Progress in the Prediction of Disruption in ASDEX-Upgrade via Neural and Fuzzy-Neural Techniques

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Abstract. The paper addresses the problem of predicting the onset of a disruption on the basis of some known precursors possibly announcing the event. The availability in real time of a large set of diagnostic signals allows us to collectively interpret the data in order to decide whether we are near a disruption or during a normal operation scenario. As a relevant experimental example, a database of disruptive discharges in ASDEX-Upgrade has been analysed in this work. Both Neural Networks (NN's) and Fuzzy Inference Systems (FIS) have been investigated as suitable tools to cope with the prediction problem. The experimental database has been exploited aiming to gain information about the mechanisms which drive the plasma column to a disruption. The proposed processor will operate by implementing a classification of the shot type, and outputing a real number that indicates the time left before the disruption will effectively take place (*ttd).*

1. Introduction

The idea of generating nuclear fusion energy is largely based on the concept of magnetic confinement. To sustain the fusion reactions, the power liberated would have to be much greater than that lost via radiation and transport across the magnetic field. Thus, a key role in the Tokamak experiment is related to the energy confinement time. Some intrinsic physical limits related to the efficiency of the confinement and possible large instabilities could limit the operational regime of the tokamak, through a rapid falling to zero of the plasma current [8]. Consequently, the early prediction of the deterioration of magnetic confinement preceding the onset of a disruptive event during the evolution of a plasma discharge in a Tokamak machine represents an important step forward in order the experimental activity around nuclear fusion to achieve a practical industrial interest. From the physical viewpoint, the phenomenon of the disruption represents a transfer of energy of the plasma to the surrounding mechanical structures. During the sudden loss of confinement and transfer of plasma energy to the machine related to a disruption, the plasma current and the thermal energy content of a tokamak plasma collapse in an uncontrollable way, thereby generating mechanical forces and heat loads which threaten the structural integrity of surrounding structures and vacuum vessel components. It is thus of primary importance to design an alarm system for detecting the onset of a disruption in tokamak plasma discharges. Neural Network models have been proposed in the recent literature as forecasting systems, with the aim of predicting the occurrence of disruptions sufficiently far in advance for protecting procedures to be switched on [2, 3]. The design of such a system is constrained from the availability of experimental examples derived from the monitoring of disruptive shots. In this paper, we will use an experimental database of discharges related to the ASDEX-Upgrade device, which has been provided by the ASDEX team. The database represents a collection of measurements carried out within the machine and of the corresponding time left before a disruptive event takes place. Each records of the database refers to a time sample of the evolution of a plasma shot. The aim of the study is to devise a processing system that could be able to predict correctly the "time-to-disruption", based on the experience gained on the available "examples" through some suitable kind of data analysis. The simulation and modelling environment is based on both Neural Networks (NN) and Fuzzy Inference Systems (FIS). We propose the use of FIS in order to improve the basic abilities of NN that refer to a black box model of the experiment. The fuzzy simulation framework is appropriate for implementing any appropriate approximate reasoning on the data before numerical treatment. The use of the concept of fuzzy is also suggested because the transition of a discharge toward the "disruptive behavior" happens without appearing continuity solution, i.e., by a "soft" transitions.

The aim of the procedure is to give a correct estimation of the time of disruption, in order to be able to activate the control system. The paper is organized as follows: the features of the available database are briefly reviewed. Then, the two problems of classification of the shot database and prediction of the disruption are assessed. Finally, the achieved results will be proposed with some comments and by indicating the future directions of research.

2. The ASDEX-Upgrade Machine

A disruption oriented database of a block of ASDEX Upgrade discharges has been set up by the ASDEX Team. In this database, there are stored a set of measurements monitoring the plasma shots, with special reference to disruptive discharges. A large number of them were analysed with the purpose of finding the technical causes, the precursors and the physical mechanisms of disruptions [4, 7].

The files under study derives from ten years of experimental activity carried out at the Institute of Plasma Physics (IPP) of Garching bei Munchen (Germany). The file training consists of about 11700 rows and 30 columns (62 shots) while the file testing consists of about 6100 rows and 30 columns (46 shots). The variables in input represent a compromise between the physics and the availability in real time. They include measurements of magnetic fields, plasma energy, input power, radiated power, a few of the divertor bolometer channels, the locked-mode signal and their time derivatives, referring to flat-top of lower single null plasmas. The shots were analysed with the purpose of inferring the technical causes, the precursors and the physical mechanisms of disruptions. Most of the plasma disruptions in ASDEX-Upgrade happen in a plasma parameter range (poor L-mode confinement) which is far away from the desired operational space (H-mode, high beta). In addition, disruptions are usually announced by well identified precursors (detachment, MARFE, growth and locking of resistive tearing modes) which can be detected by the available diagnostics.

The database is not simply manageable, and the use of standard NN processors fails to achieve the desired results. This observation suggested us to properly decompose the original problem in parts, each one of them is "specialized" to cope with a subset of the original "full" database.

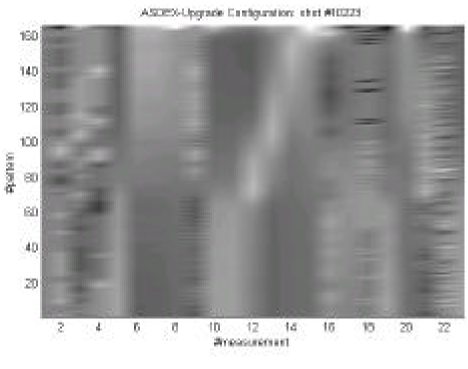
3. The problem of the disruption database decomposition

In the ASDEX-Upgrade database, each disruptive shot is described by a set of measurements from magnetic sensors and an indication of the time before the disruption will effectively take place. The available measurements represent a multidimensional input space for our problem. The true dimensionality of the space is hardly definable, however, it is inessential to solve our problem: the interesting information is instead which are the important diagnostic signals in order to correctly predict? To approach the problem, we firstly cluster the available shots by using some qualitative informations extracted from the database. In order to show how the pattern of measurement vary during the discharge evolution, we plot a grey-scale representation of the typical patterns for some discharges. We are able to extract some important information for the prediction of the disruption by means of one “visual inspection” of the database. In what follows, we shall present an application example of the proposed methodology. *FIG. 1* shows a grey-scale representation of the shot #10223: along the vertical axis we plot the successive time samples of the shot, along the horizontal axis the number of measurement. The grey-level agrees with the level of the measurement (white pixels correspond to “high” values of the measurement). The disruption occurs when the #pattern is over a typical number. For example, in the middle of figure, we can see the rapid and evident change of measurements value in the bolometer channels, #12 to #16 (oblique white line), that represents a very good qualitative information about the incoming disruption. The measurement #14 (linhc5) is able to separate the shots into two categories that we label as “Type 1” and “Type 2”. The “Type 2” shots are characterized by a peaking of linhc5 (*FIG. 2*). In addition, when the time course of linhc5 presents a peak, we are yet far from the disruption. This kind of qualitative information can be used for the separation of the database in sub-sets. By inspection of the figure, we can say that measures #13 (linhc4) and linhc5 can be used like a “mark” of the shot in the classification of disruption. We can discriminate the shots in the plane #13 vs. #14. By inspection of plots like *FIG. 2*, we are able to write some qualitative fuzzy rules about the incoming disruption, as follows:

Rule #1 **IF** *linhc4* is Very High and *linhc5* is Medium
THEN the ttd is high

Rule #2 **IF** *linhc4* is High and *linhc5* is Very High
THEN the ttd is low

Rule #3 **IF** *linhc4* is High and *linhc5* is Very High
THEN the disruption is coming



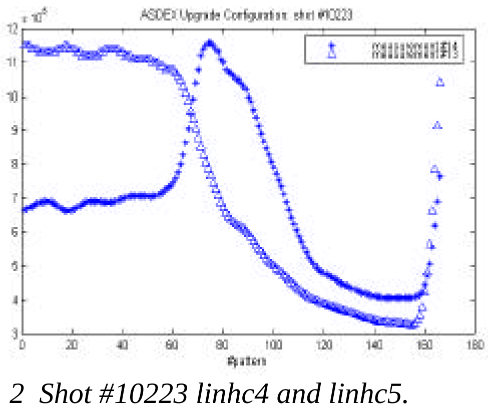


FIG. 1 Grey-scale representation of shot #10223. FIG. 2 Shot #10223 linhc4 and linhc5.

This is a very simple bank of fuzzy rules about the prediction of incoming disruption. Each rule is in the **IF**…**THEN** form with double antecedent because we utilize two inputs (linhc4 and lihc5), while the consequent is single because the output of the system is the time to disruption. The performance of the classifier may be quantified in terms of probability of detection versus the probability of false alarm (P_D – P_{FA} curve). By using this naive method, the obtained results are already very encouraging. It goes without saying that the performance can be improved by adding rules in the bank, for example by choosing a larger number of inputs and possibly taking advantage of the expert knowledge.

4. The Identification Problem: Generation of Fuzzy Identification Systems

As a first example, we have separated the categories by means of the reading of the variables linhc4 and lihc5. We have constructed several FIS by using the whole set of measurements and various subsets of them. The extraction of fuzzy rules can be carried out by direct inspection. However, a potential advantage of the FIS approach is that the rules could be derived directly from expert knowledge on physical aspects of the problem. We have used the MatLab toolbox GENFIS to extract a set of rules that is able to model the data behavior. The rule extraction method determines the number of rules and the antecedent FMFs and then uses line ar least squares estimation to determine each rule's consequent. Adaptive Neuro-Fuzzy Inference System (ANFIS) routine allows us to tune the FIS by means of a learning algorithm based on the input-output data. A network structure facilitates the computation of the gradient vector for computing parameter corrections in a FIS. Once the gradient vector is obtained, we can apply a number of optimization routines to reduce an error measure (sum of the squared difference between actual and desired outputs, entropy maximization,…). We have achieved good results by using a combined GENFIS+ANFIS approach. The GENFIS Toolbox is able to choosing a priori the number of rules; the membership functions are labeled in such a way that each rule associates those of same name; the membership functions of each variable are labeled by mf1, mf2, mf3, ... GENFIS extracts the rules so that all the input variables participate to every rule. *FIG. 3* and *FIG. 4* show examples of time to disruption estimation for the shots #10044 and #10106. For the second shot, the time to disruption estimation is not good at the beginning of the discharge. However, this is not so important to the aims of the disruption prediction because the incoming starts at the middle of the discharge. Therefore it is inessential to gain a high precision in the early stages of the discharge. The plotted estimation derives from the analysis of a subset of the original database which has been extracted by a FIS working with the whole input (sensor) pattern. Similar results could be achieved by using a limited subset

5. Results and Conclusions

The FIS and the fuzzy NNs represent an alternative method to the problems of the prediction of the time to disruption in Tokamak machines. An advantage of the approach consists in the possibility to write the rules directly from a numerical analysis of the available database, but they can be integrated or improved by means of the expert knowledge. The results achieved for the prediction of the time to disruption can be considered of interest and can be resumed in the following statement: the probability of correctly switching on an alarm in the range from 400 ms to 0.5 ms before the disruption is in the order of 78%, and a very limited number of false alarms were detected. The classification step (partitioning of the original shot database) by visual inspection has given the following results: 75% of the shots can be considered of the “Type 2”, while 25% are of the “Type 1”. About 4 shots are not satisfyingly classified. Within the two parts of the database, we achieve a relevant performance in terms of rms estimation error (true ttd vs. estimated ttd). In particular, the full scale rms error is of 8.5% for the “Type 1” databse and of 5.5% for the “Type 2” database. Of course, the results should be referred to the cardinality of the two different databases.

The NN approach has been successfully applied for solving different problems to be faced during work, namely, the detection of redundancy in the input data; the ranking of the input variables, and finally, the automatic extraction of rules from the database to be proposed to experts for further interpretation. Future works will focus on analysing the impact of measurement noise on the model and on the data fusion and integration aspects. The most important aspect to be devised is the correction of the model based on expert knowledge. Indeed, the interesting results achieved are susceptible of easy improvement by implementing in the network structure some a priori rules possibly available.

From the analysis of the result we are able to say that the onset of the disruption is predictable within a practically interesting time interval.

Finally, the proposed "visual" approach gives us a simple way to automatically classify the different kinds of possible disruptions. From the reading of the pattern, we are able to simply express a guess about the target. The FIS model that uses a reduced number of diagnostics as input is sufficient for interpreting the evolution of the shots, once the kind of shot has been categorized.

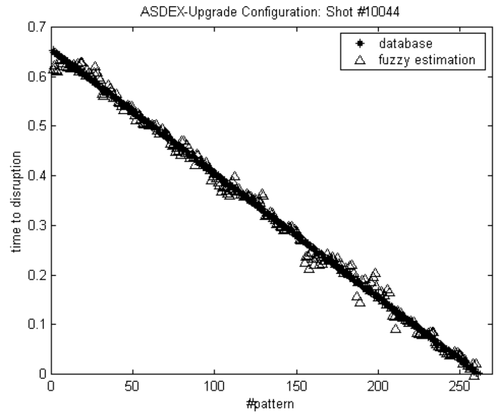


FIG. 3 Good Shots: time to disruption estimation by FIS for shot #10044

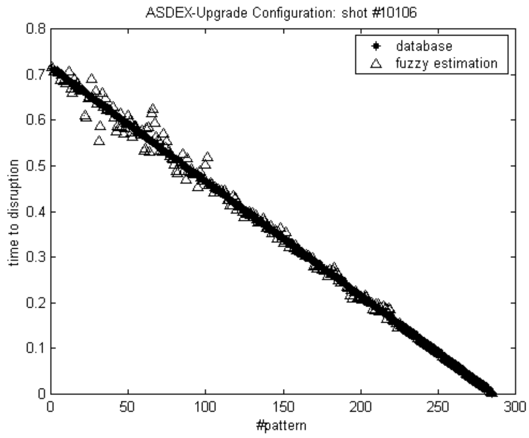


FIG. 4 Good Shots: time to disruption estimation by FIS for shot #10106

7. References

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