EXPLAINABLE AI REVEALS GROWTH OF INSTABILITY FOR FORECASTING ELM ONSETS: TOWARD MULTI-MACHINE PREDICTIONS

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Explainable Artificial Intelligence (AI) methods reveal underlying Edge Localized Mode (ELM) burst mechanisms in an AI model for the ELM onset predictions via two-dimensional (2D) pedestal turbulent fluctuation measurements [1,2]. We also demonstrate that our proposed technique is transferable between DIII-D and KSTAR, paving the path to interpretable AI-based ELM controls for multi-machines, together with real-time E×B rotational frequency optimizations.

We present that the ELM prediction neural network inherently understands ELM trigger mechanisms, solely taking the pedestal turbulent fluctuations from the beam emission spectroscopy (BES) system (Fig. 1). Firstly, our beam emission spectroscopy neural network (BES-NN) can predict the ELM onset (Fig. 1(b)) where the ELM onset probability increases approaching the ELM onset. Secondly, extracting physical insight from a NN is important but challenging, thus we show that the interpretable AI-based network representation in a feature-map space (Fig. 1(c)) correlates with the increase of instability growths estimated via energy transfers between fluctuating quantities during the ELM onset forecasting (Fig. 1(d)). In other words, our network encodes instability growth patterns from 2D BES data under the network architecture internally. This demonstrates that the network utilizes the growth of instabilities for the reliable ELM onset forecasting, which gives confidence in the use of AI for the instability avoidance/prediction.

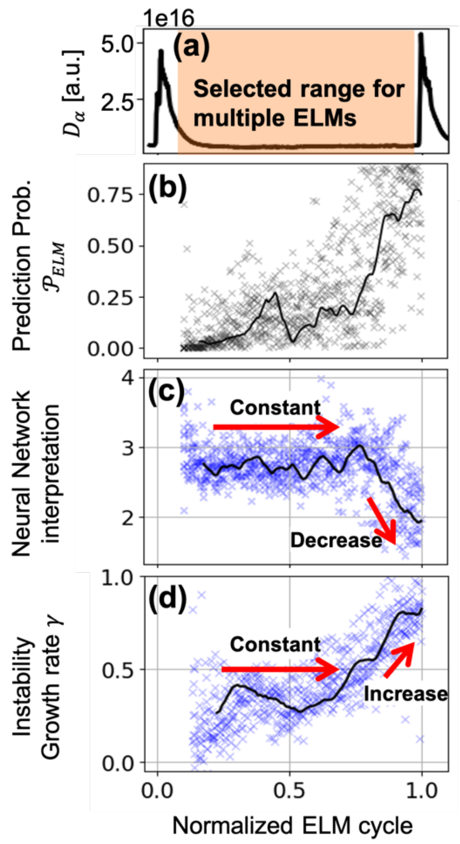

Fig. 1. Neural network internal feature extraction for the ELM onset prediction. The two distinct features between pre- and post-ELM are identified, which correlates to the growth of instabilities γ.

First demonstration of cross-machine turbulence-based ELM onset prediction demonstrates the robustness of our AI approach (Fig. 2) in DIII-D and KSTAR. Despite differences in the BES configura -tions between two tokamaks [3,4], our network successfully predicts the first ELM onset after the L-H transition in both DIII-D and KSTAR using frequency-filtered BES signals (Fig. 2(b)), exhibiting ~90% of true positive rates with $\sim 10^3$ experiment discharges. These DIII-D and KSTAR results suggest that the ELM onset forecasting can be accomplished based on fundamental aspects of the turbulent fluctuations across different tokamaks. We expect that the proposed technique can also lead to turbulence-aware tokamak control for future reactors. We also test the feasibility of using multiple diagnostics for the ELM onset prediction as a multimodal neural network.

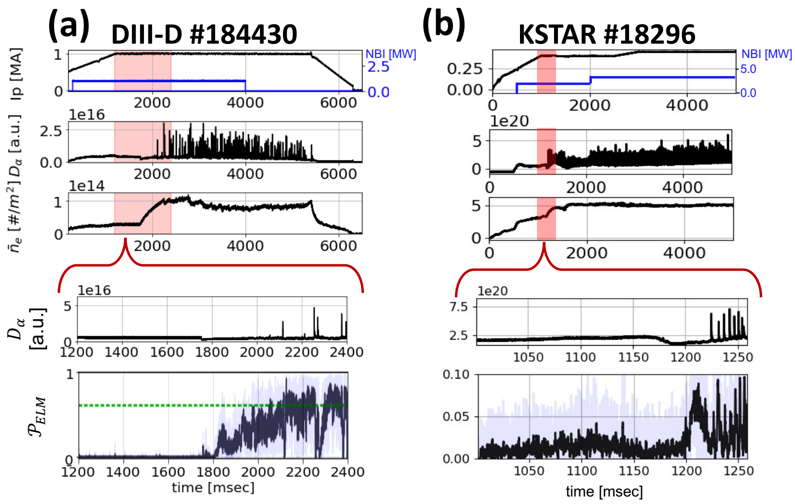

Fig. 2. DIII-D and KSTAR ELM onset prediction based solely on the BES system with our neural network (BES-NN). Based on the frequency-filtered BES signals, the first ELM onset after the L-H transition is reasonably predicted though the different magnitude of the ELM probability is estimated due to the intensity difference between two BES systems presumably.

Furthermore, our turbulence-based AI framework can monitor E×B rotation frequency in real time for enhanced adaptive RMP controls (Fig. 3). Our neural network successfully learns the poloidal fluctuation velocity v_{BES} from the BES measurement (Fig. 3(a)). v_{BES} is validated with the charge exchange recombin-ation spectroscopy system under (1) the rotating barber pole effect (i.e., the toroidal mean plasma flow $\gg$ the poloidal one during L-modes) and (2) E×B drift by assuming $v_{E\times B} \gg$ turbulent phase velocities, where $v_{E\times B}$ is the E×B drift velocity. We approximate the E×B rotational frequency $\omega_{E,BES}$ from v_{BES} by assuming $v_{BES} \sim v_{E\times B}$ to present the change of $\omega_{E,BES}$ tendency during the adaptive RMP ramp. This allows us to suppress ELM bursts during ramping down RMP currents preemptively before re-entering ELMy regimes (Fig. 3(b)). Our approach-based experime-nts will be conducted during the DIII-D FY25 campaign.

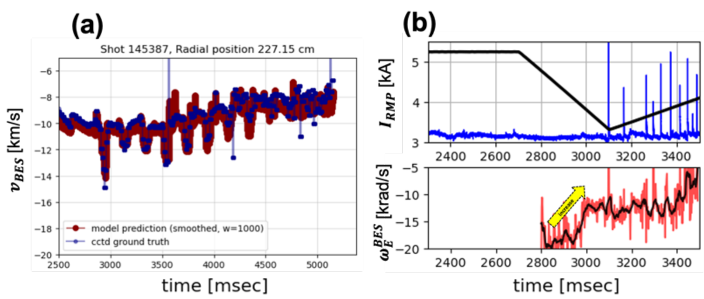

Fig. 3. Feasibility of $\omega_{E,BES}$ neural network estimation. (a) The neural network (brown) successfully learns v_{BES} (blue), so that we can use (b) $\omega_{E,BES}$ to avoid re-entering the ELM burst phase preemptively.

This turbulence-based multi-machine development demonstrates the poten-tial value of turbulence information for tokamak operations, which can provide a practical pathway toward future tokamaks via not only turbulence diagnostics available in ITER but diagnostic-to-diagnostic approaches [5], i.e., mapping parameters extracted from turbulence data to ITER-relevant diagnostics.

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