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Artificial Intelligence/Deep Learning FRNN Software for Prediction & Real-Time Control of DIII-D Plasma Control System (PCS)

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Final report

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1. Abstract summarizing the general topics addressed during the award.

This collaborative project integrated an improved version of the Artificial Intelligence/Deep Learning FRNN prediction and control software into the real-time DIII-D PCS (plasma control system). A key AI/DL software challenge is to build a modern high-performance computing (HPC) enabled “synthetic plasma simulator” capable of carrying out HPC-driven real-time plasma control applications. This involves development of a deep learning framework to train the surrogate model for a first-principles-based instability analysis simulator (“SGTC”) derived from the global gyrokinetic code GTC. The role of SGTC is to provide accurate and detailed plasma instability information from a real-time AI-based simulator capability to complement the deep learning prediction and control from experimentally-measured signals, such as ECE Imaging, supplemented by synthetic SGTC-ECEI.

2. Brief technical description of most relevant projects/publications.

1. [Reconstruction of tokamak plasma safety factor profile using deep learning](#), Xishuo Wei, Shuying Sun, William Tang, Zhihong Lin, Hongfei Du, Ge Dong, *Nuclear Fusion* **63**, 086020 (2023).

The motional Stark effect (MSE) diagnostic has been a standard measurement for the magnetic field line pitch angle in tokamaks that are equipped with neutral beams. However, the MSE data are not always available due to experimental constraints, especially in future devices without neutral beams. Here we develop a deep-learning based model (SGTC-QR) that can reconstruct the safety factor profile without the MSE diagnostic to mimic the traditional equilibrium reconstruction with the MSE constraint. The model demonstrates promising performance, and the sub-millisecond inference time is compatible with the real-time plasma control system.

2. [Implementation of AI/DEEP learning disruption predictor into a plasma control system](#), William Tang, Ge Dong, Jayson Barr, Keith Erickson, Rory Conlin, Dan Boyer, Julian Kates-Harbeck, Kyle Felker, Cristina Rea, Nikolas Logan, Alexey Svyatkovskiy, Eliot Feibush, Joseph Abbatte, Mitchell Clement, Brian Grierson, Raffi Nazikian, Zhihong Lin, David Eldon, Auna Moser, Mikhail Maslov, *Contributions to Plasma Physics* **63**, e202200095 (2023).

This paper reports on advances in the state-of-the-art deep learning disruption prediction models based on the Fusion Recurrent Neural Network (FRNN) originally introduced in a 2019 NATURE publication. In particular, the predictor now features not only the “disruption score,” as an indicator of the probability of an imminent disruption, but also a “sensitivity score” in real

time to indicate the underlying reasons for the imminent disruption. This adds valuable physics interpretability for the deep learning model and can provide helpful guidance for control actuators now implemented into a modern plasma control system (PCS). The advance is a significant step forward in moving from modern deep learning disruption prediction to real-time control and brings novel AI-enabled capabilities relevant for application to the future burning plasma ITER system. Our analyses use large amounts of data from JET and DIII-D vetted in the earlier NATURE publication. In addition to “when” a shot is predicted to disrupt, this paper addresses reasons “why” by carrying out sensitivity studies. FRNN is accordingly extended to use more channels of information, including measured DIII-D signals such as (i) the “ $n=1$ rms” signal that is correlated with the $n=1$ modes with finite frequency, including neoclassical tearing mode and sawtooth dynamics; (ii) the bolometer data indicative of plasma impurity control; and (iii) “ q_{min} ”—the minimum value of the safety factor relevant to the key physics of kink modes. The additional channels and interpretability features expand the ability of the deep learning FRNN software to provide information about disruption subcategories as well as more precise and direct guidance for the actuators in a PCS.

3. [Transfer Learning Nonlinear Plasma Dynamic Transitions in Low Dimensional Embeddings via Deep Neural Networks](#), Zhe Bai, Xishuo Wei, William Tang, Leonid Oliker, Zhihong Lin, Samuel Williams, *Machine Learning: Science and Technology* **6**, 025015 (2025).

Deep learning algorithms provide a new paradigm to study high-dimensional dynamical behaviors, such as those in fusion plasma systems. Development of novel, data-driven model reduction methods, coupled with detection of abnormal modes with plasma physics, opens a unique opportunity to identify plasma instabilities through automated construction of parsimonious models that can be tuned to balance accuracy and cost. Our fusion transfer learning (FTL) model demonstrates success in rapidly reconstructing nonlinear kink mode structures by learning from a limited amount of nonlinear simulation data. The knowledge transfer process leverages a pre-trained neural encoder–decoder network, initially trained on linear simulations, to effectively capture nonlinear dynamics. The low-dimensional embeddings extract the coherent structures of interest, while preserving the inherent dynamics of the complex system. Experimental results highlight FTL’s capacity to capture transitional behaviors and dynamical features in plasma dynamics—a task often challenging for conventional methods. The model developed in this study is generalizable and can be extended broadly through transfer learning to address various magnetohydrodynamics modes.

4. [AI-machine learning-enabled tokamak digital twin](#), William Tang, Eliot Feibush, Ge Dong, Noah Borthwick, Apollo Lee, Juan-Felipe Gomez, Tom Gibbs, John Stone, Peter Messmer, Jack Wells, Xishuo Wei, Zhihong Lin, Submitted to *Nuclear Fusion*, 2024.

In addressing DOE’s April, 2022 announcement of a Bold Decadal Vision for delivering a Fusion Pilot Plant by 2035, associated software tools need to be developed for the integration of “real world engineering and supply chain data” with advanced science models that are accelerated with Machine Learning. An associated R&D effort has been introduced here with promising early progress on the delivery of a realistic “Digital Twin Tokamak” that has benefited from accelerated advances by Princeton University’s AI/Deep Learning innovative near-real-time simulators accompanied by technological capabilities from the NVIDIA Omniverse™ — an open computing platform for building and operating applications that connect with leading scientific computing visualization software. Working with the CAD files for the GA/DIII-D tokamak including equilibrium evolution as an exemplar tokamak application using Omniverse, the Princeton-NVIDIA collaboration has integrated modern AI/HPC-enabled near-real-time kinetic dynamics to connect and accelerate state-of-the-art, synthetic, HPC simulators to model fusion

devices and control systems. The overarching goal is to deliver an interactive scientific digital twin of an advanced MFE tokamak that enables near-real-time simulation workflows built with Omniverse to eventually help open doors to new capabilities for generating clean power for a better future.

3. Paragraph indicating the number of presentations made and venues. Indicate presentations given at national labs, industry, universities, national and international professional meetings.

Invited Presentations at Professional Conferences:

- 2023 -- 28th International Tokamak Physics Activities (ITPA) (online);
-- 49th European Conference on Plasma Physics, Bordeaux, France.
- 2024 -- US-EU Transport Task Force Workshop, Asheville (invited talk by Xishuo Wei);
-- Fusion Energy R&D on Advanced and Long Pulse Tokamaks Principal Investigator Meeting, Norfolk.
- 2025 -- 4th International Fusion and Plasma Conference (iFPC 2025), Daejeon, Korea;
-- Annual Meeting of Asia-Pacific Physical Society (AAPPS-DPP2025), Fukuoka, Japan.

Invited Presentations at Educational, Governmental Institutions

- 2022 -- ITER International Organization
- 2024 -- Seoul National University, South Korea
- 2025 -- Princeton University

4. Personnel Involvement.

Postdoc at UC Irvine: Xishuo Wei.

PhD students at UC Irvine: Handi Huang, Alex Zarta.

5. Unexpended funds.

None.

6. Listing of all published articles acknowledging support by the award.

1. [*Reconstruction of tokamak plasma safety factor profile using deep learning*](#), Xishuo Wei, Shuying Sun, William Tang, Zhihong Lin, Hongfei Du, Ge Dong, *Nuclear Fusion* **63**, 086020 (2023).
2. [*Implementation of AI/DEEP learning disruption predictor into a plasma control system*](#), William Tang, Ge Dong, Jayson Barr, Keith Erickson, Rory Conlin, Dan Boyer, Julian Kates-Harbeck, Kyle Felker, Cristina Rea, Nikolas Logan, Alexey Svyatkovskiy, Eliot Feibush, Joseph Abbate, Mitchell Clement, Brian Grierson, Raffi Nazikian, Zhihong Lin, David Eldon, Auna Moser, Mikhail Maslov, *Contributions to Plasma Physics* **63**, e202200095 (2023).

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4. [AI-machine learning-enabled tokamak digital twin](#), William Tang, Eliot Feibush, Ge Dong, Noah Borthwick, Apollo Lee, Juan-Felipe Gomez, Tom Gibbs, John Stone, Peter Messmer, Jack Wells, Xishuo Wei, Zhihong Lin, Submitted to *Nuclear Fusion*, 2025.