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Disruption Anticipation in Tokamak Reactors: A Two-Factors Fuzzy Time Series Approach

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Abstract

Disruption in a Tokamak reactor is a sudden loss of confinement that can cause a damage of the machine walls and support structures. In this paper, we propose the use of the Fuzzy Time Series (FTS) approach for anticipating the onset of disruption in Tokamaks. Two-Factors Fuzzy Time Series models will be shown to be advantageously used for making prediction of the disruption's onset in Joint European Torus (JET) machine. The use of soft computing technique is suggested by the very nature of the variables involved and by the consideration that a single time series of a physical variable is hardly representative of the whole kind of disruptions experimentally observed.

1. Introduction

The development and engineering of the basic concept of magnetic confinement has potentially allowed the generation of nuclear fusion energy. Tokamak machines are designed in research centers in order to facilitate energy confinement experiments where the confinement time of the plasma plays the relevant role. The efficiency of the confinement and various instabilities strongly limit the operational regime of Tokamak machines till the falling to zero of the plasma current [1]. During the sudden loss of confinement and transfer of plasma energy, plasma collapses in an uncontrollable way, thereby generating mechanical forces and heat loads which threaten the structural integrity of surrounding structures and vacuum vessel components. The early prediction of the deterioration of the confinement magnetic thus represents an important step to anticipate the onset of a disruptive event during the evolution of a plasma discharge in the experimental machine. Success in developing a reliable alarm system for disruption anticipation would have important implications both for the design of future reactors (e.g., ITER), and for the developments of short term strategies to either limit or abort an impending disruption. In recent years, signal processors based on Neural Networks have been exploited as prediction systems, with the aim of predicting the occurrence of disruptions sufficiently far in advance for protecting procedures to be switched on [2], [3]. Recently, we proposed the use of fuzzy inferences and neuro-fuzzy inferences systems to cope with the disruption prediction problem in experimental Tokamak reactors, namely ASDEX-Upgrade [4], [5], [6], by deciding, among a set of physical observables, which are positively correlated with the time to a disruption. The aim of the present study is to develop a processing system that should be able to predict correctly the "time-to-disruption" (*ttd*) indirectly through the tracking of a related measurable physical quantity. The processing system will make use of the Fuzzy

Time Series (FTSs) approach [7], [8]. In particular, we propose the use of the two factors time-varying fuzzy time series model to deal with the forecasting problem. We exploit here two algorithms, typically referred to as *B* and *B**, in which the prediction of the main factor, a variable referred to as Mode_Lock, strongly linearly correlated with the *ttd*, which is not directly measurable by a physical sensor, is assisted by a suitable secondary factor, namely, a judiciously selected magnetic parameter of the plasma, also easily measurable. The rest of this paper is organized as follows: In the next Section, we describe the features of the available database, that refers to the JET machine. In Section III, we briefly review the fuzzy time series concept. Section IV describes the way how the algorithms can be applied to the disruption prediction problem. The achieved results are reported in Section 5. The paper ends with Section 6 which contains the main conclusions of the work.

2. The JET Experimental Database

A disruption oriented database of JET discharges has been set up by the JET Team. In this database, a set of measurements monitoring the plasma shots are stored. A large number of them were analysed with the purpose to find the technical causes, the precursors and the physical mechanisms of disruptions. The analysed files derives from many years of experimental activity carried out at the Culham Center, Oxfordshire, London (United Kingdom). The database was built starting from the dynamics of a disruption in the zone of flat-top of the plasma current in which the plasma is monitored to obtain a constant plasma current (IPLA) and a stable confinement in terms of shape and position. The choice of the variables to be used as *predictors* among the ones available in the database is always the result of a compromise between the physical availability of measurements and reliability of the related sensors and the peculiarities of the processing model (kind of NNs) carried out in previous works. In the case of missing data, some kind of filtering is used in order to complete the time series. The interval of observation of the variables was limited to the time interval of [*td-440ms; td-40ms*] according to some physical insight; the left 40ms were omitted as not being relevant, since there is no sufficient time left to control the shot. The time of sampling is 20ms and 20 samples for each channel have been used. In order to test the null hypothesis and verify the percent of false positive occurring, we have considered 1167 shots without disruption, and 701 disruptive shots, related to experiments carried out between 1997 and 1999. Within the database, a record distinguishes the kind of shot: the outputs of the network are labelled by means of *vtargetTS* for training database, *vtargetVS* for validation database and *vtargetTest* for testing database. The outputs were identified by considering that, in correspondence of a shot without disruption, we have a series of 20 zeros (non disruptive shot). If the shot is a disruptive one, the series of 20 values is a set of numbers in the range (0,1) and thus a sigmoidal function is used to represent the risk of disruption. In the present approach, the series of 20 numbers is reconstructed on-line after the prediction of the *Mode_Lock* variable.

3. Fuzzy Time Series: A Bird's Eye Overview

In a time series representing the observed values of a dynamic process, the reading is represented by means of crisp numbers. In contrast, in a fuzzy time series the observed values of a dynamic process are represented by means of linguistic values [8]. To understand how the FTS works, let us consider a subset of real numbers *K(t),* (t=0, 1, 2, …), referred to as the Universe of Discourse (UoD), X, and let us assume $\mu_i(t)$ are the fuzzy sets identified by means of suitable membership functions (defined on the UoD to range into [0, 1]), defined on *K(t)*. Assume that $A(t)$ is a collection of $\mu_i(t)$; then, $A(t)$ is a fuzzy time series of $K(t)$. $A(t)$ is a function of time t, and $\mu_i(t)$ are linguistic values of *A(t),* where $\mu_i(t)$ are represented by fuzzy sets. If *A(t)* is generated by *A(t-1),* then, this relationship can be represented by:

$$A(t)=A(t-1)\circ R(t,t-1)$$

where *R(t, t-1)* is a fuzzy relationship between *A(t)* and *A(t-1)*. If $A(t)$ indicates the main factor (*Mode_Lock*, correlated to the *ttd*) of our prediction problem, at the same way, a novel fuzzy time series, $H(t)$, is related to the secondary factor (another physical quantity, the *Plasma Density*). Both $A(t)$ and $H(t)$ deal with the prediction problem by means of a sort of two factors fuzzy time series.

4. Fuzzy Time Series Model for Disruption Anticipation

In [4], we have proposed a neuro-fuzzy model for the prediction of disruption that exploited a single time series. As anticipated in the previous sections, rather than using the *ttd* time series, we exploit here the Mode_Lock variable to predict in due time the incoming of disruption. Nevertheless, a temporal event detected in a single time series can be affected by several factors. In our case, the prediction of *ttd* depends on many factors which could be only inferred by the evolution of the reading of sampled magnetic measurements, carried out by suitable sensors located along the vacuum vessel contour. In this Section, we firstly describe the *B* algorithm [7].

The *B* algorithm starts by the definition of the UoD for both factors. In particular, regarding the *Mode_Lock* (main factor), we determinte its variations between any two continuous data computing the maximum decrease D and the maximum increase I. The UoD X for *Mode_Lock* is defined as follows $X = [D-\varepsilon, I+\varepsilon]$ where ε is a suitable positive real value. X has been divided into n disjointed intervals x_j.

In this paper, we have considered seven partitions for X, however, for other applications a different number of partitions can be advantageously taken into account. For each interval x_j, we associate a linguistic label L_i represented by fuzzy sets whose membership functions $\mu_{L_i}(x_j)$, i=1,…, h j=1,…, n.

The Universe of Discourse, UoD, Y of the secondary factor is defined as:

$$Y=[\min(Plasma\ Density),\max(Plasma\ Density)],$$

where min(*Plasma Density*) and max(*Plasma Density*) are the minimum and maximum of the possible values for secondary factor. We divide Y into n disjointed intervals y_i (the same number of partitions for X, but additional partitions can be introduced). As for the main factor, to each interval y_j of the secondary factor we associate a fuzzy set B_j whose membership functions are $\mu_{B_i}(x_j)$ i=1,…, h j=1,…, n. Note that, for each interval x_j and y_j, $\mu_{L_i}(x_j)$ and $\mu_{B_i}(x_j)$ are constant values selected by qualitative inspection of database. The next step of the procedure is the fuzzification of the data. In particular, if the variation δ of the *Mode_Lock* belongs to

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the interval x_j, we know that the maximum membership value of L_i, occurred at x_j, then the fuzzified variation of δ is L_i. The same procedure can be exploited in order to fuzzify the secondary factor. To predict the *Mode Lock* at time t, it is imperative to choose the temporal windows w in order to get the criterion vector $C(t)$ and the operation matrix $O^w(t)$ at time t defined in (1) and (2), where $a(t-1)$ is the fuzzified variation of the *Mode_ Lock* between time t-1 and t-2; n is the number of the elements of X (UoD for *ttd*); C_j are crisp values ($0 \le C_j \le 1$ and $1 \le j \le n$) and O_{ij} are crisp values ($0 \le O_{ij} \le 1$, $1 \le i \le w-1$, $1 \le j \le n$).

$$C(t) = a(t-1) = \left[C_1\ C_2 \cdots C_n\right] \tag{1}$$

$$O^w(t) = \begin{bmatrix} a(t-2) \\ a(t-3) \\ \vdots \\ a(t-w) \end{bmatrix} = \begin{bmatrix} O_{11} & O_{12} & \cdots & O_{1n} \\ O_{21} & O_{22} & \cdots & O_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ O_{(w-1)1} & O_{(w-1)2} & \cdots & O_{(w-1)n} \end{bmatrix} \tag{2}$$

Once the *Mode Lock* has been properly processed, it needs to treat the secondary factory by means of the definition of the *secondary factory vector* $S(t)$ defined in (3), where $S(t)$ is the secondary factor vector at time t; $h(t-1)$ is the fuzzified data of secondary factory and n is the number of the elements of X;

$$S(t) = h(t-1) = \left[S_1\ S_2 \cdots S_n\right] \tag{3}$$

The next step of the procedure is to define the relationship between the two factors. Chen et al., [7], proposed a model of fuzzy relationship between the criterion vector, $C(t)$, the operation matrix, $O^w(t)$, and the *secondary factor vector* $S(t)$, defined in (4) and (5):

$$R(t) = O^w(t) \otimes S(t) \otimes C(t) \tag{4}$$

$$R(t) = \begin{bmatrix} O_{11} \times S_1 \times C_1 & O_{12} \times S_2 \times C_2 & \cdots & O_{1n} \times S_n \times C_n \\ O_{21} \times S_1 \times C_1 & O_{22} \times S_2 \times C_2 & \cdots & O_{2n} \times S_n \times C_n \\ \vdots & \vdots & \cdots & \vdots \\ O_{(w-1)1} \times S_1 \times C_1 & O_{(w-1)2} \times S_2 \times C_2 & \cdots & O_{(w-1)n} \times S_n \times C_n \end{bmatrix} = \begin{bmatrix} R_{11} & R_{12} & \cdots & R_{1n} \\ R_{21} & R_{22} & \cdots & R_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ R_{(w-1)1} & R_{(w-1)2} & \cdots & R_{(w-1)n} \end{bmatrix} \tag{5}$$

Once $R(t)$ is computed, the fuzzified variation of $A(t)$, $a(t)$, between time t and time t-1, is calculate as reported in (6):

$$a(t) = \begin{bmatrix} \max\left(R_{11}, R_{21}, \ldots, R_{(w-1)1}\right) \\ \max\left(R_{12}, R_{22}, \ldots, R_{(w-1)2}\right) \\ \cdots \max\left(R_{1n}, R_{2n}, \ldots, R_{(w-1)n}\right) \end{bmatrix} \tag{6}$$

The last step of the B algorithm is to defuzzify the predicted variations of *Mode_Lock.* If the membership value of the predicted variation is 0, then the predicted variation is 0; else, if the maximum membership value of the fuzzified predicted variation occurred at x_j, then the predicted variation is the midpoint of x_j. In case the maximum membership value of the predicted variation occurred at several intervals, then the predicted variation is the average of their midpoints.

B Algorithm*

In [7], Chen et al. proposed a novel version of the previously described B Algorithm, referred to as B* Algorithm, that takes into account the further enhancement of the

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predicting accuracy and to reduce the errors. The modification is only related to the defuzzification procedure. In other words, by means of an α-significance level $(a(t))_\alpha$ of the fuzzified predicted variation $a(t)$ defined in (12), where $a(t)$ is the fuzzified predicted variation and $\alpha \in [0,1]$, we can achieve a more precise defuzzification,

$$a(t) = [a_1 \; a_2 \cdots a_n] \quad (a(t))_\alpha = [a_{1\alpha} \; a_{2\alpha} \cdots a_{n\alpha}] \qquad (13)$$

If $f_i \geq \alpha$, we fix $f_{i\alpha} = f_i$; else if $f_i < \alpha$, then $f_i = 0$. If the membership values of $(a(t))_\alpha$ are all 0, then the prediction variation is 0; else if the membership value of $(a(t))_\alpha$ have only one maximum falling into x_j, then the predicted variation is its midpoint. In case the membership values of $(a(t))_\alpha$ occurred at several intervals, , the predicted variation is the average of their midpoints. Naturally, the prediction data is equal to the predicted variation plus the actual data. By using the Matlab® language we have implemented the so-called Algorithm B and B*.

The secondary factor has been selected though the fuzzy curve approach: the result of the selection and ranking procedure was that the *Plasma Density* quantity is the most suitable to be used at this scope.

5. Performance of the Model

The aim of a disruption prediction system is to design a processor capable of predicting the onset of a disruption sufficiently in advance for intervention using a control action. This paper's approach was to use the B algorithm to solve the anticipation problem, while the B* algorithm was just used as a cross-check technique. The main result in using the B* algorithm with respect to the B algorithm is a slight improvement of accuracy to be paid by a corresponding increase in the computational burden of the procedure implemented.

The used detection criterion is as follows: once the *Mode_Lock* value is greater than a fixed threshold (0.2 T/A), the disruption is incoming. Figure 1 shows the results achieved for the prediction of the *Mode_Lock* 400ms in advance (a window slice of w=3 was used, after a sensitivity analysis has been carried out, as reported in Table 1).

The performance of the B algorithm as predictor of disruptive events can be resumed in the following statements:

- the probability of correctly switching on an alarm in the range (w=3) before the disruption is in the order of 90%;
- a limited number of false alarms were detected, while the number of false positive is very limited within the test and validation databases;
- the fuzzy time series model has been applied to both simple problems of prediction with single shots and to small group of shots, in order to assess the robustness of the procedure. The results can be considered more than encouraging; in fact, it is possible to predict the disruption with a time-lag of 15ms, with the accuracy reported in Table 1 in terms of root mean squared error.

6. Conclusion

In this paper, a novel soft computing approach has been exploited for solving the problem of early prediction of disruptions in JET Machine. As seen, from the analysis of the achieved results, it is possible to say that the onset of a disruption is predictable within a time interval of interest. The comparison with the obtained results in [4] (prediction of disruptions by means of a single time series), allows us to claim that the use of a two-factors model may improve the performance. In the future, the extension of the two-factors time series models into multi-factors time series models is hoped.

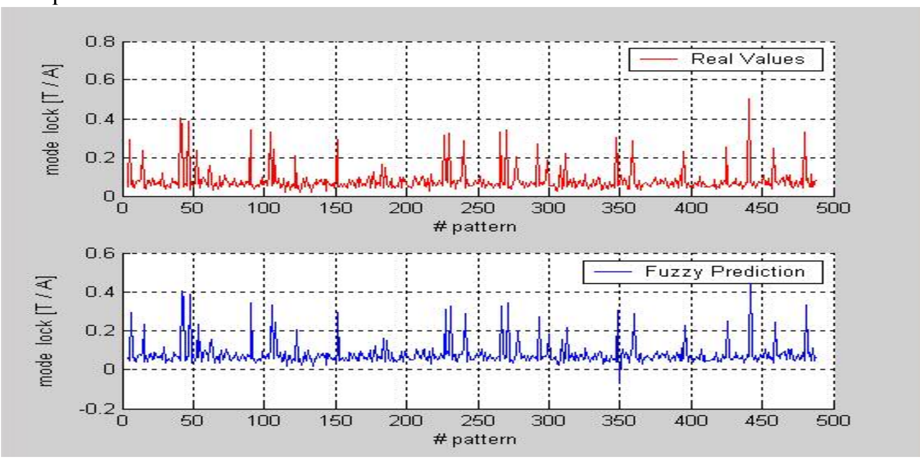

Figure 1. Prediction of Mode Lock for w=3

Window size "w"	RMSE [T/A]
1	---
2	0.083
3	0.085
4	0.0853
5	0.091

Table 1: Sensitivity of the prediction accuracy to the selected window size

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