

Final Report for DOE Grant Award Number DE-SC0021275

Machine Learning for Real-time Fusion Plasma Behavior Prediction and Manipulation

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Narrative

This project set out with an ambitious goal: to develop and apply machine learning-based methods of discovering new controllers and operating regimes for achieving better performing plasmas in tokamaks. As summarized in the dozens of papers below, the project was a huge success. It developed several machine learning components and integrated them into a single ML system that was added to the DIII-D PCS. That functionality was demonstrated over a series of experiments on DIII-D. A summary of these results is given here with the details in the published papers below.

Princeton University/PPPL - Egemen Kolemen

Tearing avoidance at DIII-D using ML

For efficient fusion power generation, we need to push up the plasma pressure (β_N) as much as possible. We developed a novel technique to avoid disruptive tearing instability in a tokamak, using the reinforcement learning method. The AI-based tearing avoidance system actively controls the beam power

and the plasma shape to maintain the possibility of future occurrence of tearing instability at a low level. The record performances on DIII-D were robustly achieved by the AI controller in different shots.

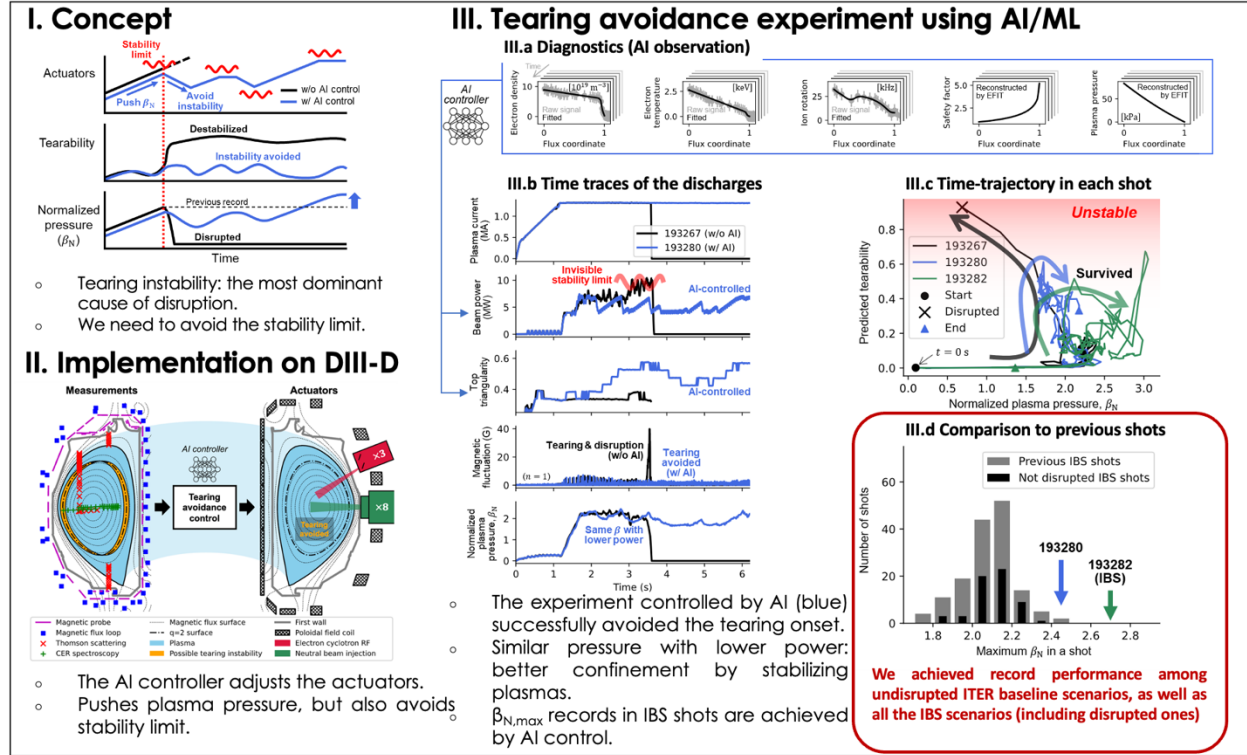


Figure 1: Detailed analysis with different DIII-D experiments controlled by AI tearing avoidance system.

Shot 193280 shows the record performance among undisrupted ITER baseline experiments and shot 193282 shows the record performance among the shots even including disrupted ones (Figure 1).

Alfvén Eigenmodes detection and locating.

The evolution of AEs as a function of actuator input is very hard to predict using physics-based numerical simulation. However, ML approaches trained on a database of ECE measurements under various equilibrium and actuations can give us the insight needed to adjust the control to suppress AEs. In order to

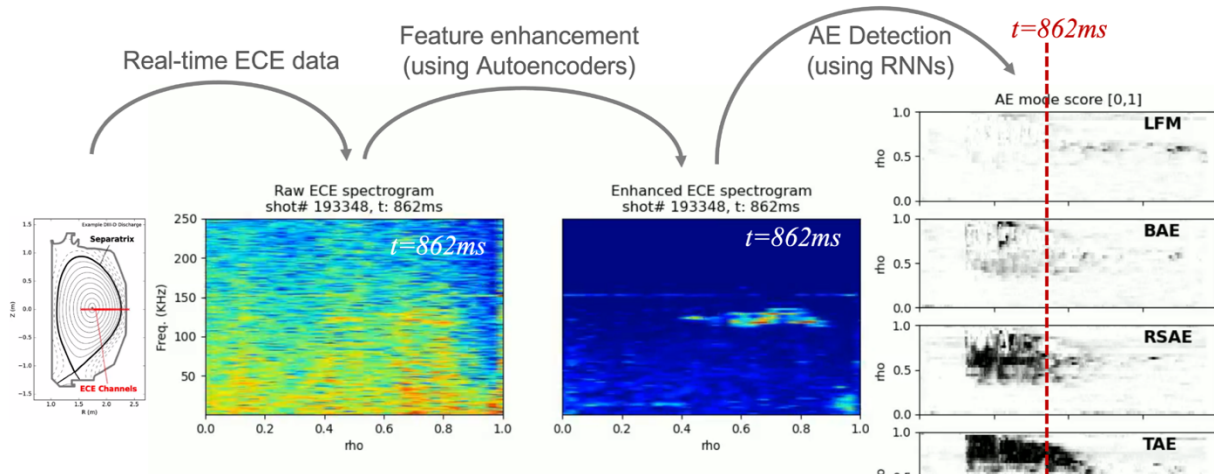


Figure 2: Example of the NN-based AE locator which detects the AE modes on the noise-enhanced spectrogram of each ECE channel separately. By concatenating the output of the model for each channel, an overview of the location of the AE modes is made.

locate the AE modes, we trained an NN model to analyze spectrograms of each ECE channel separately. Since the 40-channel ECE system measures from the edge to the core of plasma, concatenating the model's outputs for all ECE signals of a shot provides spatiotemporal information about the probability of each AE mode (See Figure 2).

Since the ECE signals are usually noisy, we trained an Autoencoder neural network to denoise the spectrograms before feeding them to the model. We show that the proposed spectrogram denoiser is source-invariant and we successfully utilized it to enhance CO2 and BES data. This paves the way towards multi-modal detection and prediction of plasma instabilities using machine learning algorithms.

ML equilibrium and core-profile reconstruction algorithm

The application of more advanced control solutions is typically limited by the availability and quality of real-time plasma information, such as kinetic profiles. In recent years, our group has developed an offline tool (CAKE) which performs profile fitting and consistent automatic kinetic equilibrium reconstruction (without a physicist in-loop). The aim is to have CAKE-quality plasma profiles available in real-time. However, since CAKE evaluates a time slice in the order of seconds, hence too slow for real-time applications, we have initialized multi modal neural network versions of CAKE (CAKINN, RTCAKINN). RTCAKINN is trained to produce CAKE-quality output using real-time inputs such as magnetics, MSE, CER, Thomson. Tests show CAKINN is on par with CAKE as the main metric of average error achieved in CAKINN output and CAKE outputs are the same. In specific cases the neural network performs even better than CAKE (See Figure 3).

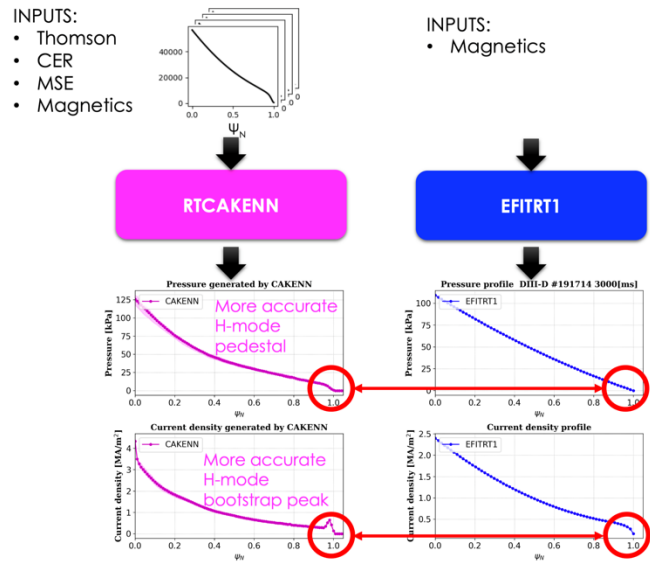


Figure 3: CAKINN reproduces important physics pattern.

Plasma Profile evolution prediction with ML accelerated physics models

PU and CMU groups have implemented various neural network models trained on empirical data to predict plasma profile evolution: ion and electron temperature and density radial profiles (T_e , T_i , n_e , n_i); safety factor (q) profile; plasma rotation radial profile, with the LSTM+CNN model giving the best results thus far. A key to the success of our ML-based prediction and control approach was the tremendous effort by several graduate students at PU and CMU to collect, clean, categorize and prune a large dataset of profiles and actuators from the DIII-D discharges database to make a training database.

The CMU team learned a dynamics model for the DIII-D tokamak. The team drew from over 10,000 previous plasma discharges from the device to train a deep recurrent network. In particular, the network was trained on the real-time and post-shot diagnostics that measure the magnetic equilibrium and plasma parameters. The team found that learned models are able to predict these measurements for entire shots remarkably well. Figure 3.2-5 shows the good performance of the model in forecasting several scalar parameters of the plasma over time. This work validates the use of purely data driven models for modeling both 0D and 1D plasma state evolution.

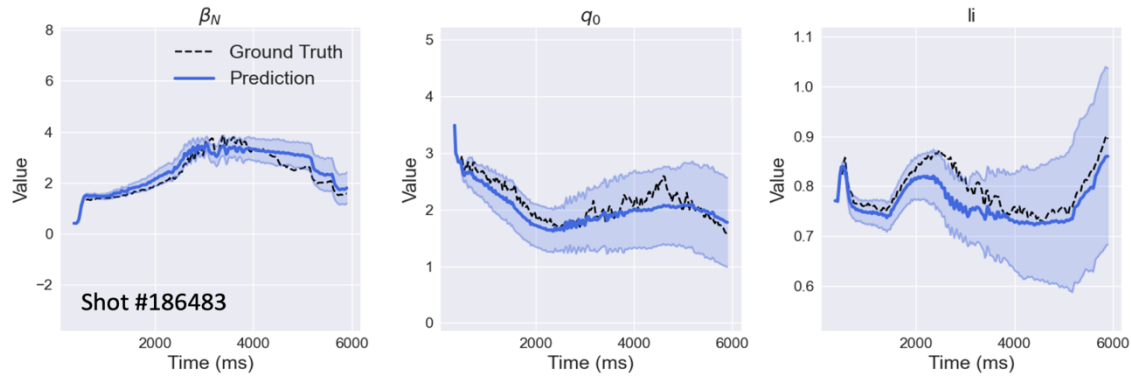


Figure 4: Forecast of selected 0D parameters in a test shot. The black dashed line shows the ground truth for the shot, the solid blue line shows the mean prediction of the model, and the light blue region shows a one standard deviation prediction interval. Note that the model only sees the first state and then predicts the full shot in an autoregressive fashion.

Carnegie Mellon University - Jeff Schneider

Data driven plasma models

Over 10K shots from DIII-D were downloaded and used to learn surrogate plasma models for DIII-D. These models were demonstrated to be more accurate than existing simulation models and provided the foundation for the control policy learning.

Uncertainty quantification (UQ) methods

When discovering and learning new control policies, uncertainty quantification of the models is critical for efficient exploration of the search space. We developed better performing methods for this and in addition to using this for our control policy learning and publishing papers, we published an open-source project that has become the most popular uncertainty quantification toolbox.

Open loop planning methods using reinforcement learning (RL)

We developed efficient and robust algorithms to search for high performing open loop trajectories for execution on DIII-D. These methods rely on both the plasma models and the UQ that goes with them (Figure 5).

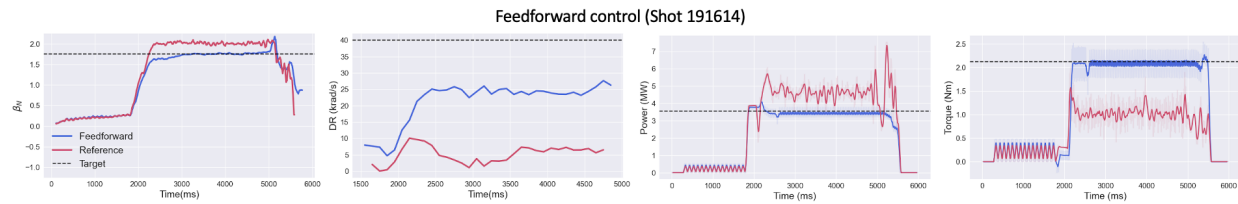


Figure 5: Feedforward control for β_N and Differential Rotation. The blue line shows the achieved value during the experiment, the dashed black line shows the target for each signal, and the red line shows the reference shot that the experiment was based on.

Closed loop controller learning using RL

We developed efficient and robust algorithms to learn high performing closed loop controllers for execution on DIII-D. These methods rely on both the plasma models and the UQ that goes with them.

Bayesian optimization (BO)

We developed new low sample BO methods for online optimization of parametric forms of DIII-D control strategies. These also rely on ML-based modeling and UQ (Figure 6).

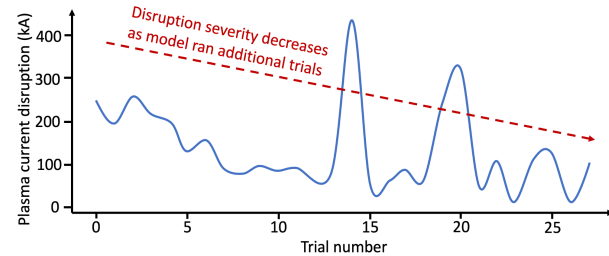


Figure 6: Plasma currents at disruption of shots in the test group over time.

DIII-D Experimental Results

- Improved rampdowns and reduction of flux consumption. We used our BO methods over several dozen piggyback experiments to reduce the average plasma current at rampdown disruption by a factor of 6. We applied the same methods to reduction of central solenoid flux consumption in a high poloidal beta scenario. We achieved promising results but did not get enough valid shots to demonstrate statistical significance.
- Simultaneous differential rotation and beta_N Control. We used our open loop planning methods to demonstrate simultaneous control of DR and beta_N, producing levels of both that were substantially different from the reference shots.
- Closed loop beta_N tracking in multiple scenarios. We demonstrated the performance of a single learned beta_N tracking controller across several different scenarios in individual and piggybacked experiments.

University of Wisconsin-Madison - David Smith

The most notable recent progress are two journal articles:

Tokamak edge localized mode prediction with deep neural network and pedestal turbulence

The article (S. Joung et al) describes initial results for ELM onset prediction using the BES data stream, and the article is under review at **Nuclear Fusion**. The article demonstrates that ELM onset prediction is feasible with neural network analysis of high-bandwidth fluctuation signals. Specifically, the article shows accurate ELM onset prediction around 3-4 ms in advance of the ELM event. **Figure 7** shows an example where the model predicts ELM onset events around 5 ms in advance of the ELM event on unseen data and about 40 ms in advance on the first ELM following the LH transition. The present prediction horizon of 3-4 ms is too short for control actuators, but we are confident that a longer ~10 ms prediction horizon is possible for compatibility with the fastest ELM control actuators. Finally, results in the article also show that the neural network can predict the timing of the first ELM event after the LH transition. Prediction of the first ELM timing is important because it allows for precise activation of ELM control mechanisms after the LH transition and prior to the first ELM, and this capability is critical for ITER.

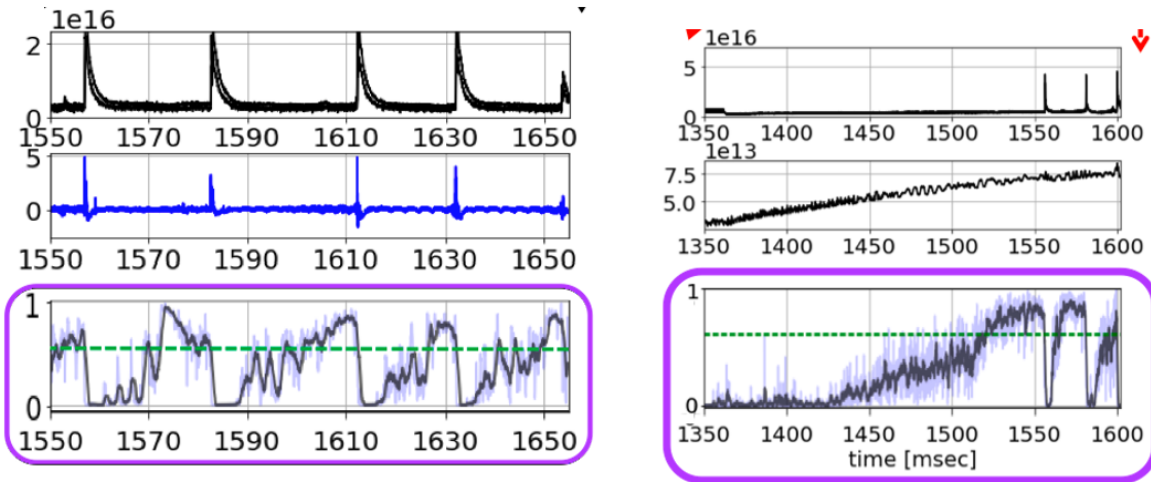


Figure 7: (Left) Model predictions for ELM onset likelihood (lower frame) during an ELMy H-mode phase. (Right) Model prediction for ELM onset likelihood (lower frame) after the LH transition and approaching the first ELM.

Real-time plasma confinement regime classification with convolutional neural networks and high bandwidth edge fluctuation measurements in DIII-D

The second article (K. Gill et al) describes initial results for real-time confinement mode classification using the BES data stream, and the manuscript is under internal review in the DIII-D tracker for submission to **Machine Learning: Science and Technology**. The article describes a neural network that can accurately classify the confinement along L-mode, H-mode, QH-mode, or wide pedestal (WP) QH-mode using only a 1 ms window of BES data. **Figure 8** shows example results for confinement model inference on unseen test data. The confinement classification model shows good performance distinguishing QH-mode and WP QH-mode in the left group. The confusion matrix in the right plot shows overall performance on the four confinement regimes with F1, precision, and recall scores around 95% for unseen test data. An accurate real-time indicator of the confinement mode will facilitate reinforcement learning of control schemes to access and sustain enhanced confinement modes.

Finally, ongoing work is extending the results described above:

- Iterating with our SLAC collaborators to implement neural net models on the BES FPGA device
- Extend the ELM onset prediction horizon by assembling a new dataset with longer inter-ELM phases and with additional metadata for filtering ELMy scenarios
- Expanding the confinement mode classification to additional scenarios such as intrinsic ELM-free H-mode and RMP ELM-suppressed H-mode
- Developing a multi-task model in which a single feature space drives multiple tasks such as ELM onset prediction and confinement mode classification
- Exploring strategies to incorporate ML explainability and physics-informed neural networks into our model development.

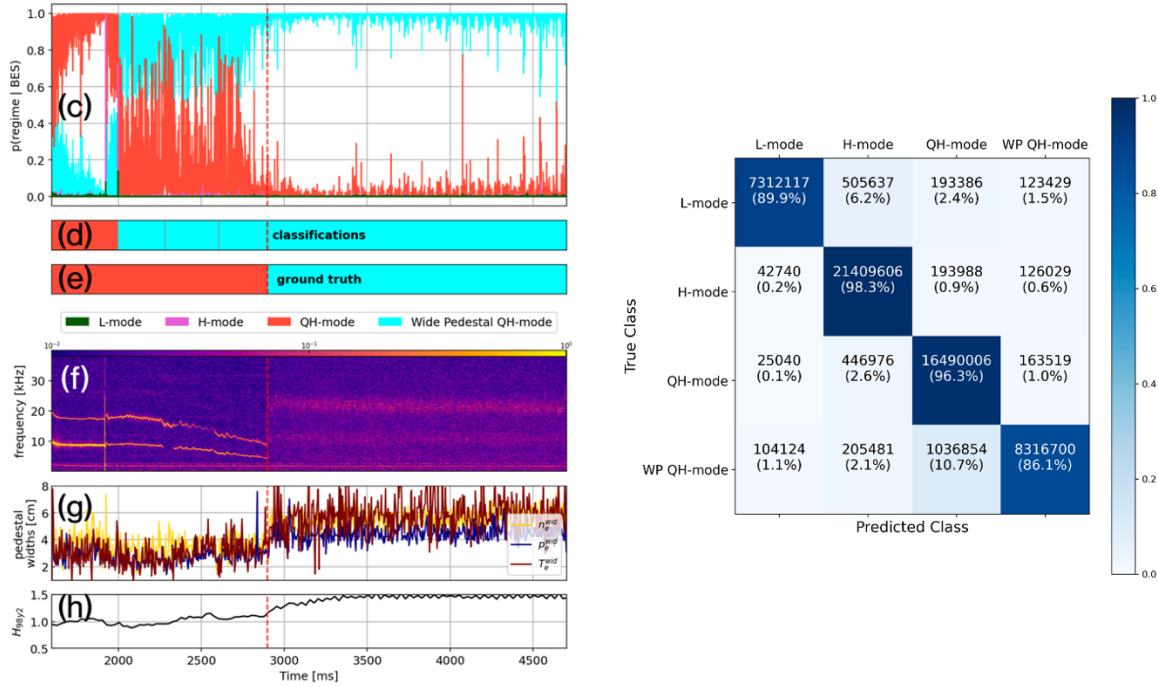


Figure 8: (Left) Confinement mode inference on unseen test data across the transition from QH-mode to WP QH-mode; (Right) confusion matrix for the four confinement regimes on unseen test data.

SLAC – Stanford University - Ryan Coffee

The research for the development of an Edge Localized Modes (ELM) labeling model for the DIII-D dataset, involves using machine learning (ML) techniques to automatically identify and label ELM events within the data. This is part of the broader effort to apply Edge-ML (machine learning algorithms executed at the "edge" of the network, near the data source) for real-time diagnostics analysis in fusion plasma control.

Optimization of Real-Time Data-Flow Architecture

The project has optimized a real-time data-flow architecture in FPGA (Field Programmable Gate Arrays) to handle the high-speed fluctuation data from diagnostics like BES (Beam Emission Spectroscopy), which is essential for capturing the fast plasma dynamics associated with ELMs.

Development of Edge-ML Models

The team has developed Edge-ML models to process the raw high-speed fluctuation data from BES diagnostics. These models aim to efficiently reduce signals for the central Plasma Control System (PCS), allowing for the real-time identification and labeling of ELM events.

Deployment of FPGA-Based Edge-ML System

The project has implemented an FPGA-based Edge-ML system at DIII-D, which is designed to combine the signals from BES diagnostic detectors with CO2 interferometer detectors in a neural network to identify and predict ELM events in real-time.

ELM Identification and Prediction

The team has developed a neural network that serves as an ELM identifier. This network has been trained with a clean dataset of microsecond-level labeled ELMs from BES, showing promising results for prediction and detection of ELMs (See Figure 9). To detect ELMs in the large DIII-D dataset Coincident Anomaly Detection (CoAD) splits the time series signals into two groups, passes the data to two networks, and then trains the networks by requiring correlation between the outputs of the two networks. After training, the networks will each produce an estimate of the probability that a particular sample is an ELM (shown on the right in logit-space). Points in the upper right of sq-space are labeled ELMs and all others are considered normal (not an ELM). To prepare the data for the networks, we average the 64 channels of the beam energy spectroscopy (BES) together and rescale them. All other channels are up sampled to 1 MHz (to match the BES), differentiated, and rescaled. Each 1024 microsecond time window is labeled to contain an ELM or not.

Hardware Integration and Testing

The Edge-ML system, along with the developed ELM labeling model, is being integrated and tested within the DIII-D PCS. This involves implementing the model in the FPGA hardware to ensure real-time processing and labeling of ELM events.

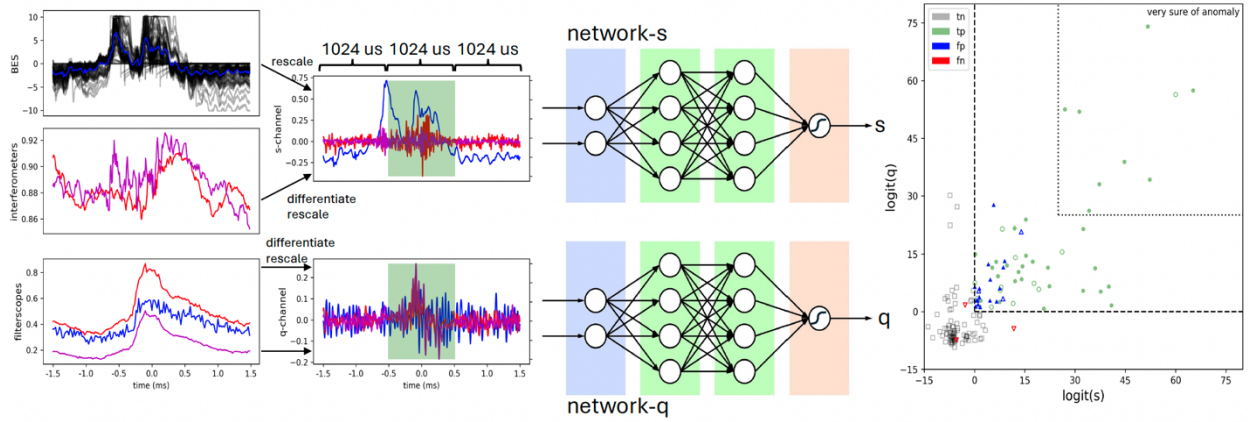


Figure 9: Data flow of the Coincident Anomaly Detection (CoAD) model for detecting ELM in DIII-D dataset using BES and Interferometer diagnostics.

Publications

1. A. A. Kaptanoglu et al., 'Exploring data-driven models for spatiotemporally local classification of Alfvén eigenmodes', Nuclear Fusion, vol. 62, no. 10, p. 106014, 2022.
2. J. Seo et al., 'Multimodal prediction of tearing instabilities in a tokamak', in 2023 International Joint Conference on Neural Networks (IJCNN), 2023, pp. 1–8.
3. A. V. Garcia et al., 'Alfvén eigenmode detection using Long-Short Term Memory Networks and CO 2 Interferometer data on the DIII-D National Fusion Facility', in 2023 International Joint Conference on Neural Networks (IJCNN), 2023, pp. 1–8.
4. L. Malhotra et al., 'Machine learning models for real-time, high bandwidth inference of ELM events and confinement regime with 2D BES at DIII-D', in APS Division of Plasma Physics Meeting Abstracts, 2021, vol. 2021, pp. CP11-067.
5. P. Arora et al., 'Machine learning autoencoder models for compressing and reconstructing 2D BES data for real-time classification tasks', in APS Division of Plasma Physics Meeting Abstracts, 2021, vol. 2021, pp. JP11-107.

6. A. Garcia, A. Jalalvand, W. Heidbrink, E. Kolemen, and M. Van Zeeland, 'Classifying Alfvén eigenmodes using deep learning and CO 2 interferometer data at DIII-D', in APS Division of Plasma Physics Meeting Abstracts, 2021, vol. 2021, pp. PP11-133.
7. A. Kaptanoglu et al., 'Spatially-localized Alfvén eigenmode classification using convolutional neural networks', in APS Division of Plasma Physics Meeting Abstracts, 2021, vol. 2021, pp. CP11-101.
8. E. Kolemen et al., 'Machine Learning for Real-time Fusion Plasma Behavior Prediction and Manipulation', in APS Division of Plasma Physics Meeting Abstracts, 2021, vol. 2021, pp. UM10-003.
9. E. Ahn, A. Jalalvand, E. Kolemen, D.-D. Team, and Others, 'Localizing Alfvén eigenmodes in plasma based on high resolution ECE spectrograms at DIII-D using autoencoders and image processing techniques', in APS Division of Plasma Physics Meeting Abstracts, 2021, vol. 2021, pp. JP11-102.
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11. S. Joung et al., 'Real-time confinement mode classification and ELM onset prediction with the BES diagnostic system at DIII-D', in APS Division of Plasma Physics Meeting Abstracts, 2022, vol. 2022, pp. UP11-085.
12. A. Jalalvand et al., 'Data-Driven Prediction and Control of Alfvén Eigenmodes at DIII-D', in APS Division of Plasma Physics Meeting Abstracts, 2022, vol. 2022, pp. BP11-004.
13. M. Kim et al., 'Detecting ELM originated by sawtooth', in APS Division of Plasma Physics Meeting Abstracts, 2023, vol. 2023, pp. UP11-100.
14. M. Curie, J. Abbate, A. Jalalvand, and E. Kolemen, 'Autoencoding and noise reduction of plasma diagnostics in Tokamak', in APS Division of Plasma Physics Meeting Abstracts, 2023, vol. 2023, pp. NP11-084.
15. A. Rothstein et al., 'Tearing mode avoidance using reinforcement learning and classical delta prime stability analysis on DIII-D', in APS Division of Plasma Physics Meeting Abstracts, 2023, vol. 2023, pp. UP11-102.
16. A. Jalalvand et al., 'Implementing Data-Driven Models for Real-Time Detection and Control of Alfvén Eigenmodes at DIII-D', in APS Division of Plasma Physics Meeting Abstracts, 2023, vol. 2023, pp. JO08-015.
17. A. Garcia et al., 'Identification of Alfvén eigenmodes using recurrent neural networks, a labelled database and CO 2 interferometer data on DIII-D', in APS Division of Plasma Physics Meeting Abstracts, 2023, vol. 2023, pp. NP11-023.
18. S. Joung et al., 'Deep neural network based real-time ELM prediction and reconstruction of turbulent flow based on the DIII-D BES measurement', in APS Division of Plasma Physics Meeting Abstracts, 2023, vol. 2023, pp. NP11-028.
19. K. Gill et al., 'Real-time plasma confinement mode classification with deep neural networks and high-bandwidth edge fluctuation measurements in DIII-D', in APS Division of Plasma Physics Meeting Abstracts, 2023, vol. 2023, pp. UP11-098.
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22. V Mehta, J Abbate, R Conlin, E Kolemen, J Schneider, "Controlling Plasma Profiles in a Learned Model via Reinforcement Learning", APS Division of Plasma Physics Meeting Abstracts, 2021, GP11. 037
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24. I Char, Y Chung, M Boyer, E Kolemen, J Schneider, "A Model-Based Reinforcement Learning Approach for Beta Control", APS Division of Plasma Physics Meeting Abstracts 2021, PP11. 150
25. M Boyer, J Wai, M Clement, E Kolemen, I Char, Y Chung, W Neiswanger, ..., "Machine learning for tokamak scenario optimization: combining accelerating physics models and empirical models", APS Division of Plasma Physics Meeting Abstracts 2021, PP11. 164
26. V Mehta, I Char, W Neiswanger, Y Chung, A Nelson, M Boyer, E Kolemen, J Schneider, "Neural Dynamical Systems: Balancing Structure and Flexibility in Physical Prediction", IEEE Conference on Decision and Control, 2021.
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29. ME Fenstermacher, et al, "DIII-D research advancing the physics basis for optimizing the tokamak approach to fusion energy", Nuclear Fusion 62 (4), 2022.
30. V Mehta, B Paria, J Schneider, S Ermon, W Neiswanger, "An Experimental Design Perspective on Model-Based Reinforcement Learning", ICLR, 2022
31. AA Kaptanoglu, A Jalalvand, AV Garcia, ME Austin, G Verdoolaege, J Schneider, C Hansen, S Brunton, W Heidbrink, E Kolemen, "Exploring data-driven models for spatiotemporally local classification of Alfvén eigenmodes", Nuclear Fusion 62 (10), 2022.
32. V Mehta, I Char, J Abbate, R Conlin, M Boyer, S Ermon, J Schneider, W Neiswanger, "Exploration via planning for information about the optimal trajectory", Advances in Neural Information Processing Systems 35, 2022.
33. V Mehta, I Char, J Schneider, W Neiswanger, S Ermon, J Abbate, R. Conlin, M. Boyer, "Sample-efficient plasma control by planning for optimal trajectory information", ICML Workshop on Adaptive Experimental Design and Active Learning in the Real World, 2022.
34. I Char, J Abbate, V Mehta, Y Chung, R Conlin, K Erickson, M Boyer, N Richner, L Bardoczi, N Logan, J Barr, E Kolemen, J Schneider, "Differential Rotation Control for the DIII-D Tokamak via Model-Based Reinforcement Learning", Bulletin of the American Physical Society, 2022.
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41. V Mehta, J Abbate, A Wang, A Rothstein, I Char, J Schneider, E Kolemen, C. Rea, D. Garnier, "Towards LLMs as Operational Copilots for Fusion Reactors", NeurIPS AI for Science Workshop, 2023.
42. J Schneider, I Char, V Mehta, Y Chung, "Reinforcement Learning for Plasma Control in Tokamaks", IAEA Fusion Energy Conference (FEC), 2023

43. V Mehta, J Barr, J Abbate, MD Boyer, I Char, W Neiswanger, E Kolemen, J. Schneider, "Automated experimental design of safe rampdowns via probabilistic machine learning", Nuclear Fusion 64 (4), 2024.

Presentations (in addition to the presentations of the papers above)

1. E. Kolemen, "Overview of Fusion Research at Plasma Control Group," Plasma Physics Colloquium, Applied Physics and Applied Mathematics, Columbia University, New York, NY, Jan. 2023
2. E. Kolemen, "Data-Based Control", ITER Summer School, UCSD, San Diego, CA, Jun. 2022
3. E. Kolemen, "Machine Learning for Real-time Fusion Plasma Behavior Prediction and Manipulation", *Invited Presentation* APS-DPP Mini-Conference: Machine Learning in Plasma Sciences: Today and Tomorrow Pittsburgh, PA, Nov. 2021
4. E. Kolemen, "Real-time Prediction and Avoidance of Fusion Plasmas Instabilities using Feedback Control," *Invited Presentation* IAEA Technical Meeting on Plasma Disruptions and Their Mitigation, ITER Headquarters, France, remote, Jul. 2020
5. J Schneider, "Reinforcement Learning for Controlled Nuclear Fusion in Tokamaks", General Electric EDGE Symposium, Niskayuna, NY, Sep 20, 2023.
6. "Reinforcement Learning: From Self-Driving Cars to Nuclear Fusion" , CMS Large Hadron Collider Annual Meeting, Pittsburgh, PA, May 31, 2023.
7. "Reinforcement Learning for Controlled Nuclear Fusion", Cosmic Connections Symposium, Flatiron Institute, New York, NY, May 23, 2023.
8. "Reinforcement Learning for Nuclear Fusion in Tokamaks", Seminars on Physics informed Artificial Intelligence in Plasma Science, (online), Jan 23, 2023.
9. J Schneider, "Reinforcement Learning: from Self Driving Cars to Nuclear Fusion", United Nations AI for Good, (virtual), May 19, 2022.
10. J Schneider, "Reinforcement Learning for Controlled Nuclear Fusion", Google X Seminar Series, Mountain View, CA, (virtual), Mar 22, 2022.
11. J Schneider, "Reinforcement Learning for Fusion: Self Driving Cars to Controlled Fusion", International Atomic Energy Agency (IAEA) Technical Meeting on Artificial Intelligence for Nuclear Technology and Applications, Vienna, Austria, Oct 25, 2021.
12. J Schneider, "Machine Learning for Prediction and Manipulation of Fusion Plasmas", ITER Seminar, Saint-Paul-les-Durance, France, Oct 11, 2021.
13. S. Joung et al, "Real-time ELM onset prediction based on the BES system using deep neural networks in DIII-D", ICDDPS 2023, Okinawa, Japan

Software

1. <https://github.com/PlasmaControl/data-fetching>: An open-source toolbox to fetch and store DIII-D discharge data
2. <https://github.com/PlasmaControl/plasma-profile-predictor>: An open-source toolbox to train ML-model for predicting DIII-D plasma profile
3. <https://github.com/uncertainty-toolbox/uncertainty-toolbox>: An open-source uncertainty quantification toolbox with 119 forks, 1700 stars, and 8 contributors.
4. <https://github.com/PlasmaControl/spectrogram-enhancement>: An open-source toolbox for enhancing the DIII-D high resolution diagnostic spectrograms.
5. Integration into DIII-D PCS. Closed loop RL, Open loop RL, High-beta profile closed loop control, and Bayesian Optimization experiments were all run on DIII-D and the corresponding code from the publications above was integrated into the PCS for those experiments.