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ABSTRACT
JET plasmas are affected by various instabilities, which can be particularly dangerous in high performance discharges. An identification method, based on the use of advanced neural networks called Recurrent Neural Networks (RNNs), has been applied to ELMs and sawteeth. The approach is. The potential of the recurrent networks to identify the dynamics of the instabilities has been first tested using synthetic data. The networks have then been applied to JET experimental signals. An appropriate selection of the networks topology allows identifying quite well the time evolution of the edge temperature and of magnetic fields, considered the best indicators of the ELMs. A quite limited number of periodic oscillations are used to train the networks, which then manage to follow quite well the dynamics of the instabilities, in a recurrent configuration on one of the inputs. The time evolution of the aforementioned signals, also during intervals not used in the training and never seen by the networks, are properly reproduced. A careful analysis of the various terms in the RNNs has the potential to give clear indications about the nature of these instabilities and their dynamical behaviour.

1. INTRODUCTION
Tokamak plasmas are affected by a series of instabilities, which can affect the performance and even compromise the operation of experiments. A lot of progress has been achieved in the last decades to understand the main causes of these instabilities but various aspects of their dynamics remain not completely understood. Even the instabilities with the most evident macroscopic implications, such as ELMs, sawteeth and Neoclassical Tearing Modes [1], are a subject of active investigation. Among the difficulties in understanding the dynamics of these instabilities is the fact that the data analysis is often demanding and requires significant efforts. Automatic data analysis tools to identify the main aspects of the instabilities, from the signatures they leave on the measurements, would therefore be quite beneficial.

In the last years, quite significant experience has been gathered in using new machine learning tools, which have a lot of potential and can be quite effective in identifying even complex behaviours. In particular Recurrent Neural Networks (RNN) are very powerful in identifying even quite complex dynamic behaviour, as shown for the case of coupled pendula in [2]. RNN are neural networks whose topology presents at least one feedback loop [3]. This means that at least one of the outputs of the network neurons is fed back to one of the inputs. RNNs are very powerful and it can be demonstrated that any nonlinear dynamic system can be approximated to any level of accuracy provided the network has a sufficient number of neurons [3]. The architectural layout of RNN can take many different forms but the ones, whose results are presented in this paper, are of the input-output type, which means that there is a basic feedback loop from the outputs to the input of the entire network.

With regard to the structure of the paper, in the next section the main lines of the identification approach are introduced. Section 3 is devoted to the discussion of the results for type I and type III

ELMs. Conclusions and possible lines of future investigations are summarised in the last section 4 of the paper.

2. OVERVIEW OF THE IDENTIFICATION APPROACH AND THE NETWORK TOPOLOGY

The general topology of the network, used to identify the signals reported in this paper, corresponds to the following "ansatz":

$$\begin{cases} T(n) = f_1[T(n-2)] + f_2[T(n-1)] + h_1[B(n-3)] + f_3[B(n-2)] + \\ \qquad +f_4[B(n-1) + f_5[B(n)] \\ B(n) = l_2[T(n-3)] + g_1[T(n-2)] + g_2[T(n-1)] + l_1[T(n)] + \\ \qquad +g_3[B(n-3) + +g_4[B(n-2)] + g_5[B(n-1)] \end{cases}$$

The topology of the network implementing ansatz (1) is shown in figure 1. The squares correspond to non linear neurons, whereas the diamonds are linear ones. The activation function chosen for the nonlinear neurons is the tanh. The training process consist first of the identification of a certain number of instability cycles with the one step ahead approach. The network is trained to estimate the value of the signals at the next time step. To prove the quality of the identification, the network is then applied in recurrent configuration by short circuiting the outputs to the inputs. Starting from suitable initial conditions, the network should be able to reproduce the time evolution of the signals. This can be tested not only on the signals used for the training but also to subsequent time intervals, provided the parameters of the dynamic system are stationary.

To assess the potential of the approach, the network has been trained and tested with the synthetic signals of figure 2.

The shape of these synthetic signals has been chosen such that they are representative of experimental cases and also quite challenging (they present abrupt variations). In the same figure 2 the outputs of the network are also reported to show the quality of the identification. These outputs have been obtained with both outputs fed back to the inputs, so with both branches of the network in recurrent configuration, starting from suitable initial conditions. It is worth noticing the difficulty of the identification. Even with a noise level of only 5%, the errors tend to accumulate and cause a shift of the reconstructed signals. On the other hand, the main features of the signals dynamics are very well and robustly reproduced.

3. EXAMPLES OF ELM IDENTIFICATION

As a relevant experimental example, the previously described approach has been applied to the identification of ELMs on JET. Since various types of ELMs have been experimentally and theoretically investigated, the long term goal of this type of work could be the automatic discrimination of the various types of ELMs. In this perspective, the first step consists of proving the capability of RNNs to identify the experimental signals, which present clear signatures of ELMs.

After a careful analysis of the available signals, it has been decided to start by trying to identify the perturbations caused by the ELMs on the edge temperature, as measured by the Electron Cyclotron Emission Diagnostic (ECE), and on the magnetic field, as measured with the pick up coils. Examples of the time evolution of these signals for type I and type III ELMs are reported in figure 3 and 4. Given the quality of the signs and the fact that the discharges are not strictly stationary, some form of signal preprocessing is necessary. Filtering, to eliminate the highest frequency components of the noise, and detrending, to eliminate the slow drifts, are the first steps. The normalization of the signals is performed next to give the RNNs inputs in the interval [−0.8, 0.8] as required for the optimal use of the tanh activation functions to avoid saturation.

After identifying the signals with the network corresponding to the full topology, the weights of the various terms in (1) have been analysed. The smallest ones have been then eliminated up to the point when the performance of the networks degrades. This method allows converging on networks topologies with the minimum number of elements in the "ansatz" capable of learning the dynamics of the signals.

For the ELM I case of figure 3, the process converges on the following equations for the network:

$$\begin{cases} T(n) = f_1[T(n-2)] + f_2[T(n-1)] + f_4[B(n-1)] + f_5[B(n)] \\ B(n) = g_2[T(n-1)] + g_5[B(n-1) \end{cases}$$

The quality of the identification is shown in figure 5.

For the case of the type III ELMs of figure 4, the final ansatz, after elimination of the non relevant elements in (1) is:

$$\begin{cases} T(n) = f_3[B(n-2)] + f_5[B(n) \\ B(n) = g_2[T(n-1)] + g_3[B(n-3)] + g_5[B(n-1)] \end{cases}$$

Again the quality of the identification for this case is reported in figure 6.

The identification has been repeated for a number of cases (basically the statistics is limited by the quality of the measurements available). The optimal configurations of the networks for the various cases is summarised in table I. The results of the identification process indicate that there seems to be a systematic difference between the two types of ELMs. In particular, the Type III ELM analysed is the only one which does not require f2 (feedback on the temperature at time t-2); it is also the only case, which requires g2 (temperature feedback on the field at time t-2). Of course the limited statistics available and the preliminary nature of the present studies do not allow drawing conclusions on the physics of the instabilities. On the other hand, these preliminary results indicate that RNNs are very powerful and they have the potential to identify complex dynamical systems, provided measurements of acceptable quality are available.

CONCLUSIONS AND FUTURE DEVELOPMENTS

The potential of recurrent neural networks, to identify complex dynamical systems, has been investigated. In addition to the case of synthetic signals, the RNNs have also been applied to experimental data. In particular the time evolution of the edge temperature and magnetic field due to Type I and Type III ELMs have been identified quite successfully with networks of the appropriate topology. The identification of experimental signals has proved to be quite challenging mainly because of two main factors: a) the complex dynamics of the instabilities b) the significant level of noise. Notwithstanding these difficulties the results are quite encouraging since RNNs seem to have the potential to identify the signals of the ELMs. Moreover there could be a clear relation between the topology of the optimal RNN for identification and the nature of the instability. A additional point worth investigating is the potential of RNNs to identify also the coupling between various instabilities, such as the mutual influence of sawteeth and ELMs.

ACKNOWLEDGEMENTS

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Pulse No:	f1	f2	f3	f4	f5	g1	g2	g3	g4	g5	g6	l1	h1
79389 Type I ELMs	1	1	0	1	1	0	1	0	0	1	0	0	0
79837 Type I ELMs	1	1	0	1	0	0	1	0	1	1	1	0	0
79371 Type I ELMs	0	1	1	0	1	1	1	0	1	1	0	1	1
79398 Type I ELMs	0	0	1	0	1	0	1	1	0	1	0	0	0

Table I: Summary of the “ansatzes” found optimal for examples of Type I and Type III ELMs.

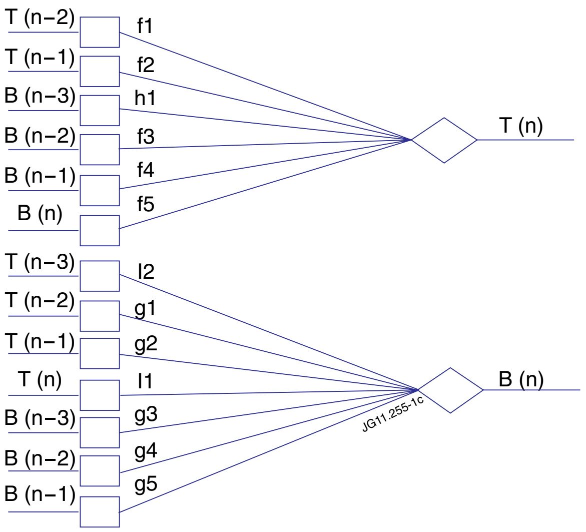

Figure 1: Topology of the network corresponding to the general "ansatz" of relation (1).

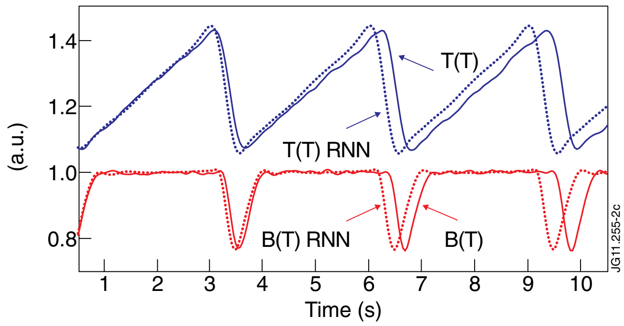

Figure 2: Continuous lines: Synthetic signals used for the training training Dashed lines: outputs of the RNN. The functions of relation (1) used to identify the signals are: f1,f2,f3,f4,g1,g2,g3,g4.

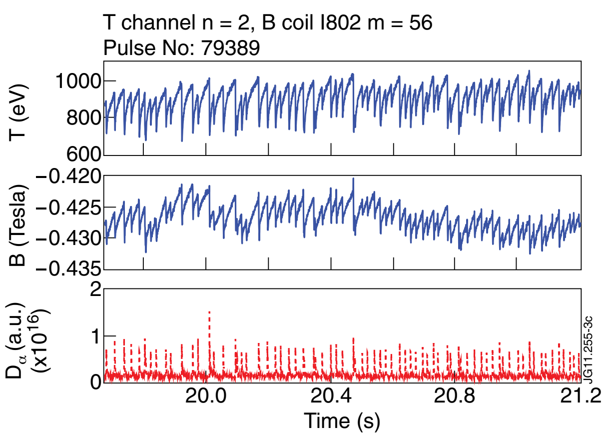

Figure 3: Time evolution of the signals for a type I ELM.
Top: electron temperature at the radius 3.7m. Measured with the ECE
Middle: Magnetic field measured with a fast coil
Bottom: A D_α signals in the outer divertor.

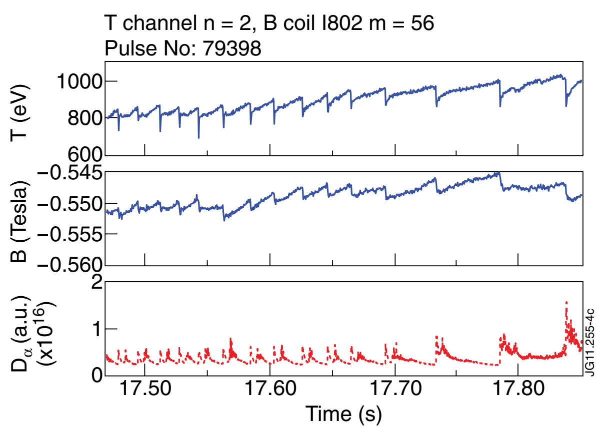

Figure 4: Time evolution of the signals for a type III ELM.
Top: electron temperature at the radius 3.76m. Measured with the ECE
Middle: Magnetic field measured with a fast coil.
Bottom: E D_α signals in the outer divertor.

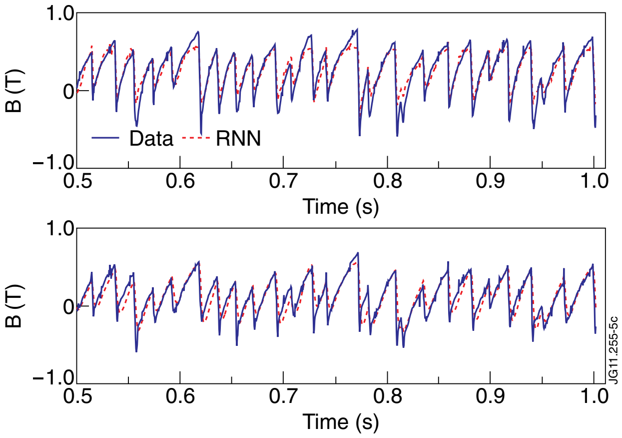

Figure 5: Top: Test signal T (blue) and network output signal T (red) in recurrent configuration on T.
Bottom: Test signal B (blue) and network output signal B (red) in recurrent configuration on B.

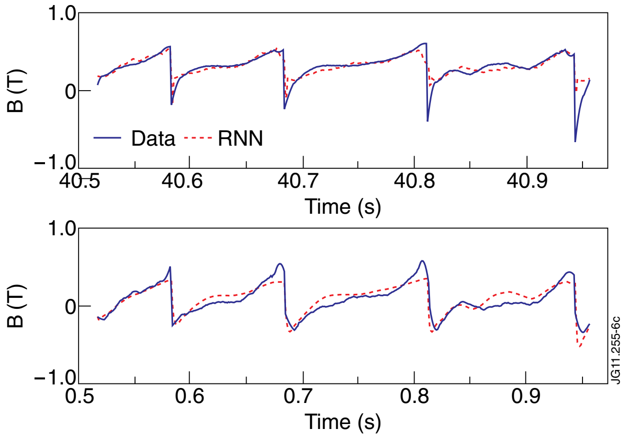

Figure 6: Top: Test signal T (blue) and network output signal T (red) in recurrent configuration on T.
Bottom: Test signal B (blue) and network output signal B (red) in recurrent configuration on B.