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Combining Adaptive Learning and Physics-Guided Machine Learning for Prediction and Control of Anomalies and Disruptions in Tokamaks

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Disruptions are one of the most critical issues in tokamak operation. In fact, the rapid termination of plasma magnetic confinement leads to significant heat and electromagnetic loads on the plasma-facing components, threatening the integrity of the reactor. Moreover, continuous early terminations of plasma discharge can cause variations in the energy production, limiting the amount of energy produced and the economic and environmental advantages of nuclear fusion. Despite the development and testing of effective strategies for disruption mitigation and prevention in recent years, the ultimate goal clearly remains the avoidance of disruptions. However, this solution requires the recovery and/or avoidance of plasma anomalies. Such an approach necessitates that the control system can act on the plasma when instabilities are in their early stages, small enough not to require termination of the discharge or mitigation actions.
Therefore, an algorithm capable of predicting disruptions in advance and detecting and classifying plasma anomalies is essential to provide the control system with all the information required to perform the correct countermeasures. Historically, disruption predictors and anomaly detectors have been based on two types of approaches: physics-based indicators, which are simple, easy to transfer, and interpret but often inaccurate, and AI data-driven algorithms [1], which are performant but usually obscure and not fully transferable.
This work aims to present a new approach that combines data-driven and physics-guided methodologies into a hybrid physics/data-driven AI algorithm capable of detecting, classifying, and predicting anomalies and disruptions. The algorithm is easy to interpret, highly performant, and easily transferable between tokamaks thanks to the combination of physics-informed machine learning with adaptive learning [2,3]. The algorithm has been tested in various JET campaigns, including the Deuterium-Tritium (DTE2) campaign, without a pre-training from previous campaigns. Very high detection and classification performances have been obtained, suggesting that a hybrid physics/data approach may play a relevant role in future reactors.

References:
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