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Continuous update of machine learning disruption prediction and prevention models at JET

The complex interplay of physics phenomena, which can cause plasma disruptions, hinders the development of predicting models. Recently, satisfactory Machine Learning predictors have been deployed on different devices. These models extract information from the high-dimensional data spaces of fusion experiments and help to detect and classify disruptions. Nevertheless, Machine Learning predictors have two main limitations: their performances deteriorate if the operating scenario evolves and they are difficult to interpret so that it is problematic to use them to study the physics of disruptions. This second reason motivated the development of interpretable Machine Learning algorithms, whose outputs can be interpreted in terms of the underlying physics. The GTM model [1], which is implemented on the PETRA system at JET, is an unsupervised mapping method, whose clusters can be colored using the knowledge over a set of suitably chosen plasma parameters. During the model training, this knowledge was given by manually identifying the beginning of the pre-disruptive phase of a selected set of disrupted discharges, which describes the disrupted operational space. Moreover, the disruption free operational space was described considering the flat-top phase of the plasma current for a selected set of regularly terminated discharges. The obtained GTM achieved very good performances and it was possible to study the evolution of its outputs by looking at the projection of the discharge over the map.
As every Machine Learning Algorithm, the GTM performance degrades as the operational space of the machine changes. This change can be highlighted by the statistical analysis reported in Table 1, which compares some plasma parameters of the regularly terminated discharges in the experimental campaigns performed at JET from 2011 to 2013 (C28-C30), those in 2016 (C36), and those in the more recent 2018-2019 campaigns (M18-01/M18-04). As we are working in a continuously changing environment, also the disruption predictor should be upgraded. However, the manual identification of the pre-disrupted phase is a time-consuming task, which does not allow to increasingly update a model in a context of continuous operational change. To automate the process of the data labelling necessary for the model update, we developed an algorithm to identify, for each disrupted discharge, the starting time, Tpre-disr, of the pre-disruptive phase [2]. The automatic Tpre-disr is estimated with a statistical approach, based on similarity measures between distributions, to quantify how much a disruptive pulse is becoming dissimilar from a typical regularly terminated discharge during its time evolution. This approach allowed to successfully train a GTM with the C36 discharges, where the manual identification of the Tpre-disr was not available. Preliminary results, on M18-01/M18-04 pulses, show that an updated GTM model trained with C28-C30 and C36 discharges is able to recover 2 of the 3 false alarms triggered by the model trained with the C28-C30 discharges.

Reference
[1]A. Pau, et al., Nucl.Fusion 59 (2019) 106017,(22pp).
[2]E. Aymerich, et al., "A statistical approach for the automatic identification of the start of the chain of events leading to the disruptions at JET", EUROfusion pinboard, proposed for Nuclear Fusion.

Table 1: Ranges of plasma parameters over the three considered sets of regularly terminated discharges

	C28-C30		C36		M18-04/M18-01	
Plasma Parameter	Min	Max	Min	Max	Min	Max
Plasma Current [MA]	1.448	2.983	1.633	3.273	2.261	3.545
Poloidal beta [a.u.]	0.096	0.971	0.125	0.760	0.126	0.669
Total Input Power [MW]	0.715	21.676	0.196	30.453	1.277	36.010
Total Radiated Power [MW]	0.100	7.715	0.100	12.657	0.532	22.608
Safety factor q95 [a.u.]	2.328	4.917	2.571	5.476	2.936	3.810
Line Integrated Density [10^{19} m^{-2}]	2.763	22.099	2.876	23.632	3.296	23.570
Temperature peaking factor [a.u.] *	1.157	3.051	1.109	2.613	1.442	2.395
Density peaking factor [a.u.] *	0.762	1.625	0.706	1.714	1.097	1.753
Radiation peaking factor: Core-Versus-All [a.u.] *	0.441	2.278	0.365	1.580	0.627	1.704
Radiation peaking factor: Divertor [a.u.] *	0.760	1.896	0.803	1.857	0.609	1.730
Internal Inductance [a.u.]	0.836	1.224	0.822	1.190	0.780	1.105

*Defined as in [1]

Figure 1:

Member State or International Organization

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Track Classification: Prediction and Avoidance