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ABSTRACT.
Neural networks have been trained to classify different types of plasma disruptions in a Tokamak experiment using several diagnostic signals as input. Tests refer to data collected from disrupted pulses that occurred during four years of JET experiments. The results show the feasibility of a reliable neural network classifier.

1. INTRODUCTION

Plasma disruption consists in a sudden loss of magnetic confinement. Energy stored in the plasma is released to the surrounding structure in a few milliseconds, producing heat fluxes and electromagnetic forces capable of damaging machine parts. The events that occur during a disruption are not completely understood: although some of the mechanisms that can lead to disruptions have been identified, it is still difficult to classify them. In this paper a Neural Network (NN) approach has been adopted to classify disrupted pulses using signals from a large number of plasma diagnostics. Data for both training and test has been selected from the JET (Joint European Torus) database. A team of physicists at JET has manually classified selected pulses. This procedure proved to be difficult and time-consuming, indicating the appropriateness of automatic classification. A set of Multi Layer Perceptron (MLP) neural networks has been successfully trained to classify four disruption classes. Indeed multiple classifiers systems [1, 2] have been used in order to improve network performance. The numerical results, which refer to off-line tests conducted with real-time diagnostic data, although limited by the size of available data, prove the feasibility of the proposed approach.

2. RELEVANT DIAGNOSTIC SIGNALS AND DATABASE SELECTION

In this paper, only unprocessed data available in real-time has been used. For each disrupted pulse, selected input sequences consist of three consecutive samples taken at [t_D – 120ms, t_D – 80ms, t_D – 40ms] where t_D is the time at which the disruption occurs. The sampling time is equal to 40ms. On the basis of physical considerations and previous experiences on disruption prediction [3, 4], 10 diagnostic signals available in real-time have been selected:

– Plasma current	I_{pla}	(A)
– Locked Mode Mode	Lock	(T/A)
– Radiated power	P_{rad}	(W)
– Plasma Density	n_e	($1/m^3$)
– Input Power	P_{in}	(W)
– Internal Inductance	l_i	(a.u.)
– Stored energy derivative	W_{dia}	(W)
– Safety factor	q_{95}	(a.u.)
– Poloidal Beta	β_p	(a.u.)
– Plasma centroid vertical position	P_{cvp}	(m)

The selected pulses classified belong to seven disruption classes: Density Limit (DL), Mode Lock (ML), high Radiated Power (RP), Vertical Displacement (VD), H-mode/L-mode (HL), and Internal Transport (IT). There are also 15 Unclassified Pulses (UC) that do not fall into any of the above categories. Training and validation sets consist of disrupted pulses observed during experiments performed at JET between March 1999 and October 2002, selected from pulse number interval 47830-57346. In total 146 disrupted pulses have been classified. The unclassified pulses have not been considered during network training; moreover, the VD class (22 pulses) has been excluded because the time frame of a VDE excludes classification at td-40ms. It is worth noting that pulses distribution is not uniform. In particular, the DL class consists of fifty pulses, while RP class has only five elements. Moreover, the conditions just before the disruption are quite similar for these two classes, thus they have been merged, as suggested by physicists. Table I shows the distribution of the 109 pulses used for network training among the four remaining classes. In order to avoid overfitting 20% of the pulses (21 pulses) have been used for cross-validation. In a subsequent phase, 20 new pulses have been classified by the physicists: and they have been used as a test set. Their distribution is also shown in Table I.

CLASS	ML	DL/RP	HL	IT
TRAIN	12	55	37	5
TEST	6	5	4	5

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TABLE I: Training and test pulses distribution among disruption classes.

3. THE NEURAL MODEL

Several networks have been trained. All networks training has been performed using the Matlab Neural Network toolbox, with the Levemberg-Marquardt algorithm, which gave the best results in terms of training Mean Square Error (MSE). Network architecture with one hidden layer sigmoidal activation function has been used. Each trained network has 10 input nodes and 3 output nodes. The training patterns are constituted by an input-output couple corresponding to each of the three samples of the selected pulses. The input pattern has 10 value corresponding to the 10 diagnostic signals sampled at the same time-instant. The corresponding output pattern realises a binary three digit coding of the considered classes. The hidden layer nodes have been selected by a trial-and-error procedure. As sigmoidal activation function has been considered in the output layer, a quantization threshold has to be considered to convert the real value of the network output, in a binary number. The threshold has been set equal to 0.5. A generic pulse is assigned to a specific class if at least two of the three samples of that pulse are assigned to the same class by the network. Otherwise the pulse in unclassified.

4. RESULTS

The results in terms of disagreement between human and network classification are for the training set equal to 0.00% and the same percentage for the validation set. Since the majority of the networks produce similar results during validation, it is difficult to choose which one will have the best generalisation capabilities on the basis of validation error. Indeed, selecting the best classifier is not necessarily the ideal choice, since potentially valuable information may be wasted by discarding the results of less-successful classifiers. In order to avoid this potential loss of information, the outputs of all classifiers can be pooled before a decision is made. In particular multiple classifiers [1] approach has been adopted, using two different combining methods: simple averaging in output space [2] and majority voting with reject option (a pattern is assigned to the specific class if more than half of the classifiers decide for the same class, otherwise the pattern is rejected). Five complementary classifiers have been selected and used to build the Multiple Classifier. Both combining methods gave the same results during test, exhibiting the same performance of the best classifier. Table II shows the results given by the 5 selected classifiers and the ones obtained with majority voting. To further assess the effectiveness of the neural approach, a *k*-Nearest Neighbours (*k*-NN) classification algorithm, enhanced with a reject option based upon distance in signal space, has been tested on the same data set. The results obtained with *k*–NN are reported in the same Table II. In particular a maximum rejection rate of 30% has been imposed as suggested by the literature. Hence, the percentage of disagreement has been calculated with respect to the accepted pulses. As can be seen, the performances of *k*-NN is considerably lower than that exhibited by NNs

NET	1	2	3	4	5	MV	k–NN
VAL	0.00%	0.00%	0.00%	0.00%	4.76%	0.00%	N.A.
TEST	15.00%	15.00%	15.00%	15.00%	10.00%	10.00%	28.57%

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TABLE II: Percentage of disagreement for Test set

It can be noted that, all networks classify the HL pulses 50772 and 50632 as DL. This error is likely due to the small amplitude of the selected sampling time window. Indeed, in both cases the HL transition occurs about 700 ms before the disruption, i.e., more than 500 ms before the sampling is started.

CONCLUSIONS

Disruption classification has been demonstrated to be a difficult and time-consuming procedure. A multiple classifier based on several MLPs has been used to automatically classify disruptive events at JET. The real-time dataset used for experiments assesses its reliability as well as its good generalisation capabilities. NNs are demonstrated to be good, fast and reliable disruption classifiers, suitable for real-time usage if the multispace state parameters which identify the operational window of the experimental devices are sufficiently well defined, and if suitable diagnostic signals can be supplied in real-time to the online NN.

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