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# INSPECTION OF DISRUPTIVE BEHAVIOURS AT JET USING GENERATIVE TOPOGRAPHIC MAPPING

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**Abstract**

Tokamaks are the most promising configuration of magnetic confinement fusion devices. However, a physical phenomenon that leads the plasma out to its operational bounds, called disruption, remains unavoidable. Disruptions cause the abrupt termination of the discharge and in addition to affecting the execution of the research program, they can constitute a risk for the structural integrity of the machine. Their occurrences have proven to be unavoidable, particularly in high performance scenarios.

In this article two important aspects that can facilitate the better understanding of the phenomenon are presented. First, the selection of the physical parameters and their main characteristics related to disruptions are reviewed. This feature extraction procedure consists in the selection of the most adequate plasma measurements and the processing of each selected signal to extract and condense the disruptive-related characteristics. Second, the application of Generative Topographic Mapping (GTM) to visualize and compare disruptive and non disruptive experiments at different times is shown. The resulting maps are aimed to evidence the evolution of the phenomenon, since it is unrecognizable till it can be distinguished. The identification of the instant when precursors of disruptions can be noticed is highly relevant in nuclear fusion since it determines the time margin the control systems have to apply mitigation or avoidance actions.

**Key words**

Nuclear Fusion, JET, GTM, Disruptions, Feature extraction

## 1 Introduction

Tokamaks are the most promising configuration of magnetic confinement fusion devices. Presently, the biggest and most important machine of this kind is the Joint European Torus (JET), located in Culham (UK). A dangerous physical phenomenon often occuring in tokamak operation is called disruption: the plasma (a heated and ionized gas) confinement is suddenly lost and in tens of milliseconds its energy content is transferred to the first wall. As a consequence of the subsequent plasma abrupt current quench, large eddy currents can be induced in the vacuum vessel and surrounding structures creating forces potentially capable of producing severe damage to the device.

To measure the physical quantities of interest inside the vacuum vessel, advanced sensors systems are attached to the device. Those diagnostics transform the acquired quantities into electrical signals. Most of the resulting data after every experiment are temporal evolution signals. Also images are acquired and contour plots, profiles and scatter graphs are calculated and stored. This information provided by the diagnostics can be utilized to detect unusual instabilities or disruptions precursors to notice in advance the phenomenon and consequently to apply control or mitigation actions to reduce the possible damages. Due to the complex nonlinear interaction of the involved variables that lead the plasma to its abrupt end, it has been impossible so far to develop a complete an unfaultable theoretical model to prevent their occurrence. In this article two important aspects that can facilitate the better understanding of the phenomenon are presented. First, the selection of the physical measurements [Breiman, 1993] [Murari, 2008] [Cannas, 2006] and their main characteristics related to disruptions are reviewed [Ratta, 2008]. Second, the application of Generative Topographic Mapping (GTM) [Bishop, 1998] to visualize and compare the evolution of disruptive and non disruptive experiments is detailed. This unsupervised method can be considered as visual proof of the evolution of the phenomenon at different time periods before its occurrence.

## 2 Feature extraction

### 2.1 Introduction

This section is devoted to detail the feature extraction procedure. The feature extraction is aimed to provide the adequate input characteristics to the GTM algorithm. The procedure consist in two general tasks, detailed in subsections 2.2 and 2.3. The first one explains the implementation of CART [Breiman, 1993] to choose the set of plasma measurements that carries the disruptive related information. The second subsection is focused on the adequate processing of the selected signals to obtain the feature vectors.

### 2.2 Selection of the plasma measurements

The selection of the most informative physical quantities is fundamental to properly identify a disruptive activity. On the one hand, too many signals could lead to the impossibility of an adequate comprehension of the phenomenon. On the other hand, too few could not provide enough information to perform a reliable inspection. It must be chosen an appropriate set of plasma parameters to study the phenomenon. To this end, decision trees, as the Classification and Regression Trees (CART) [Breiman, 1993] have been employed. They consist on tree shaped diagrams that represent a classification system or predictive model (see Figure 1).

To explain the basic properties of the approach, it is necessary to focus the discussion on the case of our interest, the two types of discharges to be distinguished: disruptives or non-disruptives. For the adequate comprehension of the method, some nomenclature must be stated as follows:

$x_i$ is the selected split variable (splitter) and $a_i$ is the selected split value for the ith node.
The root node is the starting node of the tree, node 1 in Figure 1.
A child node is a node output of the splitting process of a higher level node called father node.
A terminal node is a node which is not split further.
A leaf node is any other node which is neither a root nor a terminal one.

The algorithm traverses the database attempting for each input variable to find the value that splits the dataset into the two preconceived groups of discharges. This value is called 'split value'.

Several criteria are available for determining the splits, as is detailed in [Breiman, 1993]. To find the best variable for splitting a node, the algorithm checks all

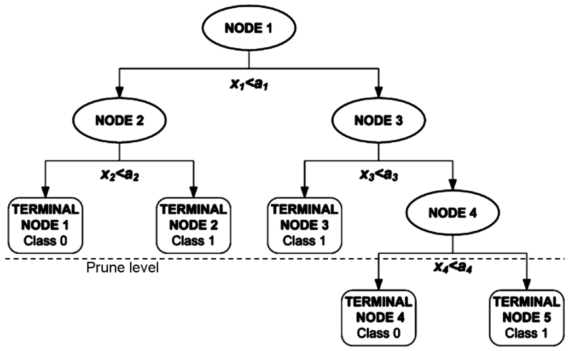



Figure 1. Typical CART output for a two class classification problem. $x_i$ is the selected split variable (splitter) and $a_i$ is the selected split value for the $i_{th}$ node.

possible splitting variables (splitters), as well as all possible values of the variables, aiming at the minimization of the average 'impurity' of the two child nodes produced after the splitting. The formula to calculate the impurity has been the following one:

$$I_G(i) = 1 - \sum_{j=1}^{m} p(i,j)^2 = \sum_{j \neq k} p(i,j)p(i,k), \quad (1)$$

where m is the total number of classes. p(i, j) denotes the probability of class j in the node i and p(i, k) is the probability of class j in the node i. The equation reaches its minimum (zero) when all cases in the node fall into a single target category. This 'maximum purity' of the node occurs when the probability of one class in a node is equal to 1 (and as a consequence the probability of the other class in that node is 0).

A perfect separation is typically not achievable with one single split. Consequently, the procedure has to be repeated for the child nodes until reaching pure terminal nodes (i.e. nodes which are not split any more) or when the terminal nodes contain no more cases than a pre-specified fraction.

The tree obtained at this stage is called a maximal tree. The next step consists on the pruning. It is required to converge to an improved compromise between the tree complexity and its performance. This phase consists of eliminating the final nodes, which increase the complexity of the tree without bringing sufficient improvement in the classification. The obtained tree has the more important variables towards the root and the ones with less explanatory power towards the terminal nodes. Starting with 35 signals (each one sampled at 2 kHz), this method allowed selecting the collection of the 13 most relevant ones. These signals are:

1. Plasma current. 2. Poloidal beta. 3. Poloidal beta time derivative. 4. Mode lock amplitude. 5. Safety factor at 95% of minor radius. 6. Safety factor at 95% of minor radius time derivative. 7. Total input power. 8. Plasma internal inductance. 9. Plasma internal inductance time derivative. 10. Plasma vertical position. 11.

Plasma density. 12. Stored diamagnetic energy time derivative. 13. Net power (total input power minus total radiated power).

Three previous studies [Murari, 2008] [Cannas, 2006] [Ratta, 2008] agree that a condensed number of waveforms (between ten and thirteen, and mostly the same ones) is enough to describe the phenomenon without a significant loss of information. This first step is crucial to decrease the complexity of the problem by dividing almost by 3 the amount of waveforms to be taken into account.

### 2.3 Creation of feature vectors

Still, the reduction in the selection of measurements has not been enough. To attain good results it is necessary to reduce redundant or useless data and to highlight the disruptive-related information. The 13 selected plasma parameters present amplitudes which differ by several orders of magnitude. To assign similar weights to all the signals they have been normalized according to the formula:

$$\text{Normalized signal} = \frac{Signal - Min}{Max - Min} \tag{2}$$

where Min and Max, respectively, represent the minimum and maximum values of each signal in the dataset.

On the other hand, it is possible to recognize by a visual inspection that disruptions are rather linked to higher frequency components in the signals. Consequently, in a previous study [Ratta, 2008], two additional procedures have been followed. The first one consists in splitting every signal in time windows of 30 milliseconds. By this way, the analysis can be performed on the 30 ms time portions of the signal instead on the whole waveform. The second procedure is based on compressing the information of the 30 ms time windows of shot in a single feature vector. To achieve this second step, after the normalization detailed in ec.2, the standard deviation of the fast Fourier transform of each temporal window is calculated. The positive part of the obtained spectrum is retained, discarding the first component (off-set). Then, every shot is described by a sequence of 30 ms feature vectors. This procedure is performed over the whole available database, including a total of 220 disruptive and 220 non disruptive experiments.

The feature extraction procedure can be summarized as follows:

Let's consider as an example the specific time window of experiment [-60 ms, -30 ms] before the disruption.

The steps to attain the feature vector$_{[}-60ms, -30ms]$ are:

1. FFT of each [-60 ms, -30 ms] time window of signal (applied independently to each one of the 13 signals).

   The offset component of each one of the 13 obtained spectra are discarded. Only their positive parts are retained.

2. The standard deviation of each one of the 13 retained spectra are calculated. As result, one value per [-60 ms, -30 ms] of signal is attained.
3. Finally, the 13 values are concatenated, creating the feature vector.

Summarizing, the initial set of 35 signals per experiment, with a total of 525 samples per 30 ms of shot (0.5 samples per ms x 30 ms x 35 signals) have been condensed to feature vectors of 13 values per 30 ms of discharge. The dimensionality reduction is considerable (from 525 data to 13 features per time window). For each shot, this feature extraction procedure has been applied to the time windows from [-30 ms, 0] to [-360 ms, -330 ms] before the disruption.

## 3 Generative Topographic Maps for a Visual Identification of the Phenomenon

To provide an estimation of how different the behaviour of a disruptive and a non disruptive experiment are, the feature vector collections of the entire database, for different time windows before the disruption, were input to the GTM algorithm [Bishop, 1998]. The purpose of GTM is to find a configuration of data points in a low-dimensional space such that the proximity between objects in the full-dimensional space is represented with a high level of reliability by the distances between points in the low-dimensional space. This implies that the objects that are close together in the high dimensional space became points also placed closely in a bi-dimensional space. The GTM algorithm is based on the self-organized maps [Kohonen, 1998] but it provides some advantages. It uses a cost function (using the well known Expectation Maximization algorithm [Martinez and Martinez, 2005]) and provides convergence guarantees [Bishop, 1998].

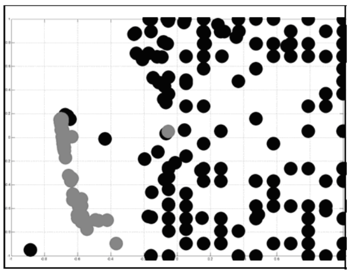
For this application, and due to the fact that there are two different sets of discharges (disruptives and non-disruptives), it would be expected to visualize two clearly different groupings in the data. As feature vectors are closer in time to the disruption, a more clear distinction between clusters would have to be shown. On the contrary much in advance of the disruption, the distinction is expected to completely disappear.

A reference time is required to compare disruptive and non disruptive shots. Consequently, a 'disruptive equivalent' time, for non disruptive discharges, has been calculated. It has been determined as 7 seconds after the plasma X-point is created, the statistically most probable time for a discharge to disrupt at JET. Then, all the time windows to be compared are linked either to the disruption time or the 'disruptive equivalent' time for shots that end safely.

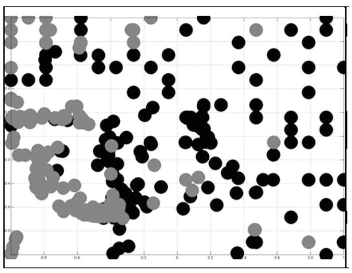
The feature vectors belonging to the different time windows of the database are provided to the GTM.

Then, a map per each time window under analysis, for the 220 disruptive and the 220 non disruptive shots, has been developed. Three of them have been plotted in Figure 2. There, the grey points represent the low dimensional mapping of the non disruptive discharges and the black ones symbolize the disruptive ones. It should be noticed that in the top graph the phenomenon is evident and therefore the bi-dimensional representation of the experiments shows two clear groups of data. Also, it can be appreciated that, comparatively, the safe discharges are more similar themselves at those times than the disruptive ones. This issue can be explained in physical terms, because the operation during safe experiments is usually restricted to several well-known parameters. Besides, many types of disruptions and not only one exist and the signals near these events present a wide range of behaviours.

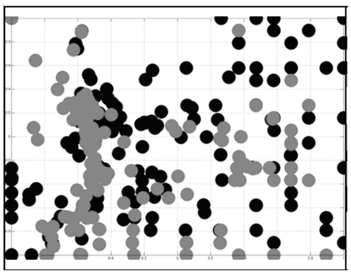
The transition between clear separation and the overlapping of the points in the selected feature space corresponds to the interval [-210, -180]. Finally, far away in time from the phenomenon, the serials of disruptive and non disruptive shots are completely mixed, meaning that at those times even disruptive experiments behave as safe and therefore no clear distinction can be done between them.



*30 to 60ms Before D*



*180 to 210ms Before D*



*300 to 330ms Before D*

Figure 2. 2D mapping of three different time windows before the disruption. Each map (in arbitrary units) represents the feature vectors of the 220 non disruptive (grey circles) and 220 disruptive (black circles) shots. As the discharges get closer to the disruption, the phenomenon becomes more evident.

## 4 Discussion

The results obtained with the GTM support the initial assumption that the closer in time the shots to the disruptions are the higher the differences between the physical parameters of the experiments are. Through this technique, an extremely high dimensional and complex phenomenon has been summarized in bi-dimensional plots where a simple visual inspection helps to understand the times when the behaviour of the disruptives discharges becomes more evident.

In spite of the dimensional reduction, this algorithm has the advantage of preserving the relative distances of the input data. To this end it can be also applied to any other high dimensional physical phenomena for the best comprehension of their evolution through a simple visual inspection.

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