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Evolution of Data-driven Disruption Prediction: from Machine Learning to Deep Learning

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Because of the need to obtain a real-time predictive model of the complex disruption behaviour, a great effort has been devoted in the last decades to apply data-driven models to disruption mitigation and avoidance, starting from the first black-box neural network approaches to the more physics-based Machine Learning (ML) models up to the latest models based on Deep Learning techniques. In the present contribution, the authors describe the evolution of the disruption predictors to overcome the inherent limitations of the data-driven approach. In [1], a Generative Topographic Mapping (GTM) maps the high dimensional plasma operational space in a 2D map where different disruption risk can be easily identified. Tracking the discharge evolution on the map, the chain of events leading a disruption is followed. One of the key challenges to obtain a performing ML predictor is to identify, with as much precision as possible, the disrupted phase of the disrupted discharges. A good labelling of the discharges avoids to providing contradictory information to the ML model during its training. To meet this need, a statistical approach has been proposed in [2], framed into the anomaly detection techniques, which detects the off-normal behavior of the plasma in a disruption. This helps to implement a continuous learning system that could be automated overcoming the well-known ageing of whatever data-driven methods. Another critical phase of ML approaches is the need to extract the more informative features from multidimensional diagnostics, such as temperature, density and radiation profiles, which have proved essential for achieving high performance. In the case of ML algorithms, profile information must be synthesized into 0D signals, such as the peaking factors proposed in [1, 2]. In order to avoid the complex hand-engineered feature extraction, in [3] a deep learning prediction model, based on deep Convolutional Neural Network (CNN), has been implemented. The CNN extracts the spatiotemporal information from 1D plasma profiles. The features are automatically produced by a cascade of filtering blocks, interconnected through nonlinear activation functions. A Multilayer perceptron combines them producing the output of the network through a Softmax layer that gives the likelihood of the input to belong to a regularly terminated or a disrupted discharge. The achieved performance is proven to be better than the one obtained with GTM model trained with the 0D peaking factors, reaching, on the test set, about 93% of successful predictions, 4% of false alarms, and alarm times suitable for avoidance actions. The modularity of the deep learning approach eases the introduction of additional 2D and 1D signals from, for example, Fast Visible Cameras or spectrograms from Mirnov coils.

References

[1] Pau A. et al, 2019, Nucl. Fusion 59 106017.
[2] Aymerich E. et al, 2021, Nucl. Fusion 61 036013.
[3] Aymerich E. et al, 2022, Nucl. Fusion 62 066005.

Speaker's title

Mr

Speaker's email address

enrico.aymerich@unica.it

Speaker's Affiliation

University of Cagliari

Member State or IGO

Italy

Primary authors: Prof. FANNI, Alessandra (University of Cagliari); Prof. CANNAS, Barbara (University of Cagliari); Mr AYMERICH, Enrico (University of Cagliari); Dr PISANO, Fabio (University of Cagliari); Prof. SIAS, Giuliana (University of Cagliari)

Presenter: Prof. SIAS, Giuliana (University of Cagliari)

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