Avoiding plasma instabilities with artificial intelligence

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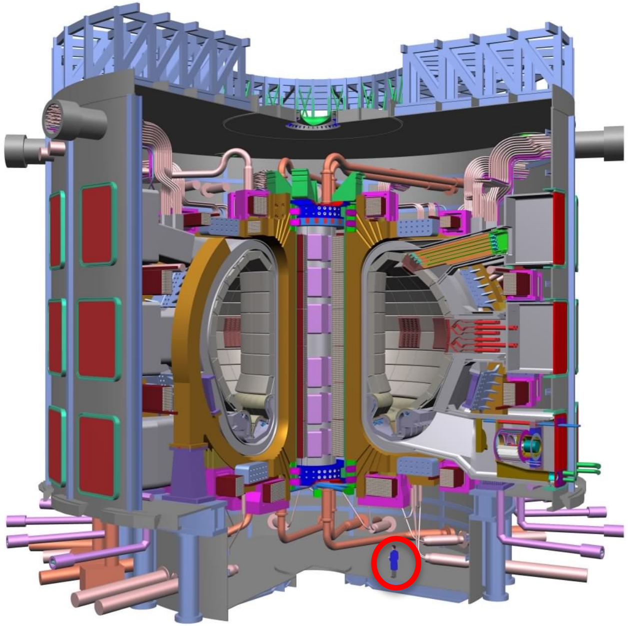
Princeton Plasma Control
control.princeton.edu

KSTAR
PPPL PRINCETON PLASMA PHYSICS LABORATORY
Plasma Control

Next Step: ITER, Net Energy Production from Fusion

ITER



An ITER Fellow

- **ITER collaboration between US, EU, China, India, Russia, S. Korea (Largest research endeavor >CERN)**
- **500 MW of fusion power (10x input power) ➔ Fusion as an energy source**
- **To be finished in 2020s (Independent Fusion Private Companies are also developing reactor option)**

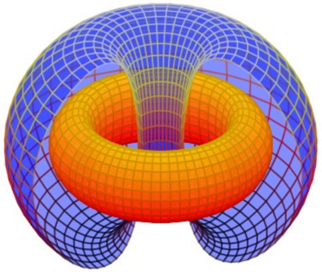
Tokamak Disruption (C-Mod)

Plasma Control

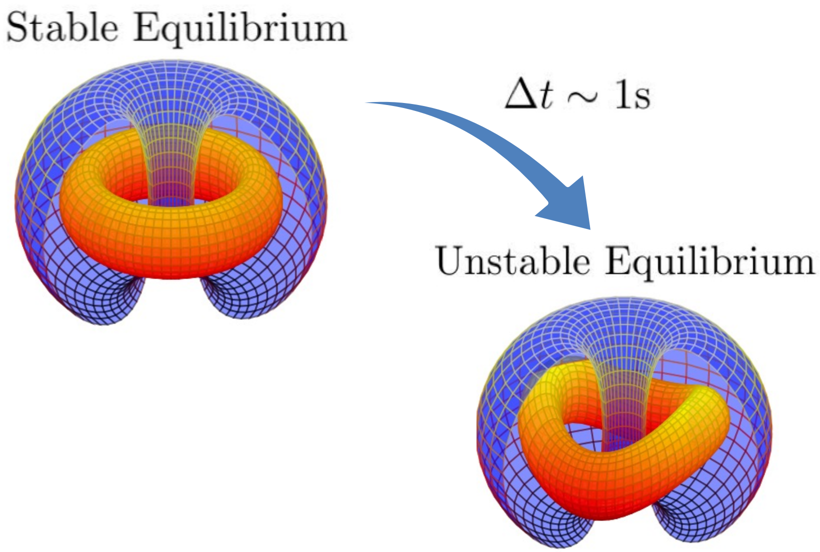
youtu.be/CUfR819hIDg

Steer the Plasma Away from Unstable Equilibria with Real-time (RT) Stability Analysis and Control

Stable Equilibrium



Steer the Plasma Away from Unstable Equilibria with Real-time (RT) Stability Analysis and Control



Plasma Control

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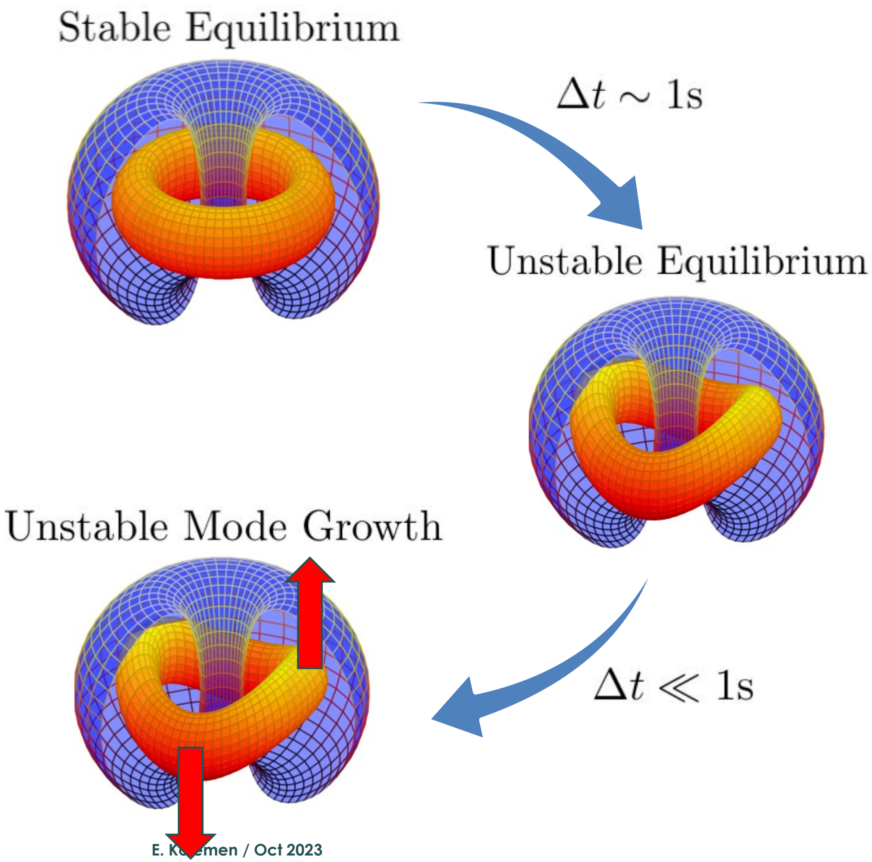

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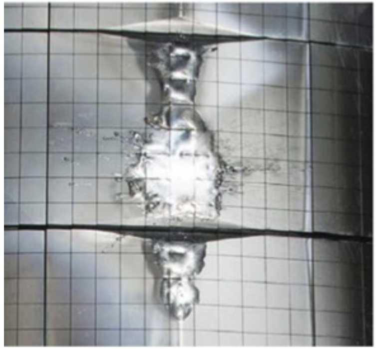
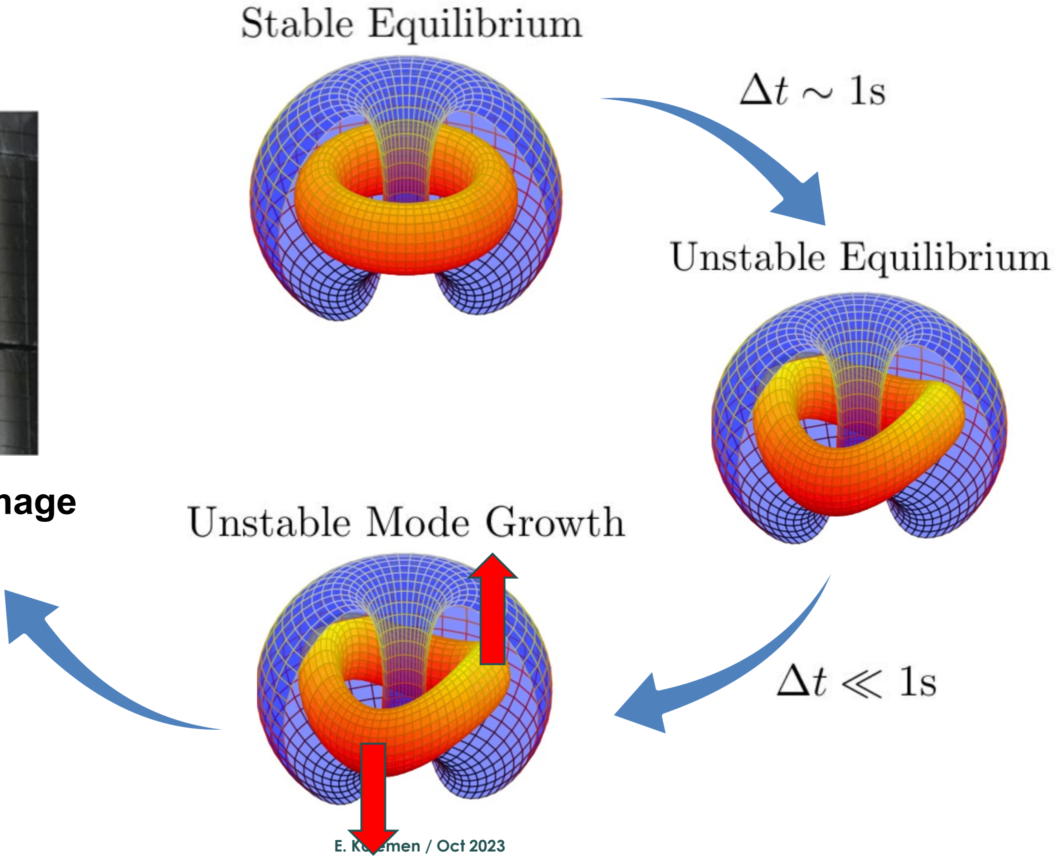


Example Wall Damage from JET

Matthews et al.
Physica Scripta,
T167, 2016



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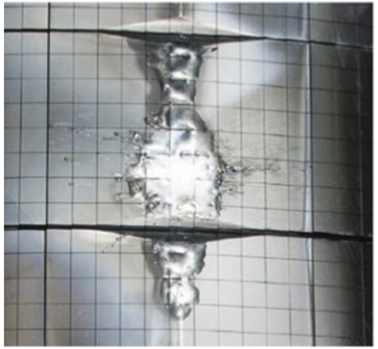

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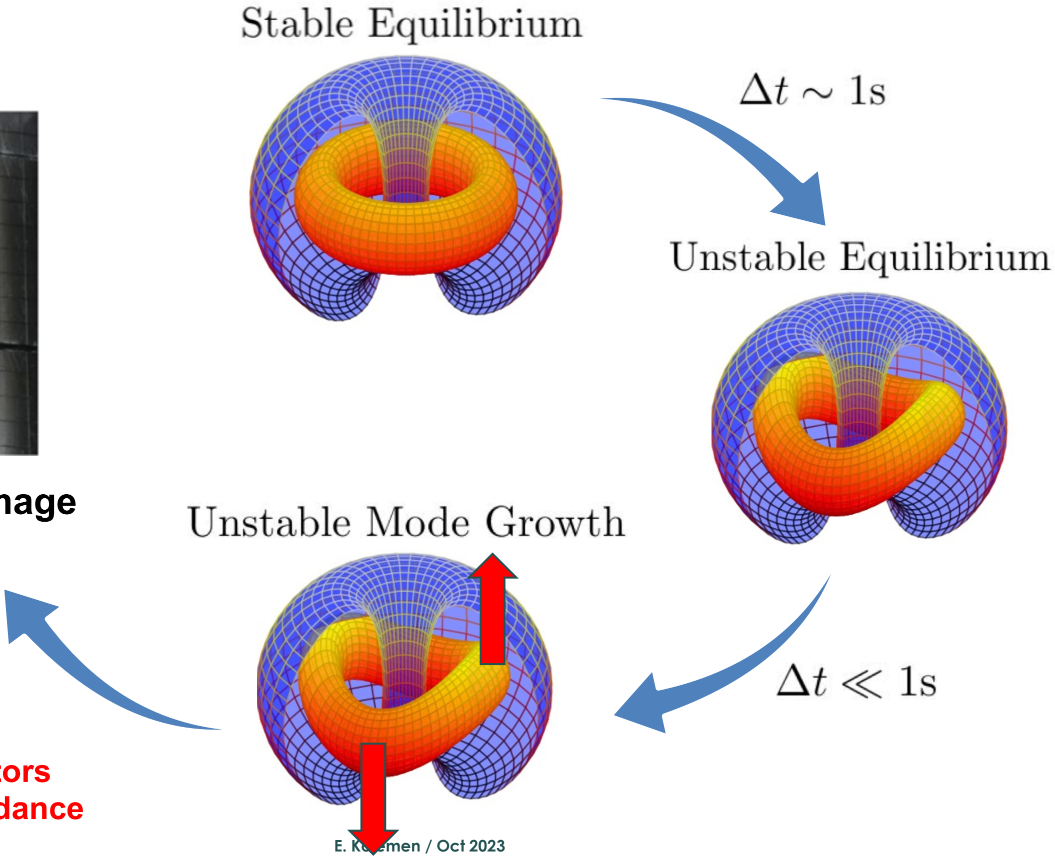
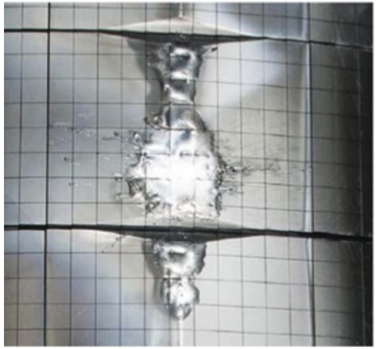


ITER and future reactors need disruption avoidance solutions

Plasma Control

Steer the Plasma Away from Unstable Equilibria with Real-time (RT) Stability Analysis and Control



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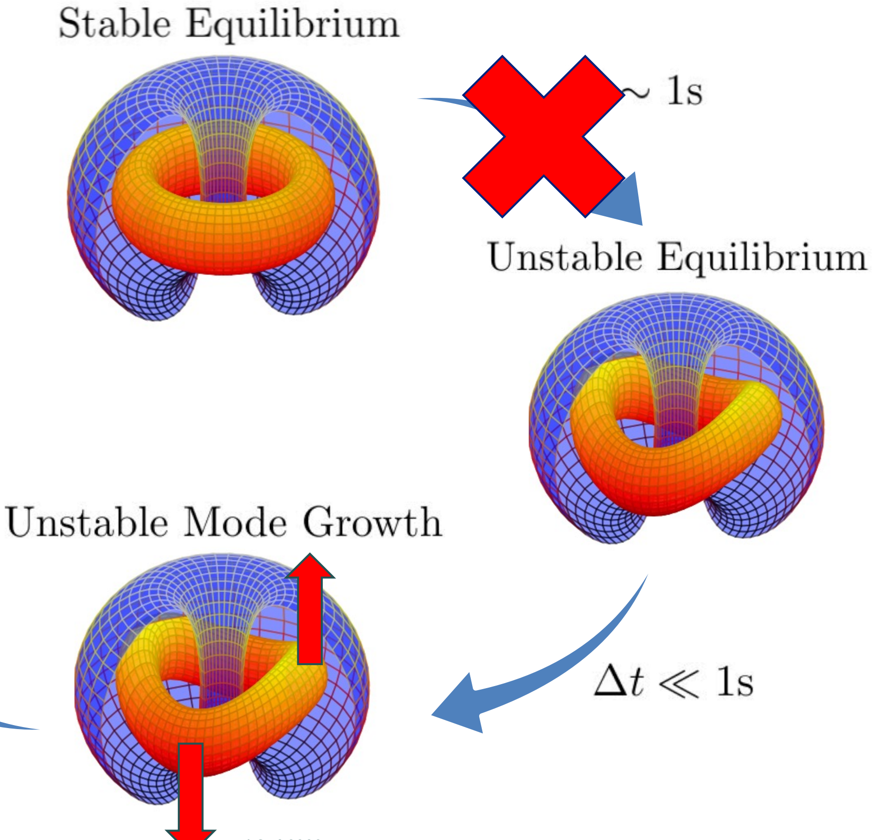
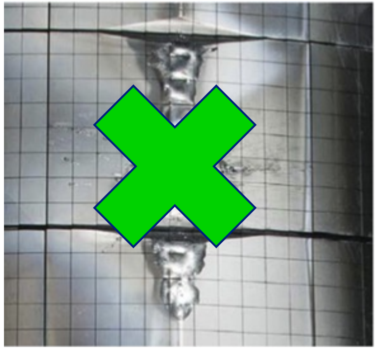
ITER and future reactors need disruption avoidance solutions



Plasma Control

Steer the Plasma Away from Unstable Equilibria with Real-time (RT) Stability Analysis and Control



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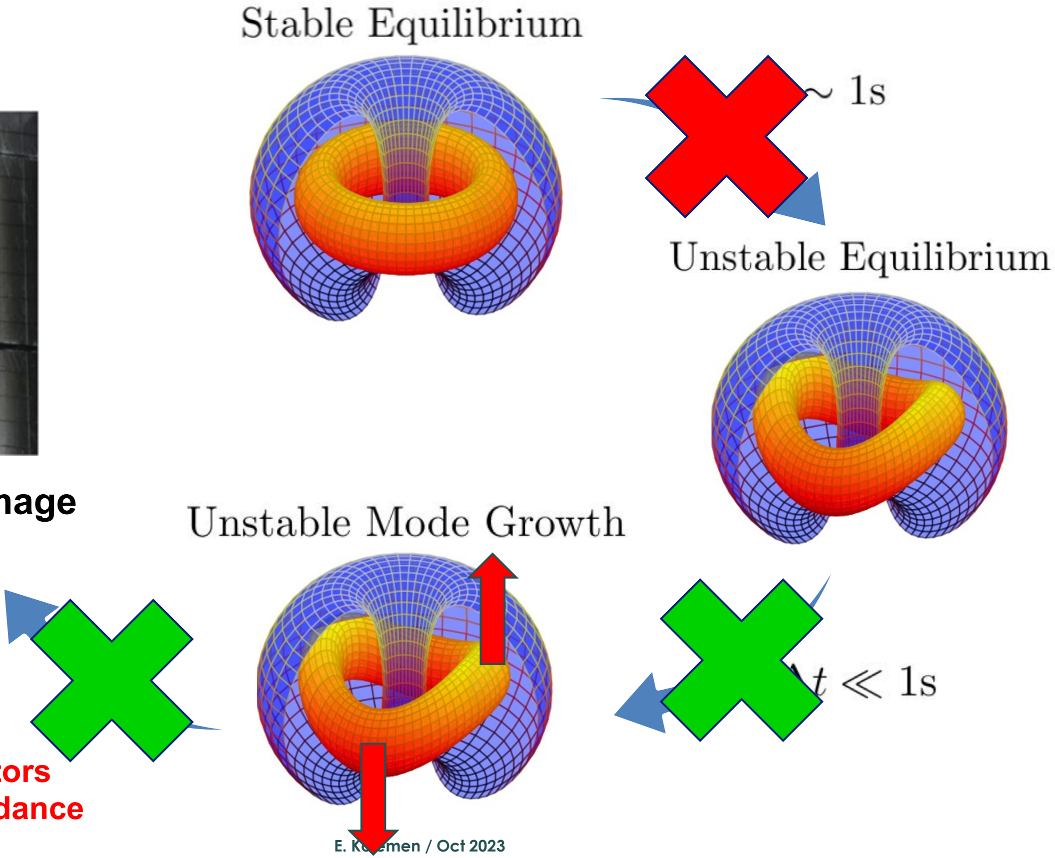
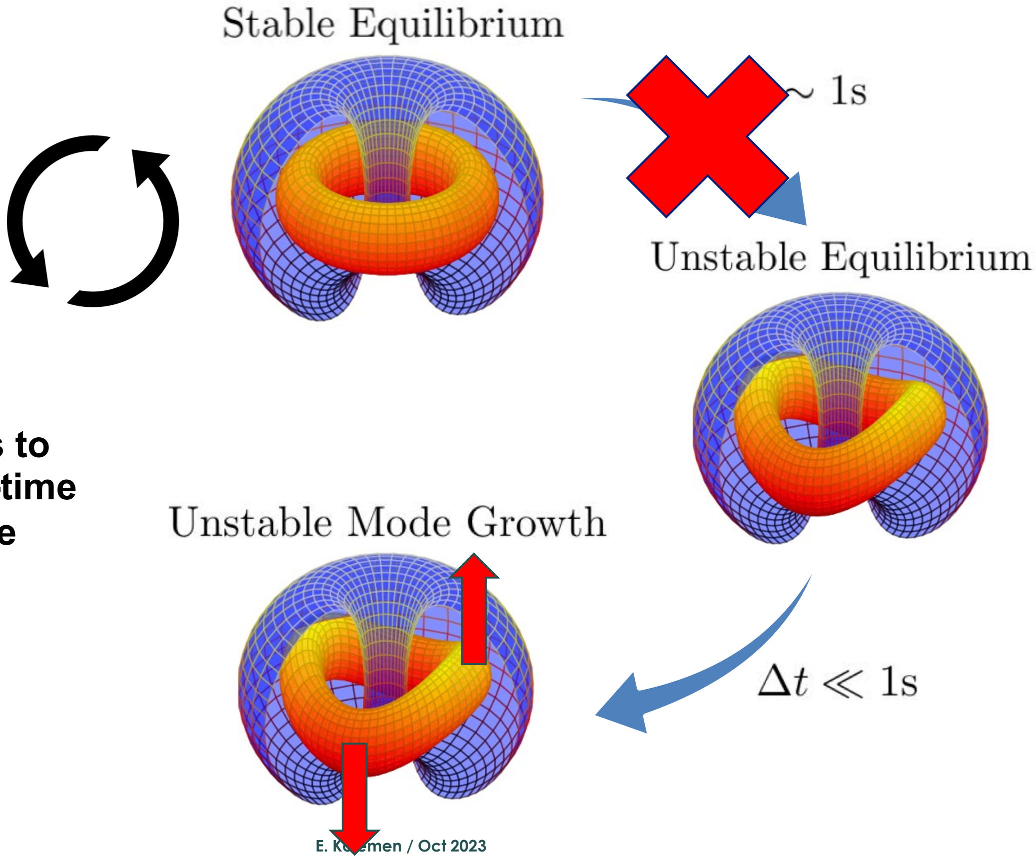


ITER and future reactors need disruption avoidance solutions

Plasma Control

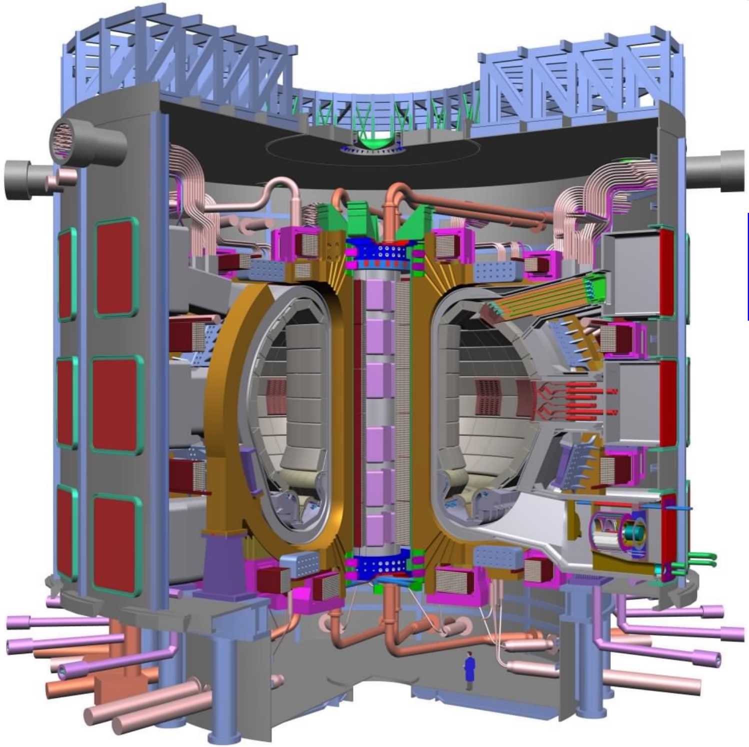
Steer the Plasma Away from Unstable Equilibria with Real-time (RT) Stability Analysis and Control

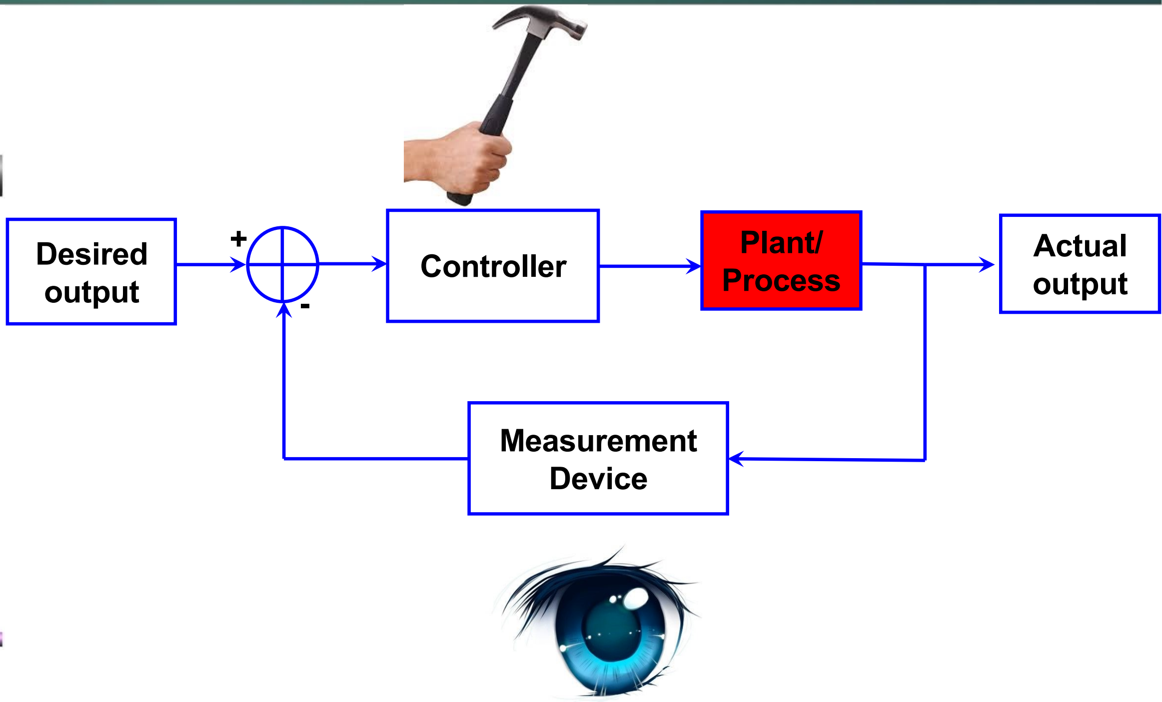
Develop fast algorithms to analyze stability in real-time for disruption avoidance



Plasma Control

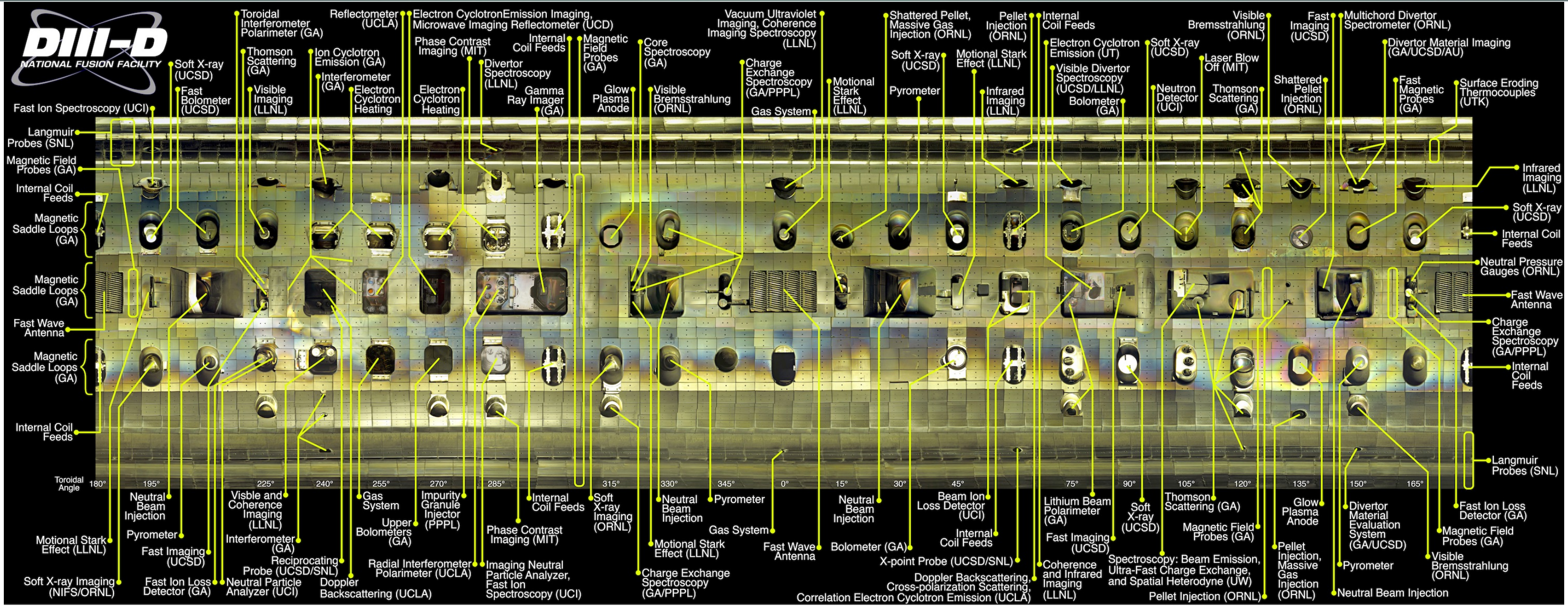
Data-Based Control for Fusion





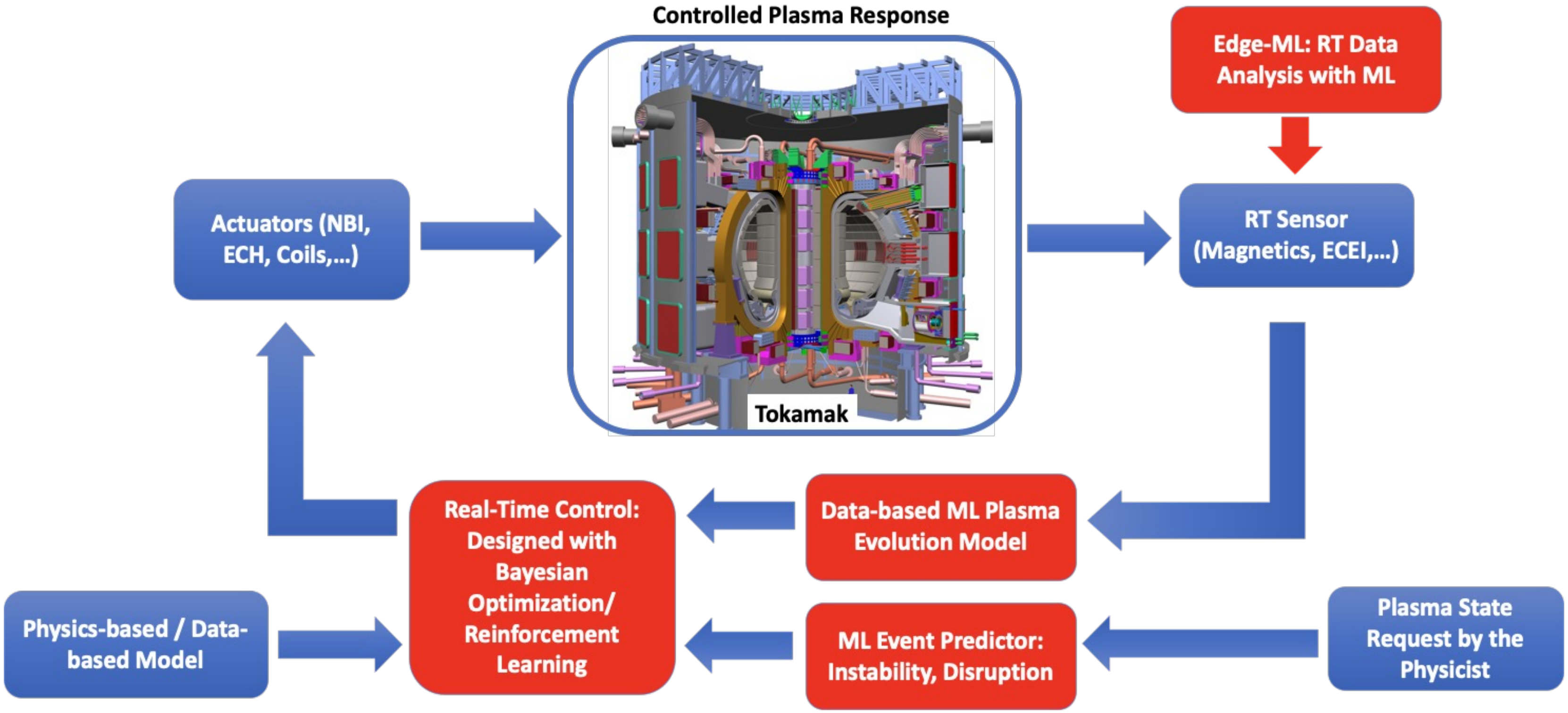
- Fusion plasmas/reactors has very complicated physics
- There is a lot of diagnostic measurement
- Prime target for data-based control design!

Fusion Has Huge Amounts of Data: How to Utilize This for Control?



- **How can we bring this immense information into control?**
  - ***Many not available or usable in real-time (RT)***
  - ***Too much data to pass to a central CPU***
  - ***Mostly not automated: Post-discharge analysis by physicists***
- **Machine Learning → RT data featurization + automated analysis + control design**

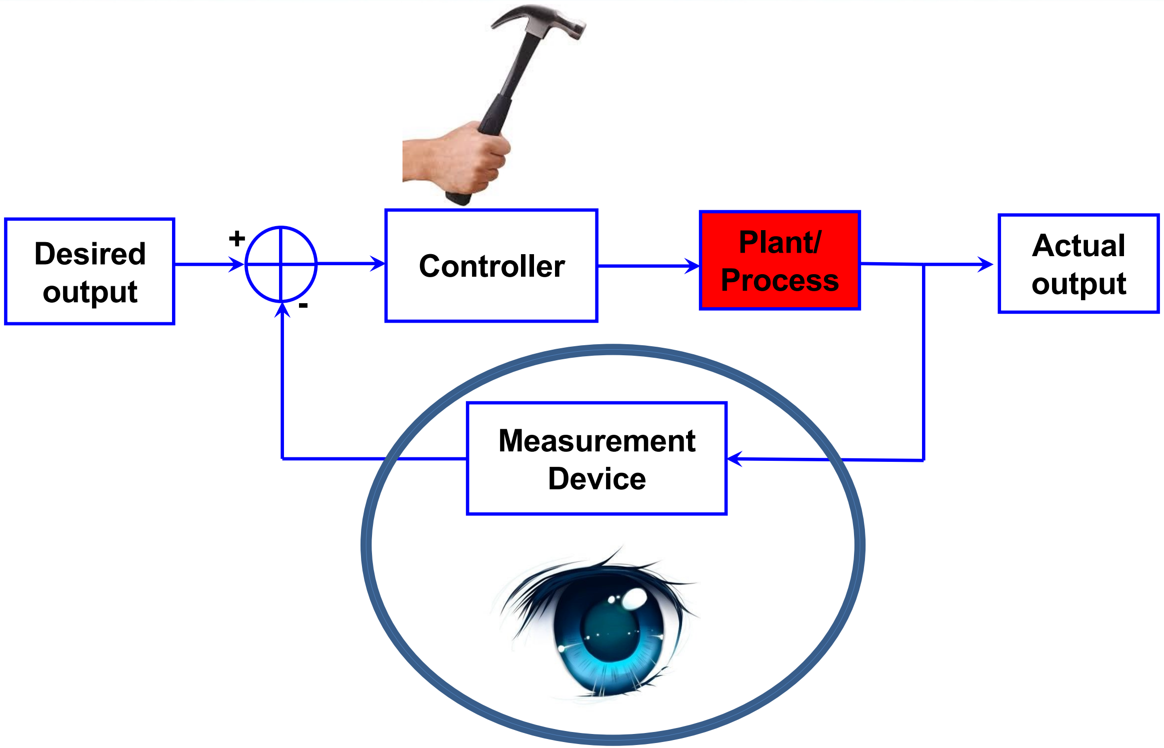
Machine Learning for Real-time Fusion Plasma Behavior Prediction and Manipulation



I lead a big multi-institutional program on ML Control for fusion
PU (lead), PPPL, SLAC, CMU, UWM

Plasma Control

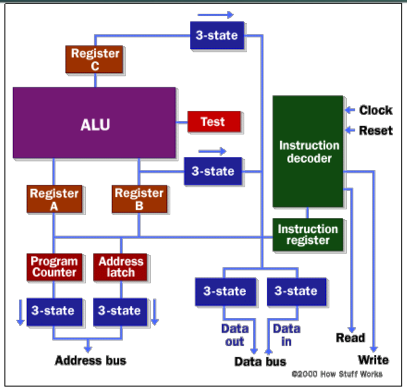
ML for Plasma State Prediction



ML as eyes

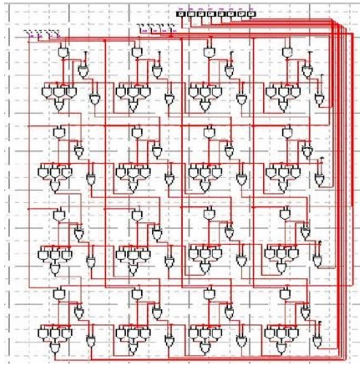
Plasma Control

EDGE-ML with FPGAs Allow Fast Real-time Analysis of Diagnostics on DIII-D (With SLAC Ryan Coffee)

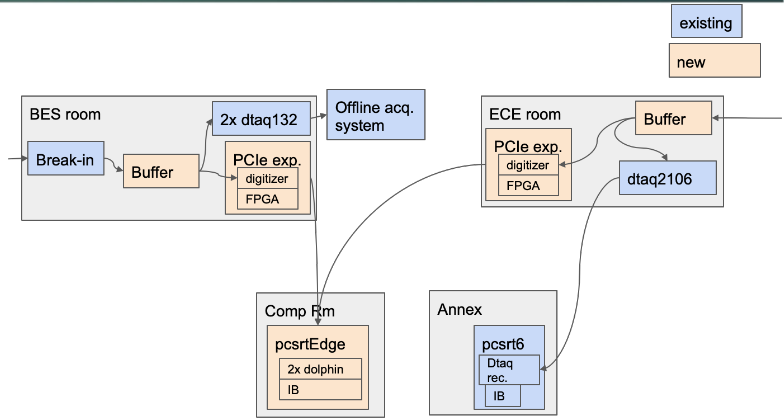


CPU/GPU: instruction set, registers, buses, addresses

➔



FPGA: bits flowing through gates



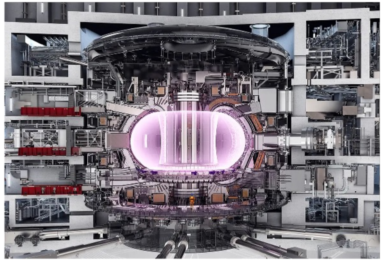
FPGA systems on DIII-D Tokamak

- **Extend RT control to fast plasma dynamics and fluctuation diagnostics**
- **Fluctuation diagnostics capture fast plasma dynamics with MHz sampling**
- ***RT calculations on ~10-100 signals at ~1 MHz is not feasible on CPU/GPU → requires FPGA at sensors – "Edge ML"***
- **Calculation output captures information about fast plasma dynamics and output is available to downstream plasma control system**
- **Diagnostics: BES, interferometers, ECE**

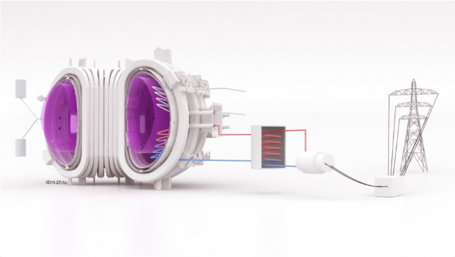
Obtain robust and minimal diagnostics set for fusion reactors using ML

DIII-D

ITER



DEMO



- **Nuclear environment → Minimal Diagnostics**
- **Nuclear environment → Faults/Failures expected**

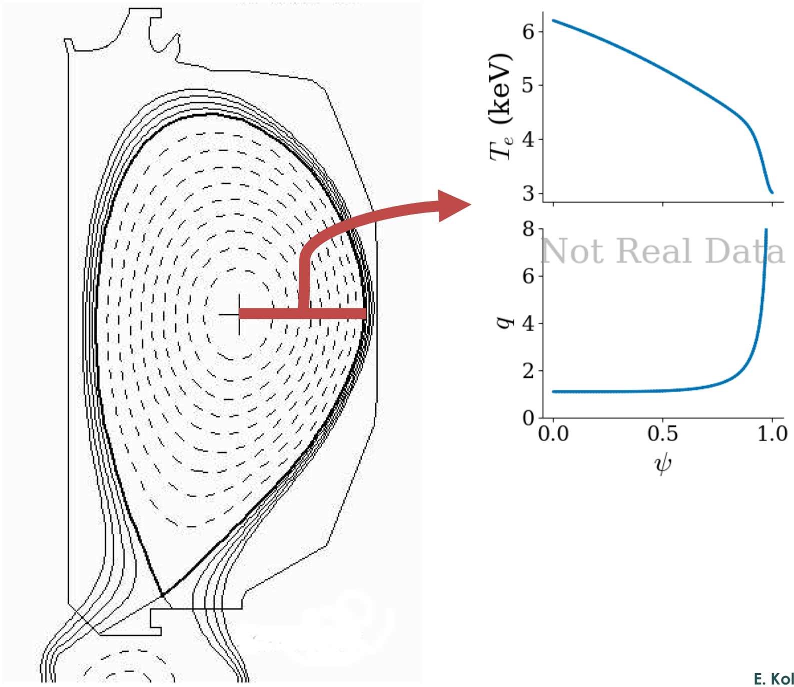
- ***How to be robust?***
- ***What is the minimal diagnostics set necessary?***

- **ML to the rescue!**

Plasma Control

Plasma State Prediction with ML

Plasma State: Shape + 1D profiles

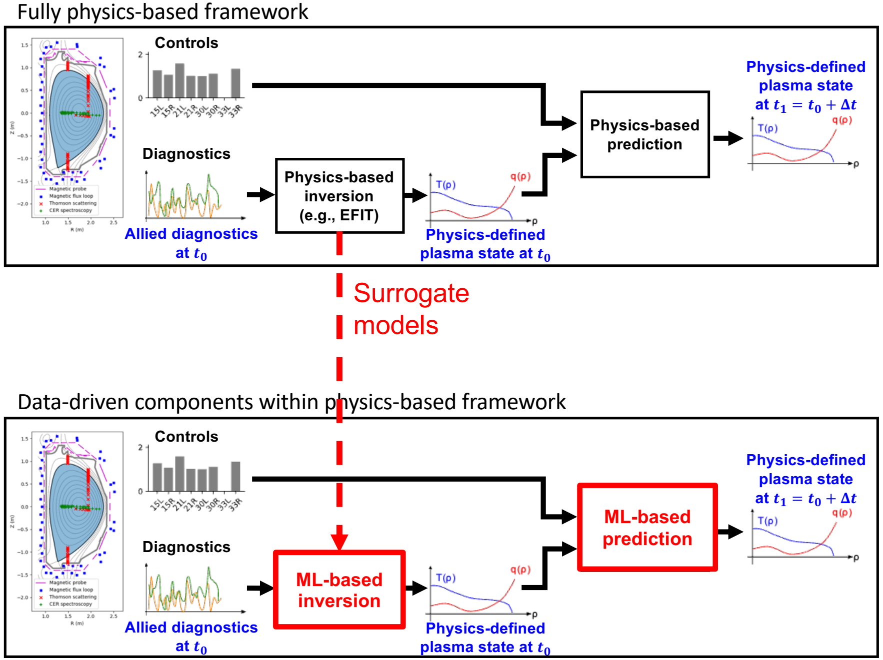


- First find the shape of the plasma
- Then, 6x1D profiles
- Due to symmetry and high transport along flux sections

Full state of plasma determined by 1D profiles:

- Pressure (P)
- Current (J)
- Electron temperature and density (T_e, n_e)
- Ion temperature and density (T_i, n_i)
- Rotation (Ω)

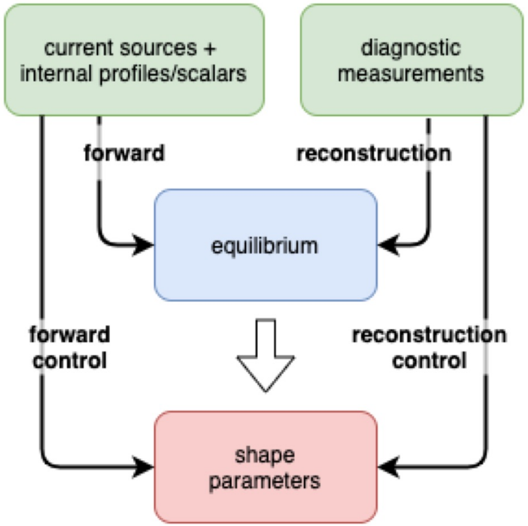
Plasma State Prediction with ML using Surrogate Models

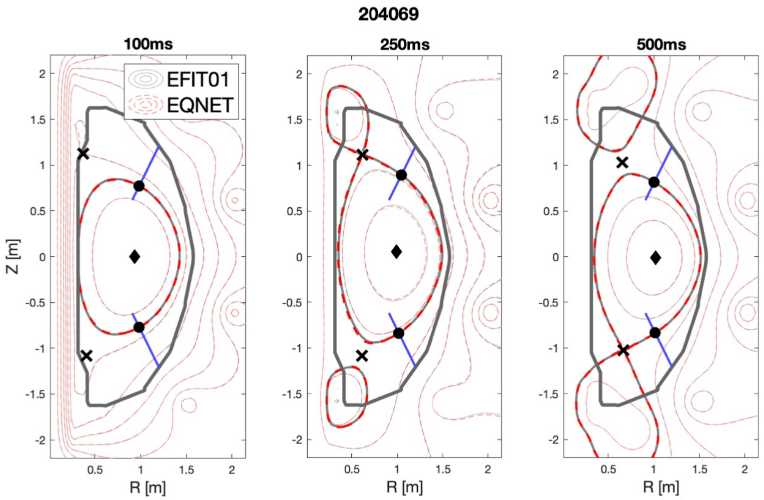


ML-based model should not only be real-time and reliable,
but also efficient to meet the computing limitation of the PCS!

RT Plasma Shape Prediction with ML Surrogate of Physics Model (EQNet): Faster, More Robust

- Surrogate of Nonlinear PDE (Grad-Shafranov Eqn) that solves Plasma Shape
- *More accurate* than rt-EFIT (<1ms)

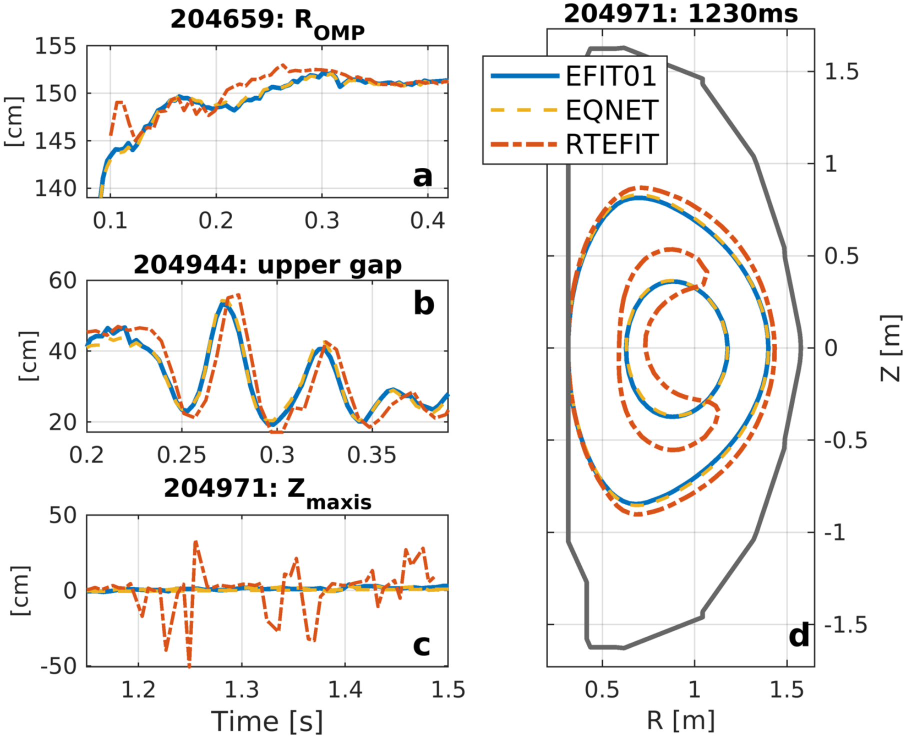




J.T. Wai, M.D. Boyer, E. Kolemen, "Neural net modeling of equilibria in NSTX-U", *NF*, 2022.

RT Plasma Shape Prediction with ML Surrogate of Physics Model (EQNet): Faster, More Robust

- **Neural net responds better to dynamic changes and induced vessel currents than online method**
- **Faster: Removes 5ms phase delay during oscillations – improves controller chance for recovery**
- ***Robust: Trained with all good and bad sensors. ➔ Losing a sensor degrades prediction BUT does not fail***
- **ML can output Linear State Space System which can then be used in control**

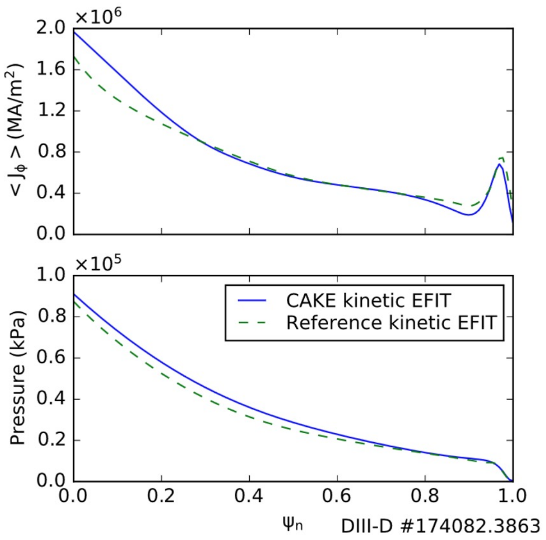


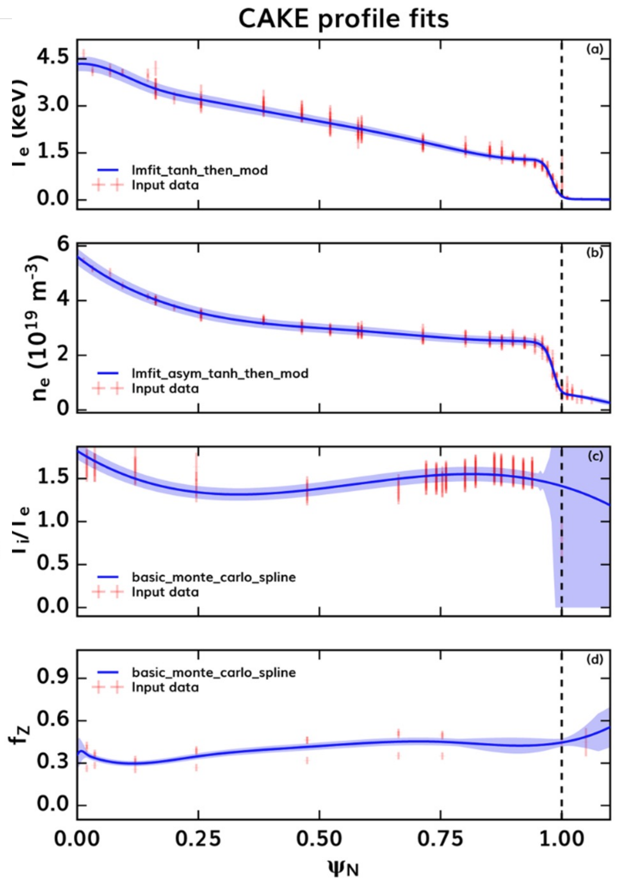
[Wai NF 2022]

1D Profiles + Shape: Offline tool Consistent Automatic Kinetic Equilibrium reconstruction (CAKE) provides kinetic EFITs without

CAKE [Z. Xing et. al, FED '21]:

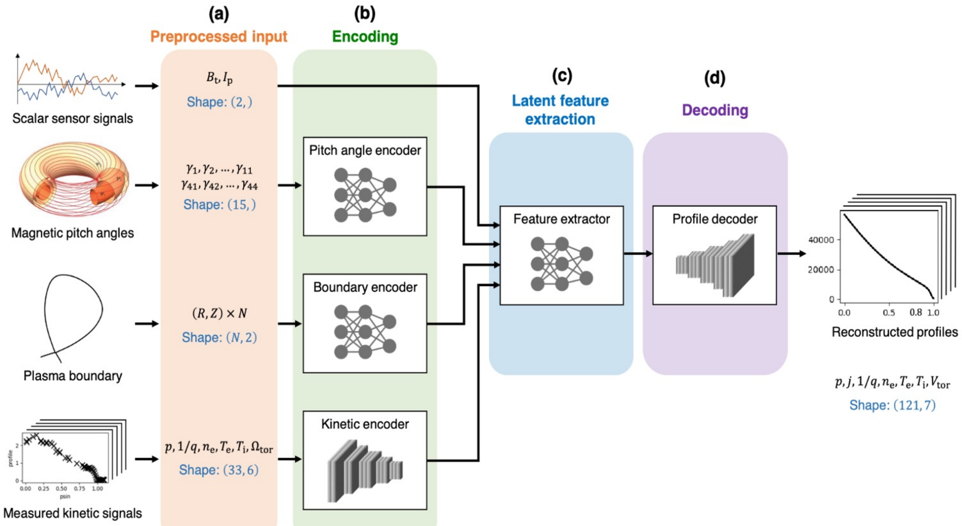
- Low error kinetically constrained reconstructions
- No human intervention
- Handles limited quality & quantity of data
- Runs whole shots post-shot (CAKE01,CAKE02)
- Takes order(minutes) per slice

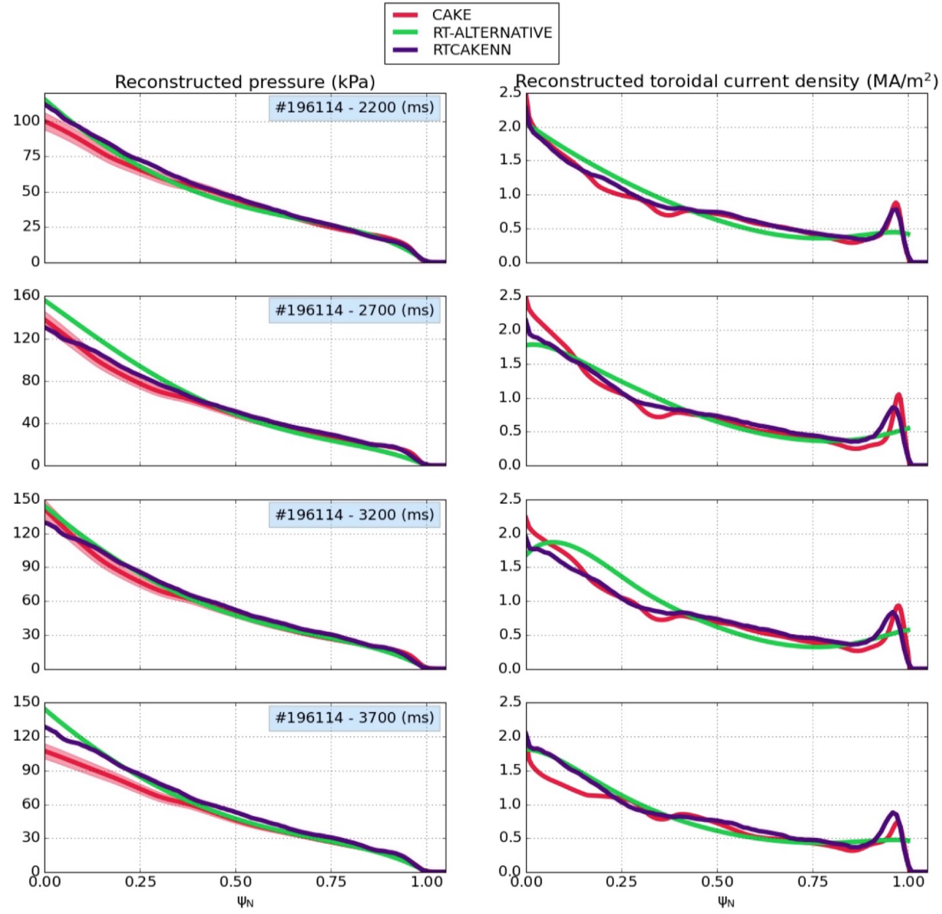




Real-time CAKE Surrogate model RTCAKENN allows

- **RTCAKENN achieves CAKE-level outputs, while giving it access to only PCS-quality inputs in ms**



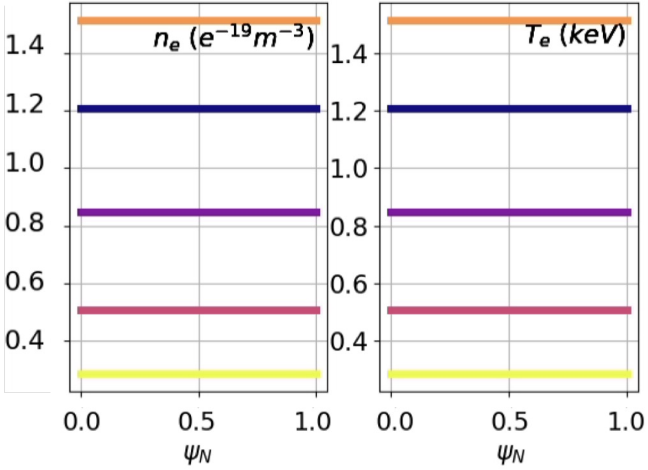


[Shousha NF 23, In Review]

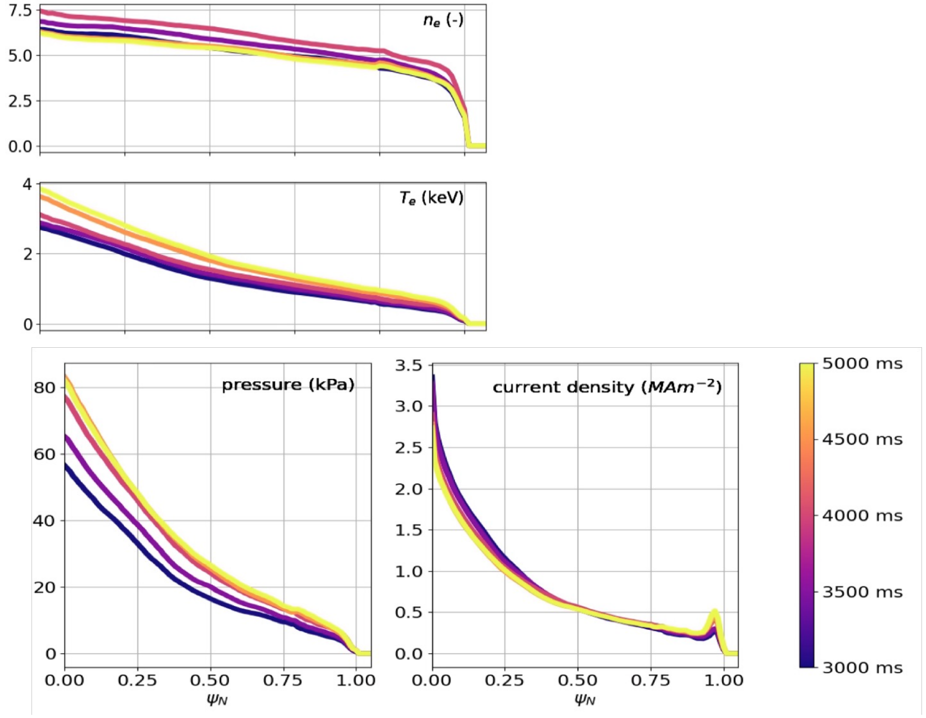
RTCAKENN is robust against absence of TS data, still providing physical outputs

RTCAKENN provides reasonable Te, ne and remaining profiles in absence of TS inputs

BAD TS INPUT DATA:



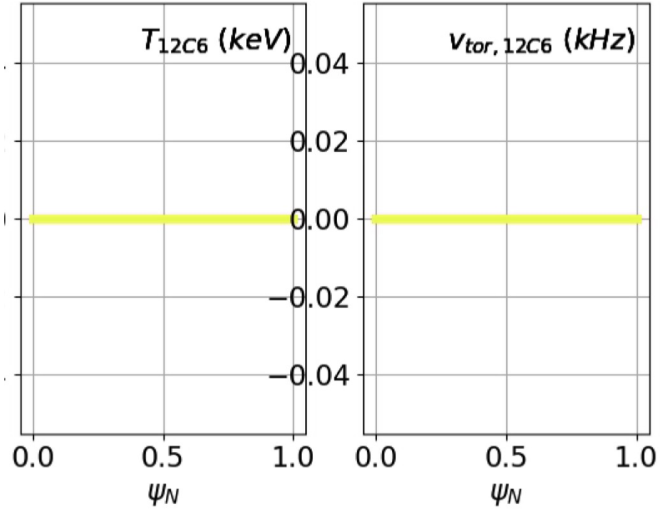
GOOD RTCAKENN OUTPUT DATA:



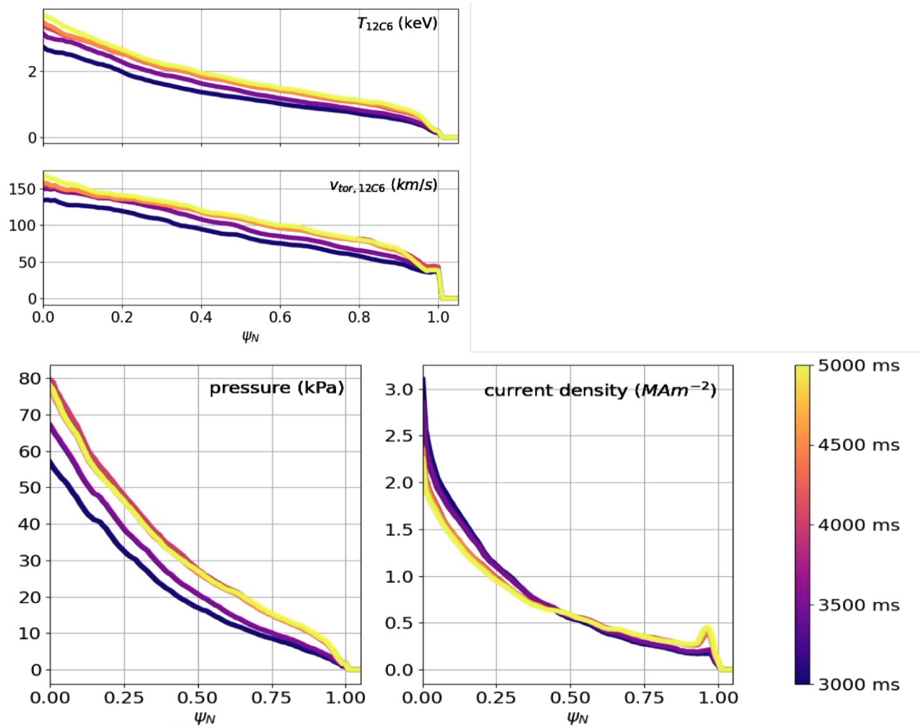
RTCAKENN is robust against absence of CER data, still providing physical outputs

RTCAKENN provides reasonable Ti, vtor and remaining profiles in absence of CER inputs

BAD CER INPUT DATA:

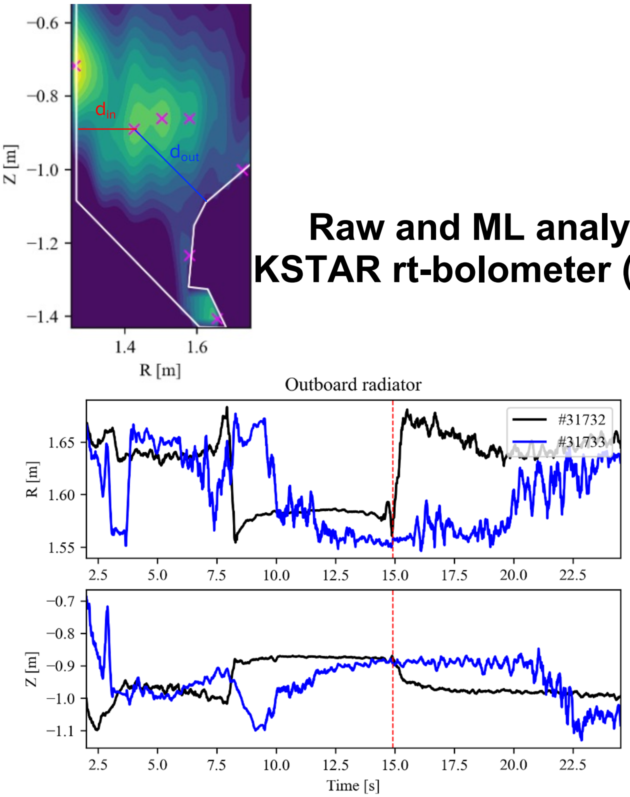


GOOD RTCAKENN OUTPUT DATA:

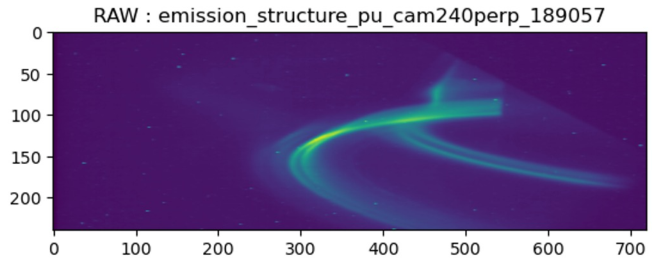


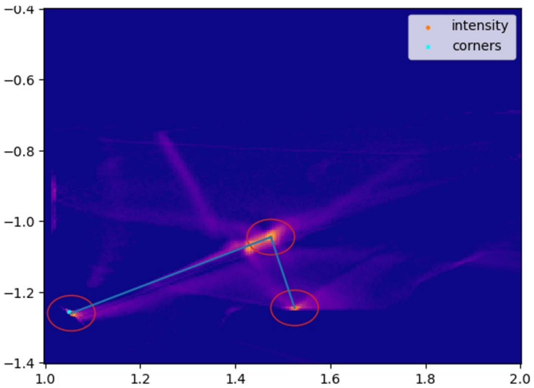
Extended Plasma State: Detachment/Radiation (KSTAR+DIII-D)
With LLNL (Dr. Scotti) and KIAST (Dr. Oh) – C. Byun + N. Chen (Princeton)

Radiation (2D Bolometer) and Detachment (2D visible camera) Detection and assignment



Raw and ML analyzed KSTAR rt-bolometer (KAIST)



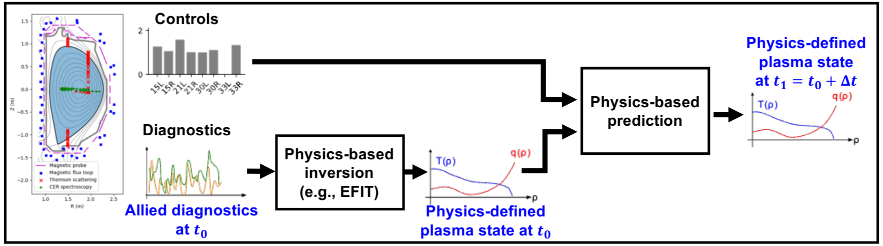


Raw and ML analyzed DIII-D TangTV (LNLL)

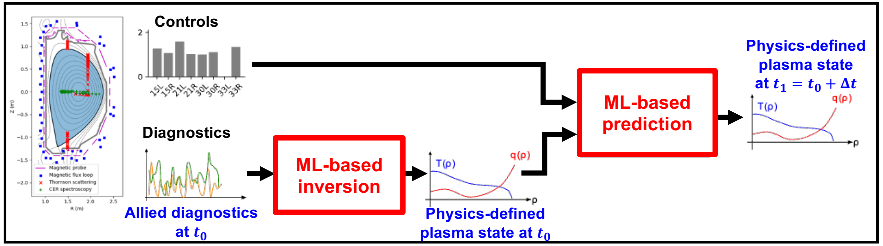
Plasma Control

Diag2Diag: Data-First Approach to Prediction of Fusion Dynamics and Reactor Scenario Design

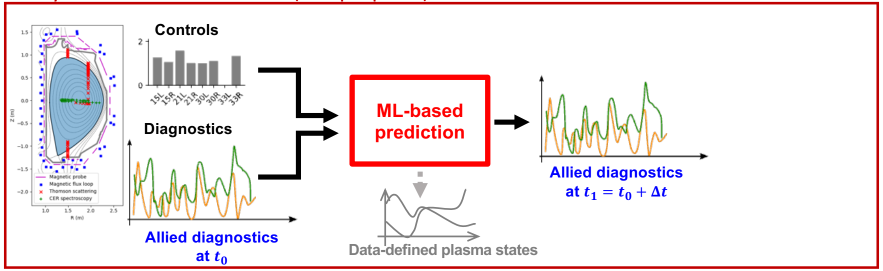
Fully physics-based framework



Data-driven components within physics-based framework

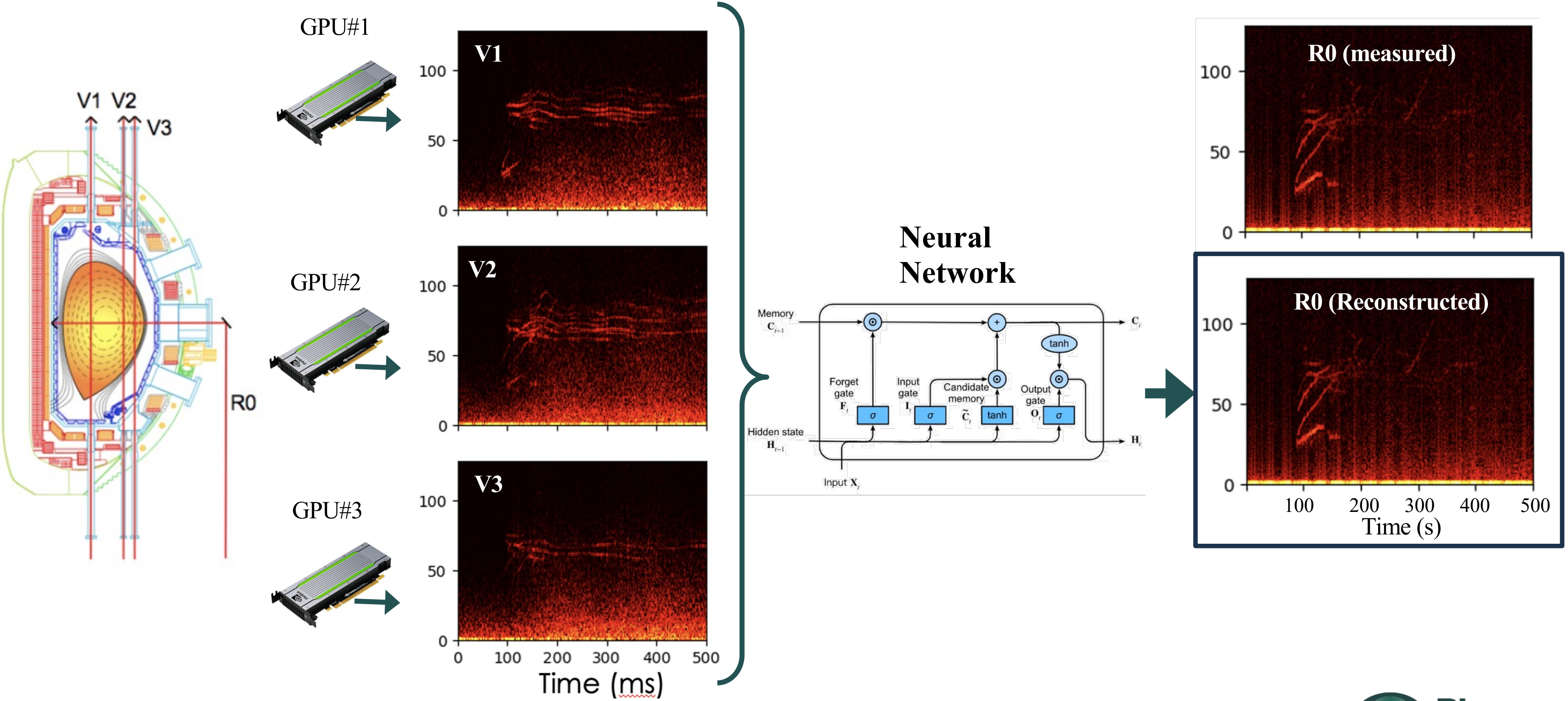


Fully data-driven framework (this proposal)



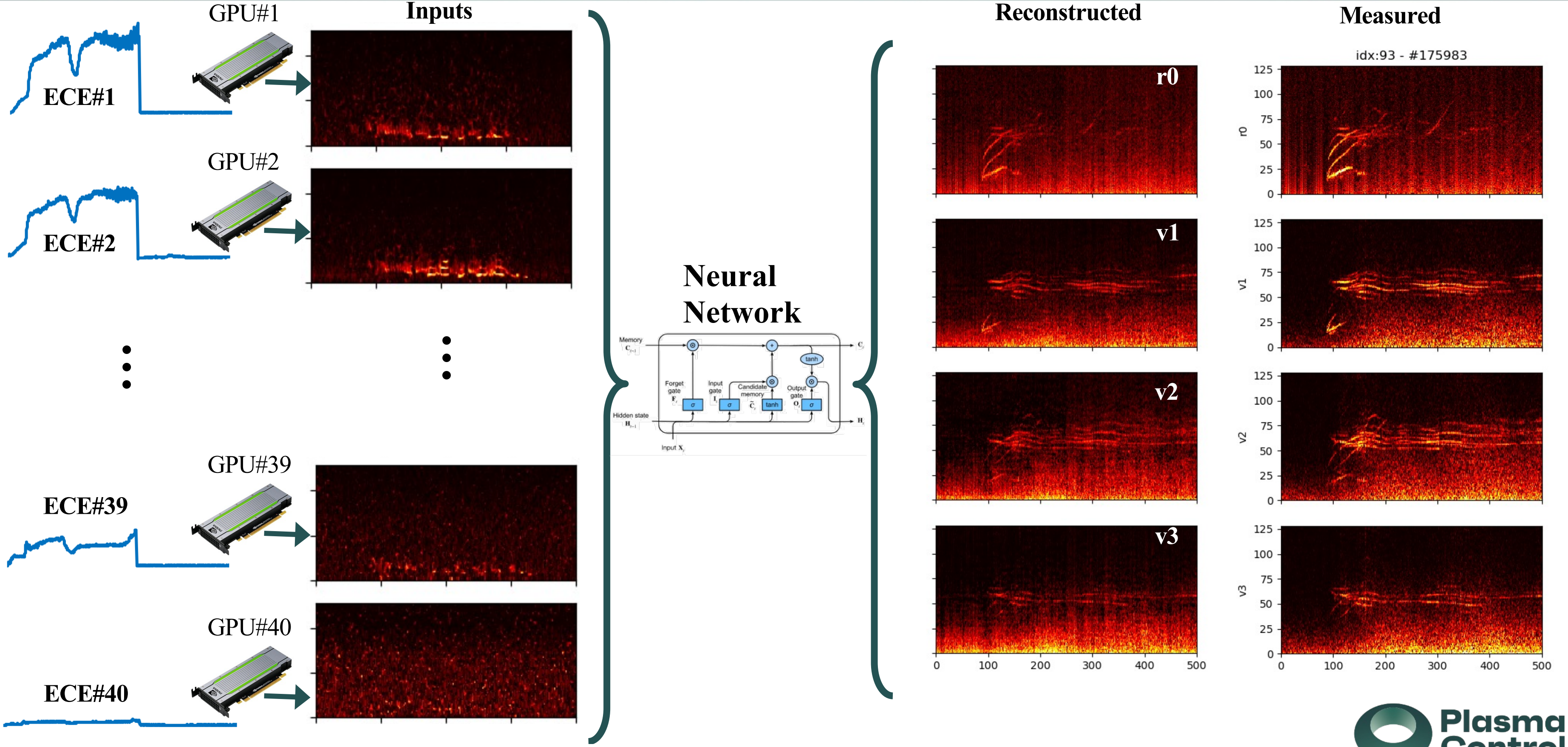
E. Kolemen / Oct 2023

Diag2Diag: ML allows robustness to channel loss and find the minimum set of channels



- **Reconstructing one CO2 interferometer cord from the others**

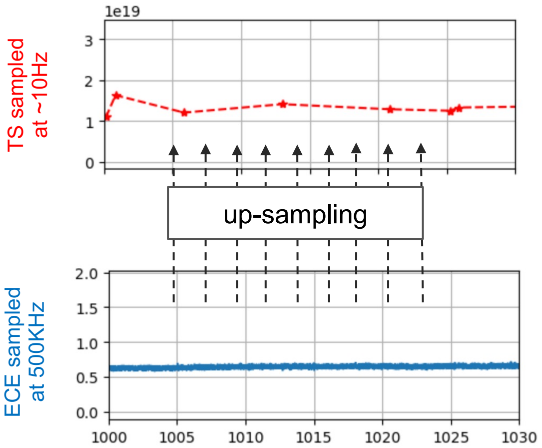
Diag2Diag: ML allows robustness to diagnostics loss and find the minimum set of diagnostics



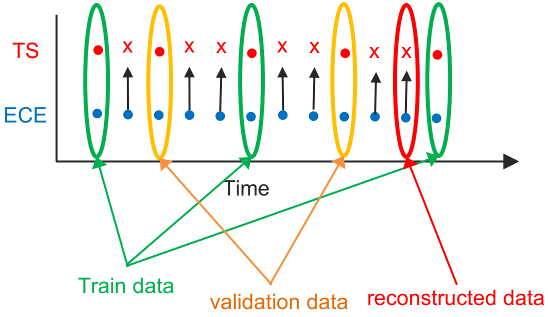
Reconstructing all CO2 interferometer cords from ECE diagnostics

Plasma Control

Diag2Diag: ML allows combining cheap high frequency diagnostics with expensive low frequency ones

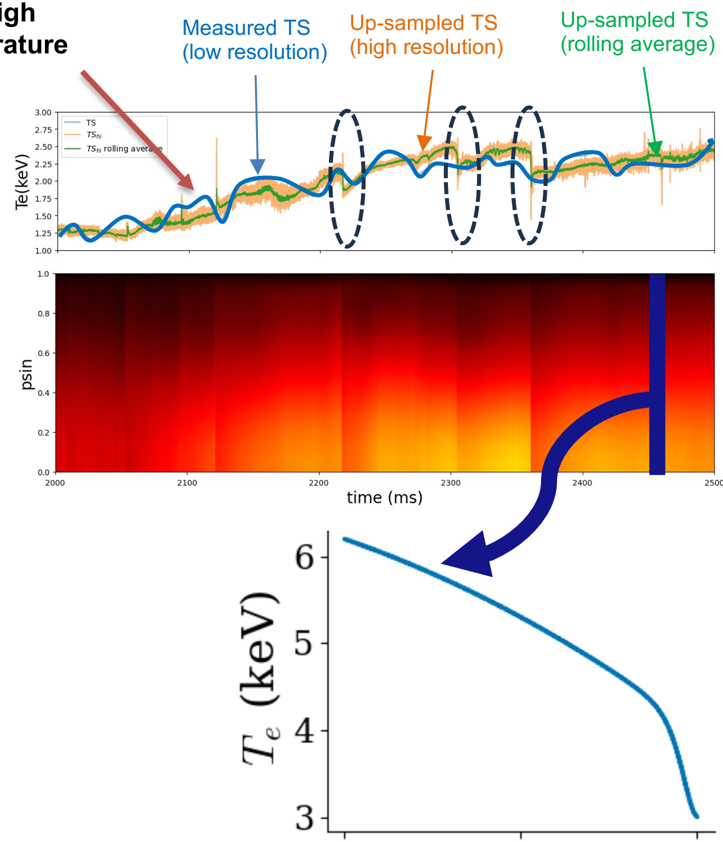


The existing TS datapoints were used for train and validation of the Neural Network



- Thomson Scattering gives Te, ne at high quality but expensive laser system only 50 Hz
- Use cheap high res (1 MHz) ECE diagnostics to fill-in the blanks
- The development of a high temporal resolution equilibrium profile is currently on going.

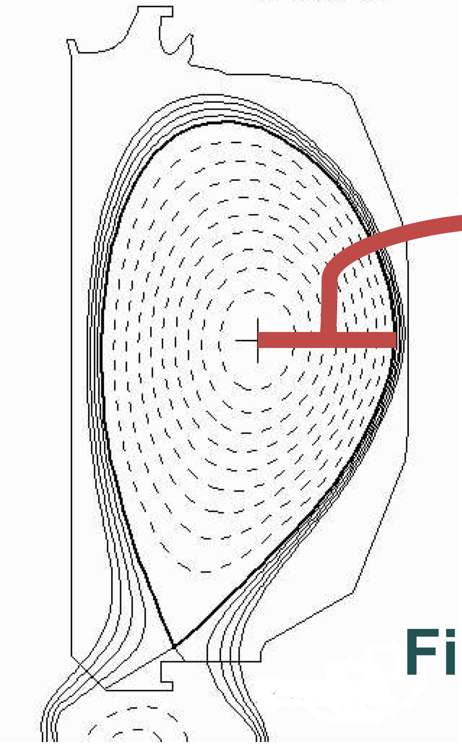
Comparing one channel of low resolution and high resolution TS temperature

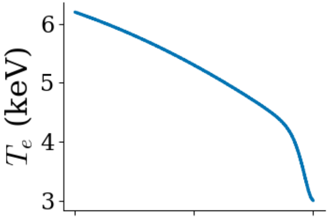


Plasma Evolution Prediction

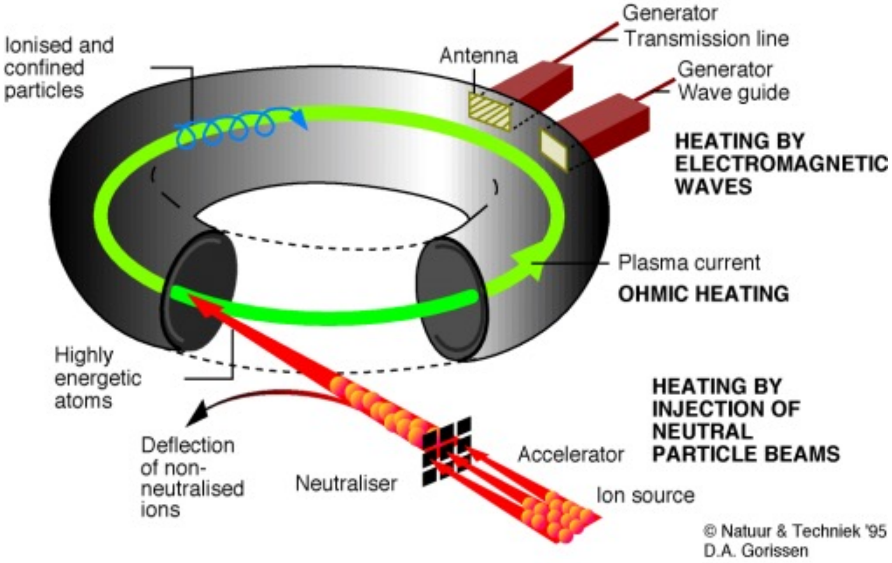
Dynamics model: predict evolution of plasma state given actuators

$\boldsymbol{x}$ = state (Shape + 1D profiles)



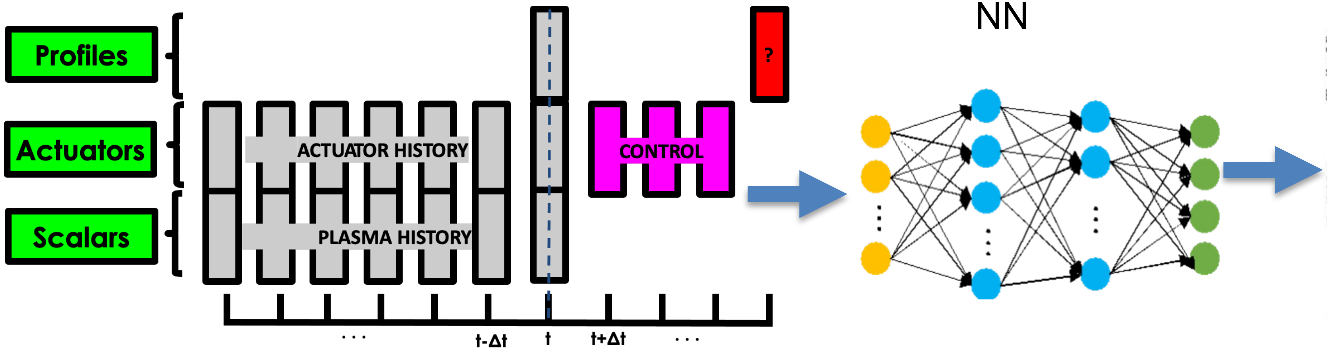


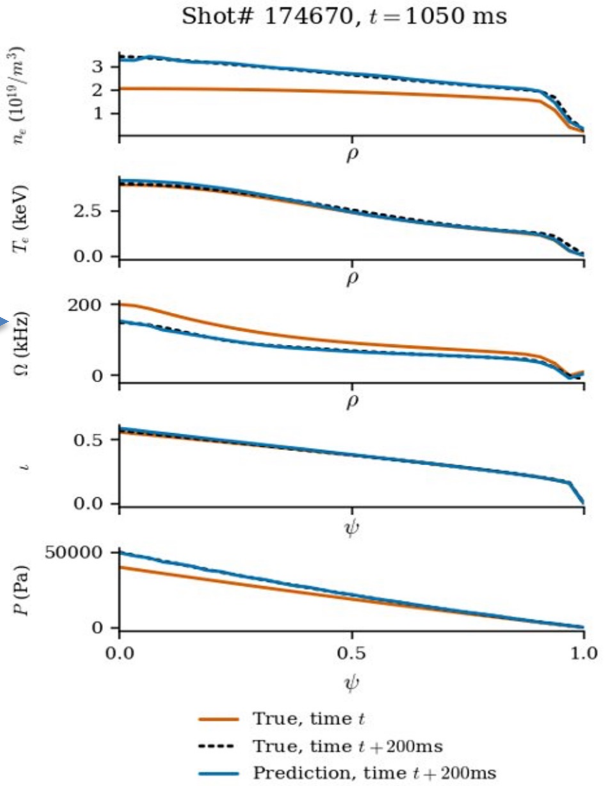
$\boldsymbol{u}$ = actuators



Find mapping f s.t. $x_{t+1} = f(x_t, u_t, u_{t+1})$

ML as Plasma Evolution Model: Experimental Data-Based Profile Prediction



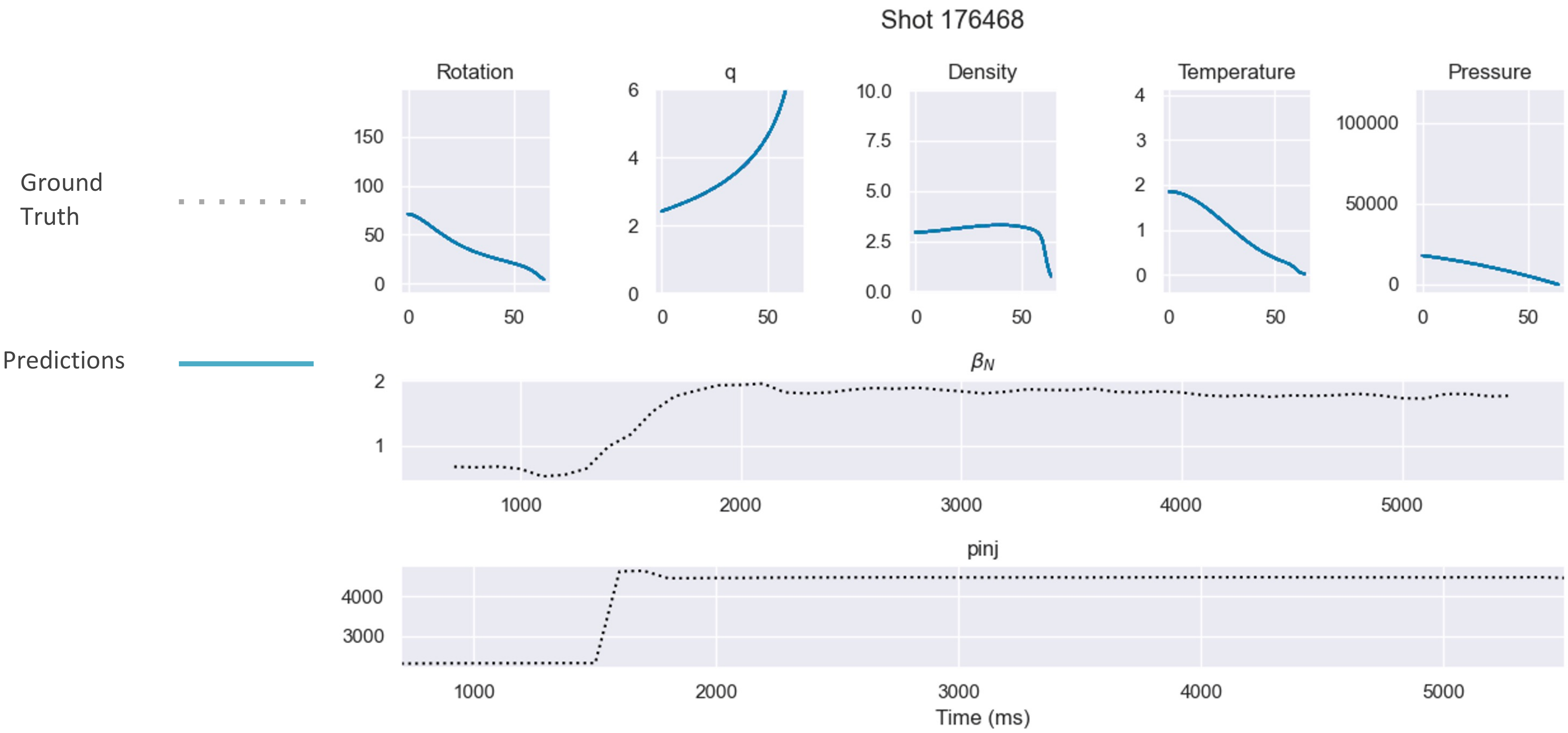


- **ML-Based Prediction of Profile Evolution**
- **Input:** DIII-D Historic Data (5 Profiles, Shape, NBI, Density,…)
- **Output:** Profile Evolution predicting NN

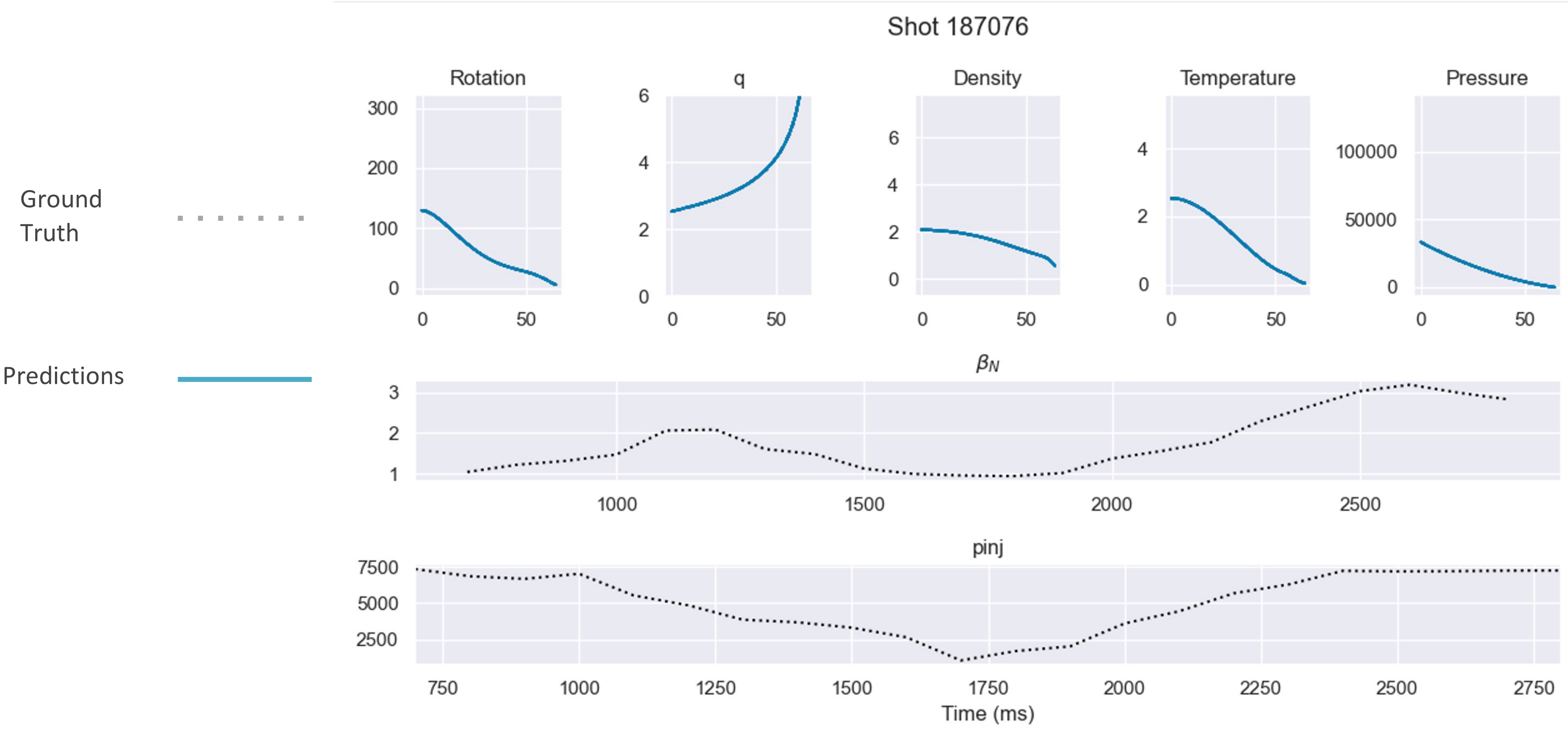
[Abbate, Conlin NF 2021]

Plasma Control

Replaying a test set shot for BetaN, Li prediction (Ian Char, CMU, J. Abbate Princeton)



Replaying a more interesting test shot (Ian Char, CMU, J. Abbate Princeton)



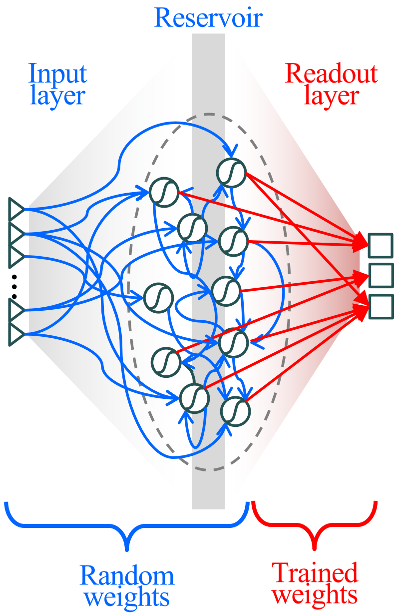
Realtime Adaptive ML Plasma Model: Reservoir Computing Network (RCN)

A **recurrent** neural network with **random** and **sparsely connected** early layers.

Only the last layer is trained using **linear regression**.

Specifications of RCN:

- Projects the inputs to a random very high-dimensional space.
- Ability to process **temporal information** (time-series data analysis)
- Much **faster** and **easier training** procedure compared to DNNs.
    - LSTM: **5 hours** on GPU
    - RCN (with similar performance to LSTM): **4 Minutes** on CPU
    - Easy & fast training makes "in-situ" **model adaptation** possible



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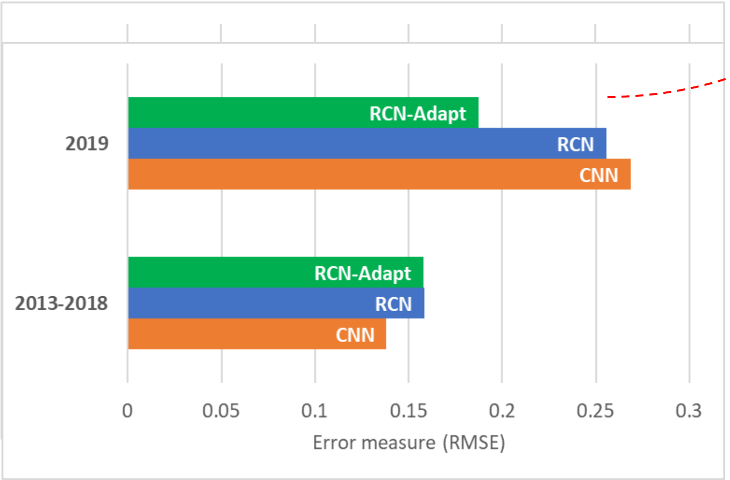
GHENT UNIVERSITY

andlinger center for energy+the environment

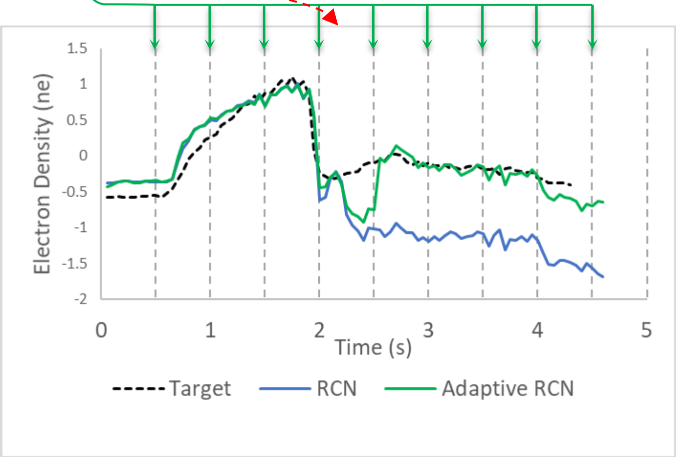
Adaptive Data-driven Profile Prediction Model

* A. Jalalvand, J. Abbate, R. Conlin, G. Verdoolaege, E. Kolemen,
"**Real-Time and Adaptive Reservoir Computing with an Application to Profile Prediction in Fusion Plasma**",
IEEE Trans. on Neural Net. & Learning Systems, 2021.

	CNN/LSTM	RCN
Training	5h on GPU	45s on CPU
Performance	SOTA	Close to DNN
Adaptation	Difficult	Easy (100ms)



Real-time Adapting
every 500ms

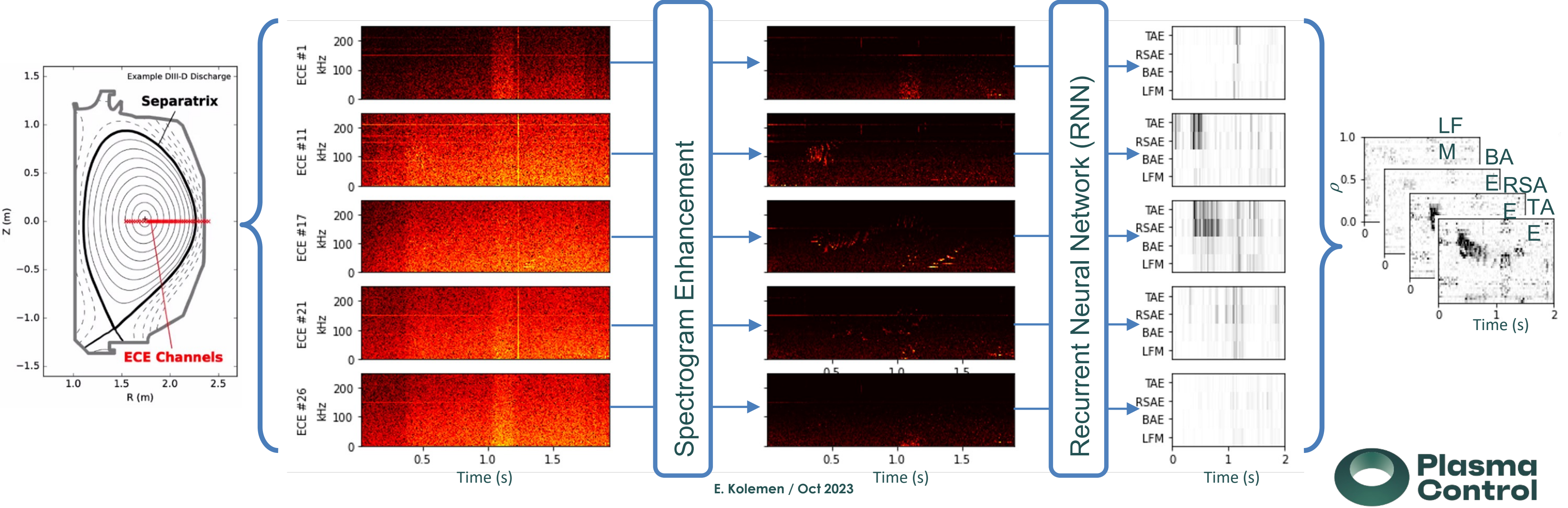


Plasma Event Detection

Detecting Alfvén Eigenmode using ECE

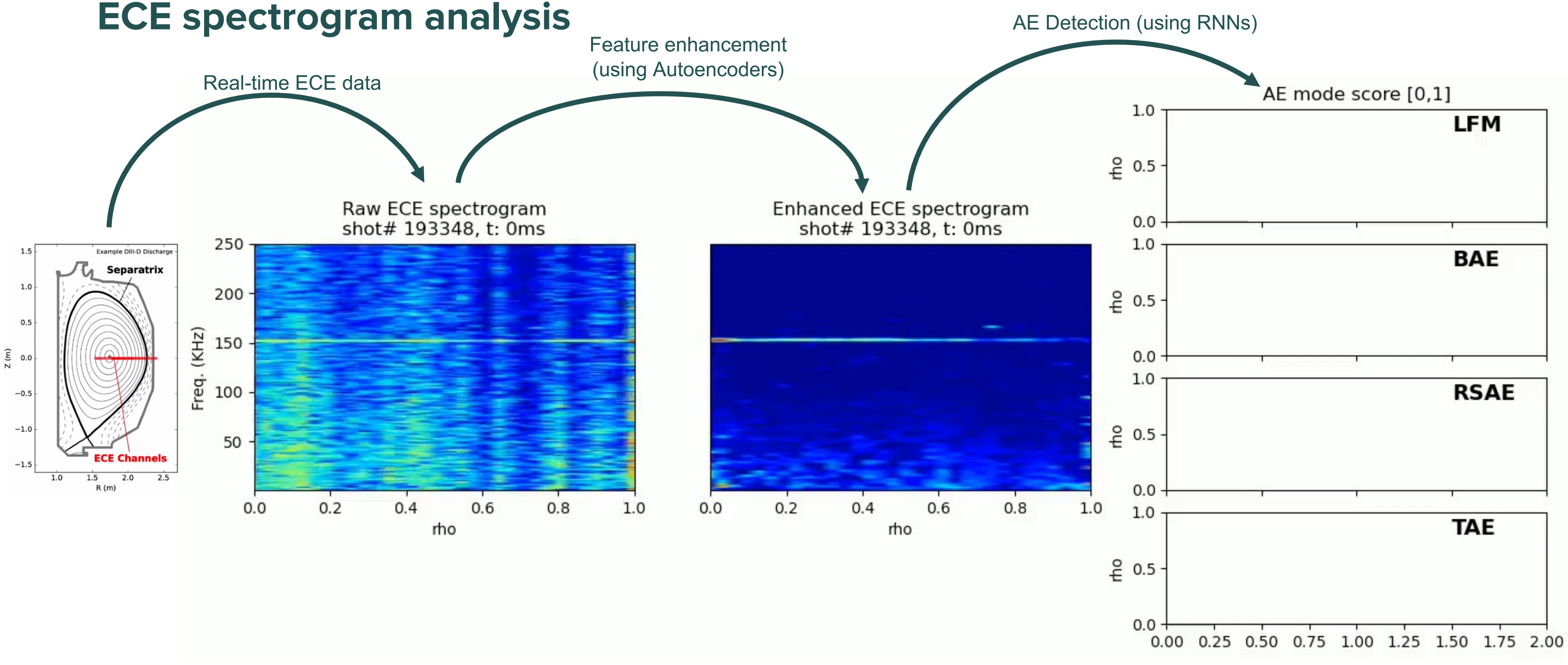
* *Jalalvand et al 2022 Nucl. Fusion 62 026007*
* *Kaptanoglu et. al., 2022 Nucl. Fusion 62 106014*

- AE modes reduces plasma performance, we would like to minimize them
- Input: Spectrogram of each ECE channel
- Process Stage 1: Enhancing spectrograms using Auto-Encoder network
- Process Stage 2: Detecting AE modes using Recurrent Neural Network
- Output: Score of AE modes per ECE per time step



Plasma Control

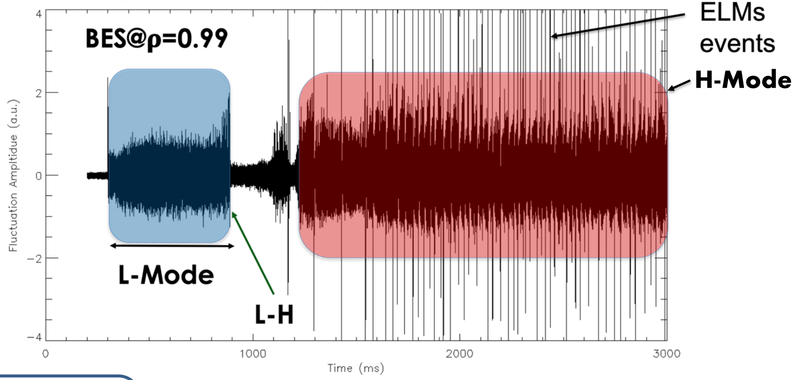
ECE spectrogram analysis



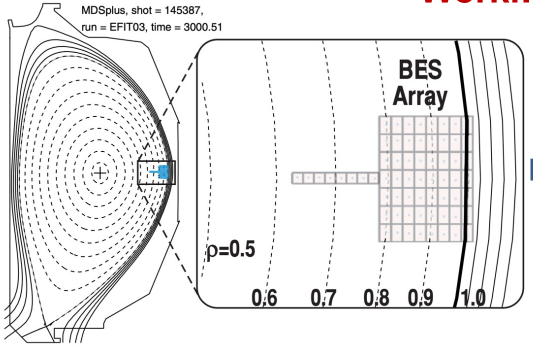
Real-time plasma confinement mode classification

Kevin Gill[1*], D. Smith[1], S. Joung[1], B. Geiger[1], G. McKee[1], J. Zimmerman[1], R. Coffee[2], A. Jalalvand[3], E. Kolemen[3]

- **Motivation: Facilitate real-time control for access and sustainment of enhanced confinement regimes**
  - **avoidance of transient events**
    - ***e.g., RMP application soon after LH transition for ELM suppression***
  - **sustainment of enhanced confinement regimes**
    - ***e.g., quiescent H-mode, wide pedestal quiescent H-mode***



Workflow



1. **Collection** raw BES signals from 48 ch. 6 x 8 x time window
2. **Pre-processing** filtering and standardizing
3. **Deep neural network**
4. **Confinement mode classification**

Dataset

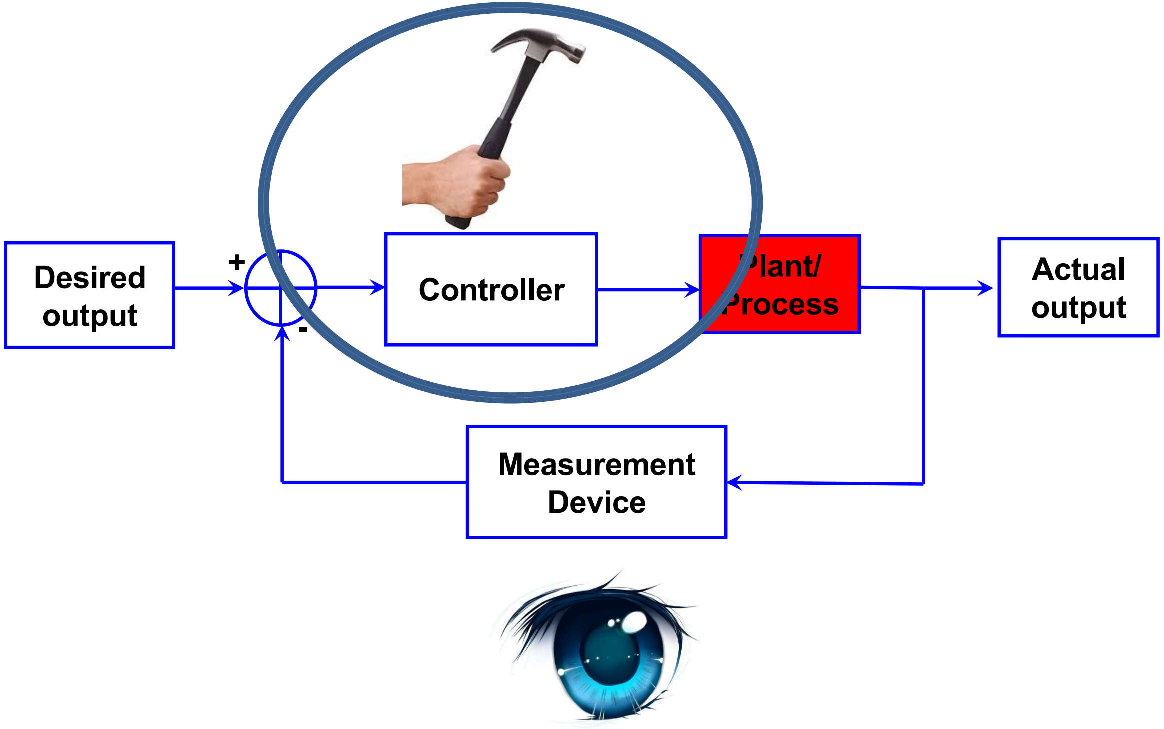
	Discharges	Time (s)
L-mode	63	48.2
H-mode	62	156.1
QH-mode	28	43.4
WP QH-mode	32	40.8

[1]University of Wisconsin-Madison, Madison, WI, US
[2]SLAC National Accelerator Lab, Menlo Park, CA, US
[3]Princeton University, Princeton, NJ, US

*kevin.gill@wisc.edu

Plasma Control

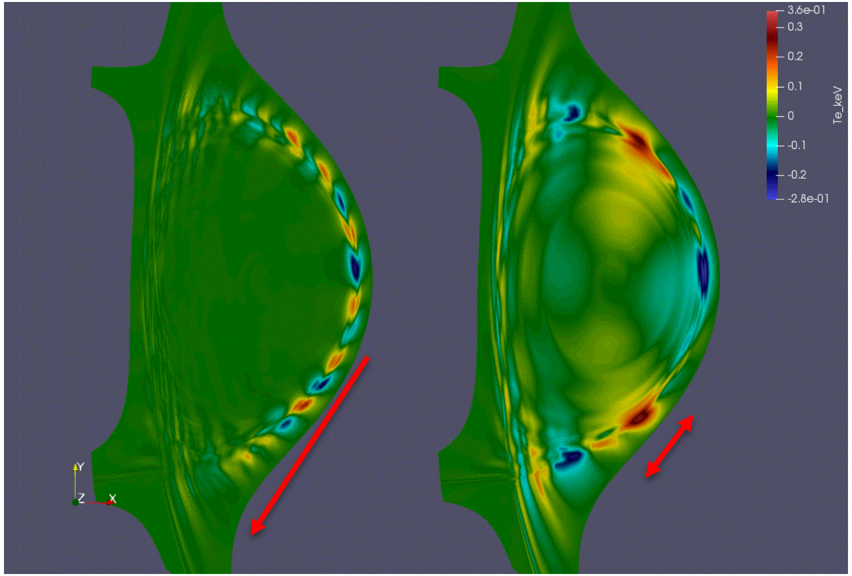
ML Control for Fusion:
ML for control calculation



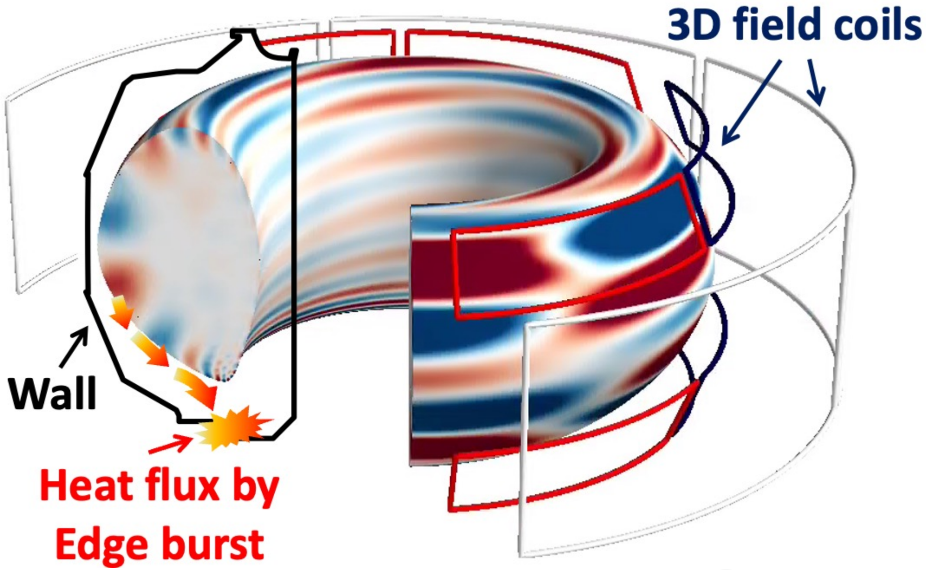
Plasma Control

Edge energy burst is a major task in tokamak fusion, making the use of high confinement state difficult

- ✓ **High confinement is critical for economic fusion plasma.**
- ✓ **Harmful edge energy burst (ELM) huddles the utilizing the high-confinement state.**
  - Due to the strong pressure gradient at the boundary.
  → A 3D field is a promising approach in ITER to suppress it.

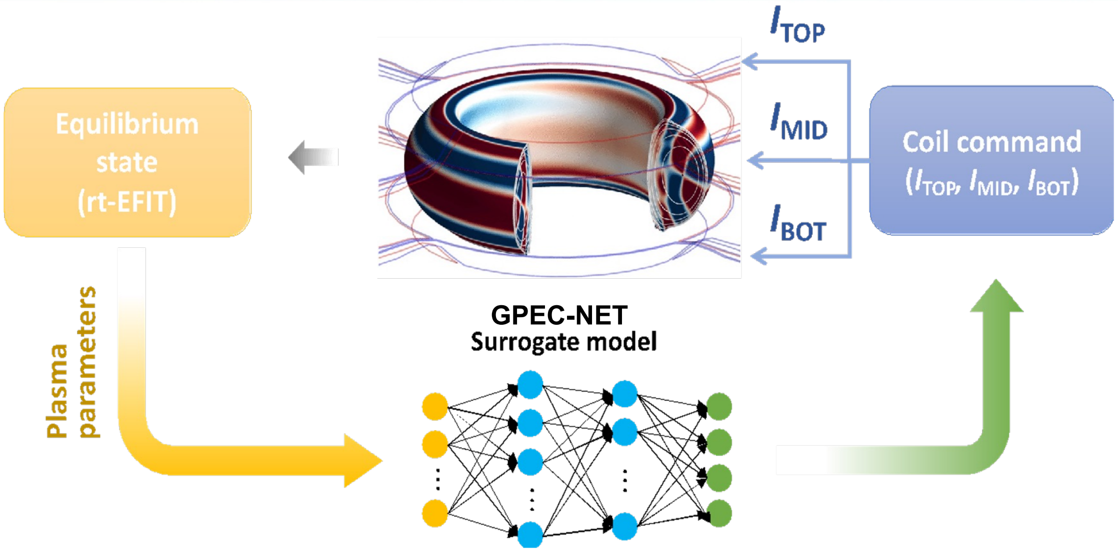


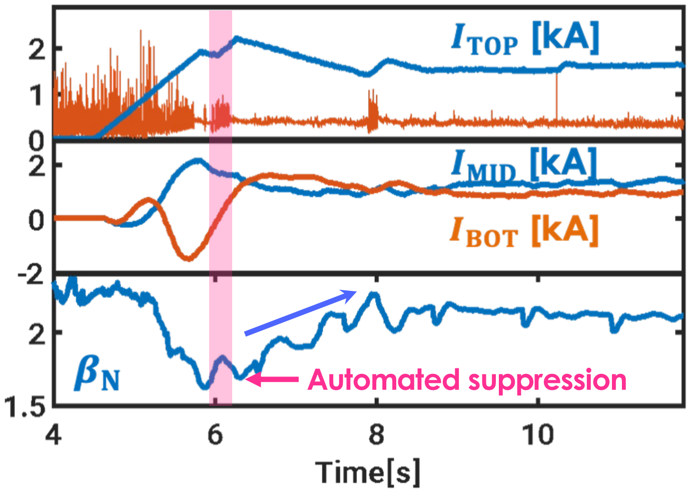
ELMy vs RMP-suppressed
[Large Scale Hybrid Simulation JOREK+PENTRC]



Plasma Control

ML-based adaptive ELM controller for automated safe ELM suppression without empirical approach

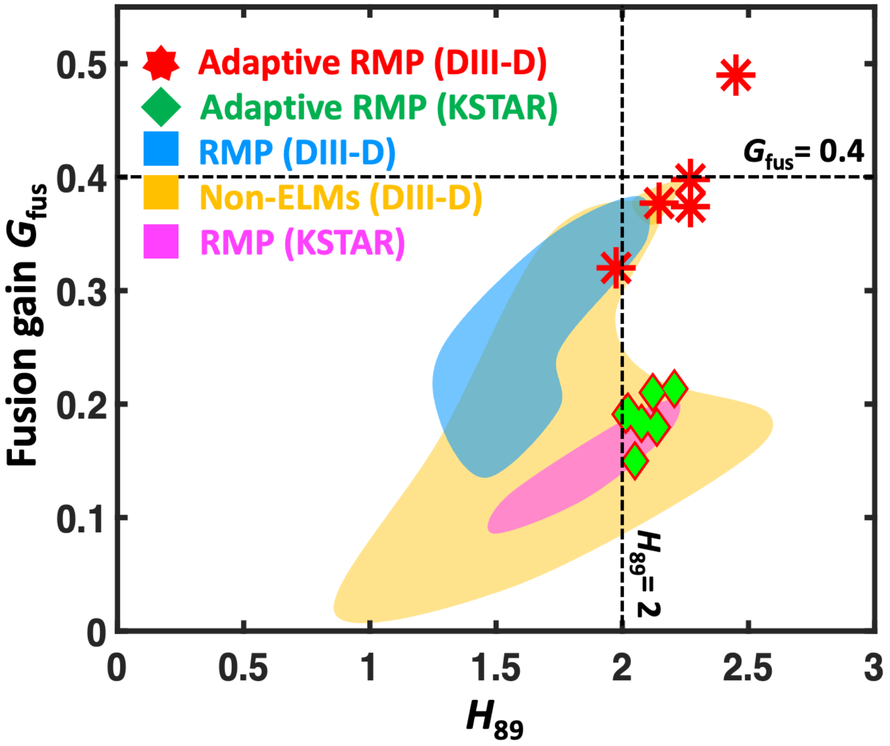




- ✓ Conventional 3D-field has empirically optimized waveform (Coil configuration).
  → Non-ITER applicable.
- ✓ ML-surrogate model to the Physics Model (GPEC-NET) for automatic coil configurations.
  [J.-K. Park NP 19, S.M. Yang NC 23]
- ✓ Automated & adaptive ELM control in KSTAR without human decision. [S.K.Kim NC in review]
- ✓ Keras2c GITHUB developed to make rt C code [Conlin EAAI 21]

Adaptive ELM control is key to achieve highest fusion performance without harmful edge energy burst

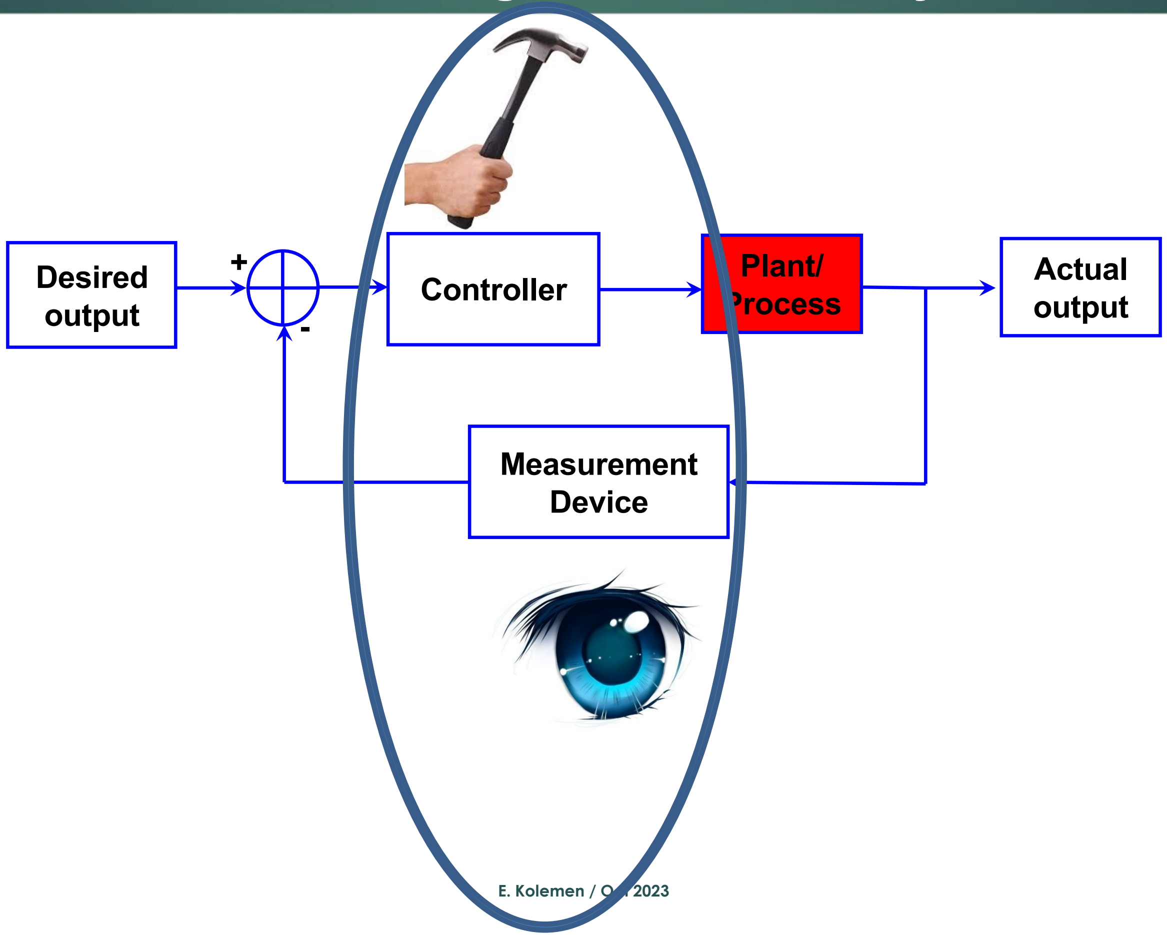
- ✓ Fusion gain (G)
  -Effectiveness of fusion power production
- ✓ Confinement quality (H):
  - Efficiency of energy confinement.
- ✓ Highest values achieved in two devices.



[S.K.Kim Nature Communication in review]

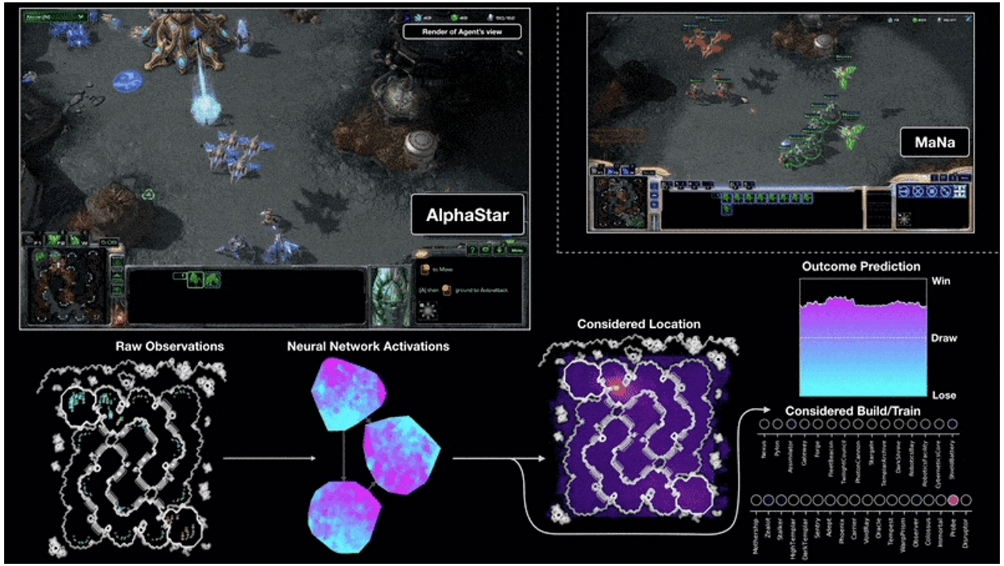
Plasma Control

ML Control for Fusion:
ML to design control directly



Plasma Control

Reinforcement Learning has shown remarkable promise in game playing, robotics, and beyond.



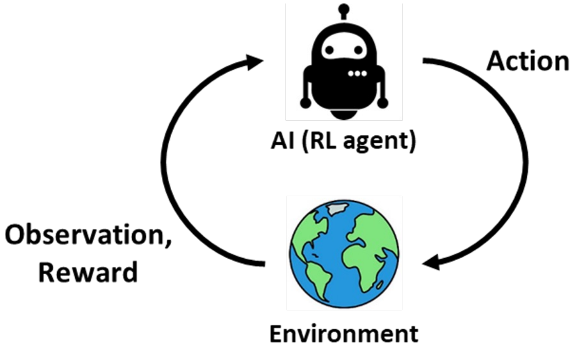
DeepMind AlphaStar

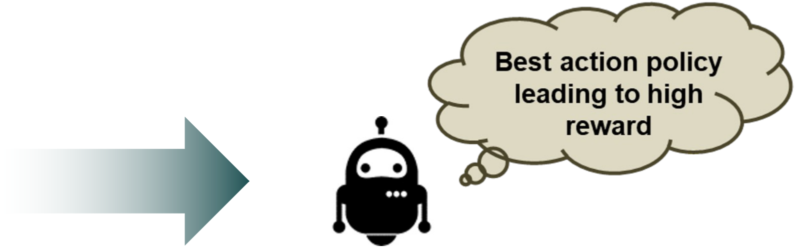
While these works are impressive, they have access to relatively cheap accurate simulators.

<u>What do we do if we do not have access to such a simulator?</u>
<u>Data-based RL</u>

RL-based Tearing Mode Instability avoidance control

- **Deep reinforcement learning:** ***“Finding the best action (control) policy”***

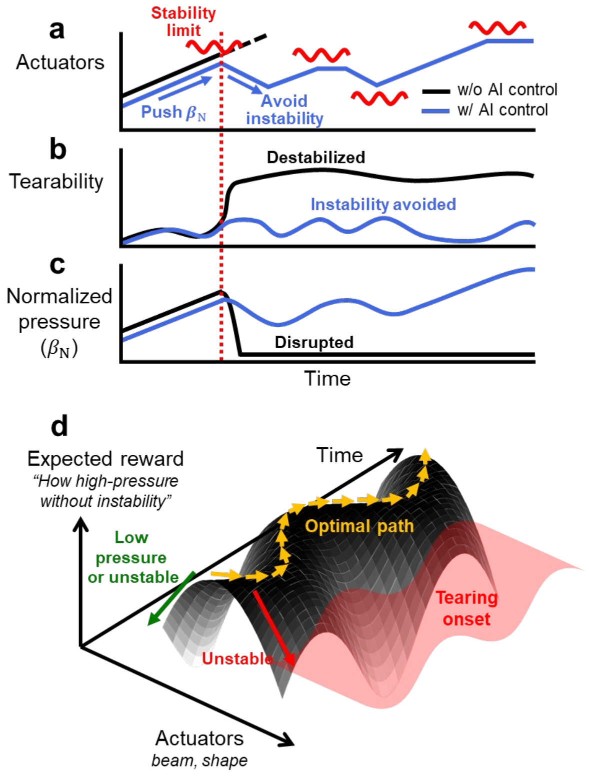




- **RL for instability avoidance control**
  - ***Observation***: Plasma state (Shape, 1D profiles)
  - ***Action***: Beam, ECH, Magnet Currents
  - ***Reward***: [Fusion Gain (G), No Tearing Instability]
- **Here Reward is calculated based on experimental data**

Plasma Control

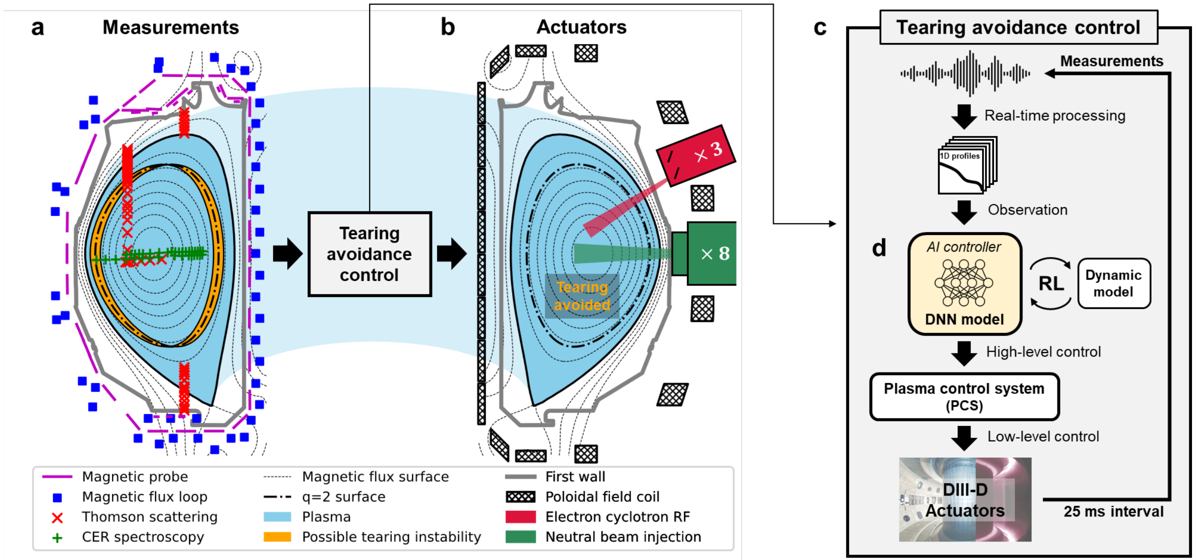
Avoiding tearing mode instabilities with RL at DIII-D (with J. Seo)



(Concept of tearing avoidance)

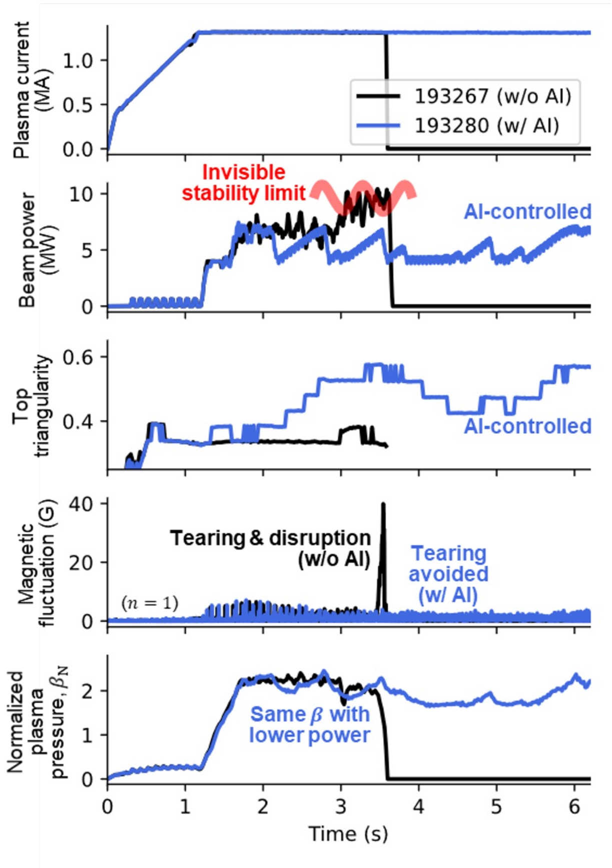
- **Preemptive control of beam power and plasma shape can avoid the onset of tearing modes.**

- **By using AI, we can avoid tearing modes while pushing up performance.**

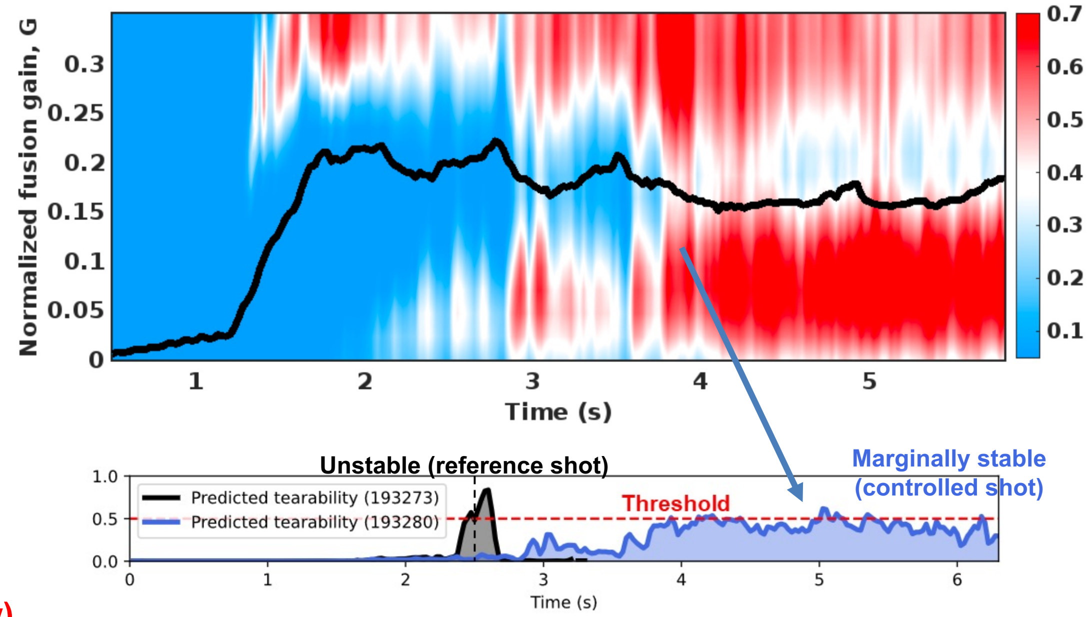


(Implementation in DIII-D PCS, Nature, In Review)

Avoiding tearing mode instabilities with RL at DIII-D (with J. Seo)

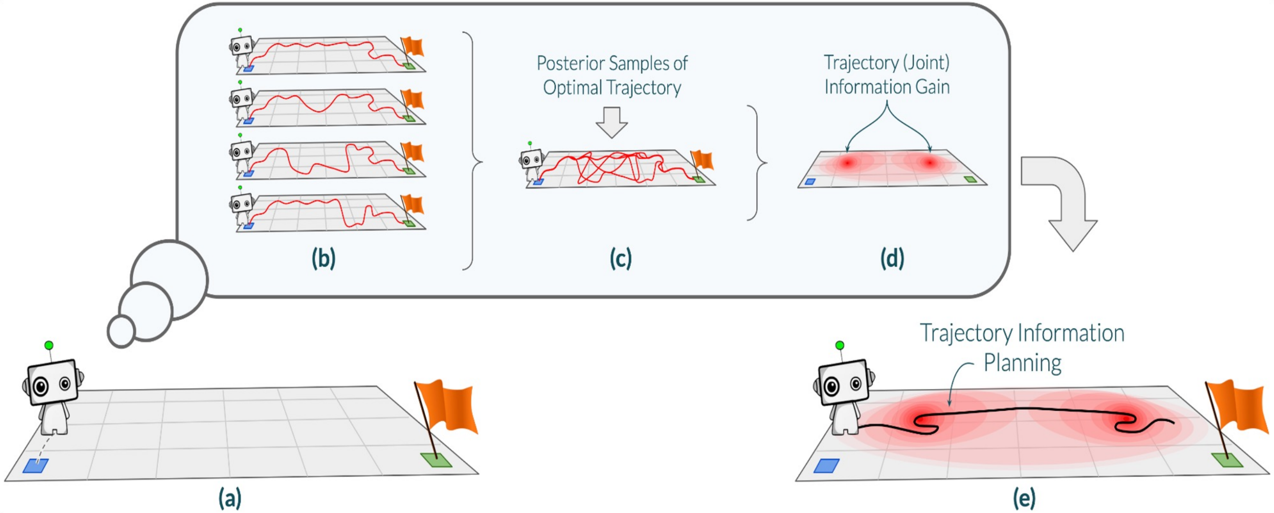


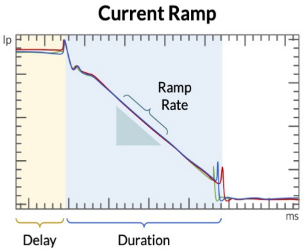
- We tested RL tearing avoidance control in an ITER baseline
- The AI-controlled shot preemptively controlled so avoided TM and achieved higher fusion gain.
- The controlled shot sustained a marginal tearability until the end of the flattop.

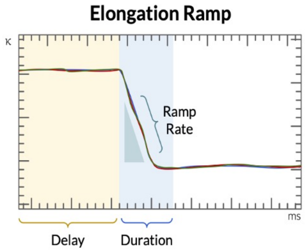


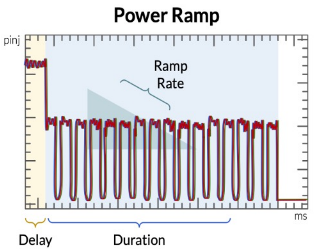
DIII-D experiment with RL controller **(Nature, In Review)**

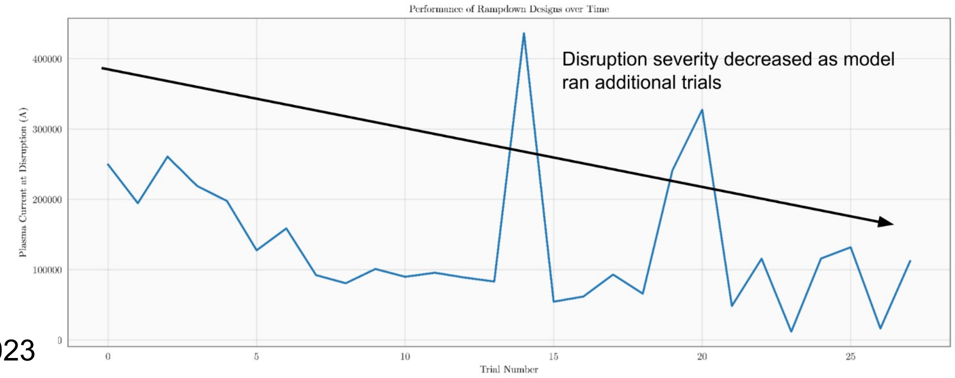
Scenario design: Ramp down the plasma with minimal left over current









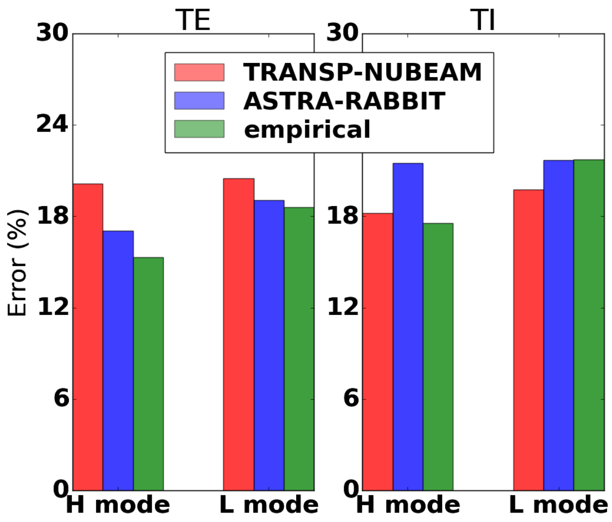


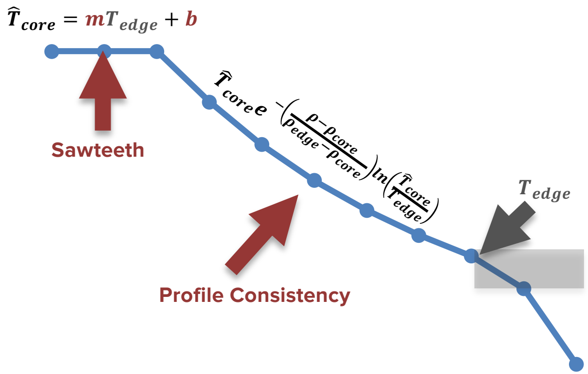
V.Mehta et al. 2023

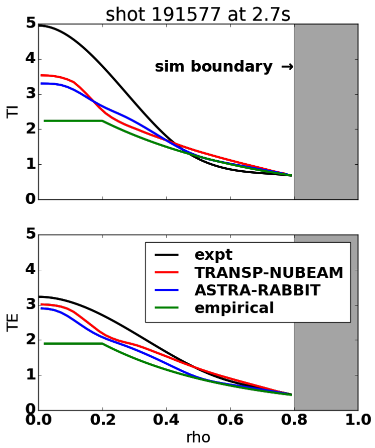
Combining Data + Physics

Issue with Simulations: 1D simulation results comparable to linear fit

- **Validate Te/Ti predictors using state-of-the-art settings**
  - **Use multiple independent implementations (TRANSP + ASTRA)**
  - **Run on ~hundreds of cases automatically**
  - **Compare to empirical (linear regression) model**







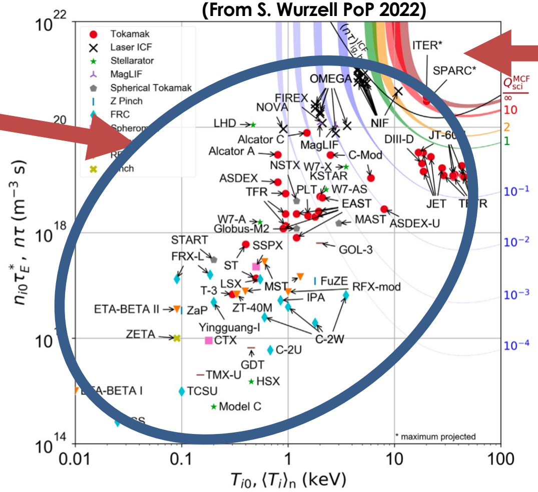
[J. Abbate, PoP, In review 23]

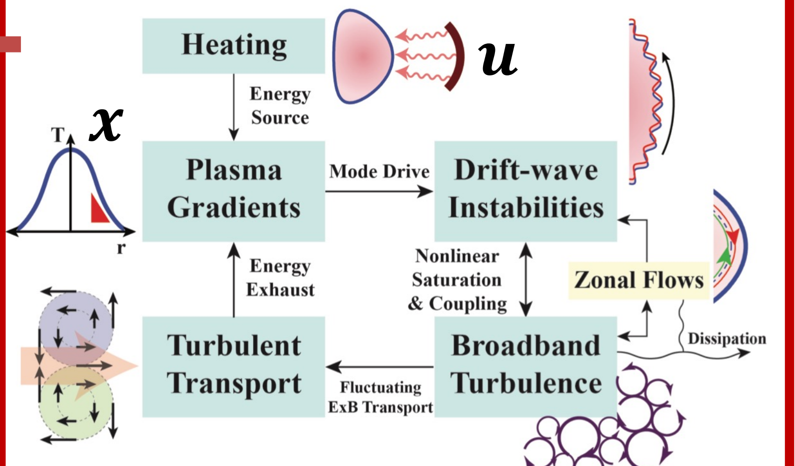
Plasma Control

Current Work: Physics Simulation + Data: Better Prediction of Unseen Space

Explored points
(historic experiments)

(From S. Wurzell PoP 2022)



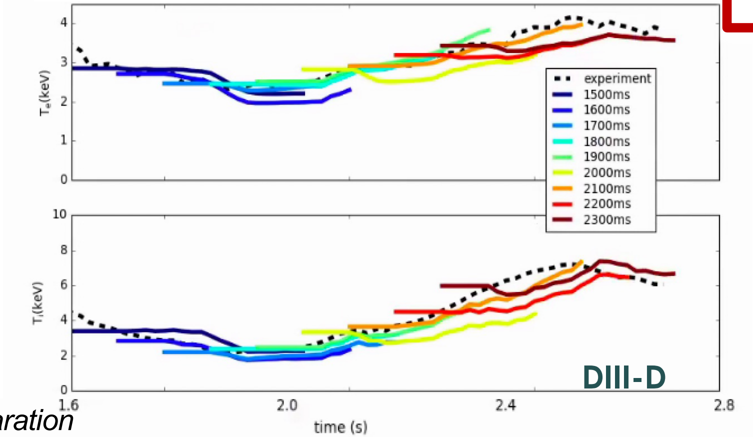


(From P. Rodriguez-Fernandez MIT thesis 2019)

Reactor regime
(explore via sims)

Train neural net on ensemble of simulations

Example:
Physics: ASTRA+ TGLF Transport Simulations
Data: AUG←→DIII-D



Abbate *in preparation*

Plasma Control

Current Work: Physics Simulation + Data: Better Prediction of Unseen Space

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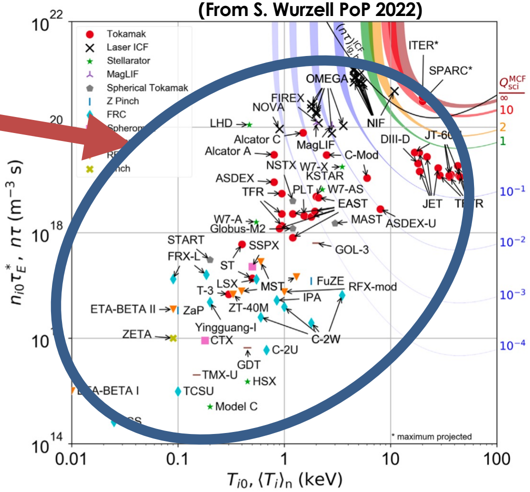
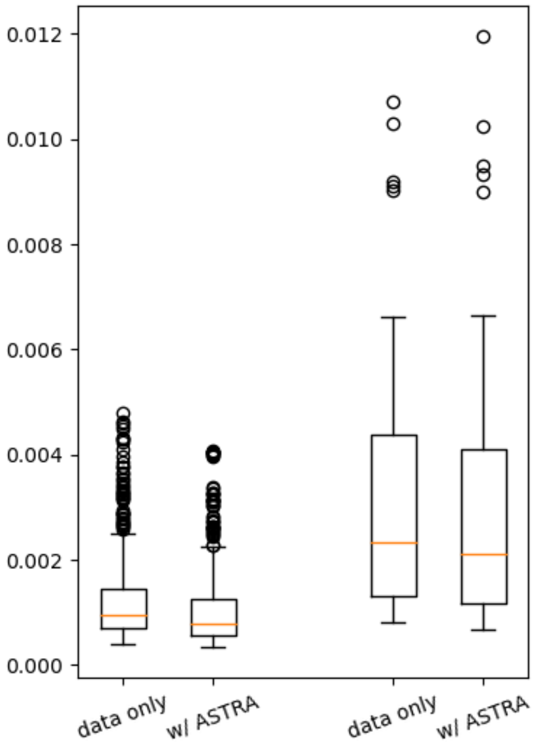


Train neural net on ensemble of simulations

Example:
Physics: ASTRA+ TGLF Transport Simulations
Data: AUG←→DIII-D

2. Example:
Predict High Current shots from Low Current Ones

➔



Low I_p High I_p

https://github.com/PlasmaControl/PlasmaEvolution

Abbate *in preparation*

Plasma Control

Conclusions

- Data-based control applied in real experiments successfully.
  - Plasma State Prediction (Shape, 1D profiles)
  - Robust diagnostics to noise and signal loss
  - Plasma Evolution Prediction
  - Instability Prediction
  - Instability Avoidance Control
- Sim+data based plasma prediction show reasonable promise.