A machine learning approach towards disruption prediction and avoidance on JET

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** See X. Litaudon et al. Nucl. Fusion 57, 102001*

I. Introduction

Disruptive events still represent one of the main concerns for the protection of in-vessel components of large size tokamaks, imposing several constraints on the design of the next step experimental devices such as ITER and DEMO. This work aims at summarizing the efforts in the development of an innovative machine learning approach, based on a generative model, towards the implementation of a disruption prediction and avoidance system. To this end, a general-purpose tool based on the Generative Topographic Mapping (GTM) algorithm [1] has been developed [2] and is being upgraded adding new features for a more advanced investigation of the mapped parameter space. GTM performs an unsupervised mapping from a low dimensional latent space, which is usually assumed to be two or three dimensional for visualization purposes, into the high dimensional original data space through radial basis functions, preserving the topology of the data space. This means that operating points close to each other in the data space will be mapped still close in the latent space. The algorithm produces a density model defining probability distributions over the data and the manifold properties, providing at the same time a quantification of the uncertainty of the model fitted to the data.

In addition to some global 0-D plasma parameters, where some of them have already been employed for disruption prediction purposes in the past, the original multidimensional space has been described by a set of dimensionless, machine-independent, plasma features. These latter have been synthesized extracting the information associated to 1-D spatial distribution of kinetic quantities and radiated power, which are suitable to describe several physics mechanisms characterizing disruptions and allow a more robust extrapolation to operational

Acknowledgement

This work has been carried out within the framework of the EUROfusion Consortium and has received funding from the Euratom research and training programme 2014-2018 under grant agreement No.633053. The views and opinions expressed herein do not necessarily reflect those of the European Commission.

domains outside the training one (and, potentially, to other tokamaks). Moreover, these plasma profile indicators have proved to be very promising for disruption avoidance [3].

In this paper, the potential of the GTM machine learning tool is discussed emphasizing its effectiveness for the investigation of the JET operational space where the relevant physics takes place [4]. Typical patterns, describing different processes and characterizing different types of disruption, have been compared for different scenarios developed at JET with the ILW, extending the analysis presented in [5] to more recent high-power experiments carried out in 2016. Moreover, the proposed approach allows us to monitor the disruption dynamics, identifying often well in advance the causes of the discharges destabilization, coherently with the physics mechanisms leading to disruptions. The paper will discuss how the imminence of the disruption can be linked to the proximity of its trajectory to the operational boundaries appearing in the 2-D parameters space.

II. Machine Learning Workflow

In the typical machine learning approach, the first step is the construction of a reliable database [6] and the proper selection of the discharge phases of interest for the study: in this paper the analysis has been mainly focused on the flat-top phase of the plasma current. In order to effectively extract the information contained in the raw signals, a feature engineering approach has been combined with the definition of physics-based indicators related to spatial and/or temporal information, such as the time evolution of the so called peaking factors of temperature, electron density, and radiation profiles [3]. In particular, two features have been synthesized from the radiation distribution in the poloidal plane, basically decoupling the contribution of the core with respect to the contribution of the divertor region. Other three dimensionless parameters have been integrated in the final dataset: the internal inductance, as representative of the current density profile; the fraction of radiated power with respect to the total input power, which has the function to connect a spatial information (related to the 1-D profile of the radiation) with the entity of the radiation collapse; the safety factor on the magnetic axis, which is connected to the presence of the resonant surface for q=1 and the sawtooth crashes due to the instability of the internal kink mode (m=1, n=1).

Data for training the GTM model have been selected from the ITER Like Wall (ILW) experimental campaigns performed on JET from 2011 to 2013. In particular, 70 regular terminations and 89 disrupted shots have been selected. These latter are mostly flat top disruptions, not terminated by massive gas injection. The selection of the training set has been performed maximizing the variety in terms of disruption types and experiments.

Making use of a tool (DIS_tool) [6], the main precursor phases of the disrupted discharges have been investigated in detail, determining, among others, also the so-called *Reference Warning Time* (Ref_{WT}) that corresponds to the start of the chain of events leading to disruption. The unstable phase of the disrupted discharges has been assumed to extend from this reference time to the disruption time, whereas all the flat top phase of regularly terminated discharges has been used to describe the non-disruptive part of the operational space. Moreover, all the "stable" phase of disruptive discharges belonging to the training set has been used to optimize the parameters required for the classification and the definition of an alarm. The resulting GTM of the operational space of JET, reported in Figure 1-a, is colored on the basis of the node composition, where the modes of the posterior probability corresponding to the input 7-D feature vectors are projected. As can be seen, a well-defined separation between the two regions representing the disruptive (red) and non-disruptive (green) classes can be recognized in the 2-D latent space. The information contained in the map can be exploited both for operational boundary studies and for disruption prediction and avoidance purposes. Indeed, the temporal evolution of the operative point during the flat top of a discharge can be projected on the map and a binary classification problem can be modeled for the separation of the disruptive and non-disruptive classes. In particular, a class membership can be defined as a function of time (see Figure 1-b), reflecting the probability of the operating point of belonging to one of the two classes. Furthermore, by using the information provided by the tracking of the discharge on the map, it is possible to define an alarm criterion, with very high performance on an independent test set selected in the same campaigns [7].

III. Generalization to high power experimental campaign

In this paper, we explored the potential of the obtained GTM map to generalize to the recent high power experimental campaign carried out in 2016.

In Figure 1-a, the trajectory of a disrupted discharge (#92221), belonging to such campaign, is reported, where a gradually changing color scale is used to show the temporal evolution of the discharge, from the lighter point at the beginning of the considered phase to the darker point that corresponds to the disruption time. Figure 1-c reports the seven parameters provided as input to the GTM where it is possible to identify the destabilization caused by an impurity influx. This makes the trajectory evolve from the non-disruptive (green) to the disruptive (red) region, initially following closely the boundary separating them, to penetrate further inside the disruptive region in the final phase, up to the onset of a locked mode and the final mitigation by Massive Gas Injection. Correspondingly, the disruptive (red) class membership jumps from low to very high values. As can be noted, it is possible to detect the onset of a disruptive behavior much in advance with respect to typical final precursors as the locked mode. It is worth mentioning that, what is being detected is consistent with the physics mechanisms that are destabilizing the discharge and the preliminary analysis confirms that it is possible to recognize similar patterns even if plasma scenarios and plasma current levels are quite different.

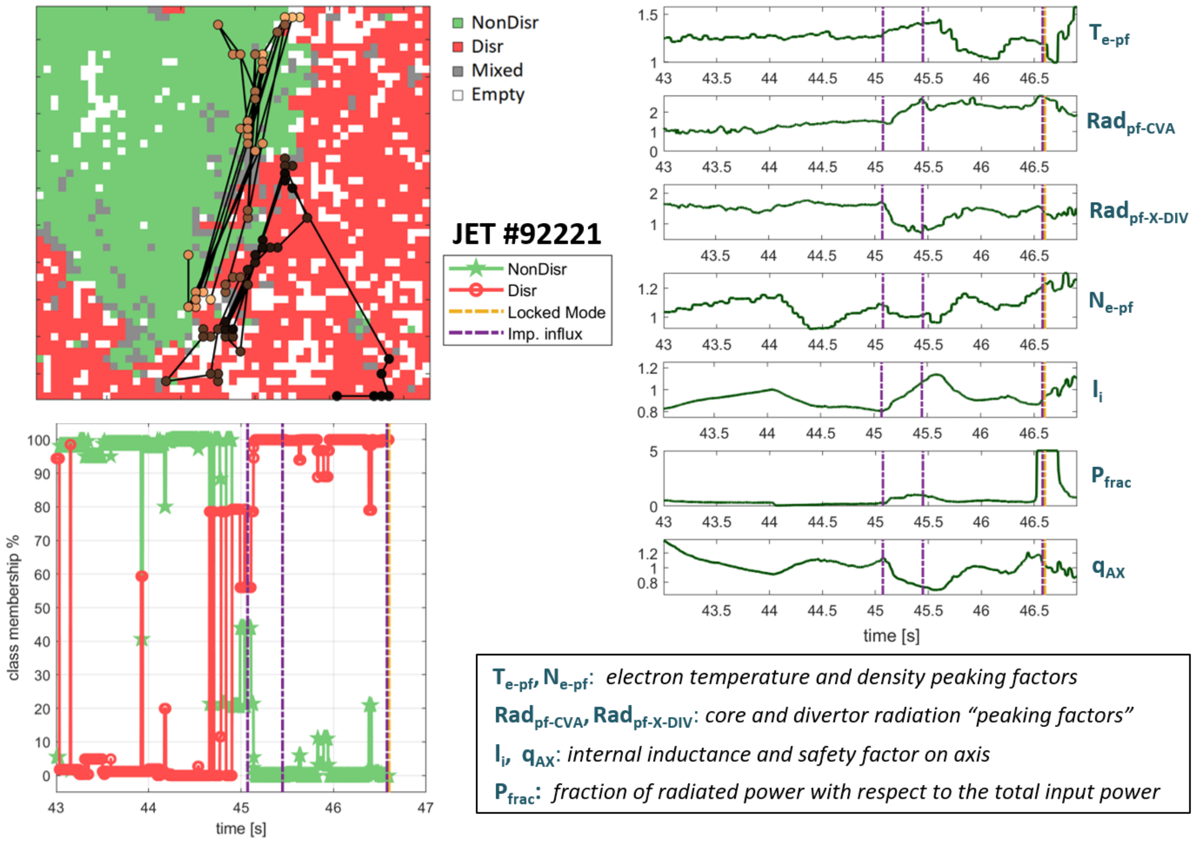

Figure 1 - a) GTM of the 7 plasma parameters: green clusters refers to the regularly terminated discharges, red clusters refers to the unstable phases of the disrupted discharges. On the map the trajectory of disrupted discharge # 92221 (black line); b) Class member functions of non-disrupted (green) and disrupted (red) classes; c) Time evolution of the 7 plasma parameters used to build the GTM. The vertical dashed lines in b) and c) correspond to the time of the influx of W and other impurities (purple), and the time of the locked mode onset (yellow).

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