Contribution ID: **113** Type: **Oral**

Plasma Instability Events Identification and Disruption Prediction in EAST Based on Multi-Task Learning

Thursday, 18 July 2024 11:40 (20 minutes)

High-performance disruption prediction and instability event identification are crucial for tokamak plasma operation. Given the intrinsic correlation between plasma disruptions and their precursor instability events, this study introduces a multi-task learning-based integrated model that concurrently processes both tasks. The model identifies three key instability events—Edge Localized Modes (ELMs), Multifaceted Asymmetric Radiation from the Edge (MARFE), and H-mode to L-mode transitions (H-L Back Transition)—while offering disruption predictions. Testing on the Experimental Advanced Superconducting Tokamak (EAST) database revealed the model significantly lowers computational costs and improves performance in prediction and identification compared to single-task methods. The model can be further extended to incorporate more plasma state characterization tasks, which is significant for the steady operation of tokamak plasmas.
The database for this study consists of 12 plasma signals such as plasma current (Ip), current control error (Iperror), stored energy(Wmhd), input power (Pinput), and loop voltage (Vloop), derived from 816 randomly selected discharges during 2016 to 2023 experiments on the EAST. The dataset comprises 816 discharges, consisting of 432 non-disruption and 384 disruption discharges. Within these discharges, there are 128 instances of H-L Back Transition, 57 instances of MARFE, and 220 instances of ELMs, all annotated by experts.The entire dataset is divided into training, validation, and test sets in approximately a 7 : 1.5 : 1.5 ratio.
The model employs a sequence-to-label neural network architecture with a feature extractor and task classifiers, enhanced by a genetic algorithm for optimal hyperparameter selection. Test results demonstrate that our model outperforms traditional single-task learning methods in performance. Specifically, for the H-L Back Transition identification task, the model's AUC value increased from 0.69 to 0.74; for MARFE identification, the AUC value improved from 0.74 to 0.82; for ELMs identification, the AUC value rose from 0.87 to 0.93; and for plasma disruption prediction, the model achieved an average warning time of 0.98 seconds, better than the single-task method's 0.87 seconds, with the disruption prediction AUC value also increasing from 0.82 to 0.87. Moreover, the model greatly reduced the demand for computational resources. On a single NVIDIA RTX 3090 graphics card, the training time of our model is approximately 139 minutes, compared to a total of about 512 minutes for training four dedicated models using single-task learning methods under the same configuration.
Future research directions will focus on the real-time deployment of the model and its transfer application across devices, aiming to enhance the model's universality and practicality. These studies not only give hope to further improve the precision and response speed of plasma control but will also provide important references for tokamak plasma research and other related fields.

Speaker's Affiliation

Hefei Institutes of Physical Science, Chinese Academy of Sciences, Hefei 230031, China; University of Science and Technology of China, Hefei 230026, China

Member State or IGO

China, People's Republic of

Primary authors: XIAO, Binjia; YANG, Qingquan; YUAN, Qiping; ZHANG, Ruirui; HU, WenHui; LIN, Xin; JIA, yunhu (中国科学院合肥物质科学研究院等离子体物理研究所)

Presenter: JIA, yunhu (中国科学院合肥物质科学研究院等离子体物理研究所)

Session Classification: Machine Learning

Track Classification: Machine Learning