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HL-2A tokamak disruption forecasting based on an artificial neural network*

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Artificial neural networks are trained to forecast the plasma disruption in HL-2A tokamak. Optimized network architecture is obtained. Saliency analysis is made to assess the relative importance of different diagnostic signals as network input. The trained networks can successfully detect the disruptive pulses of HL-2A tokamak. The results obtained show the possibility of developing a neural network predictor that intervenes well in advance for avoiding plasma disruption or mitigating its effects.

Keywords: disruption, prediction, artificial neural networks
PACC: 5255G, 5255P, 5265

1. Introduction

Disruption in a tokamak is a sudden loss of confinement and subsequent transfer of plasma energy to the surrounding structure component. The force and heat loads, induced by disruption, may damage the machine walls and the supporting structure. Thus, disruption prediction at a sufficiently early time is important for taking measures to avoid the disruption or mitigate the unavoidable hazard. Physically, disruptions have different causes, most of which have been identified but the dynamics is not known in detail. For instance, the relations between various instabilities[1−3] and disruptions remain an active research area. Therefore, the experimental operation now frequently relies on human experience and often the disruption cannot be avoided or predicted and mitigated at all. As a result, some new methods[4−12] are designed to forecast the plasma disruption. Most of them are based on the artificial neural network (ANN). For example, the off-line or on-line network disruption predictors have been developed in TEXT, ADITY, DIII-D, JET, JT-60U, and ASDEX-U.[4−9]

Early disruption prediction by ANN was carried out by using a time series approach in TEXT. The network trained with one disruptive and one successful pluses could predict the disruption 1 ms in advance.[4] The ADITYA tokamak prediction used a similar method, but the network has been extended to more input signals in order to improve the prediction capability of the system. As a result, it is able to give predictions 8ms before a disruption.[5] In addition, the high β disruption boundary was modelled in DIII-D with more input signals and more neurals.[6] In both JET and JT-60U, disruption alarms were trained to distinguish between pre-disruptive plasmas and stable plasmas.[7,8] Moreover, the network of ASDEX-upgrade was trained to calculate the time to disruption.[9] All of them have obtained excellent results.

In this paper, we report firstly the attempt of disruption prediction carried out in the HL-2A tokamak, using an artificial neural network. A new neural model is set up on the basis of the diagnostic signals' characteristics in the HL-2A plasma. It is able to relax the time and spatial resolution requirements of diagnostic signals. The results show the possibility of developing a neural network predictor that can intervene well in advance to avoid plasma disruption or mitigate its effects in the HL-2A tokamak.

2. Artificial neural network

An artificial neural network is a nonlinear function mapping one multi-dimensional space $\{x\}$ into another one $\{z\}$.[9] This function has a predefined

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structure with some network parameters. First, the structure consists of several layers, which are generally input layer, hidden layers and output layer. The neurons in these different layers are connected by activation functions (transfer function).[13] Secondly, the network parameters include weights and bias,[13] and are determined while the network is trained. The training process evaluates those parameters by minimizing the difference between the desired output and the actual output. Among several possible structures of the network, we use a so-called backpropagation (BP).[13] A backpropagation network includes biases, sigmoid activation functions and linear activation functions, which can carry out complex nonlinear mapping.

For a BP network, the output of the ith neuron in the lth layer, x_i^l, is a function of the previous layer outputs

$$x_i^l = f\Big(\sum_{j=1}^{n_{l-1}} w_{ij}^l x_j^{l-1} - \theta_i^l\Big), \tag{1}$$

where $i = 1, \ldots, n_l$; $l = 1, \ldots, L$; n_l is the number of neurons in the lth layer, w_{ij}^l is the connection weight between neuron j in the $(l-1)$th layer and neuron i in the lth layer, θ_i^l is the bias of the ith neuron in the lth layer, L is the number of layers and f is the activation function which, in the present paper, is a hyperbolic tangent sigmoid function

$$f(x) = \frac{2}{1 + \mathrm{e}^{-2x}} - 1, \tag{2}$$

or a linear function

$$f(x) = x. \tag{3}$$

As stated previously, the connection weights and biases are determined by comparing actual output x^L with the desired output d and minimizing their errors. For this goal, a number of examples, consisting of inputs and outputs, are used. Here the error E is defined as

$$E = \frac{\sum_{p=1}^{N} \sum_{j=1}^{n_L} (x_j^{(p)} - d_j^{(p)})^2}{n_L \cdot N}, \tag{4}$$

where $x_j^{(p)}$ is the value of the jth actual output in the pth example, $d_j^{(p)}$ is the value of the jth desired output in the pth example, n_L is the number of outputs and N is the number of examples. Normally, the learning process of BP network iteratively updates network weights in the direction in which the error E decreases most rapidly, i.e. in the direction of negative gradient of E. Here the iteration of the algorithm can be written as

$$\boldsymbol{w}_{k+1} = \boldsymbol{w}_k - \alpha \cdot \frac{\partial \boldsymbol{E}_k}{\partial \boldsymbol{w}_k}. \tag{5}$$

where k is the iteration number, α is the learning rate,[7] $\boldsymbol{E}_k$ is the error vector and $\boldsymbol{w}_k$ is the weight or bias vector.[9]

3. Database and neural model

In the present work, it is found that the best network architecture is composed of 13 inputs, three hidden layers with 15, 30, 10 hidden neurons, and 1 output, resulting in 955 network parameters. Thirteen input neurons are associated with 13 experimental diagnostic signals, which are, respectively, six Mirnov probes, one Hα line intensity, one channel of soft x ray detector (SXR), one line integrated density ne, one main plasma impurity detector, one bremsstrahlung signal, one bolometer, and one vacuum ultraviolet spectrum signal. The input diagnostic signals have been scaled in the interval [0,1] by dividing each input by its maximum absolute value.

We select 17 pulses, i.e. 17 examples, from the pulse interval 4200–4500, produced at HL-2A tokamak of divertor configuration in 2005 campaign. They consist of 12 disruptive pulses and 5 successful ones. In this work, the available data is divided into two subsets. The first subset is the training set including 7 disruptive pulses. It is used for computing the gradient of error and updating the network weights and biases. The second subset is the test set consisting of 10 pulses. Accordingly, it is used to test the performance of the network.

Furthermore, we denote the disruption time as t_{D} for each disruptive pulse. Then, we define the instant $(t_{\mathrm{D}} - \Delta t)$ as the pre-disruptive state for the HL-2A discharges, where Δt is time interval between the pre-disruptive state, and the disruptive state, and is less than 10 ms in the present work. In the instant $(t_{\mathrm{D}} - \Delta t)$ the desired output of network is taken as 0. Furthermore, each input diagnostic signal of each pulse consists of selected temporal sequence. Each sequence consists of 99 consecutive samples with a sampling time of 1ms. The 99 selected samples for a disruptive pulse of HL-2A tokamak belong to the time window [t_{D}–200ms, t_{D}–102ms]. In this time window, the plasma is considered to be in stable state and accordingly the desired output is taken as 1. That is, the present database contains the time sequence of 100

different instants. The data at each instant contains 14 quantities, i.e., 13 diagnostic signals (13×100 matrix as the inputs of the network) and 1 desired output (1×100 matrix as the output of the network and the value of each matrix element is 0 or 1). In our model, the desired outputs in the time window [$t_{\rm D}$–101 ms, $t_{\rm D} - \Delta t$] are neglected. Such an approach largely relaxes the time and spatial resolution requirements of input diagnostic signals because the quantities of input data are reduced to a minimum.

4. Training and predicting results

The best network configuration is obtained by optimizing the numbers of hidden layers and neurons in them. For this purpose, we have designed 14 different network architectures, which are, respectively, 13:10:10:1, 13:10:20:1, 13:10:30:1, 13:15:10:1, 13:15:20:1, 13:15:30:1, 13:10:15:5:1, 13:10:15:10:1, 13:10:30:5:1, 13:10:30:10:1, 13:15:15:5:1, 13:15:15:10:1, 13:15:30:5:1, 13:15:30:10:1. Then, the comparisons are made between the prediction results of the 14 networks. It is found that the network 13:15:30:10:1 is the best one. If a neural network is simpler than 13:15:30:10:1, such as 13:15:15:10:1, the functions of such a network is too weak to performs well. On the other hand, if the neural network is more complicated, such as 13:15:30:10:1, it is difficult for the network output to converge it to a proper value.

The saliency analysis is made from the need to assess the relative importance of different neural network inputs (diagnostic signals). The technique consists of leaving out one input variable after the other, and then recalculating the error function associated with the remaining variables. Table 1 shows that the performance lightly changes by setting zero to the 7th Mirnov signal or Hα, while setting zero to the inputs like line integrated density or bremsstrahlung yields poor results on the trained network. Therefore, the presence of both the line integrated density and bremsstrahlung signals is very important for the improvement of the artificial neural network for disruption prediction. Besides, it is found that the importance of the Mirnov signals in different positions of the device is different.

After the network is trained by using the training set with 7 disruptive pulses, it is used to forecast the test set with 5 disruptive and 5 successful pulses. As a result, Fig.1 shows the prediction for the disruptive pulse 4435. It disrupts at 980 ms. The network gives the disruption alarm at 945 ms, 35 ms in advance. The 35 ms time interval should be sufficient to take measures to avoid or mitigate the disruptions for HL-2A tokamak. The other four pulses have the similar results. For successful pulses, the network does not give a disruption alarm, as shown in Fig.2. The results show that the networks perform well. Thus, the trained networks are further used at other disruptive and successful pulses in the pulse interval 4200–4500, which are not included in the two training sets. It is found that the networks can successfully predict the disruptive events in HL-2A tokamak, up to 15–30 ms in advance and have few false alarms.

Table 1. Saliency analysis on training set for the best network.

Input full set	Error
Less $M_{\rm pol07}$	$6.89400888065338\times10^{-17}$
Less Hα	$9.47740263490103\times10^{-17}$
Less $M_{\rm pol01}$	$5.29607665894627\times10^{-16}$
Less VUV	$9.02244825692664\times10^{-15}$
Less SXR	$4.77992124362968\times10^{-14}$
Less $M_{\rm pol16}$	$1.02875690636427\times10^{-13}$
Less $M_{\rm pol04}$	$1.07894492239185\times10^{-13}$
Less $I_{\rm imp}$	$2.38320545843336\times10^{-13}$
Less $M_{\rm pol13}$	$4.72586954989941\times10^{-13}$
Less $M_{\rm pol10}$	$1.10273627132061\times10^{-11}$
Less Bolometer	$1.77853969863505\times10^{-11}$
Less $I_{\rm bre}$	$4.98710869156662\times10^{-11}$
Less $n_{\rm e}$	$6.20431888206202\times10^{-11}$

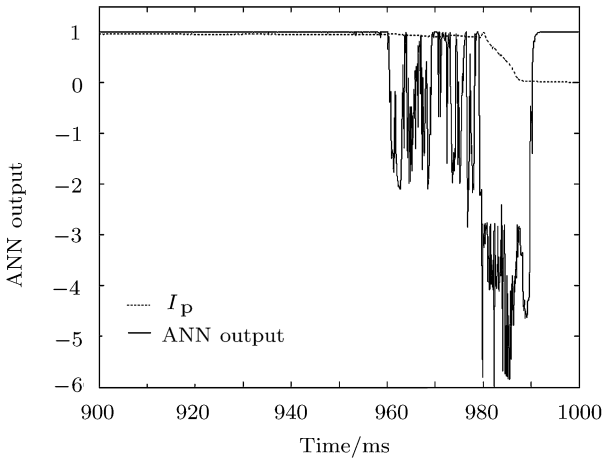


Fig.1. The network prediction on the disruptive pulse 4435.

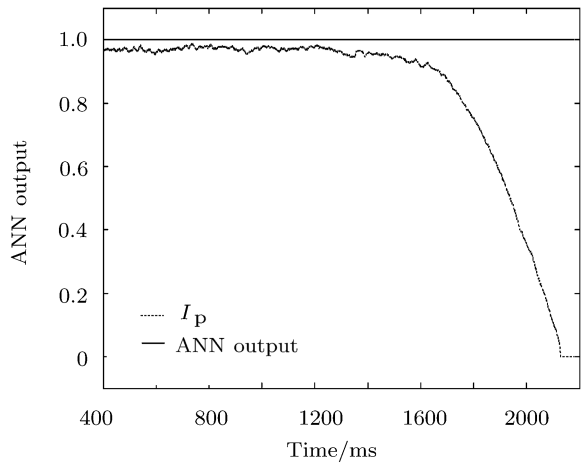


Fig.2. The network detection on the successful pulse 4436.

5. Summary

In summary, artificial neural network has been used as a disruption predictor in HL-2A tokamak. For our model, the best architecture have been ascertained, and the relative importance of different input signals have been compared. The trained networks can successfully detect the disruptive pulses. It shows that an artificial neural network may be good and reliable disruption predictor for HL-2A tokamak.

Compared with TEXT and ADITYA, we have got more satisfied results. For TEXT, they use only one Mirnov signal as input and predict disruption 1ms in advance.[4] In ADITYA, they use 6 diagnostic signals, including 4 Mirnov coils signals, 1 soft x ray and 1 Hα measurement, as inputs and predict disruption 8 ms in advance.[5] Here we use 13 input signals to train our network and detect disruption 35ms in advance. In addition, we can distinguish between disruptive pulses and successful ones. Recently the on-line prediction has been carried out in ASDEX-U,[9] using ANN. In future, we plan to improve our network farther and develop an on-line predictor. Finally, it should be pointed out that there exist some other methods based on the simulations,[14,15] which are useful supplements to disruption research.

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