Dynamic Neural Networks for Prediction of Disruptions in Tokamaks

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Abstract

In this paper, dynamic neural networks are proposed to predict the plasma disruptions in a nuclear fusion device. Disruptions are critical events where the plasma, which is magnetically confined in a vacuum vessel, becomes unstable, cools down and the confinement is suddenly destroyed. These events may damage to the vessel, so they have to be foreseen well in advance in order to take mitigating action.

Dynamic neural networks act as filters, which predict one step ahead the value of diagnostic signals acquired during a plasma pulse. The prediction error of the neural network depends on the regularity of signals. For this reason, an increasing prediction error reveals that the plasma operative conditions are changing, hence a disruption could be imminent. In this work, different diagnostic approaches, network adapting parameters, and diagnosis thresholds have been tested in order to determine the best performance in terms of prediction capability.

1. Introduction

In recent years, due to the necessity of finding new energy resources in order to satisfy the increasing demand for energy and to face the exhaustion of the fossil fuels, research into nuclear fusion has been significantly developed, by reaching important progresses. Nuclear fusion could provide enormous quantities of energy in a “clean” way; moreover, the “fuel” for this reaction, consists primarily of isotopes of hydrogen, which are practically inexhaustible.

The most promising device for nuclear fusion is the Tokamak. In a Tokamak, the plasma is heated in a ring-shaped vacuum chamber (vessel or torus) and kept away from the vessel walls by applying magnetic fields. The equilibrium of a plasma in a magnetic field can be described by the Magnetic Hydro-Dynamic (MHD) theory [1]. If MHD instabilities arise, the plasma loses its confinement, leading, in the most serious cases, to the displacements of magnetic surfaces, and ending in a disruption. Disruptions are endemic and likely unavoidable aspect of tokamak operation that potentially pose serious problems to the integrity and the lifetime of the machine.

During a disruption, the plasma energy is lost within a time span of few milliseconds. In major disruptions, taking place at high plasma current, the tokamak first wall components are subjected to high concentrated thermal fluxes and severe electro-mechanical stresses due to induced currents. The physical causes that lead to a disruption have been widely studied [2] [3]. Even if the complete dynamic behavior of a disruptive event is not yet completely understood, some precursor phenomena that lead to a disruption have been identified [1].

However, this knowledge is not sufficient to develop a deterministic mathematical model that takes into account all the complex phenomena leading to a disruptive event. On the other hand, a disruption model is of crucial importance for prediction purposes.

Recently, disruption prediction techniques have been investigated [4][5][6].

In many of these techniques neural network based approaches are used and they look promising to predict the event or, more precisely, to build an impending disruption warning indicator. The approaches based on neural networks, which have been proposed in the literature until now, use static neural networks as predictors. This derives from the hypothesis that the available measurements give complete information about the state of the plasma.

In this paper a different approach is adopted, which exploits the dynamic of the measured signals to predict the incoming disruptions. A neural network is dynamically adapted to predict the values of the measurements one time step ahead. The prediction error reflects both the capability of the network to learn the dynamics of the signals and the regularity of the signal itself. If the error prediction begins to rise, this is due to a variation of the dynamics of the signals, hence that can be interpreted as an indicator of an incoming disruption.

Therefore, the proposed disruption predictor exploits the prediction error rather than the predicted signal values. In fact, even if the prediction error is high, the performance of the alarm system would be good, provided that the error is sensitive to the disruption precursors. The hypothesis is that said error rises well before the disruption event, so that the mitigation system has enough time to intervene.

An important aspect of dynamic neural networks is that the prediction of the disruption is not based on a training set but only the temporal evolution of the pulse is taken into account, hence the proposed approach is not subject to the ageing phenomenon, which is typical of static neural networks.

The proposed approach is applied on a disruption database taken from JET [7], the biggest experimental fusion reactor in Europe. The database, used to train and test the neural networks, contains several diagnostic signals, which characterize a disruptive event (disruptive pulse) or a non disruptive event (safe pulse). The diagnostic signals have been selected in order to maximize the prediction capability of the system and accordingly to both physical considerations and availability of real-time data. A sensitivity and a salience analysis confirmed the appropriateness of the choice [6] .

The performance of the proposed approach is compared with those of the Mode Lock Indicator (MLI). The Mode Lock Indicator (MLI) triggers a shut down procedure when the Locked Mode signal reaches a prefixed threshold. MLI is actually the only on-line disruption protection system used at JET.

2. Disruptions

Disruptions pose strong limits to tokamaks range of operation in current and density.

Modifying the plasma parameters toward the desired high pressures, and increasing the plasma current to achieve better confinement, several kinds of instabilities can appear. Ideal MHD instabilities are often the most serious cases which end in a disruption. A disruption is a displacement of magnetic surfaces which lead to an irreversible loss of magnetic confinement.

During a disruption a sudden loss of plasma energy occurs and the central temperature collapses. This energy quench leaves the plasma in a cold and resistive state, leading therefore to a quickly current decay.

Additionally, during a disruption, after the thermal quench, the plasma may lose vertical stability. Both, the decreasing of the plasma current and the displacement of the current column, can induce large eddy currents in the machine structures and cause electromagnetic forces that, together with the heat loads released during the thermal quench, can damage the machine itself. In particular, intense heat loads of the order of MW/m^2 in a few tens of ms, and mechanical stresses of the order of some MN/cm^2 can occur, causing severe damage.

The physical processes involved in a disruption are not known in detail. However, a description of the sequence of events, which characterize a disruption in four phases, is reported in [1]: Pre-precursor phase; Precursor phase, Fast phase and Quench phase.

At JET, the fast phase and the quench phase last less then 40 ms [6]. During these phases the diagnostic signals are not completely reliable due to the presence of high induced currents and magnetic field variations, these two phases have not been monitored in the present work.

Defining t_{prec} as the time instant that discriminates between pre-precursor phase and precursor phase, some disruption precursors are expected to appear in the time window from t_{prec} to 40 ms before the disruption. Unfortunately, t_{prec} does not have a fixed value, and the identification of the two different phases is often a very difficult task. Presently, indexes of the transition from a phase to the other are not available.

3. State of the art for disruption prediction

The literature reports several approaches to disruption prediction using artificial neural networks (ANN): all of them are based on the identification of either the precursors events or the proximity or probability of disruption.

In the first case, one or more plasma measurements are used as targets to be forecast by the ANN. The ANN produces a set of future values of plasma diagnostic signals that can be used in conjunction with a physical model to establish if a disruption is imminent.

In [8] the authors' goal was to predict the Mirnov coil measurements in the tokamak TEXT (Universtity of Texas, Austin, USA) in order to identify m=2 MHD modes, which were indicative of an impending disruption.

Some improvements were obtained in [9] with the same approach, by adding the soft X-ray signals. By using this type of measurements, disruptions of two discharges were predicted 3 ms in advance.

In a more recent article [10], the same approach used for TEXT was adopted for the ADITYA tokamak. The network, fed by several input signals, i.e., Mirnov coil signals, soft X rays, and Hα measurements, was able to predict all input signals 8 ms in advance.

The high β disruption boundary was modelled in [11] using 33 input magnetic measurements for the DIII-D TOKAMAK (San Diego, USA). At least 90% of disruptions in the test set, composed by 28 disruptive pulses, were successfully predicted many tens of ms before the major disruption, but 20% of false alarms were generated.

Although the results obtained with all these approach are very promising, they have been experienced only in particular operation scenarios.

In this paper this precursor events approach is considered and a generalization to any operational scenario is tried.

In the second type of predictors an artificial output is assigned to a neural network to directly indicate the eventual proximity of the disruptive event.

In [12] the authors propose an approach based on a Bayesian probability assessment of the disruptive phenomenon, the Bayesian probability is modelled by a MLP neural network. The model tries to investigate if a set of parameters is useful as an incoming disruption indicator.

In [4], an on-line predictor of the time to disruption installed on the ASDEX Upgrade tokamak is presented. The prediction system uses a neural network trained on eight plasma parameters and some of their time derivatives extracted from 99 disruptive discharges. The system was implemented and tested for real-time mitigation, showing satisfactory prediction capability. However the authors highlight the deterioration of the network performance on on-line tests, due to the slight difference between the real-time signal and the stored ones. Moreover, it has been shown that new experiments, which belong to operational spaces different from those used for training, are not well predicted in the on-line implementation, thus presenting the so-called ‘ageing’ of the neural network.

Some major disruptions have been investigated in [5]. The concept of ‘stability level’, proposed in the paper is calculated from nine plasma parameters by a MLP, and the occurrence of a major disruption is predicted when the stability level decreases to a certain level, named the ‘alarm level’.

The authors in [13] combine multiple plasma diagnostic signals to provide a composite impending disruption warning indicator. To take into account the disruption precursor appearing in different time instants for different pulses, an off-line clustering procedure automatically selects the training set samples.

The work presented in [6] has been performed on flat-top JET scenarios characterized by a single null plasma. The authors trained a MLP to forecast disruptive events at JET, up to 100 ms in advance.

In [14] two neural approaches (Self Organizing Maps and Support Vector Machines) are used to determine the novelty of the output of the neural disruption predictor. The novelty detector is used to assess the reliability of the network output, i.e., samples having a low confidence have to be discarded and used off line to update the disruption predictor.

4. Approach for Precursor Prediction

The basic idea of the proposed approach is that a neural network with memory can be adapted in order to forecast given signals some steps ahead. In this work a dynamic model is obtained by introducing a delay line in the input of the neural network. The prediction error depends both on the capability of the network to adapt itself to the signal behavior and on the fact that the signal follows more or less the same evolution with time. Hence, if during the pulse the prediction error increases, this means that a variation is occurring in the signal and this is interpreted as a precursor of the disruption. In Fig. 1, the scheme of the diagnostic procedure is shown.

In order to perform the prediction, the network prediction errors on the different signals acquired on the machine have to be considered in order to obtain an unique prediction error, and a threshold has to be defined to perform the diagnosis. Different errors combinations and thresholds have been tested to trigger an alarm, but only the best results are reported here.

As in the training of static neural networks, the set of examples is divided in a training and in a test set. During the training section the cited threshold values are set. The training phase is also used to determine the adapting time interval, namely the number of samples needed for the neural network to reach the regime value of the prediction error, whose importance will be explained in the following.

Due to the philosophy of the approach, a neural network, which has low performance in predicting the input signal, could in general be suitable for the disruption prediction, provided that the error has a high sensitivity to the variations of the input signal behavior.

Another aspect concerns the fact that the error exhibits a transient in the beginning of the pulse, due to the time interval that the network spends to adapt itself to the signal, and in the meantime the alarms given by the network are not reliable. On the other hand, if the network adapts itself too fast, the regime variation of the signal could not cause an error increase, so giving rise to a missed alarm. Then a compromise has to be found between the duration of the alarms reliability interval and the sensitivity to slow changes of signal dynamics.

Therefore, several parameters have to be tuned in order to maximize the performance of the disruption predictor, in terms of ratio between correct alarms and total pulses. A number of both linear and nonlinear networks have been compared, by varying the memory depth, the number of adapting passes and, in the nonlinear networks, the number of hidden neurons.

Furthermore, due to the experimental nature of the examined pulses, the operator often intervenes to modify the functioning parameters, and this causes a modification of the regime of signals and then, in most of the cases, an alarm of the system. Therefore, the alarms have to be inhibited when the operator acts on the process regulation, the inhibition time interval depending on the duration of the transient evaluated at the beginning of the pulse.

Finally, the available signals have different attitude to trigger reliable alarms. Hence the performances obtained by considering different combinations of signals have been compared.

5. Disruptions prediction

5.1. Database

In the present paper, a large database [15] has been built based on hundreds of diagnostic signals available in the JET experimental machine. Each series of experiments consists of about 30 pulses, oriented to investigate different functional aspect of the plasma.

The pulses included in the database satisfy the following requirements:

- Plasma current I_{pla}>1.5 MA;
- X-point configuration;
- Flat-top plasma current profile.

Discharges with I_{pla} below 1.5 MA were discarded as they generally have little impact on subsequent conditioning and operation of the device.

For each pulse, nine diagnostic signals are considered, which have shown to be suitable for disruption prediction in several works presented in literature [6].

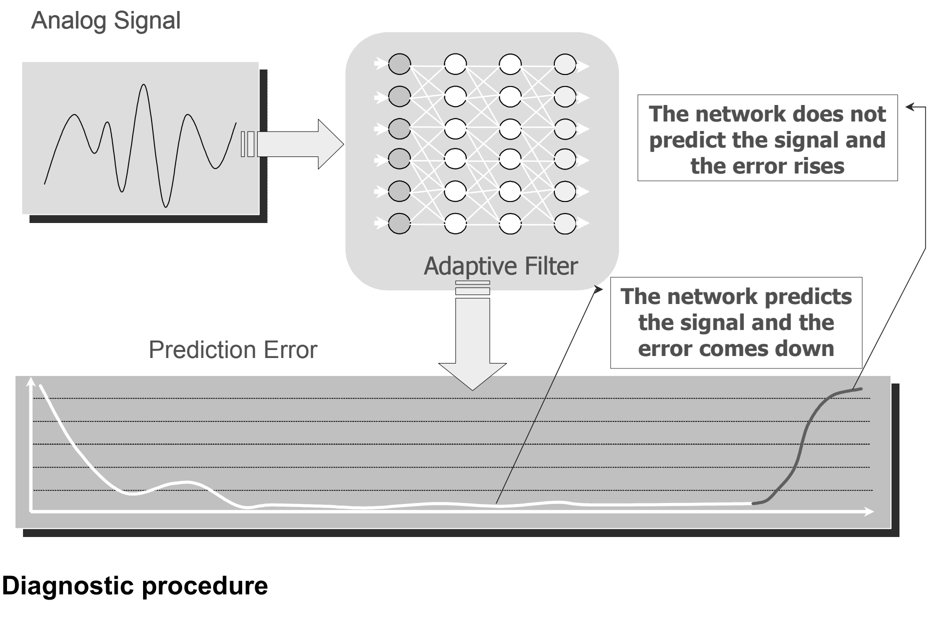

Fig. 1 Diagnostic procedure

TABLE I – DIAGNOSTIC SIGNALS

Signal	Unit	Symbol
Plasma current	[A]	I_{pla}
Locked Mode	[T]	ML
Radiated power	[W]	P_{rad}
Plasma Density	[m-3]	D_{pla}
Input Power	[W]	P_{in}
Internal Inductance		ℓ_i
Safety factor		Q
Poloidal Beta		β_p
Plasma centroid vertical position	[m]	P_v

The selected diagnostic signals are reported in Table I.

The database contains 102 pulses without disruption (safe pulses) and 154 disruptive pulses. The sampling interval is 20 ms.

The pulses have been used in this paper without performing any pre-selection of the data, neither using the classification of the different disruptions, which is known. The reason is that the aim of this work is to determine what performance can be obtained by means of the simple analysis of the signals.

To determine the adapting parameters and the thresholds described above, a training set constituted by 69 disrupted pulses has been used, while the remaining 85 disrupted pulses and all the 102 safe pulses have been used as test set.

5.2. Performance evaluation

In the proposed approach the training phase is not distinguished from the testing phase, because the training is performed dynamically during each pulse. Hence, the separation between training and test sets is made in order to define a priori the adapting parameters and the thresholds that have to be adopted during the test.

Therefore, the main attention is spent to evaluate the performance on the test set. The aim of the diagnostic system is to predict the disruption in time to undertake a form of mitigating action, so avoiding to damage the apparatus.

In particular, in the JET tokamak, at least 100 ms are necessary to terminate a pulse. Furthermore, the alarm has not to be given too early, since this should restrict the operative space. In the considered machine, an alarm is successfully given if it is triggered at most 1s before the disruption time. Finally, no alarm would be given if the pulse is safe.

The performance of the prediction systems can be evaluated in terms of percentage of false alarms (PFA), where PFA is defined as the ratio between the number of safe pulses predicted by the system as disruptive pulses, and the total number of safe pulses, in percent; and in percentage of missed alarms (PMA), where PMA is defined as the ratio between the number of disruptive pulses predicted as safe pulses, and the number of disruptive pulses, in percent.

Moreover, for disruptive pulses, the percentage of premature alarms (PPA) is defined as the ratio between the number of disruptive pulses predicted by the system too much in advance, and the number of disruptive pulses, in percent.

Finally, the prediction success (PSR) rate is defined as the success rate of the predictor in correctly predicting both disruptive and safe pulses.

5.3 Neural approach

The input of the neural network is a delay line that is fed with the nine diagnostic signals of Table I. The number of taps of the delay line is optimized by means of a trial and error procedure, in order to obtain a prediction error as small as possible. Both linear and nonlinear networks have been used to construct the predictor. In the latter, the hidden layer has to be suitably sized, in order to give enough degrees of freedom, but avoiding to over fit the network. Also this parameter has been determined by means of a trial and error procedure.

In all the cases only one adapting iteration is performed at each instant. This causes the transient duration to be long, but it guarantees that whatever variation in the dynamics of the signal causes an observable rise of the prediction error.

The output layer consists of eight linear neurons, each one corresponding to a measurement to be predicted. The unique input value that has not a correspondence in the output is the power P_{in} fed to the machine, which cannot be predicted because it is regulated by the human operator.

As said above, the prediction error is assumed as diagnostic signal. Such prediction error has been calculated in different ways.

Moreover, in order to determine a suitable alarm threshold, several procedures have been developed and compared.

The best results have been obtained by evaluating the prediction error as the weighted sum of the prediction errors on each signal, where the weights are the standard deviation on the signals, calculated in a fixed number of time steps before. A static threshold

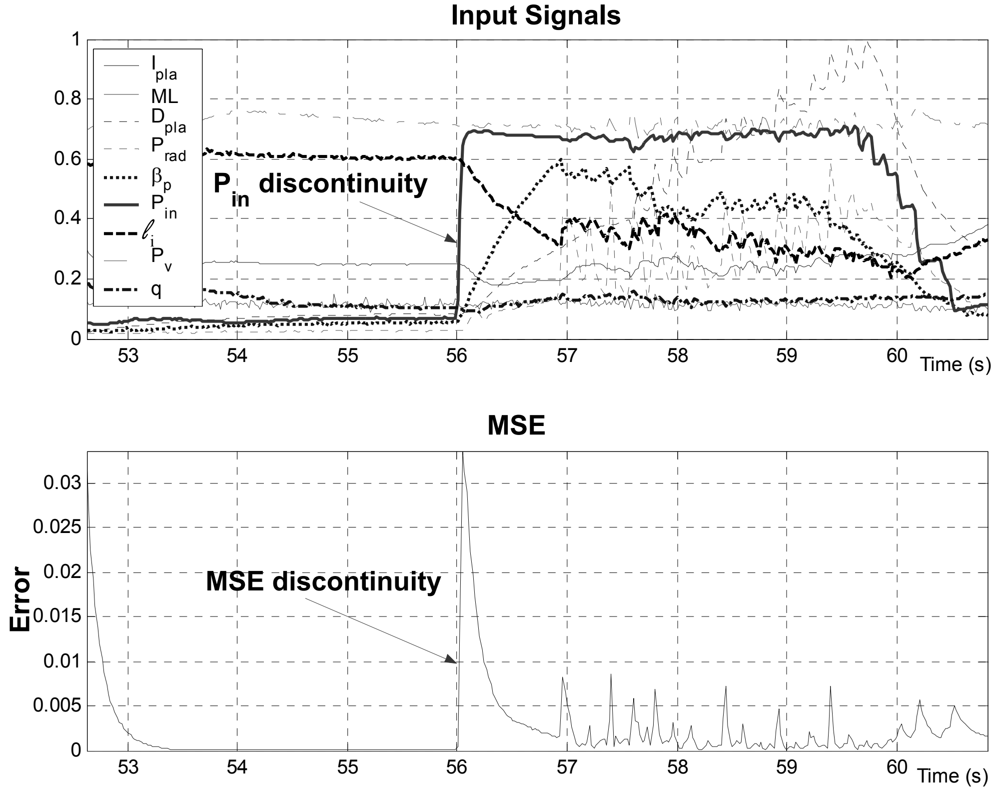

Fig. 2 Inhibition of the alarm caused by a step discontinuity of P_{in}

has been empirically determined on the basis of the training set.

The reliability of such an alarm depends on the fact that no transient is evolving, where a transient can be due to both the start of the pulse and an intervention of the human operator. In order to know if a transient is present, the time elapsed from the last cause of transient is greater than the transient time evaluated for the signal that gives the alarm.

An exhaustive analysis of the network behaviour with respect of the different signals highlighted that Input Power signal presents a step discontinuity for 60 of the 102 safe pulses (see Fig. 2) due to control action of the operator. For that reason, the alarms on P_{in} corresponding to such discontinuities have been inhibited.

6. Results

By comparing the performance of linear and nonlinear networks, we found that the latter ones are able to reach a smaller prediction error at the regime, and also they are more sensitive to the variations of the signals dynamics, but the error value greatly depends on the initial randomization of connections weights, hence this information is not reliable. On the contrary, the linear networks exhibit a greater robustness in adapting, and they show a sufficient sensitivity to the disruption precursors.

In this paper, only the best results, obtained with linear networks are presented. In Table II the results obtained on the training set are reported in terms of PMA, PPA, and PSR. Note that, in Table II, PFA are not present as the training set contains only disruptive pulses.

As it can be noted, the proposed system has an interesting predicting capability on the training set, comparable with that of other prediction systems reported in literature.

In Table III the system performance is reported for the test set in terms of PFA, PMA, PPA, and PSR. The results are very encouraging, even if the percentage of false alarms needs to be further reduced.

Moreover, the prediction capability of the neural predictor has been compared with the performance of the Mode Lock Indicator. The Mode Lock Indicator (MLI) is used at JET in the on-line disruption protection system and it triggers a shut down procedure.

As data on missed alarms are, obviously, the only data available for the Mode Lock Indicator, Table IV shows a comparison between the results of the dynamic neural network and the MLI only in terms of PMA. Note that, MLI intervenes only in the case of disruptions due to locked modes. In our test set the class of disruption is unknown, hence such comparison is significant only because MLI is the only disruption protection system presently implemented at JET.

For the training set, the MLI missed the alarm for 50 pulses, while the proposed predictor missed the alarm for 19 pulses. It has to be pointed out that the two systems correctly agree for only 17 pulses.

For the test set, the MLI missed the alarm for 43 pulses, while the proposed predictor missed the alarm for 16 pulses. It has to be pointed out that the two systems correctly agree for 41 pulses. Moreover, the proposed system is able to correctly detect further 28 disruptions.

7. Conclusion

In this paper, the dynamics of the diagnostic signals have been considered in order to predict the disruptions in nuclear fusion experiments. As a diagnostic signal, we use the error of the adapting neural network in the prediction of the signals coming from the machine. More specifically, if the prediction error begins to rise a disruption alarm is given. Several techniques have been applied to determine suitable alarm thresholds, and neural network structures. Different combinations of the prediction errors are tested, in order to obtain the best performance in terms of prediction success rate.

The obtained results show that the proposed approach could furnish a new interesting point of view in predicting disruptions in nuclear fusion experiments, even if it needs to be further investigated in order to reduce the false alarms.

Table II – Performance of the diagnostic system on the training set

PMA	PPA	PSR
28% 19/69	4% 3/69	68% 47/69

Table III – Performance of the diagnostic system on the test set

PFA	PMA	PPA	PSR
27% 28/102	19% 16/85	0% 0/85	76% 143/187

TABLE IV: COMPARISON BETWEEN PRESENT SYSTEM AND MLI

	Dynamic NN	MLI
PMA Training	28% 19/69	72% 50/69
PMA Test	19% 16/85	51% 43/85

It has to be highlighted that, the proposed prediction system is able to reduce the percentage of Missed Alarms more than 60 % with respect to the Locked Mode indicator, which is presently the only prediction system used at JET in the on-line disruption protection system.

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