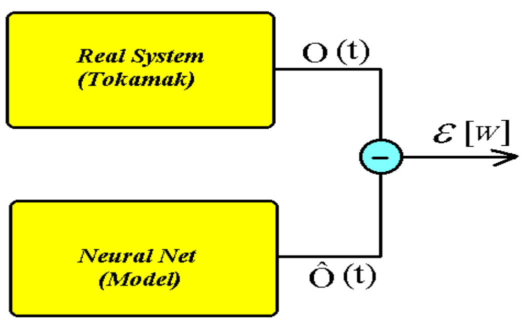

Fig. 2 – The training of the neural networks has been achieved when the error function ε {W} is minimized.

III - Forecasting Disruptions

The coupling between the m = 1 and m = 2 MHD modes has been usually accepted as the main triggering mechanism for the disruptive instabilities in tokamaks [3,4]. Therefore, both soft X-ray and Mirnov magnetic signals were chosen, alternatively, to be used in a neural network to forecast disruptions. Using the data taken during the last 200 ms of TEXT discharges, disruptions could be predicted 1.12 ms and 3.12 ms in advance, when magnetic and soft X-ray signals were used, respectively [5,6].

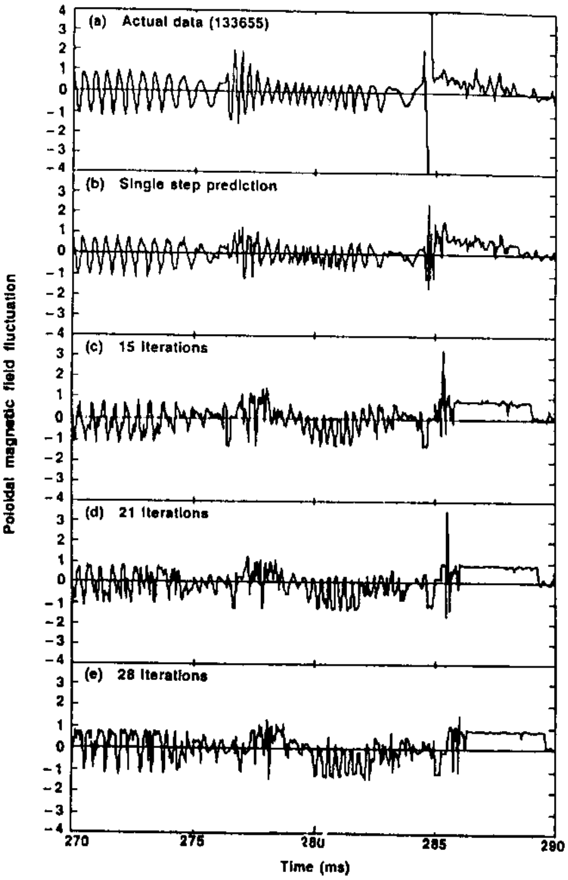

Fig. 3 – Experimental signal (a) compared with the results obtained (b – e) using magnetic signals from one Mirnov coil, in multiple time-step predictions. Even for 28 time-steps (e) the results show that both minor and major disruptions could be predicted by the neural net.

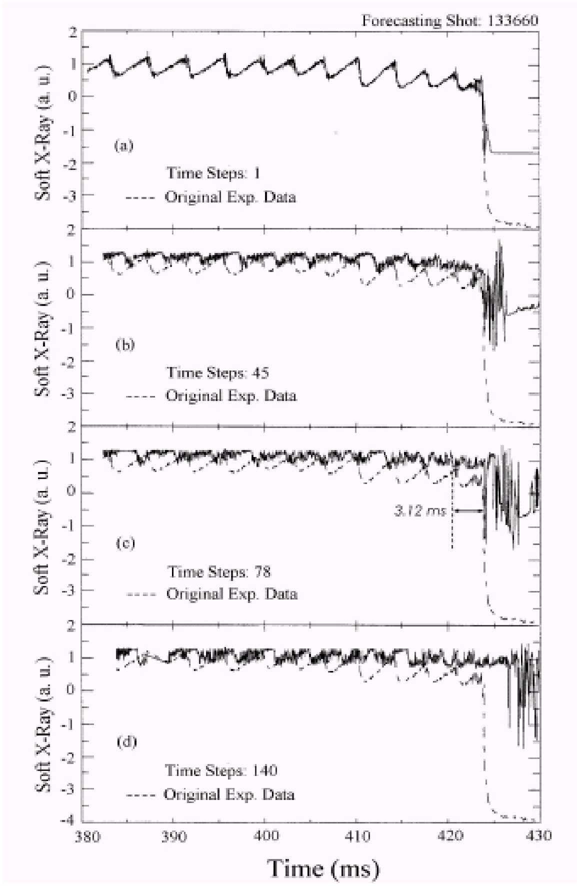

Fig.4 – Results obtained using soft X-ray signals. The major disruption is accurately predicted up to 3.12 ms in advance (c). For longer time-step predictions, a time delay is observed as compared to the experimental data (d).

More recently, however, a different neural network architecture has been tested, which yielded much better results. The new neural net used still has one input layer, two hidden layers and one output layer, but the number of neural units within each layer was chosen as to follow the relation *m:2m:m:1*, where *m* is the embedding parameter of the system. The corresponding results obtained, for the entire plasma duration, are shown in Figs 5 and 6.

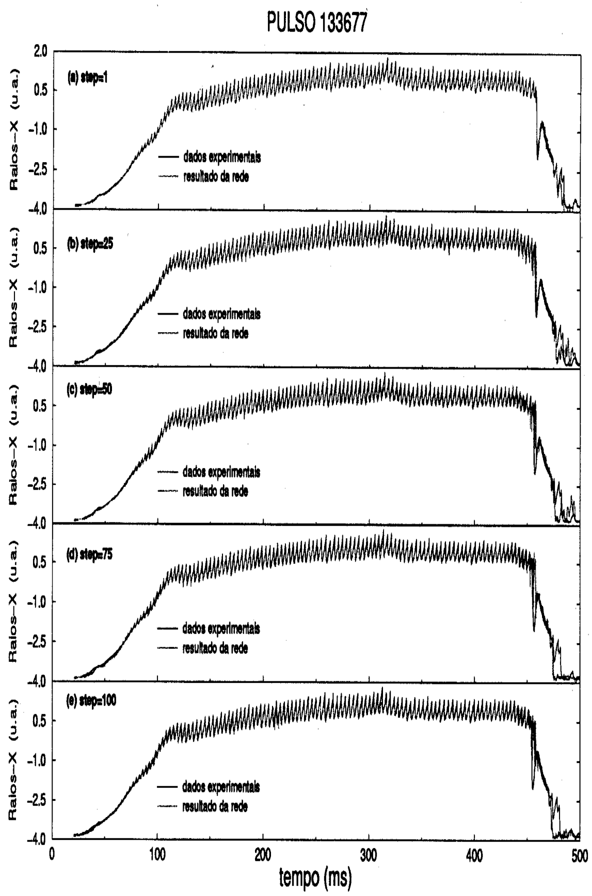

Fig. 5(Left) – Results obtained for an entire plasma duration using a neural network with architecture based on the relation m:2m:m:1, where m is the embedding parameter of the system. The major disruption could be predicted, in this case, up to 4.0 ms in advance

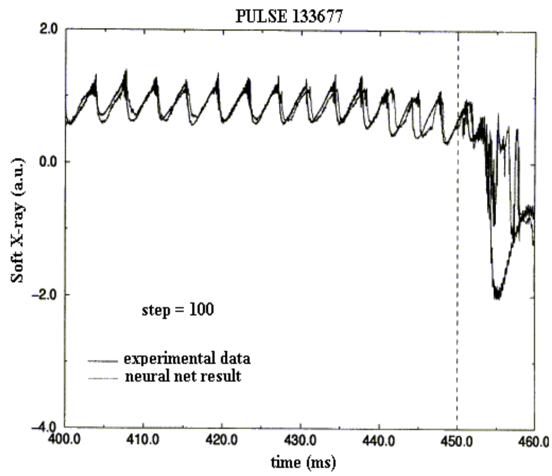

Fig. 6 – Expansion in time of the time trace corresponding to Fig. 5e.

IV – Predicting Time Series

Finally, the relation *m:2m:m:1* was also verified to be a good initial guess, for the ideal net architecture, when chaotic time series are predicted. In Fig. 7, for example, the results obtained for predicting the Lorentz series, for different time-steps, are shown [7]. Note that the prediction is practically perfect for time-steps up to $\tau = 0.5$, which indicates the network has successfully learned the dynamic of the chaotic system.

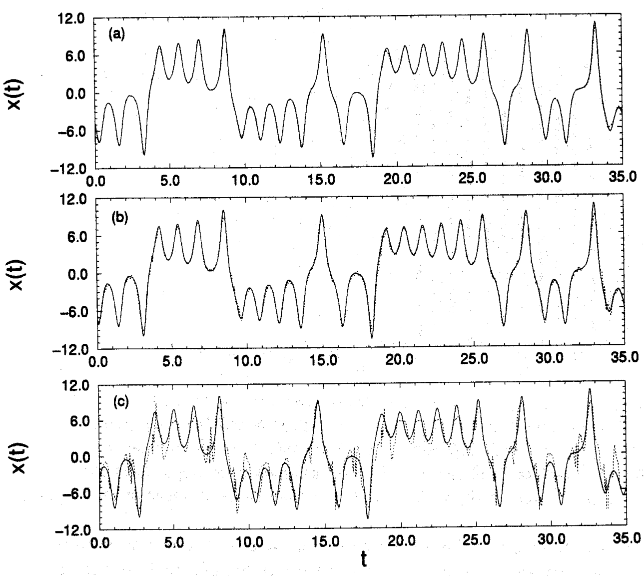

Fig.7 (Right) – Lorentz chaotic time series predictions for time steps (a) $\tau = 0.3$, (b) $\tau = 0.5$ and (c) $\tau = 0.9$.

V – Conclusions

It was demonstrated that neural networks could be successfully used to predict the future state of non-linear systems. Both minor and major disruptions can be forecasted during a tokamak plasma discharge, and even chaotic time series can be predicted using a proper architecture for the neural network. In this sense, the relation *m:2m:m:1*, where *m* is the embedding parameter of the system, has been observed to be a good initial guess for finding the best neural network architecture.

References

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