EARLY IDENTIFICATION OF DISRUPTION PATHS FOR PREVENTION AND AVOIDANCE

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Abstract

Disruption prevention in high performance, high current, long duration discharges requires a substantial evolution of the schemes applied in most of the present tokamaks. An efficient prevention scheme requires the early identification of the nature of the off-normal behaviour and the automatic selection of the appropriated countermeasure, either avoidance or mitigation. For the purpose of the avoidance, on which this paper is focused, the disruption can be seen as the result of the interplay of the physical events and of the control system responses to them and to the technical failures. The building blocks of such description should include the integration of several sets of plasma scalar data, plasma profile data, magneto-hydrodynamics (MHD) indicators and engineering data. Previous work has shown the potential of the Generative Topographic Mapping (GTM) algorithm for identification and discrimination of the disruptive operational space in tokamak devices. In the paper it is shown that the magnetic fluctuations associated with rotating MHD modes can be characterized using a set of observables derived from the Singular Value Decomposition applied to the data collected by an array of pick-up coils. They provide an input to the GTM analysis such that a clustering separating disruptive and non-disruptive timeslices can be found. A selection criterion is derived from this analysis such that a warning time of the order of seconds about the incoming disruption can be obtained.

1. INTRODUCTION

Disruption prevention in the perspective of high performance, high current, long duration plasma discharges requires a substantial evolution of the schemes applied in most of the present tokamaks. An efficient prevention scheme requires the early identification of the nature of the off-normal behavior possibly leading to a disruption and the automatic selection of the appropriated countermeasure, either avoidance or mitigation. The effectiveness of the mitigation can be ameliorated increasing the warning time for which the unavoidable incoming disruption is detected, keeping at the lowest fraction the false alarm rate. This objective can be reached developing disruption predictors based on advanced signal processing techniques applied to the standard disruption precursors in tokamak such the locked mode amplitude and also extending the range of information feeding the predictors using multidimensional analysis. For the purpose of the avoidance, on which the paper is focused, the disruption can be seen as the result of the interplay of the physical events and of the control system responses to them and to the technical failures. The success of the avoidance strategy is eased by a detailed enough description of the possible disruption paths. The development of an efficient avoidance scheme implies a complex description of the state of the system, which should include plasma features and “device control features”. The building blocks of such description should include the integration of several sets of plasma scalar data, plasma profile data, magneto-hydrodynamics indicators and engineering data with different timescales in order to allow both timely avoidance actions and mitigation actions. One important feature needed for the avoidance purpose is that the behaviour of the observables related to disruptive and non-disruptive conditions bifurcates with a significant advance with respect to the disruption time. This advance would favour the identification of a pre-disruptive phase in which a suitable restoring action can be taken. Rotating magnetohydrodynamics instabilities in many cases anticipate the development of a locked mode that ends in a disruption. Then the study of such rotating instability can provide information on incoming disruptions with the required advance. In this paper it is shown that the magnetic fluctuations associated with rotating MHD modes can be characterized using a set of observables derived from the Singular Value Decomposition applied to the data collected by an array of pick-up coils.

2. SINGULAR VALUE DECOMPOSITION ANALYSIS OF MHD DATA

MHD data analysis here presented is based on the application of the Singular Value Decomposition algorithm to a set of m=13 Mirnov probes [1]. Off line signals are pre-processed to simulate a 250 kHz sampling and filtered in the 1-60 kHz band. Samples are collected in a matrix M for time intervals 1-ms long (n=250). Application of SVD to a matrix M (m*n) allows to find two orthonormal matrices (one m^2 and one n^2) to "diagonalize" the original matrix. Non-zero elements of the resulting matrix are called "singular values" S. For a more detailed mathematical description of SVD we refer to [2][3][4]. In particular,[2] shows that the application of SVD to a set of measurements from different sensors can be interpreted as a biorthogonal decomposition, i.e. SVD allows to decompose the spatial behavior (topos or Principal Axes -PA-) and the time behavior (kronos or Principal Component -PC-) for each mode identified by a singular value. The eigenvectors and eigenvalues of the covariance matrix associated with M are equals to the collection of PA, and s^2 respectively [3][4].

Postprocessing of the singular values S provides information about the appearance and the dominance of coherent modes, while simple post-processing of the PC (related with the strongest mode, i.e. the highest S) provides information on the spectrum of the mode, and post-processing of the PA can in principle allow the identification (=m,n) of mode. Furthermore, comparing the results along time, information about the stationarity of the mode or occurrence of sudden events (as ELM and sawteeth crashes) can be obtained. Also sudden changes on the mode spatial distribution, plasma shape and position or mode-locking events can be observed.

The qualitative evolution of MHD fluctuations is described by the Shannon'entropy H as defined in [2],[5], which represents the average information associated with the set of all the computed singular values, by the differential entropy DH, which is the Kullback-Leigler divergence between two set of SVs found at different times t_i, t_{i-1}, and by DR which is the probability of the least PA according with the definitions below.

$$DH(t_i) = \frac{-\sum_{k=1\ldots M} p_k \ln\left(\frac{p_k(t_i)}{p_k(t_{i-1})}\right)}{ln(E)} \qquad (1)$$

Where $p_k = SV_k^2/E$ are the normalized squared singular values of the SVD factorization and E= $\sum_{k=1\ldots M} SV_k^2$, is the energy content being M the number of Mirnov probes.

$$DR(t_i) = \frac{P_{j'}(t_i)}{p_{j'}(t_{i-1})} \qquad (2)$$

Where

$$P_{j'}(t_i) = \sum_{j=1\ldots M} p_j(t_i) \left(\sum_{k=1\ldots M} PA_{k,j}(t_i) \cdot PA_{k,j'}(t_{i-1})\right) \qquad (3)$$

Is the probability of finding a given PA. DH is a measure of how persistent is the mode presence while DR is associated with the variation of the spatial distribution of the MHD fluctuations.

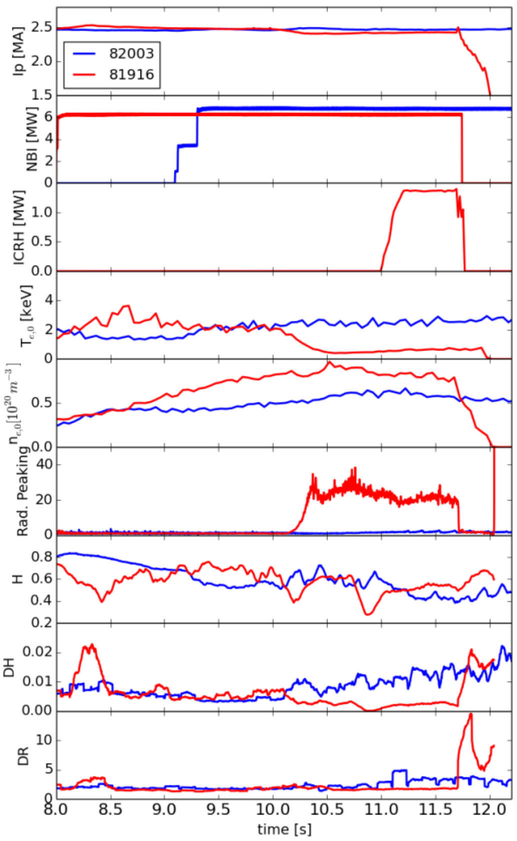

Fig. 1. *From top: time evolution of plasma current, NBI and ICRH power, core temperature and density, radiation peaking, H, DH and DR as defined in the text for the disruptive shot #81916 (red) and for the regular termination #82003 (ELMy H-mode scenario).*

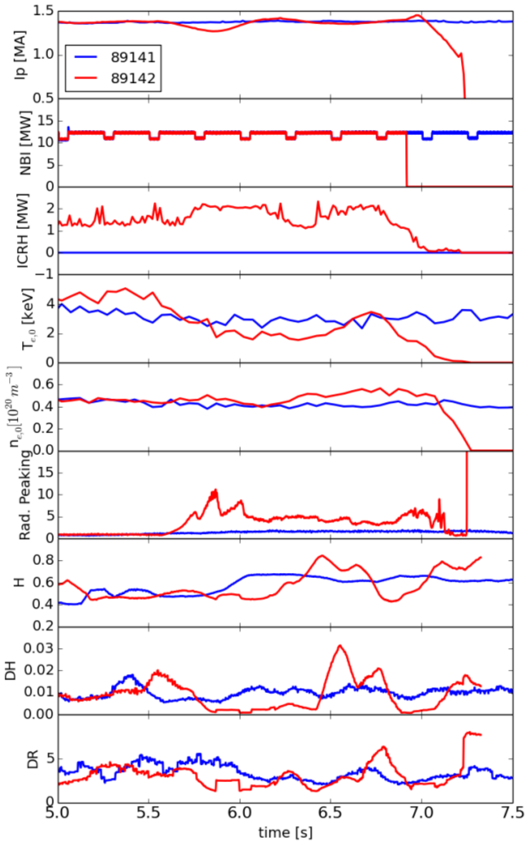

Fig. 2. *From top: time evolution of plasma current, NBI and ICRH power, core temperature and density, radiation peaking, H, DH and DR as defined in the text for the disruptive shot #89142 (red) and for the regular termination #89141 (Hybrid scenario).*

An example of the time evolution of such quantities is shown in Fig.1 and Fig.2 respectively for a pair of JET plasma discharges in ELMy H-mode reference scenario, one disruptive (#81916) and one with regular termination (#82003), and for a pair of lower current hybrid plasma scenarios, one disruptive (#89142) and one with regular termination (#89141). In particular, the value of DH reflects the radiation peaking event and the value of DR the development of a locked mode. Even if the general behaviour of the mentioned signals has a direct qualitative relation with the importance of the MHD activity, the interpretation of signals due to such changes is in general not obvious and in particular a reliable, quantitative indicator of a pre-disruptive plasma state can not be based only on them. However, a more complete set of MHD-related observables can be derived from the SVD decomposition. Besides the already mentioned three variables this set includes the first four singular values (4), the frequency estimators of the two first PCs (4) and their standard deviations (4), the first four moments of the two first PCs (mean, standard deviation, skewness and kurtosis) (8), and finally the information associated to the last singular value $-\ln(p_M)$. The probability distribution functions (PDFs) of such set of 24 variables is shown in Fig. 3 for a database of 90 disruptions and 55 regular terminations in JET campaigns with the ITER Like Wall (ILW) without the Massive Gas Injection mitigation system (MGI) (81867 to 83784, C28-C30, here named Pre-MGI database). Pulses are selected such the Neutral Beam Ion power is P_{NBI}>5MW. The absence of an active mitigation system implies that the discharges termination preserves its "natural" behaviour. In this training data set, the assignation of the timeslices to the disruptive class has been manually performed studying the plasma evolution. It can be seen that the PDFs related to the disruptive phases (red lines) are different with respect to the PDFs related to the stable phases of the non-disruptive discharges. However, none of the derived variables provide by itself the full capability of discrimination between disruptive and non-disruptive states. The question arises if a combination of such variables has better performance.

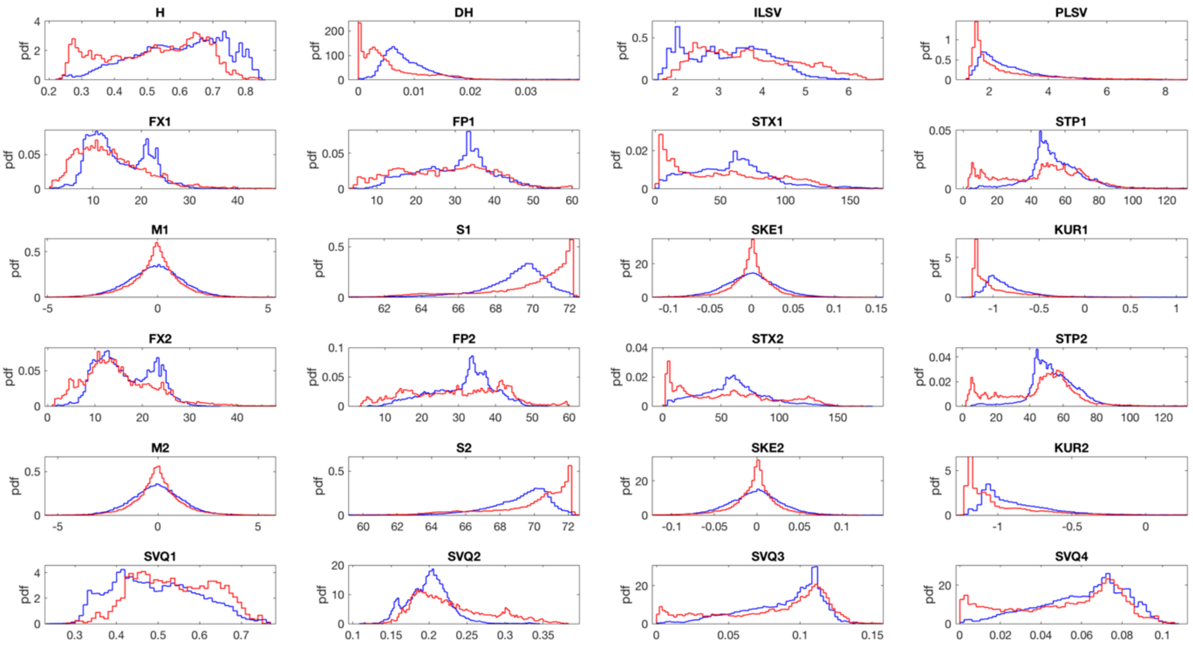

Fig. 3. *Probability distribution functions of the 24 variables derived from the SVD of the signals of the Mirnov coils array, respectively for pre-disruptive timeslices (red) and for non disruptive timeslices (blue).*

3. GENERATIVE TOPOGRAPHIC MAPPING ANALYSIS

The answer to the previous question has been sought with the help of the machine learning method called Generative Topographic Mapping (GTM) [6]. Previous work has shown the potential of the GTM algorithm for identification and discrimination of the disruptive operational space in tokamak devices [7] [8]. GTM is a machine learning technique belonging to the class of the so called manifold learning. More specifically, it is a generative model that performs the mapping of the data manifold embedded in the high dimensional space on a reduced dimensional space. The mapping, usually performed through Radial Basis Functions (RBFs), is defined by a smooth and continuous non-linear function that preserves two fundamental properties: the topographic ordering and the proximity relations. GTM model allows uncovering structures and patterns that describes the complex relations among the input parameters and is able to represent them in a reduced (2D in this case) latent space where the "pattern recognition" task is applied to the binary classification between disruptive and non-disruptive time-slices of tokamak discharges. The application of GTM to JET plasma profiles is reported in [10].

The set of 24 SVD-derived variables for the Pre-MGI database have been analysed with the same GTM tool projecting the multi-dimensional input into the latent space. The resulting clustering is shown in Fig. 4 where well defined areas for the two classes can be identified. The axes in the plot do not have a direct physics interpretation, being the latent space a discrete grid of points with a non-linear relation with the data space. The unified distance matrix (UMAT) [9] in Fig.5 is a representation of the distance between neighboring elements in the data space and shows a good separation in the clustering of the two classes. The time evolution projected in the latent space for two examples previously mentioned, disruptive (#81916) and regular termination (#82003) can be seen in Fig.6. While #82003 belongs to the non-disruptive class (green area) for most of the observed time, #81916 after the initial phase (yellow circles) crosses the boundary of the disruptive region (red area).
The class membership (disruptive/non-disruptive) versus time for the same plasma discharges is shown in Fig. 7. The top plots represent the percentage membership according to the GTM-7 analysis of plasma profiles (peaking factors of electron temperature, density, core and edge radiation, fraction of radiated power, internal inductance, safety factor on axis) [10][11], while the bottom ones according to the GTM-SVD24 analysis presented in this paper. The two sets of totally independent data both assign very high rate membership to the disruptive class about 2 seconds before the actual disruption. The different level of noise and the slightly different time behavior during the early phase of the development of the pre-disruptive condition (10-11 s) both reflect the different physics grounds originating the diagnostics signals. This may result in a potential advantage for the performance and for the flexibility of the avoidance system.

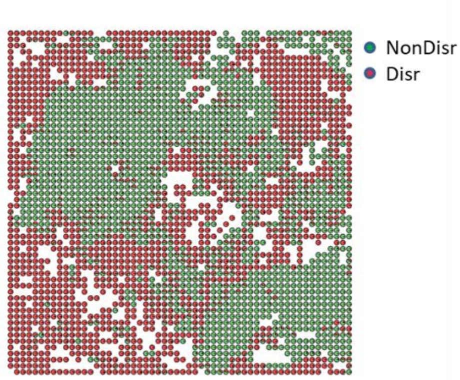

Fig. 4. GTM clustering in the latent space (see text) of the Pre-MGI database. Red: disruptive; green: non-disruptive.

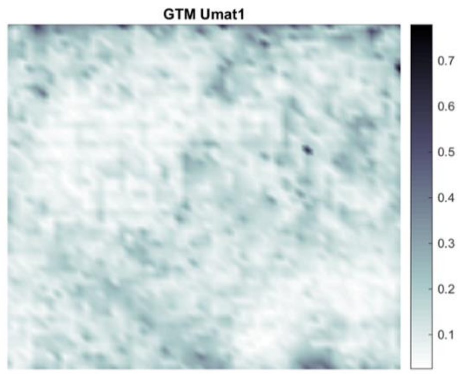

Fig. 5. Unified distance matrix of the Pre-MGI database. Grey scale in the latent space reflects distance in the multidimensional input data space.

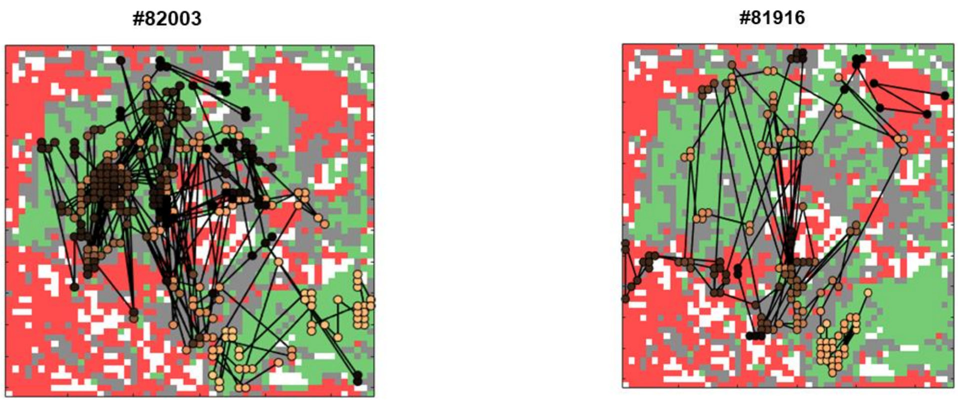

Fig. 6. Time evolution projected in the latent space (non-disruptive case #82003, left and disruptive #81916, right). Yellow circles represent the initial timeslices of the projection while the black ones the final ones.

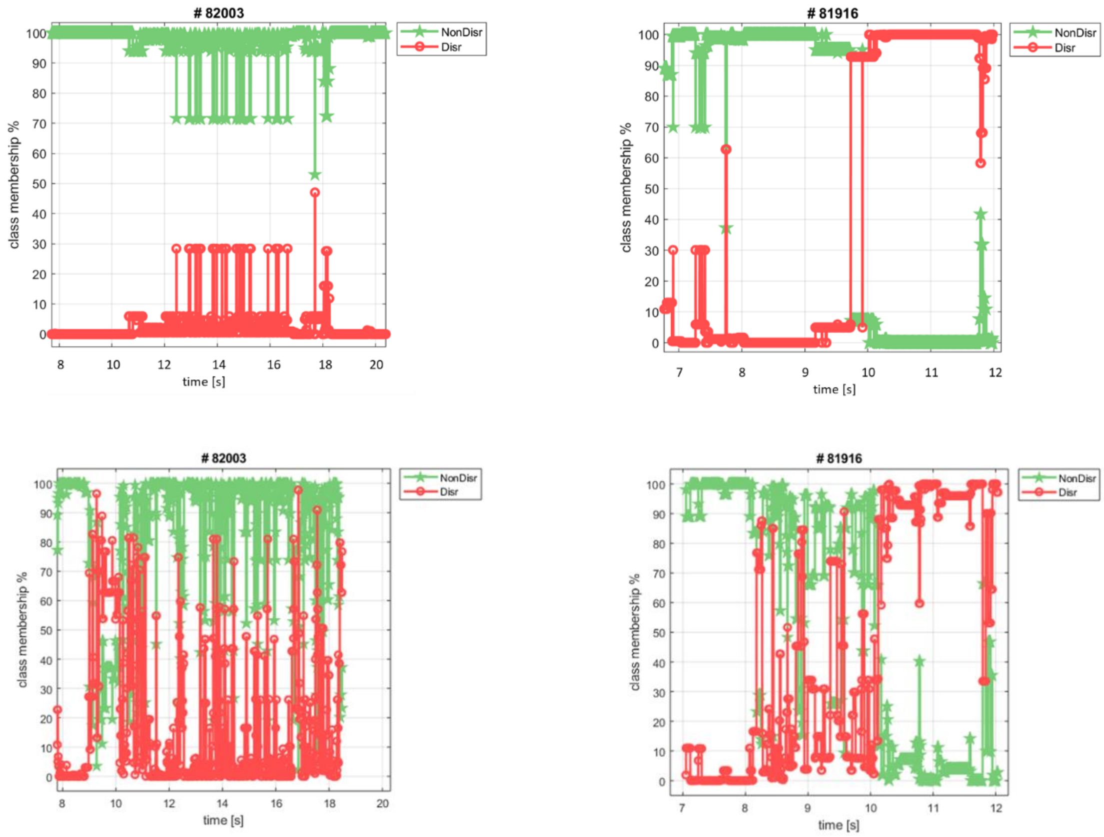

Fig. 7. Time evolution of the class membership (green: non-disruptive, red: disruptive) for JET pulse #81916 and #82003. Top: kinetic profiles analysis; bottom: SVD-MHD analysis

In principle, several different and independent sources of data can be combined using the GTM analysis. This opens the possibility to investigate and identify in the parameter space patterns and combination of parameters describing physics mechanisms leading to disruption. For the purpose of real-time application and integration in a practical control system for triggering avoidance or mitigation actions the statistics of the warning times in the database must to be considered. Fig. 8 describes a logical circuit integrating two alarm sources, the GTM-SVD24 here introduced and a standard amplitude threshold-based Locked Mode trigger (LM). The performance of such alarm scheme in terms of the accumulated fraction of detected disruptions compared with the performance of each one of its building blocks are shown in Fig. 9.

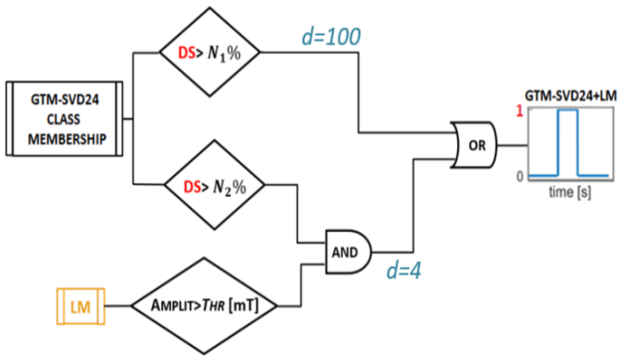

Fig. 8. Integration of the GTM-SVD24 alarm and of an amplitude threshold-based Locked Mode trigger

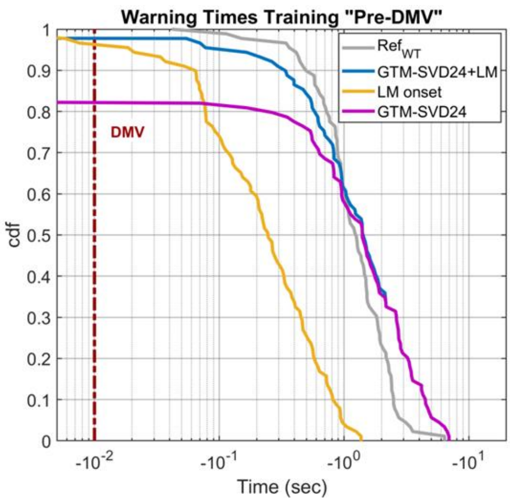

Fig. 9. Accumulated fraction of detected disruptions as a function of the warning time (see text).

The vertical dotted line is the time limit to trigger the Disruption Mitigation Valve, i.e. the MGI (10ms). The grey line is the off-line determined transition from the stable to the unstable pre-disruptive phase, derived from the analysis of the events chain leading to the disruption. The magenta line is the GTM-SVD24 for a requested disruptive membership DS>98% and assertion time AT=100ms. The combination of GTM-SVD24 and of the LM according to the scheme in Fig. 8 is represented by the blue line. Such scheme provides 87/89 successful predicted disruptions, 0 false alarms, 0 tardy alarms with 2 missed alarms. Fig. 9 also shows for comparison the performance of the stand-alone LM trigger. GTM-SVD24+LM provides a warning time of at least about 1s longer than LM. Such encouraging performance however needs confirmation once a similar analysis is applied on a larger database, different from the training set. This extension is now in progress, within the limitations imposed by the availability of a sufficient number of working Mirnov probes during the JET high power campaign C36. First results of the analysis show a reduction of the performances in terms of successful predictions and false alarms, at least partially motivated by the large percentage of disruptions in the ramp-down phase that is outside the present training test. The other extension being performed is the application to TCV and AUG tokamaks which both are well equipped with Mirnov magnetic sensors.

4. DEVELOPMENT OF MITIGATION TRIGGERS AND OPTIMIZED RAMP-DOWN

An efficient disruption management scheme requires a number of different basic ingredients among which are efficient observers of the plasma state, avoidance and mitigation triggers, avoidance schemes specialized for the kind of off-normal situation. The development of such comprehensive scheme is being pursued in a coordinate effort within the EUROfusion Consortium by a number of research initiatives including the Analysis and Modelling tasks dedicated to the disruption avoidance and plasma termination. In this section a brief summary of the activity recently performed in such framework is given.

— Termination analysis in preparation of the JET DT scenarios. Results of such analysis indicate that metal impurity radiation is the more relevant disruption cause in JET. W impurity detrimental effect is dominated by the increased W source term when the density at the separatrix decreases, leading to higher temperature on the divertor [12]. This effect tends to become runaway when the central temperature decreases about to 2 kev, which is the maximum of W radiative cooling rate. Ion Cyclotron Resonance Heating (ICRH) may be inefficient to counteract the core impurity effect at high current being dominantly ion heating. Faster than real-time predictive modelling can be used to optimize the current ramp-down in the case of emergency stop [13].

— Improvement of the mitigation triggering. Generally, all the statistical analysis methods including machine learning tools converge in indicating that a simple threshold in the LM amplitude is a disruption predictor of limited effectiveness [14] [15]. This is in the practice well balanced by the combined use of other machine-specific mitigation triggers but the problem of the extrapolation to future devices is still open. Moreover, a significant reduction of the false alarm rate (unnecessary mitigation events, which still are disruptions) is required. The false alarm study on pre-DMV data confirms that hollow electron temperature profiles which recover are an important source of false alarms for both the hybrid and standard H-mode scenarios. One promising technique to overcome this limitation is provided by the so-called Centroid method [16] in which the recognition of disruptive/non-disruptive behaviours is based on the time evolution of the amplitudes between consecutive samples. This method also provide an estimation of the time left before the disruption. The topic of the extrapolation from smaller to larger device, in particular on the basis of the exploitation of the database in the smaller one (cross-tokamak predictor) is being approached using genetic algorithms techniques [17].

— Analysis of the chain of events leading to the disruption, disruption classification and avoidance triggering. Disruption indicators based on plasma profiles analysis with warning time compatible with disruption are being developed. Several versions of a GTM tool have been proposed with the purpose of early identification of the pre-disruptive conditions [10]. Versions differ for the groups of observables used (GTM-5 profiles based on indicators of kinetic and current profiles, GTM-10 or -13 variables including also plasma engineering parameters [18], GTM-SVD-24 including indicators of the MHD activity described in this paper). GTM analysis has shown good identification capabilities (disruptive/non disruptive behaviour) with characteristic warning time long enough for the purpose of avoidance. Moreover has the capability of incorporating and combining groups of observables describing the various aspects of the unstable, pre-disruptive behaviour.

The output of this analysis work is part of the basis for the next JET experiments on disruption avoidance and plasma termination.

5. CONCLUSIONS

In this paper it is shown that the magnetic fluctuations associated with rotating MHD modes can be characterized using a set of observables derived from the SVD algorithm applied to the data collected by an array of Mirnov coils. Such data provide an input to the GTM analysis such that a clustering separating disruptive and non-disruptive timeslices can be found. Combined with a standard LM trigger, the accumulated warning time for the detection of incoming disruptions is significantly increased (>1s) with respect to the stand-alone LM. A number of other investigation efforts are being pursued to develop the tools for decreasing the disruption risk in present and future devices.

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