PPPL PRINCETON PLASMA PHYSICS LABORATORY

Adaptive and data-driven controls for fusion plasma optimization

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Speaker's resume

- **PhD in plasma reconstruction and nonlinear MHD modeling (2014-2020)**
  - Kinetic equilibria reconstruction in KSTAR
  - Nonlinear 3D MHD modeling (JOREK) on ELM and RMP in KSTAR

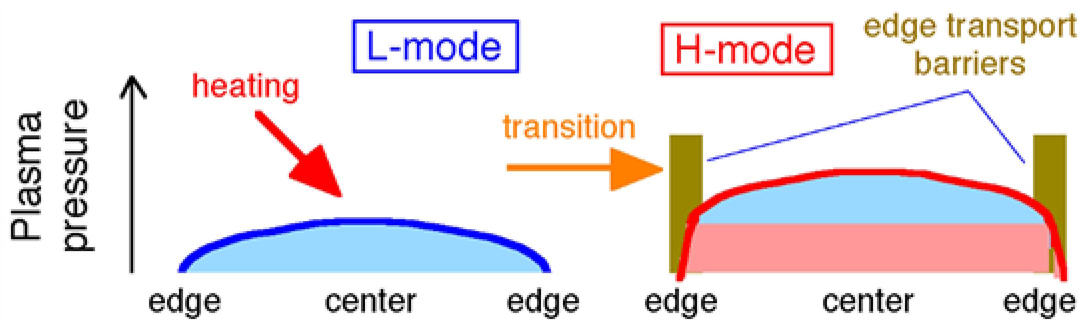
- **Postdoctoral research at Princeton University (2020-2022)**
  - Real-time instability control (ELM/TM) in KSTAR/DIII-D
  - Nonlinear RMP transport modeling in KSTAR/DIII-D

- **Staff scientist at PPPL (2023-present)**
  - Real-time optimization of 3D/detachment in DIII-D/KSTAR
  - Deputy leader for joint hybrid scenario taskforce in DIII-D/KSTAR

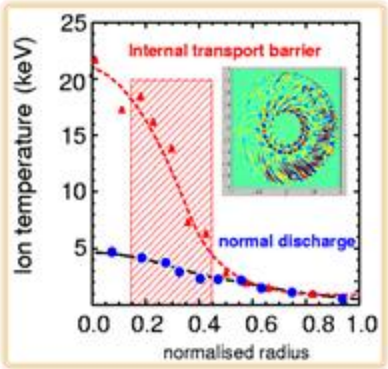
Contents (Optimization of plasma stability and confinement)

Tokamak: Way to confine the plasma against its nature

- Achieving sufficiently **high temperature and density** is key mission
  → Need to **confine** the plasma
- However, the nature doesn't like confinement
  → Try to escape through transport
- **Transport barrier** provides a promising way to achieve strong confinement
  → L to H mode or ITG, etc.



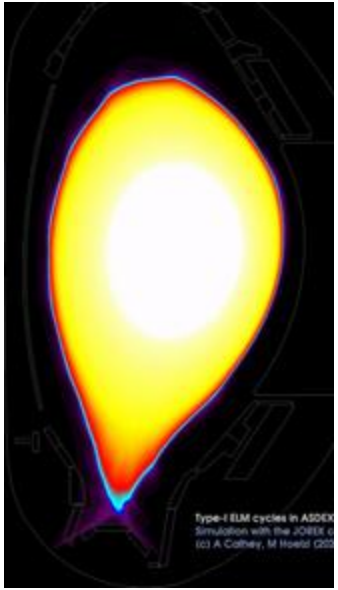
[L to H mode]



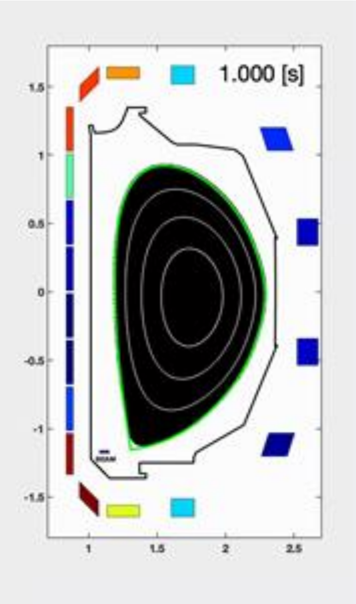
[ITB]

Confinement drives instabilities, discouraging the machine

- However, a transport barrier or strong confinement provides plasma another path to escape → Instability by gradient
- Plasma instabilities generate **macro**/micro & **transient**/continuous transport → Harms operational and mechanical safety



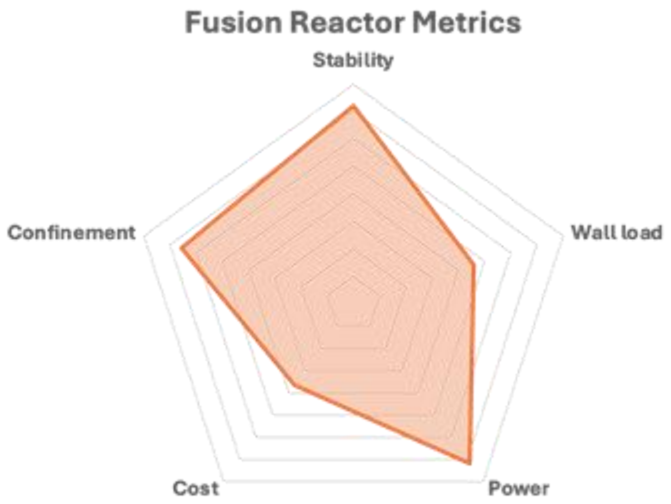
[ELM (AUG), A.Cathey 2020]



[Example of tearing mode]

Finding balanced optimal solution is key for plasma operation

- Therefore, **finding the balance** between confinement and stability is key
- In addition, **additional constraints** exist for future tokamaks
  →Heat loads to the wall, cost efficiency, etc.
- Inevitably, tokamak plasma requires a multi-objective optimization



In simple case, directly exploring system is working

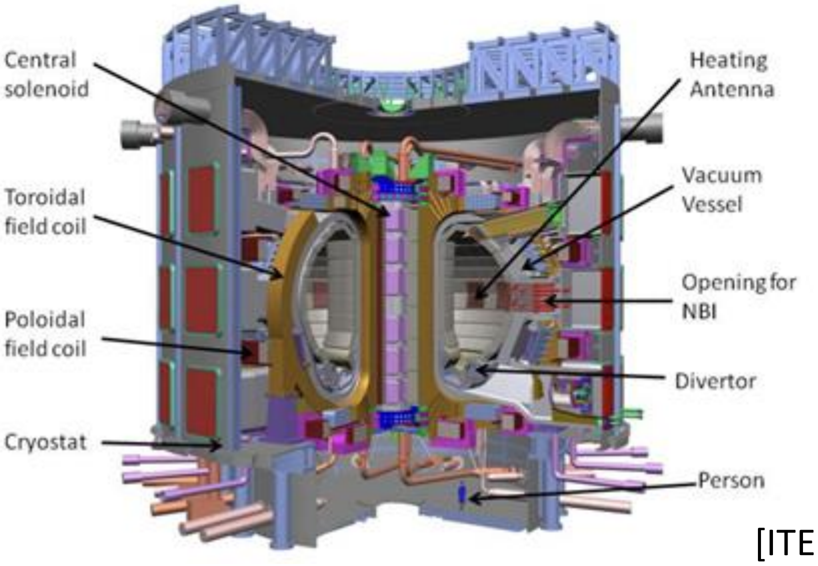
- Feedforward scan to identify system
- Directly explore the system to find the solution

However, tokamak is too complicated for simple solution

- However, **expensive** with higher dimensions and dynamical behavior
- Can potentially break things
- Inapplicable in time-evolving/nonlinear/long-term operation→ Tokamak

Tokamak: Way to confine the plasma against its nature

- Tokamak needs an optimized **solution compatible with time-evolving** scenarios → Particularly, important for stable long-pulse operation in ITER
- Translated to the **control solution** (simply linear or complicated nonlinear)



[ITER Final Design Report (IAEA 2001)]

Contents

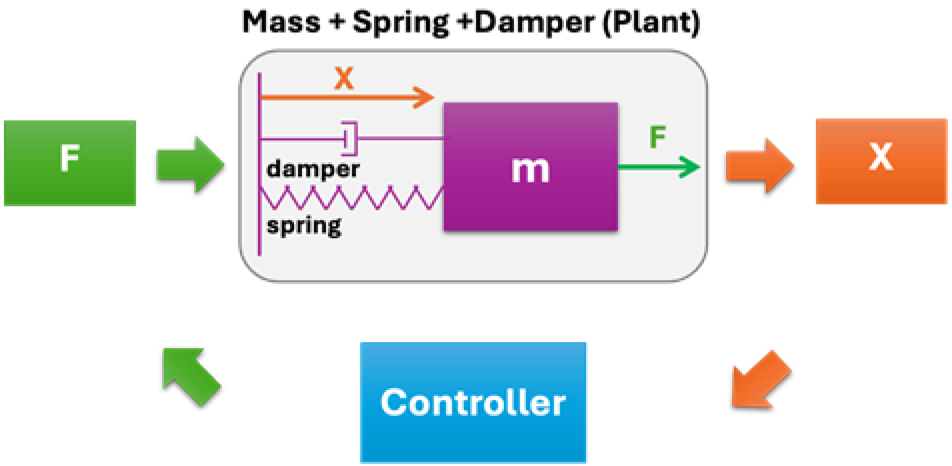
- **Introduction**

  - Needs of controls in tokamak

  - Example of controller

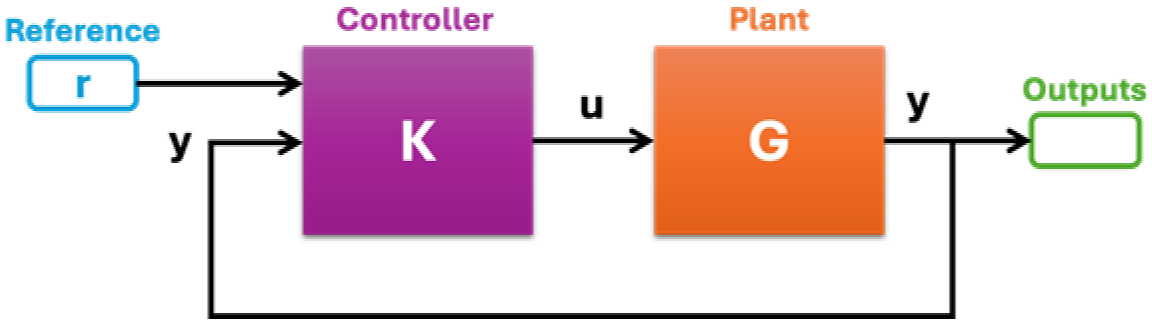
Controller for deriving desired solution

- **Controller** finds the desired solution of the **plant** through a closed-loop
  - A dynamical system driven by externally imposed **inputs (u)**
- Based on the **system model (or identification)**
  - First principle (physics): Equation of motion X(t,F)
  - Data-driven: Measured response (X) for various forms of input (F) in frequency



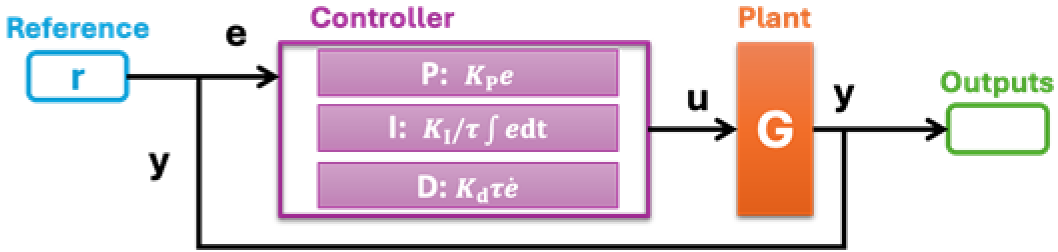
Control system

- A control system (controller, K) regulates the behavior of device/system via control loops, which takes inputs of
  - Reference signals **(r)** & Outputs **(y)** of the plant **(G)**
- And produces output of
  - Control inputs **(u)** to be applied to the plant to satisfy objectives
  - Plant outputs following the references & stabilized
  - With control inputs remain within described bounds
- Correlation of **K(r,y)→u: Control law (or policy)**

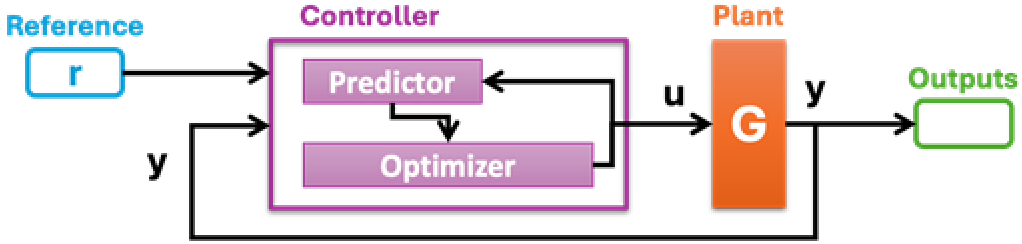


Typical type of control in tokamak

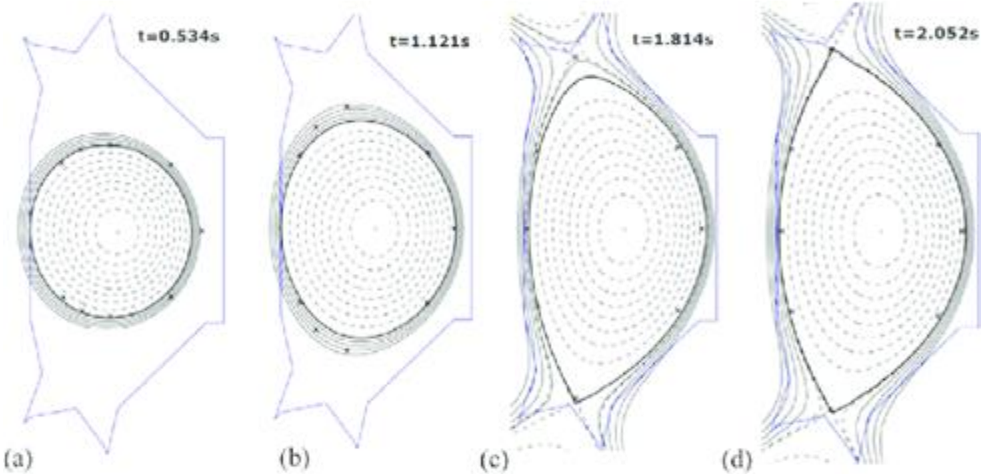
- If the system is continuous and not too nonlinear,
  Classically, the **PID controller** based on the system ID/model and tuning



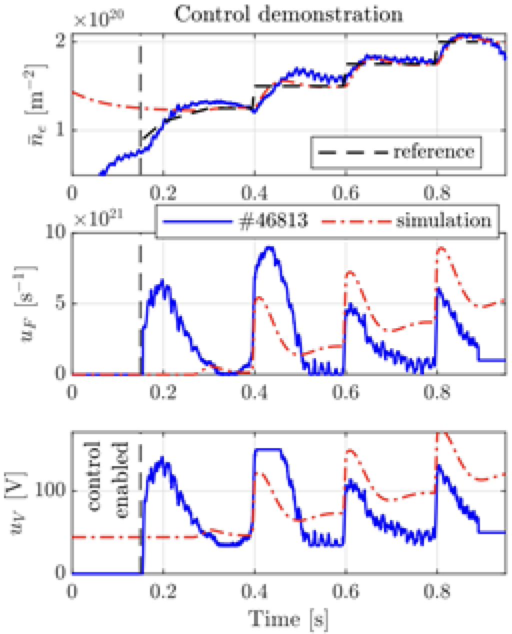
- If we know model to describe and predict plant, advanced solution is possible using **model predictive controller (MPC)**



- **Shape and Gas control (density)**
  - Good for linear system



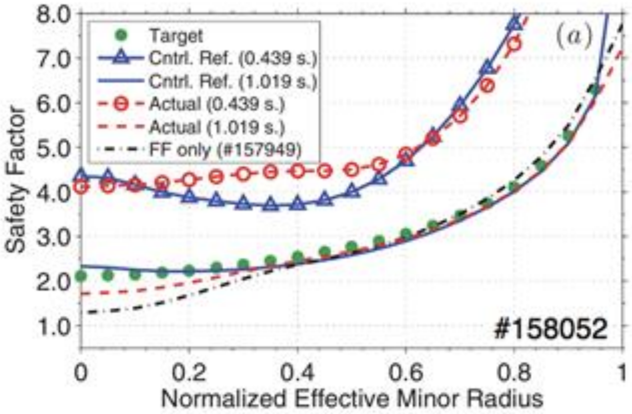
Shape control in EAST [Q.P. Yuan, NF 2013]



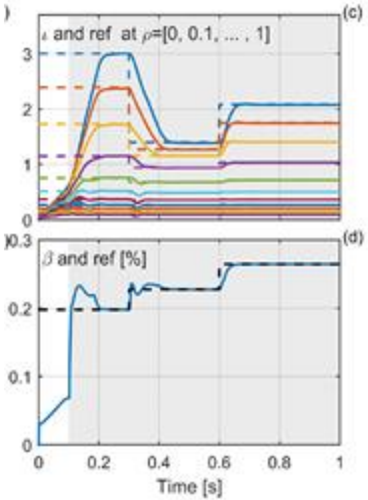
Density control in MAST-U
[G.L. Derks, FED 2024]

Example of control in tokamak - MPC

- **Plasma profile control**
  - More complicated (or nonlinear) system
  - Ex) Profiles by plasma actuators (heating, current drive)



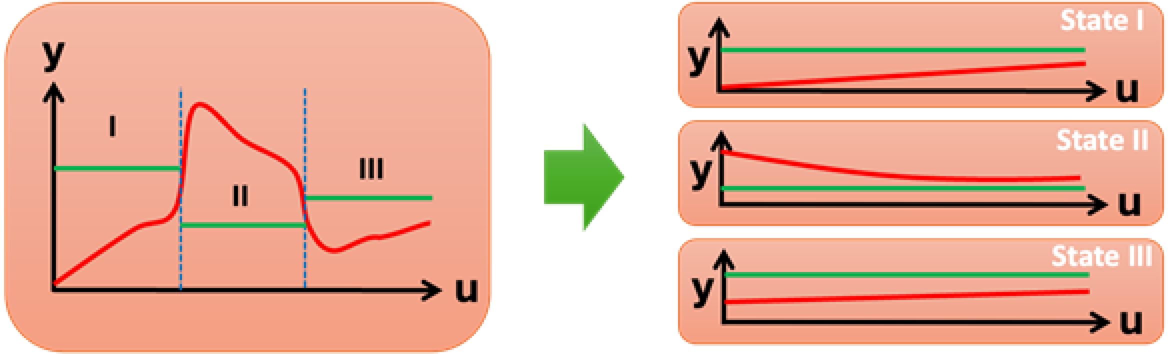
q control in DIII-D [E. Schuster , NF 2017]



q, beta control in TCV [E. Maljaars, NF 2017]

Adaptive control is simple and effective approach to handle complicate system

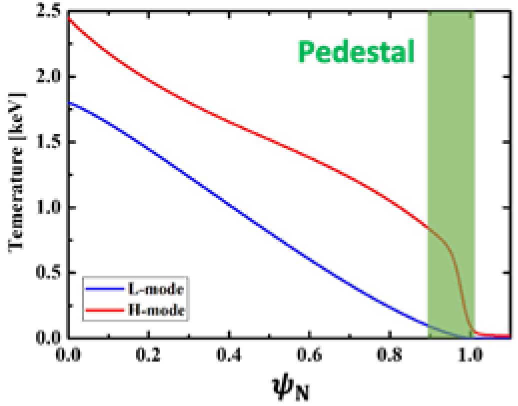
- However, plasma behavior and control objective can be highly nonlinear, **bifurcative**, where the model is unknown.
- Categorize plasma with defined **finite machine states**.
  → Effectively handle bifurcating systems and purposes.
- Adjust control policies (parameters) for (detected) states in time.
  → **Adaptive control** strategy.

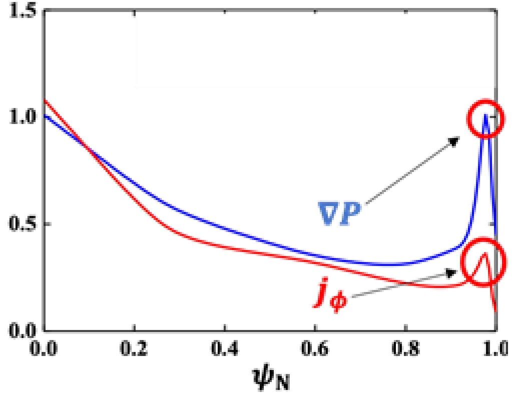


Contents

- **Edge localized mode (ELM)** driven by a strong profile gradient at the pedestal
  - Pressure gradient (∇P)
  - Edge current density (j_φ)

- ELM as a MHD instability
  - Peeling-ballooning mode (PBM)
  - ∇P: Ballooning component
  - j_φ : Peeling component

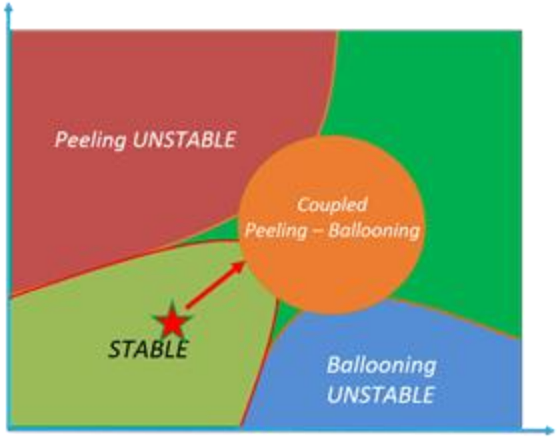




ELM drives transient heat flux on the divertor, which must be avoided

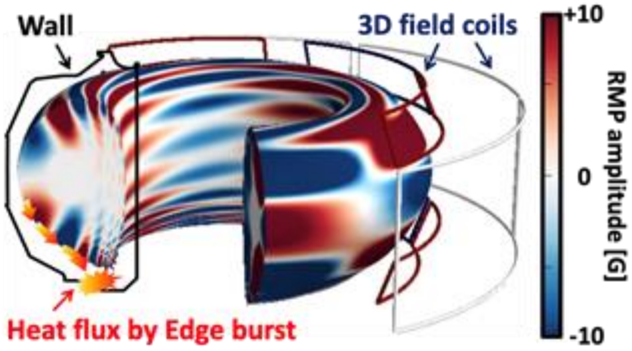
- ELM onset and crash when pedestal reaching the stability limit (**∇***P*,*j*).
- **Transient heat flux** on plasma facing component.
  → In ITER, this severely damage the machine's life span.
- Therefore, ELM must be strongly mitigated or **suppressed**.

Plasma current (j)



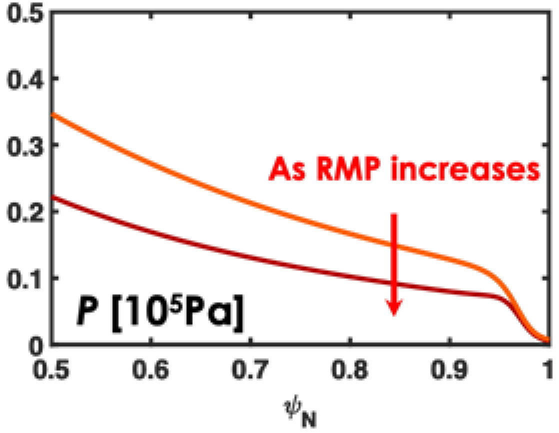
Pressure gradient (**∇***P*)

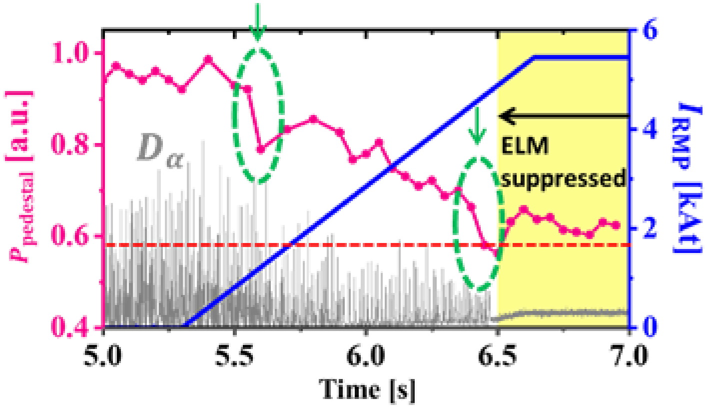
[ELM filaments in MAST (Andrew Kirk)]



Resonant magnetic perturbation (RMP): Degrading pedestal

- **Resonant magnetic perturbation (RMP)** by external field coils
- Induce transport at the pedestal
- Degradation of the pedestal leads to the suppression of ELMs
  → **RMP-ELM suppression**
- Promising method for ITER
- However, it possesses disadvantage
  → Loss of H-mode confinement



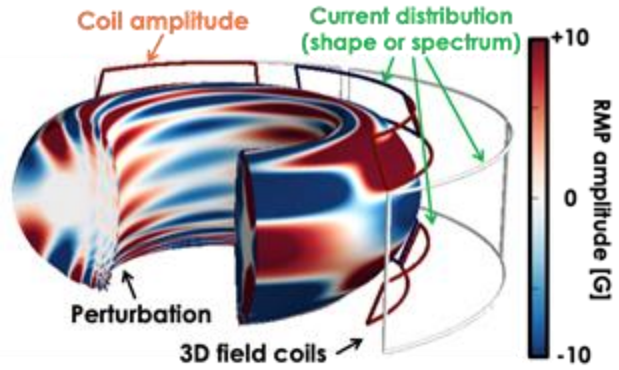


KSTAR RMP-pump [S.K.Kim, NF 23]

RMP is characterized by Amplitude and Spectrum

- RMP is changed by adjusting the **amplitude and distribution** of coil currents
  - Amplitude (I_{RMP})
  - Spectrum (S): Normalized current distributions

- Proper RMP (control) is essential for ELM suppression
  - **Sufficient I_{RMP}** for pedestal degradation
  - **Optimized S** for suppression without core-locking (plasma disruption)

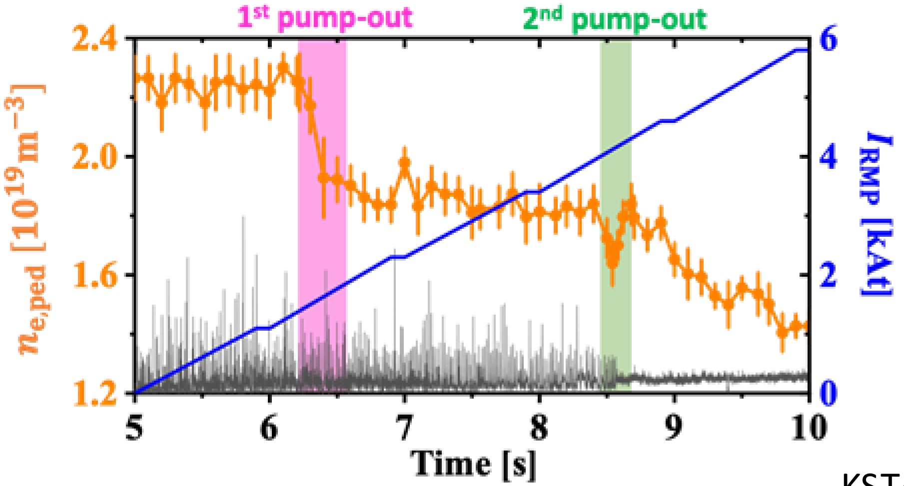


DIII-D 3D-Coil [S.K.Kim, NC 24]

RMP control is multi-objective problem in nonlinear system

- Plasma response to RMP amplitude (I_{RMP}) is nonlinear
  - Transient behavior in pedestal (confinement) degradation

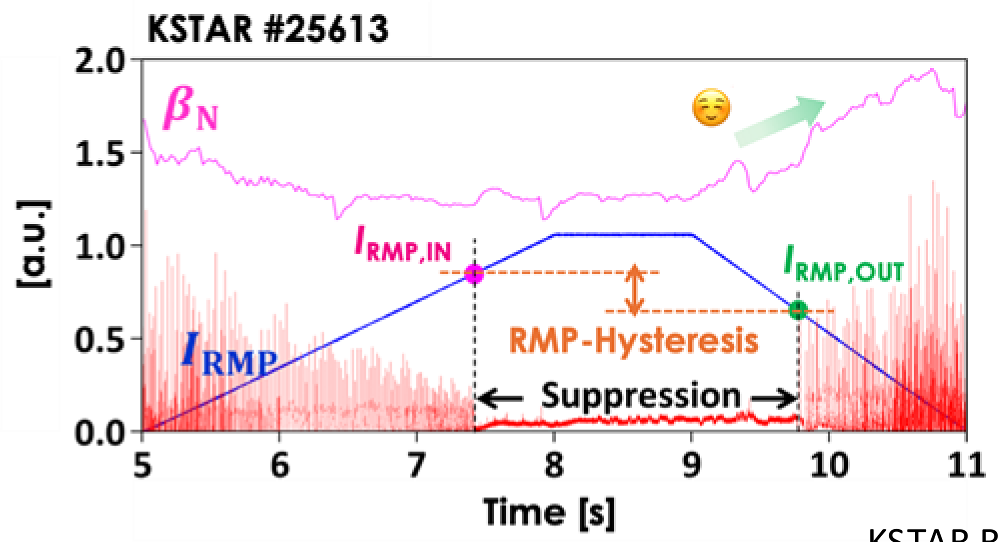
- Bifurcation in two different states: ELMy vs Suppressed
- I_{RMP} optimization: **Balancing suppression and confinement**



KSTAR RMP-pump [S.K.Kim, NF 23]

Hysteresis in RMP response allows the confinement recovery

- RMP-hysteresis in ELM suppression ($I_{RMP,IN}$ > $I_{RMP,OUT}$)
- Enables confinement recovery in a suppressed state
- However, difficulty in prediction due to nonlinearity
  → rt-control solution



KSTAR RMP-hysteresis [S.K.Kim, NF 22]

Contents

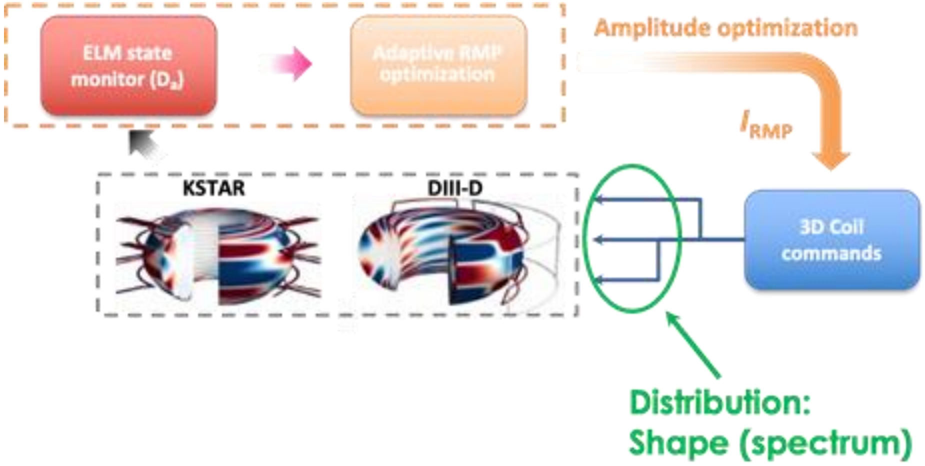
Adaptive control can provide simple solution to this problem

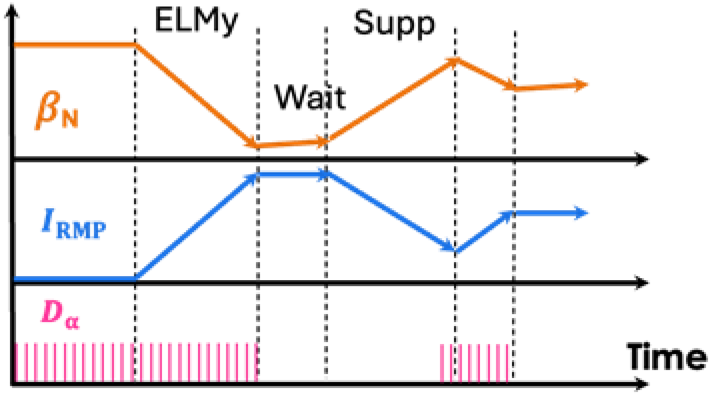
- Defined three machine states
  - ELMy (when ELM presents)
  - Wait (500ms at ELM get suppressed)
  - Suppressed (no ELMs)

- Control policies
  - ELMy: Increase I_{RMP} → To get suppression
  - Wait: Hold I_{RMP} → Give time for the system to respond
  - Suppressed: Decrease I_{RMP} → To increase confinement

Adaptive amplitude control policy while maintaining simplicity in spectrum

- The transition between machine states
  - Based on detected ELMs from the **Da signal**
- Control policy on I_{RMP} **only with fixed spectrum (empirically)**
- Implemented in DIII-D and KSTAR plasma control system (PCS)

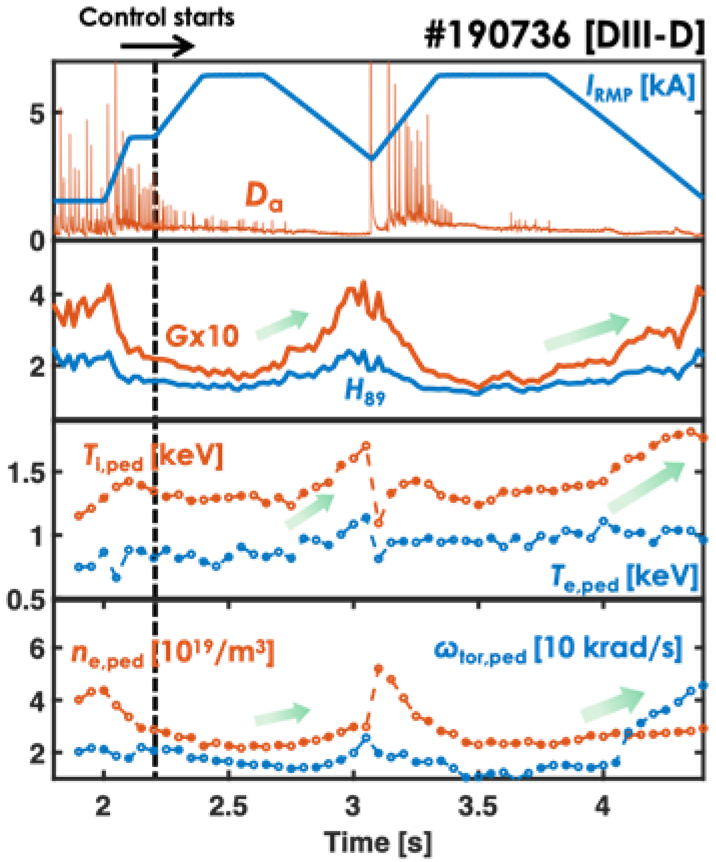




Successful demonstration: Suppression w/ enhanced confinement

- Enhanced confinement by **adaptive I_{RMP}**
  - ITER similar shape plasma
- **Pedestal recovery** by exploiting hysteresis
  - Thermal, particle, and momentum pedestal
  - Confinement quality (H_{89})
  - Figure of merit ($G=\beta_N H_{89}/q^2_{95}$)

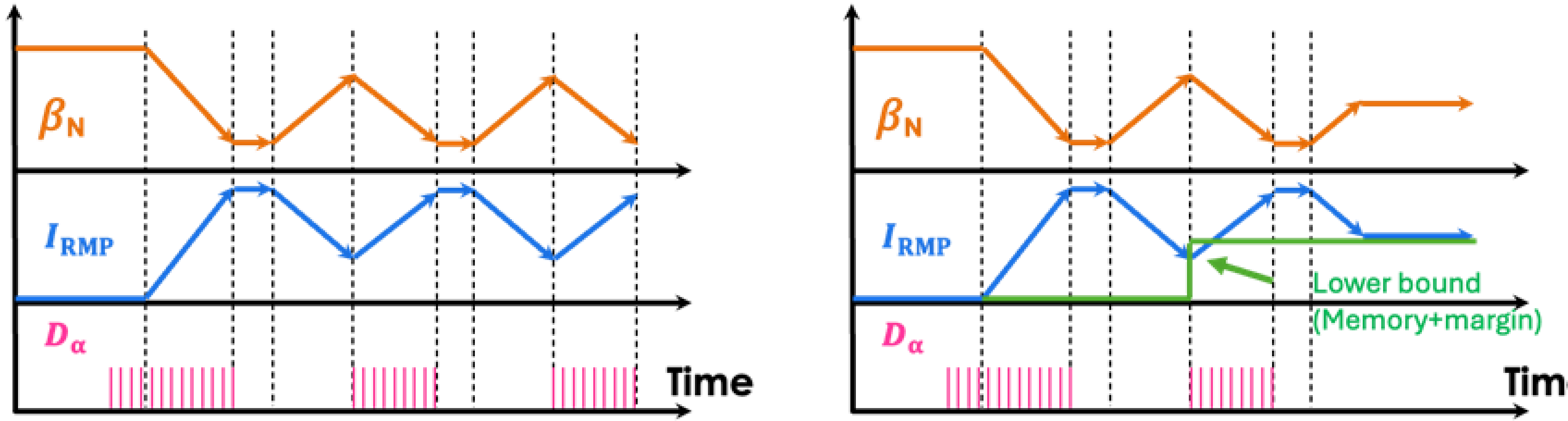
- Control **convergence is limited**
  - Limitation of bang-bang approach



[S.K.Kim, NC 24]

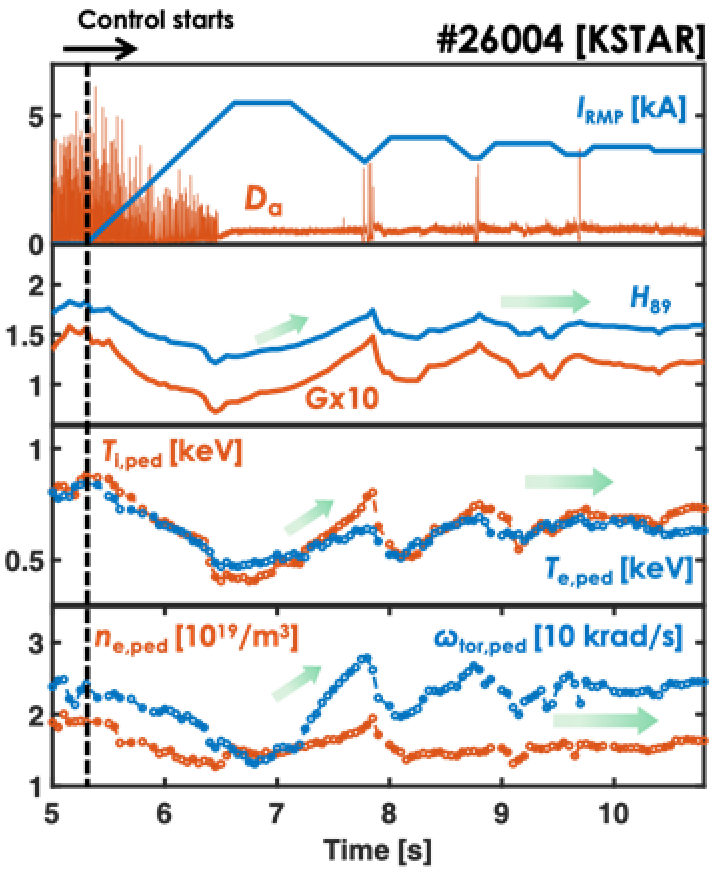
Control convergence can be improved by adding simple memory

- Two simple control policies can lead to bang-bang control.
  - Unfavorable oscillatory behavior
- Introducing memory on the condition where state transition occurs
  - Set control boundary with memory+margin(input)
  - Enable convergence



Stabilization in long pulse with simple additional constraint

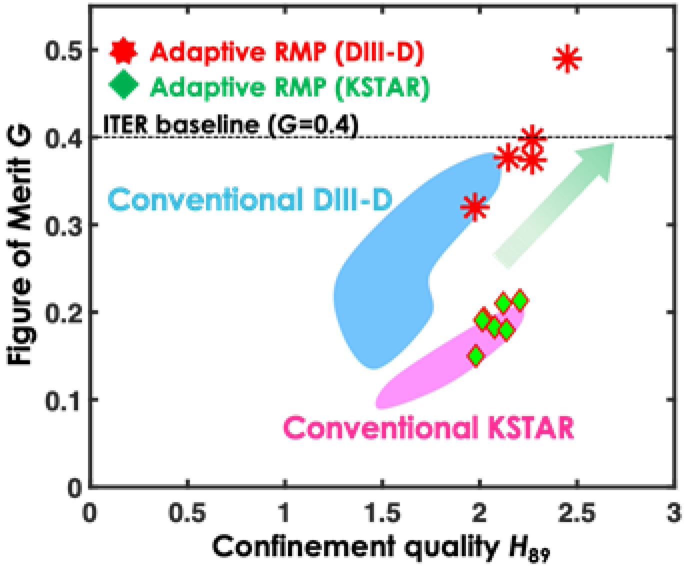
- Demonstrated in KSTAR
  - Leveraging long-pulse operation
- Confirmed **convergence**
  - Suppression with H-mode confinement
- Confirmed **multi-device capability**
  - Again, recovery in all pedestals, H and G



[S.K.Kim, NC 24]

Adaptive control is effective but we can make better

- Effective application of adaptive RMP control
  - *G*=0.4 for ITER baseline [Gormezano, NF 07]
- However, these control policies and state detection are not clever enough
- Adaptive control can be **improved** by introducing **models** and **state predictor**

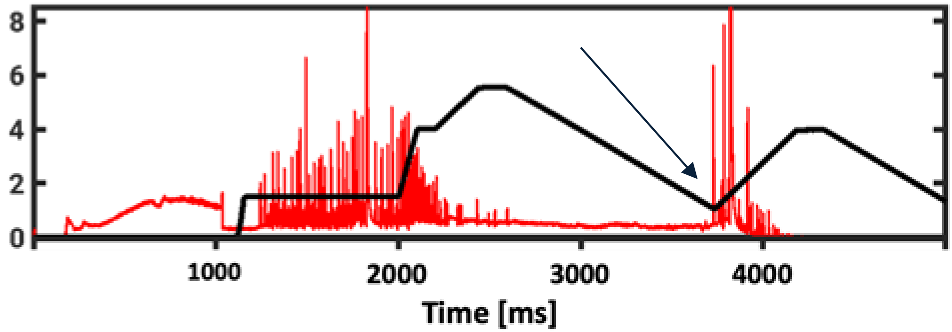


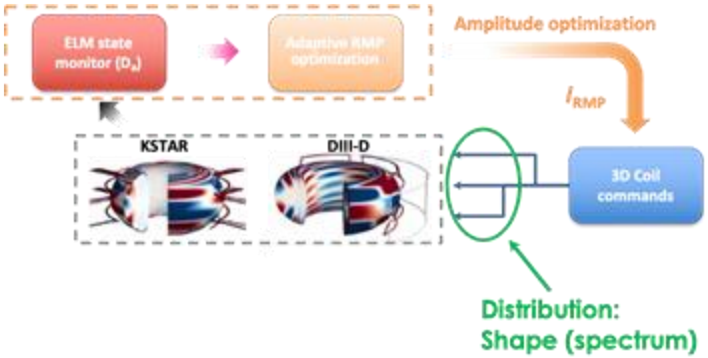
[S.K.Kim, NC 24]

Contents

- **State detector** is convenient but ineffective in avoiding **undesired state**
  → State **probing or prediction** is an effective solution

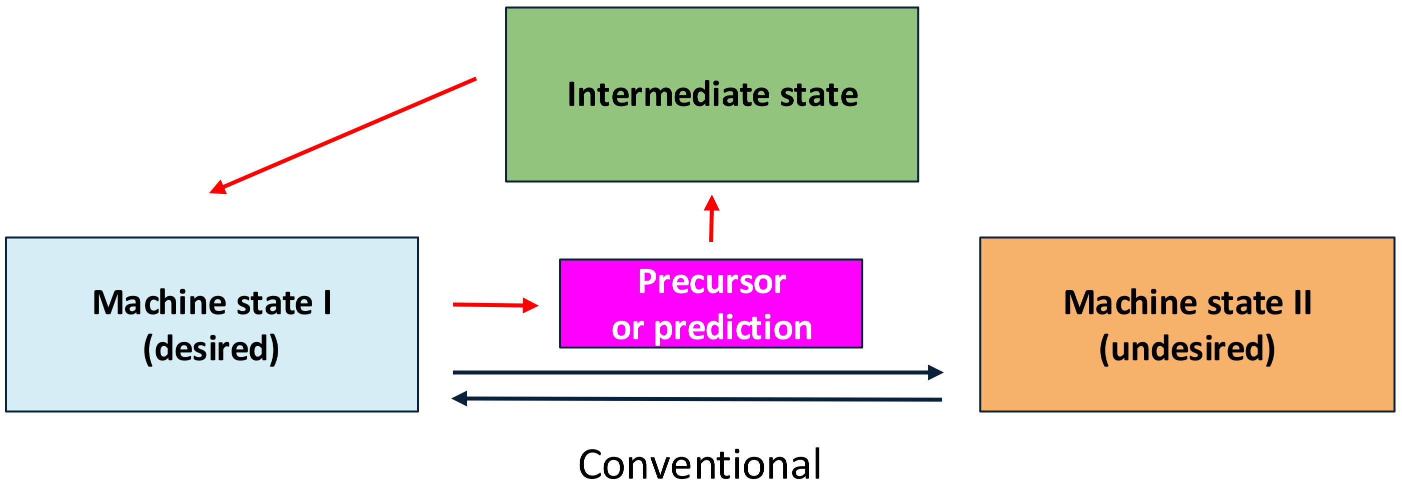
- Introducing the **physics model** allows a more flexible control policy toward an advanced optimized control solution
  → Ex. Strategy to deliver proper/optimized RMP shape (spectrum)





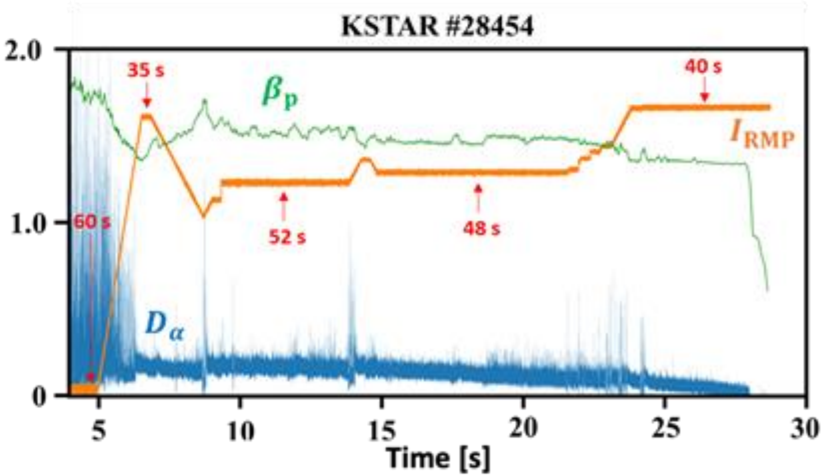
State (ELM) prediction allows earlier action to prevent it

- The conventional approach allows state transition
- Earlier switch of control policy based on state prediction
  → Intermediate state with control policy that prevents transition
- For example, maintaining ELM suppressed state by prediction and RMP control in advance to avoid state transition



Such strategy allows more effective prevention of state transition

- Memory-based prevention of state transition is effective
  → Ex. Stable convergence of ELM control
- However, memory can be outdated in the dynamical system
- In addition, the memory scheme is vulnerable to sporadic system oscillation
  → Lead to the unsuccessful optimization
  → Ex. Maintaining over RMP current and bad confinement



[S.K.Kim, APS-DPP 22]

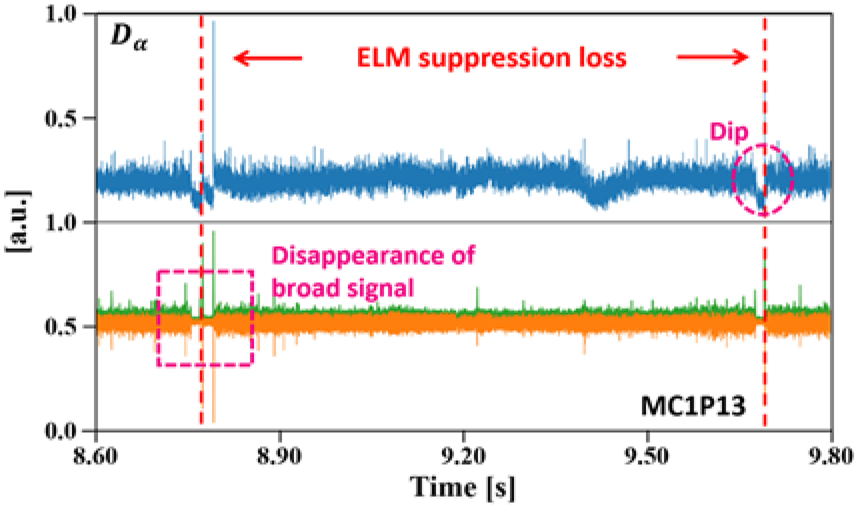
Predicting the state transition can be done through precursor detection or prediction of state evolution

- Precursor: Patterns or signals which is observed before a transition
  → Robust and straightforward to detect
  → However, not relevant to general cases

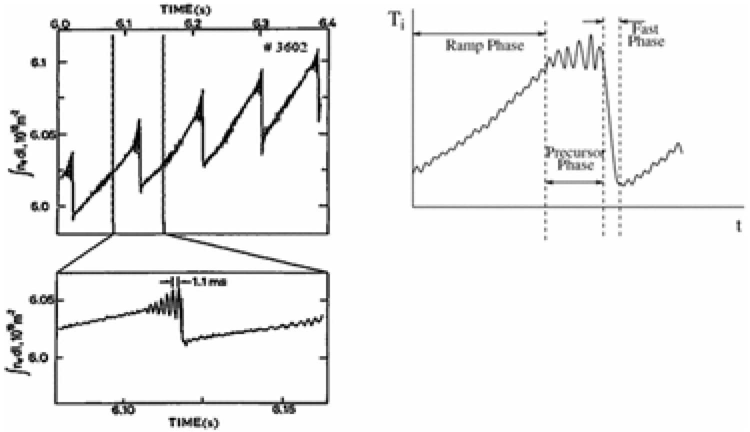
- Prediction: Foresee the future state (next 10ms, 1s,..)
  → Based on the history or unrecognized pattern
  → Enables general solutions for various cases
  → However, it is physically more challenging

Examples of precursor and prediction

- Examples of precursors for instabilities (Sawteeth, ELMs)
- The importance of checking multiple signals to explore it
  - First step to explore the feasibility of state prediction



[KSTAR-RMP ELM suppression, R. Shousha IAEA-FEC 23]

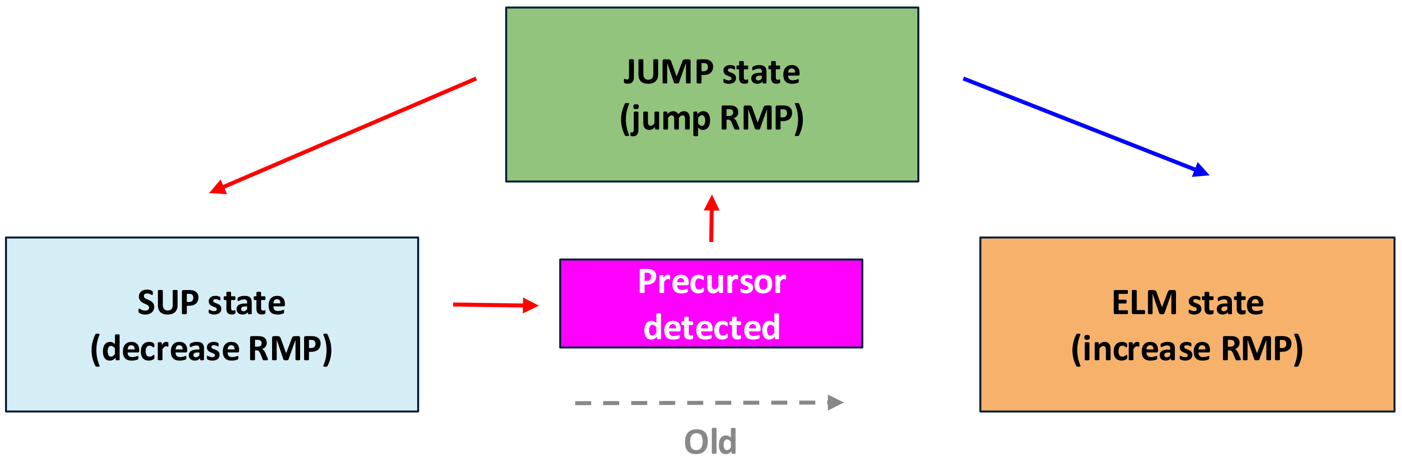


Sawtooth precursor

[I. Chapman, Active Control of Magneto-hydrodynamic Instabilities in Hot Plasmas (2014)]

Example: ELM precursor and early action to ELM prevention

- ELM avoidance/minimization during ELM suppression using precursor
  - Intermediate state (PROBE) when the precursor is detected
  - Control policy: Stepwise of RMP increase and hold
  - After the JUMP state returns to suppressed if ELM is suppressed



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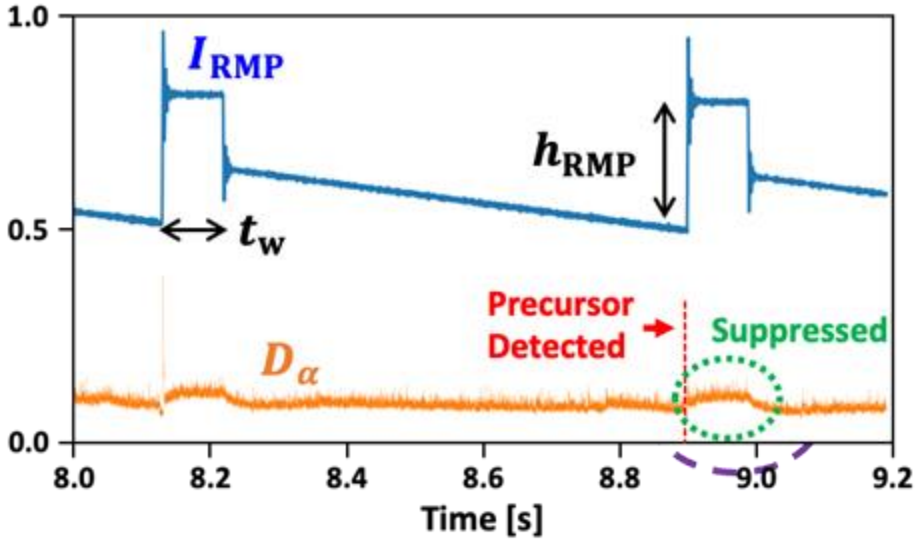
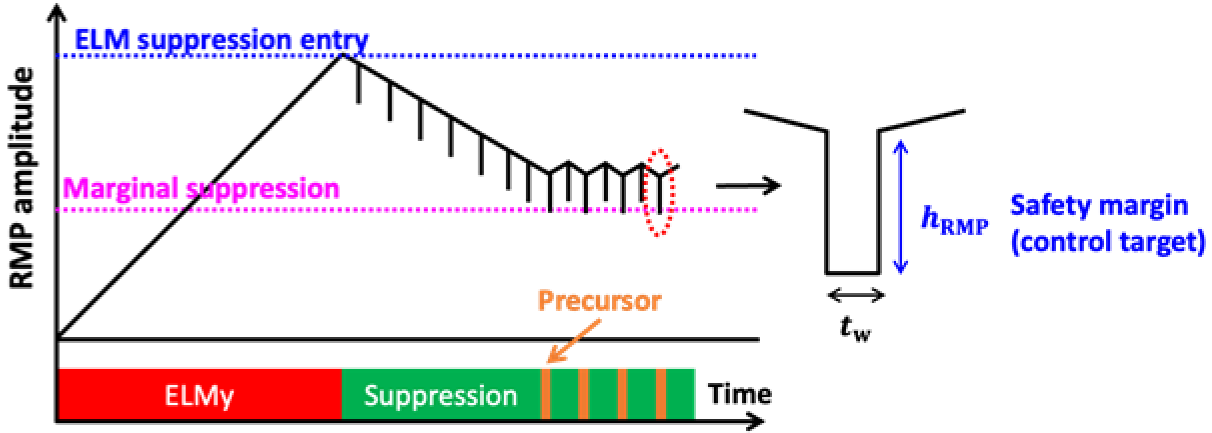


[R. Shousha IAEA-FEC 2023]

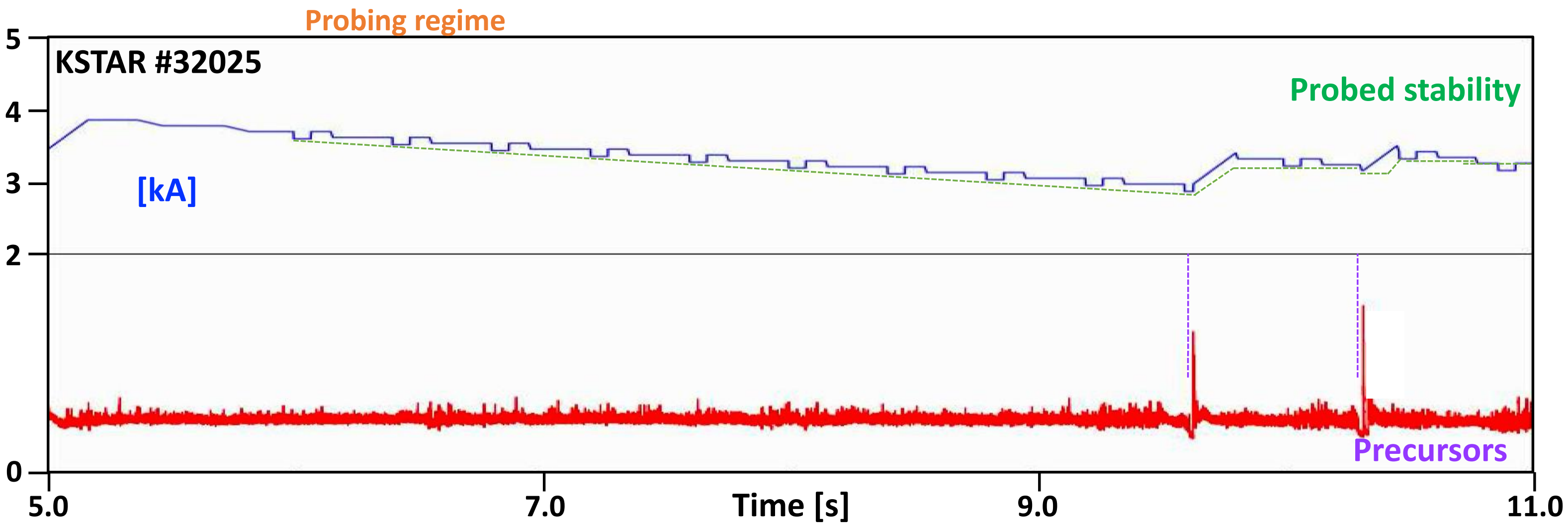
Example: ELM precursor and early action to ELM prevention

- Precursor detection can also be leveraged for **active state probing**
  - Explore the boundary where state transition occurs
- Negative pulses for state probing (or detecting marginal condition)
  - Reaching marginal level→ Occurrence of ELM precursors
- Replacing "passive" lower bound based on memory
  - Control with probed value and safety margin



Example: State probing and lower boundary control

- I_{RMP} control with probed lower bound
  - Probing leads to early detection of stability limit
  - Stable ELM suppression operation with minimal ELM onset



[R. Shousha IAEA-FEC 2023]

Limitation of precursor based approach

- However, the precursor is also sensitive to plasma condition, and time margin before state transition is not consistent
  → Prediction can provide a better path
  → However, developing rt-predictive model is hard

- Particularly difficult when the system is highly nonlinear with less knowledge
  → No model or
  → Irrelevant to real-time application

- **Data-driven model** can be an effective solution

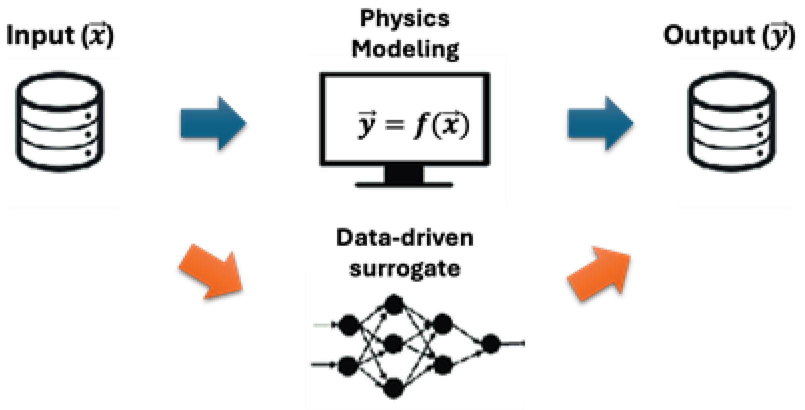
Contents

Data driven model provides effective way

- Data-driven model: Model is driven (regression) by a given database
- Possibly learns physics inside the data
- Data can be constructed from **experiments** (measurement) and **simulation**
- Effectively handles
  - Model **acceleration**
  - Model with **unknown physics**

Model-based driven: Surrogate with power for scalability

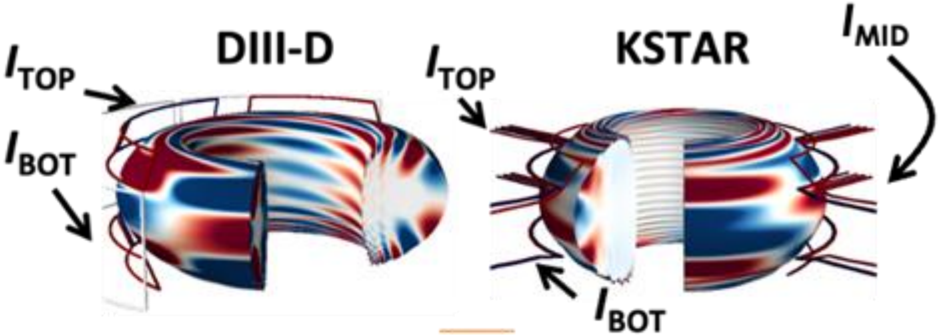
- Conventional simulation or modeling enables **physics-based prediction** and optimization
- In addition, it has good **scalability**
- However, the effort is often **limited because computational cost**
  - Ex. Linear MHD calculation takes >10s
- **Surrogate model** can be an effective solution (acceleration)

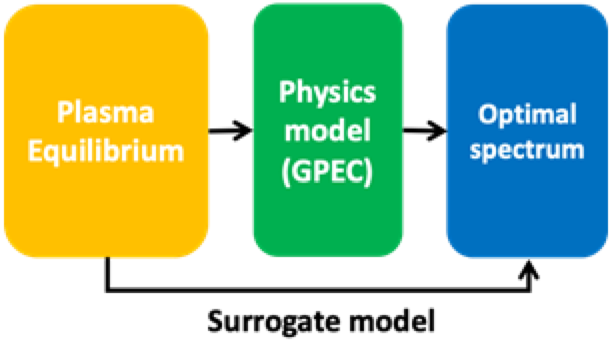


Example for surrogate: rt-GPEC

- Optimized RMP spectrum
  - ELM suppression without driving undesired instability
  - Relied on the empirical (scanned) spectrum

- Physics-based optimization [J.-K. Park(NP 18), S.M. Yang(NC 24)]
  - Experimentally demonstrated physics model (GPEC code)
  - Considerable **computation time** (~10s)

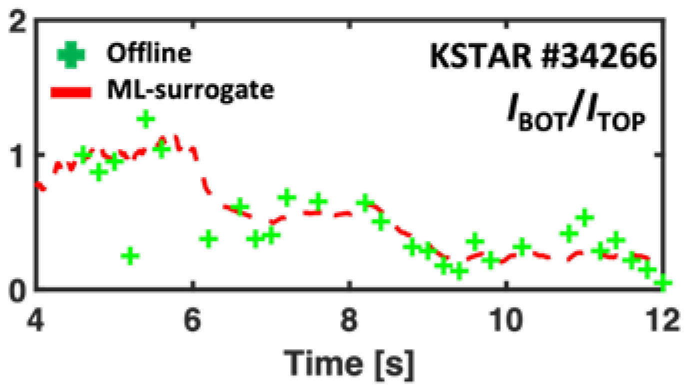


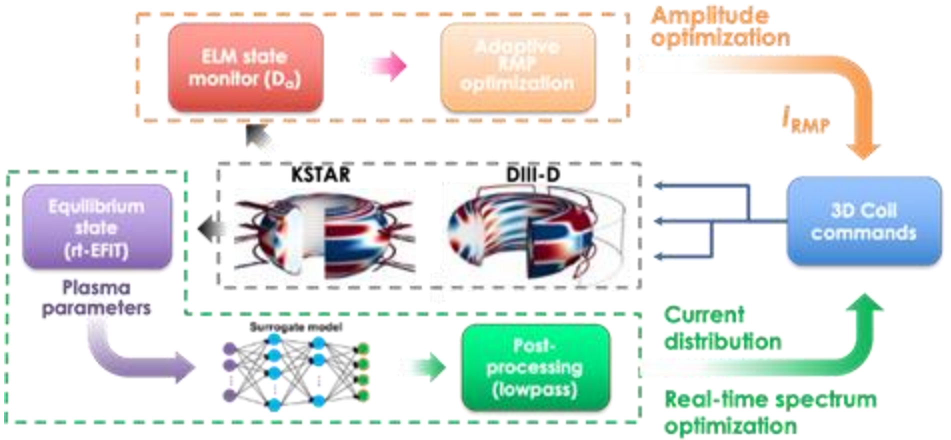


Example for surrogate: rt-GPEC

- **Model-based** surrogate models (rt-GPEC) [S.K. Kim Nat. Comm 24]
  - Accelerate to 1ms using real-time equilibrium info (EFIT)
  - Provides real-time solution

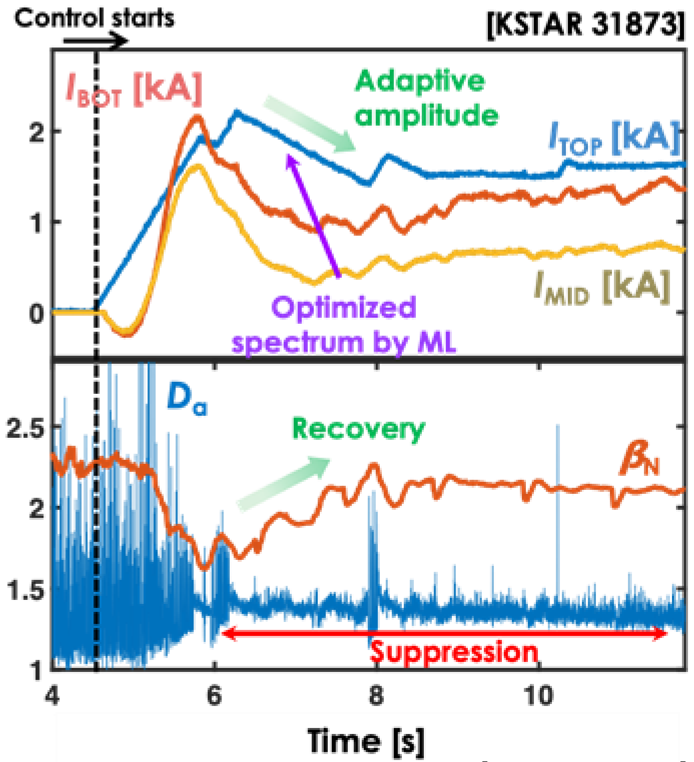
- Integrated to adaptive I_{RMP} control → Enables fully optimized RMP





Application for surrogate: Integrated ML and adaptive controls

- Successful demonstration in KSTAR tokamak [S.K. Kim Nat. Comm 24]
  - Control-driven n=1 RMP (very challenging)
  - Adaptive algorithm → I_{RMP}
  - ML-surrogate → Spectrum
- Compatible with dynamic evolution
  - Favorable for long-pulse and ITER
- **Scalability of ML model** to ITER
  - Advantage of a **physics-based** model



[S.K.Kim, NC 24]

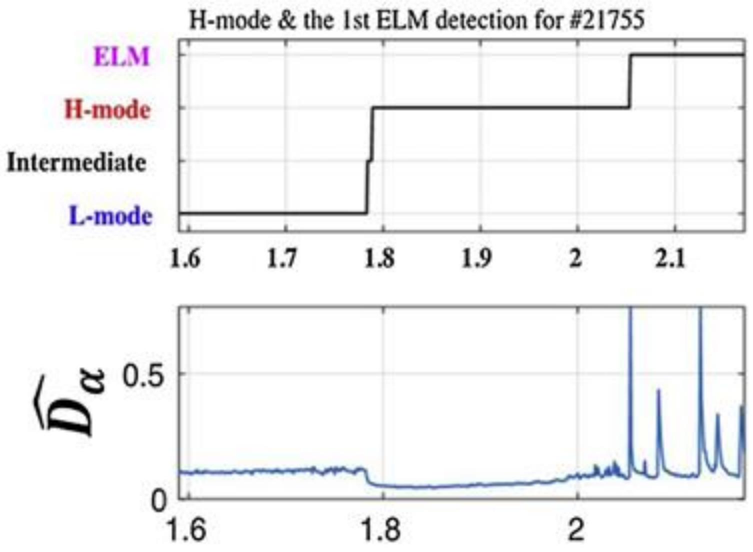
Contents

Diagnostic-based driven: Capturing un/known physics/patterns

- Database constructed from experimental diagnostic data
- Straightforward but also little knowledge of optimal mode structure before trying (Physics understanding can guide input/structure selection)
- Strong potential in finding new physics and unrecognized patterns hidden in the signals

Example: State detection (LH transition)

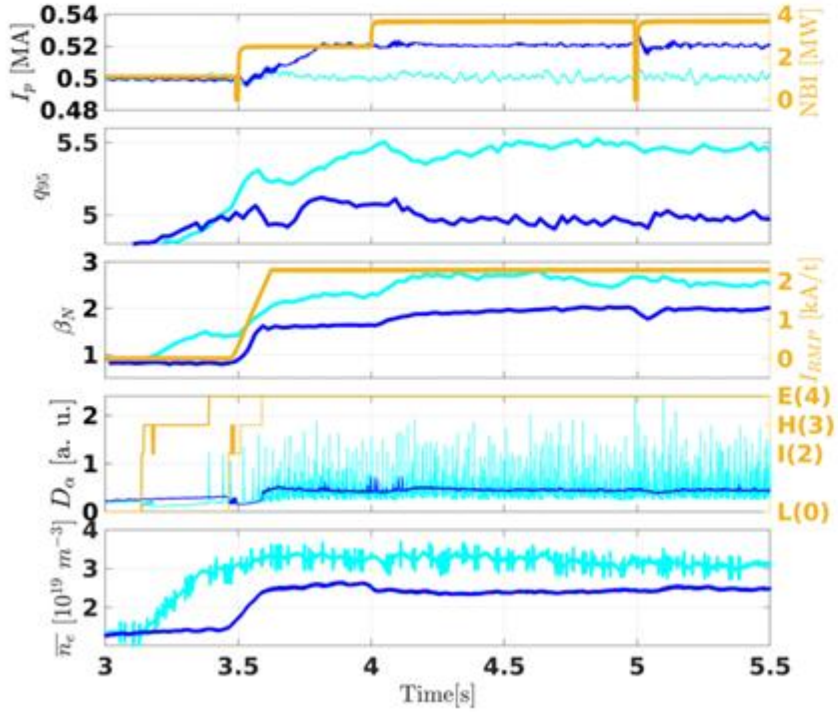
- Detecting LH transition using Da diagnostic [G.Shin NF 20]
  - LSTM based pattern detection



Application: State detection (LH transition)

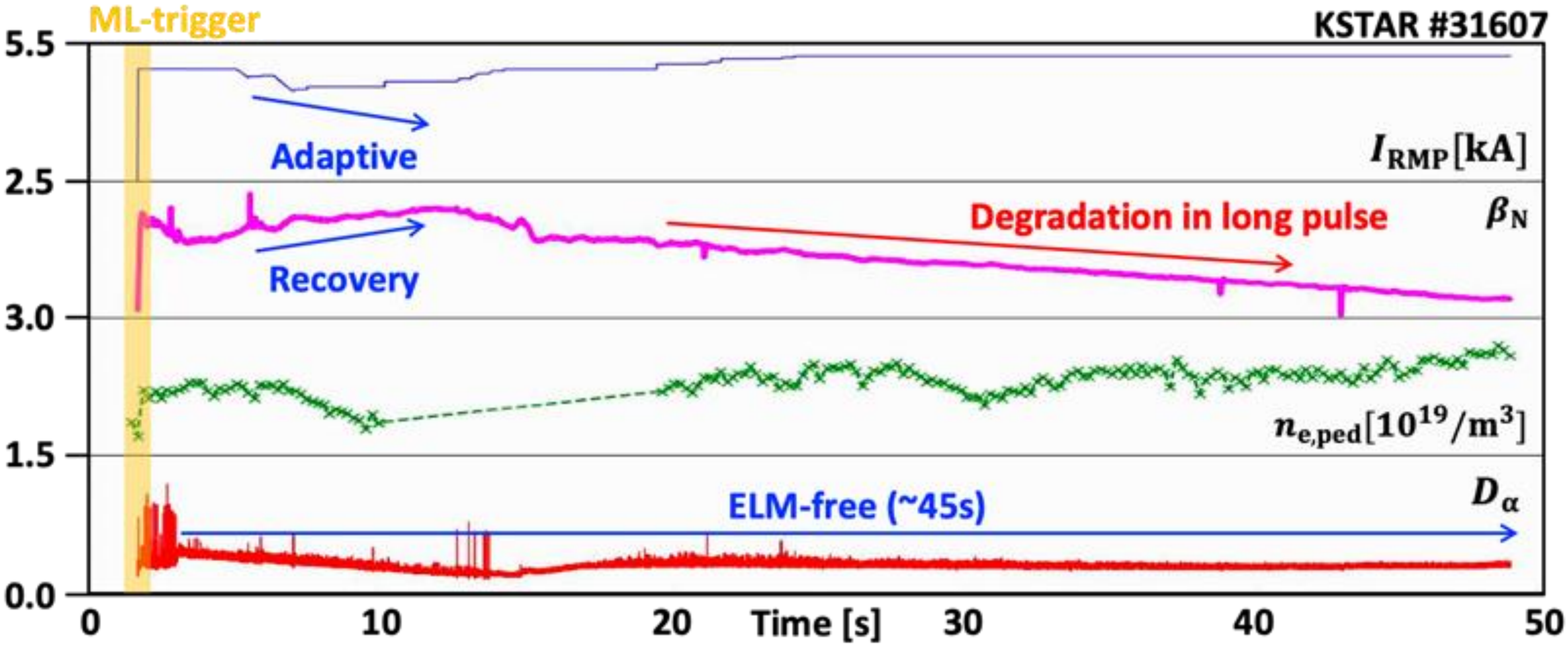
- **Suppressing first ELMs** is needed for future device
- **Early RMP** before LH transition can suppress it
- However, it has limitations
  - Easier disruption at L-mode
  - RMP can prevent H-mode access
- RMP at H-mode but before ELM
  - Accurate timing is key
  - Enabled by H-mode detector

[G.Shin NF 22]



Successful full integration to adaptive control, making high betan and pulse length records

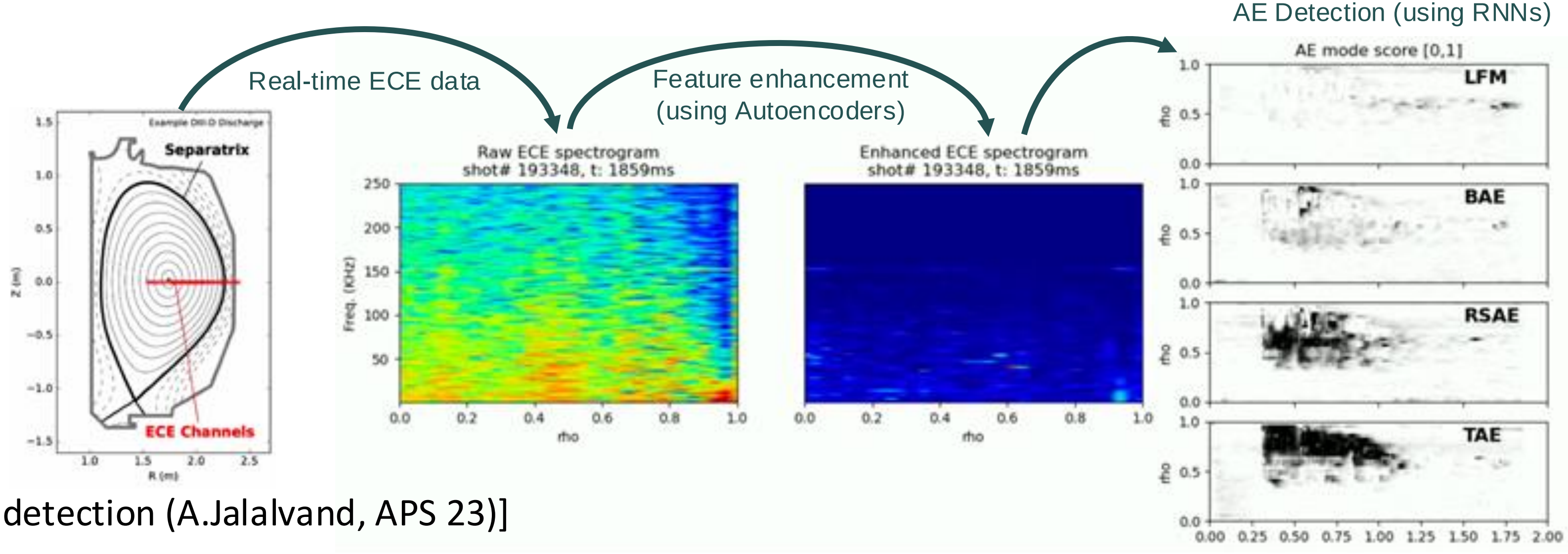
- Long-pulse record by integrating scheme with adaptive controller



[R. Shousha IAEA-FEC

Example: State detection (Alfven instability)

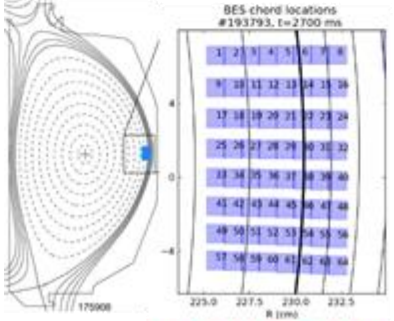
- AE modes reduce plasma performance. We would like to minimize them
- **Input:** Spectrogram of each ECE channel
- **Process Stage 1:** Enhancing spectrograms using Autoencoder network
- **Process Stage 2:** Detecting AE modes using Recurrent Neural Network
- **Output:** Score of AE modes in time-space



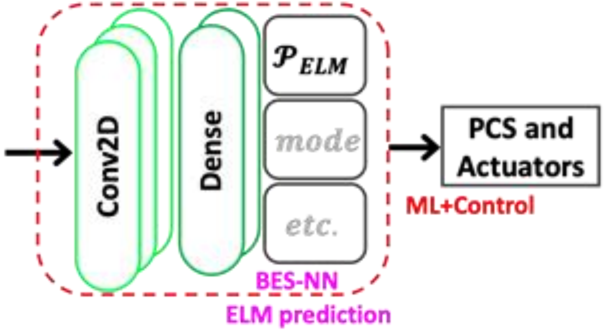
[Alfven detection (A.Jalalvand, APS 23)]

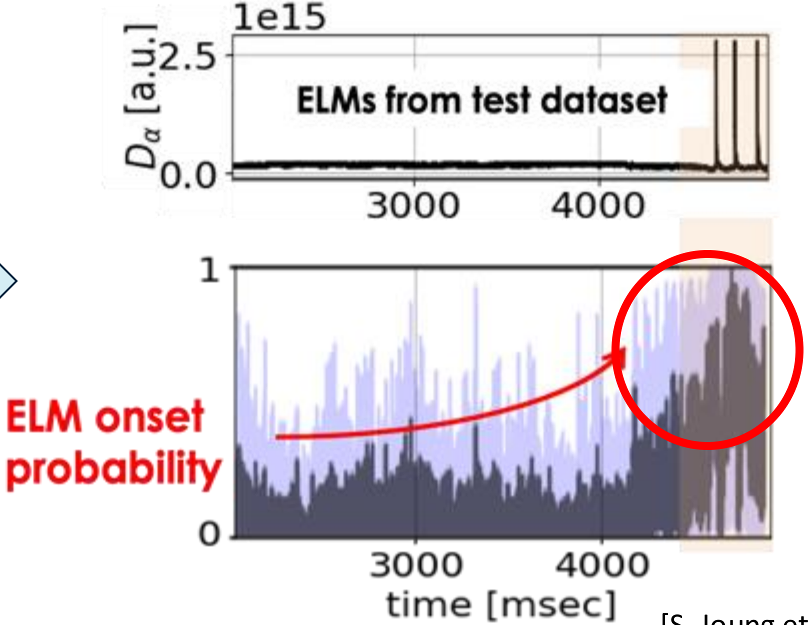
Example: State prediction (ELMy state)

- ELMy transition prediction using edge density fluctuation (BES)
- Good example in extracting hidden patterns from multi-dimensional signal
  -Trained with ~1000 DIII-D shots including H, RMP, QH-modes



Taking bandpass-filtered full 2D BES signals





[S. Joung et al., NF 64, 2024]
[K. Gill et al., MLST 5, 2024]

Example: State prediction (Tearing Mode transition)

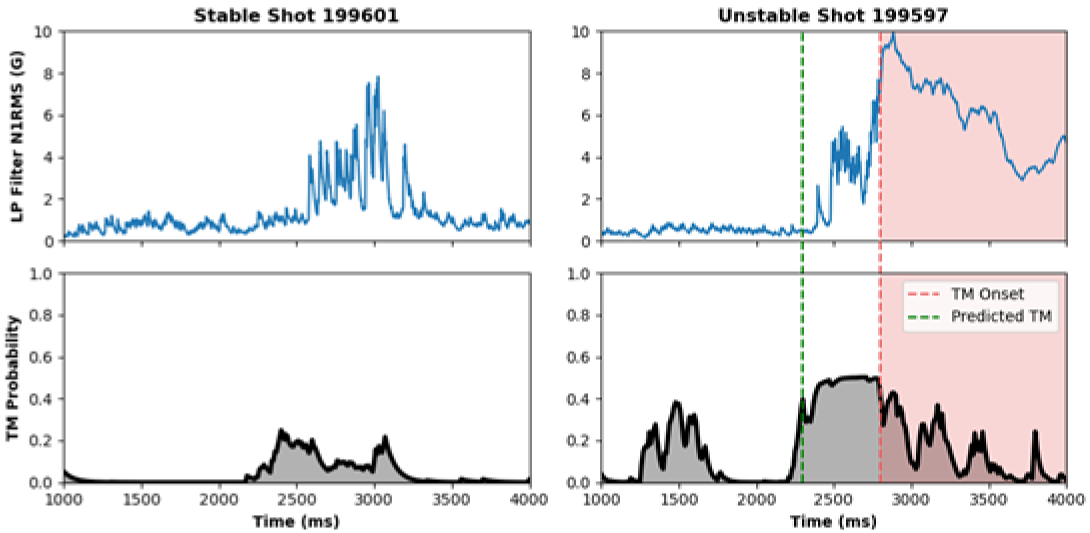
- Tearing mode (TM) is core MHD instability, must be avoided (before onset)
- Prediction models use state information to predict TMs up to **500ms** in advance

Profile Inputs

- Electron temperature (T_e)
- Electron density (n_e)
- Ion temperature (T_i)
- Rotation (v_{tor})
- Safety Factor (q)
- Pressure (p)
- Current density (J)

Scalar Inputs

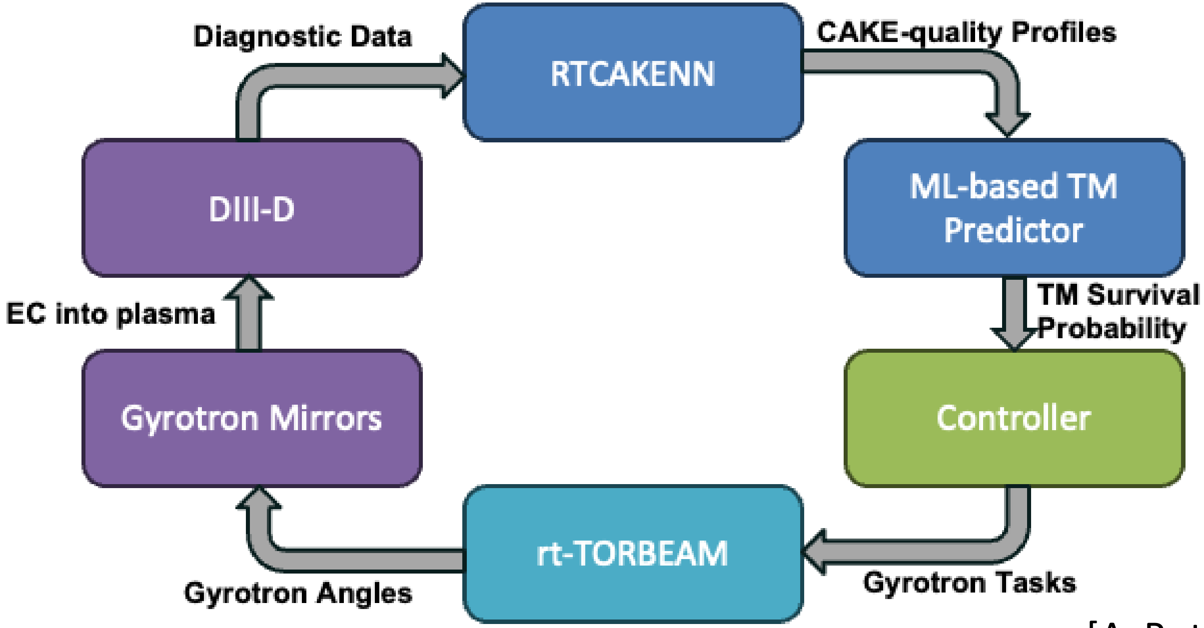
- Shape parameters: δ_{top}, δ_{bot}, κ, R_{axis}, a_{minor}
- RTEFIT scalars: q_{min}, β_N, l_i, V_{plas}
- P_{NBI}, T_{NBI}, P_{ECH}, I_P, B_T,



[A. Rothstein APS-DPP 24]

Application: State prediction (TM transition)

- Electron cyclotron heating (EC) is a good actuator to suppress TM
- Loop uses diagnostic data to predict TM stability and then steer EC to preempt (avoid) TMs

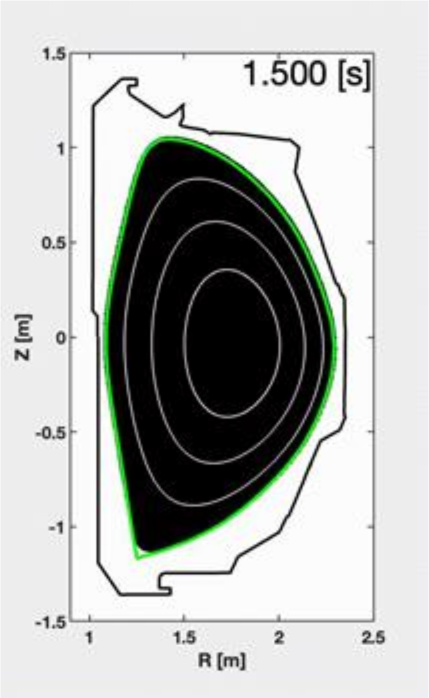


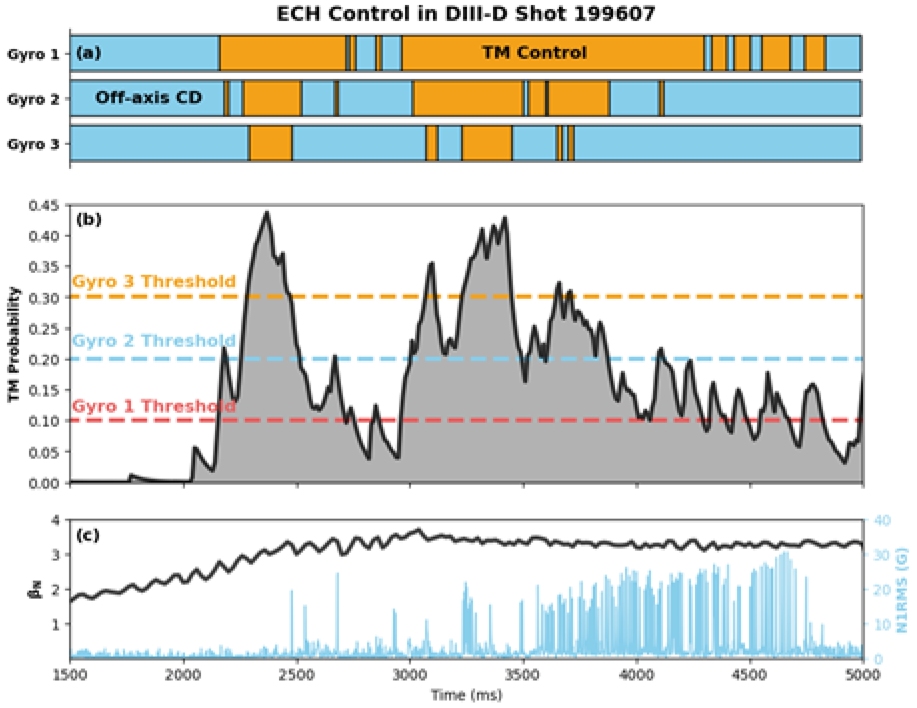
[A. Rothstein APS-DPP 24]

Application: State prediction (TM transition)

- TM controller aims EC to expected mode location when plasma state is predicted to be unstable.

[A. Rothstein APS-DPP 24]

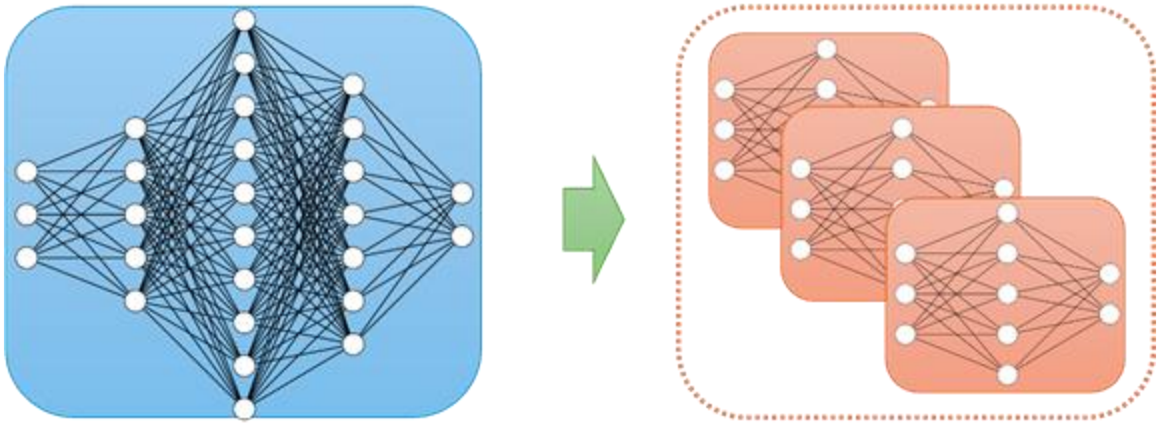




Contents

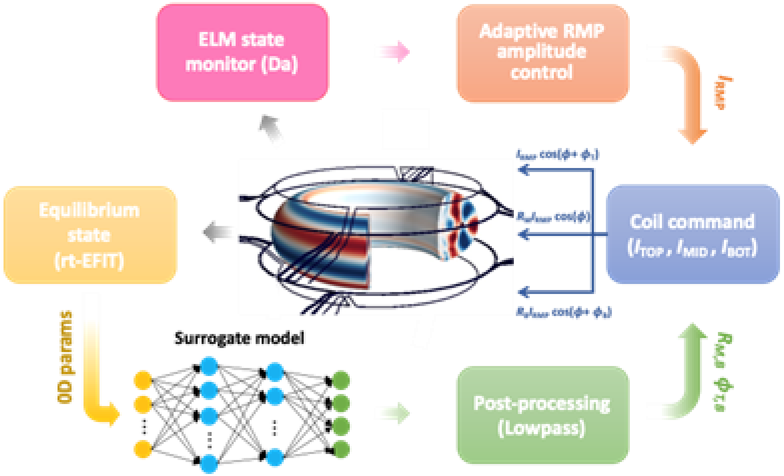
Well-known schemes to improve model capability in real-time: Reducing model size by using ensemble average of smaller model

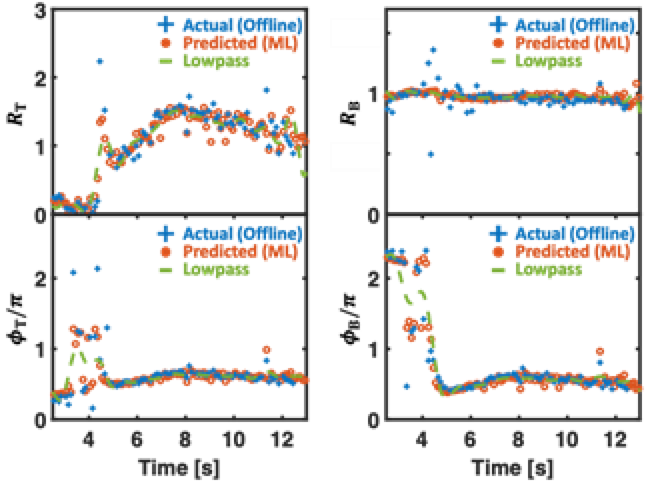
- The larger model makes it easier to capture complicated/nonlinear feature
  - However, it can be **heavy** for real-time run
- Smaller model is less vulnerable to **overfit or oscillation**, better rt-feasibility
- In addition, a smaller model is more robust oscillatory behavior
  - However, less accurate
- **Ensemble smaller models** can maintain benefits with enhanced accuracy



Well-known schemes to improve model capability in real-time: Dealing oscillatory behavior of model using low-pass filter

- Nonlinearity and sensitivity of the physics model can introduce oscillatory behavior on output (strong sensitivity of small change in input)
- Such sensitivity is generally not true or important
- **A low-pass filter** can be effective in suppressing oscillations while capturing a key aspect of model prediction

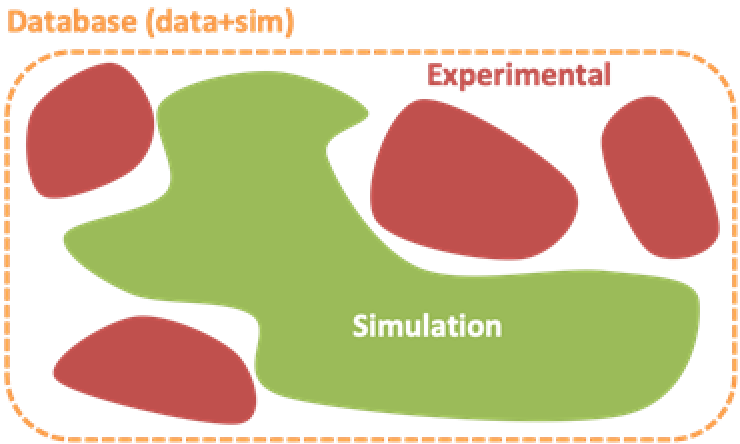


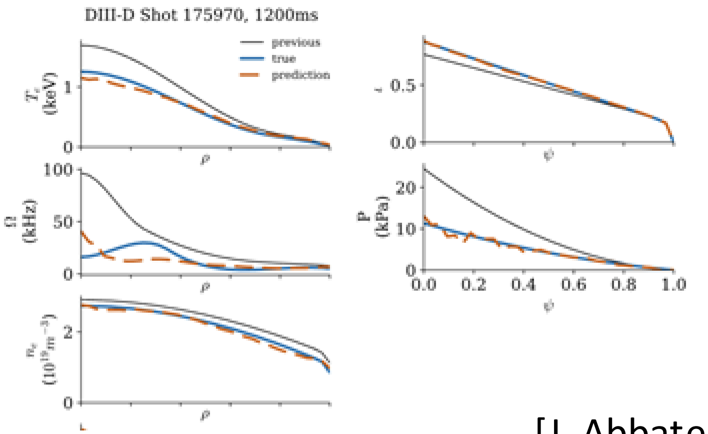


[S.K.Kim, NC 24]

Well-known schemes to improve model capability in real-time: Filling gaps in database leveraging simulation

- The diagnostic-based model may have **limitations in scalability**
  - **Extrapolation** is feasible but **not guaranteed**
- If the physics model captures the experimental trend, they may be combined to **produce a larger database (data+sim)**
- Filling the missing gaps while maintaining unveiled physics in diagnostic data





[J. Abbate NF 21]

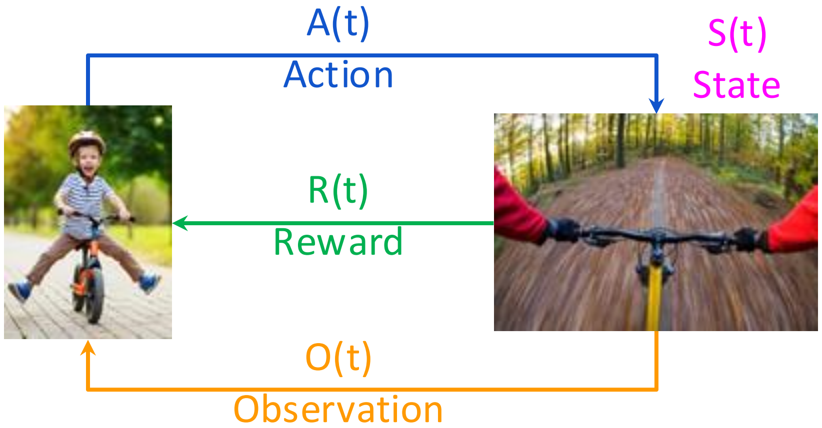
Contents

From adaptive to fully AI/ML-based control

- Derived control strategy, **directly driven** by experimental control input and output
- Nonlinear control policy **covering multiple states**
- **Lower complexity of control policy** with fewer states
- Better handling the nonlinearity
- Can provide **Novel control strategy (insight)** derived from unveiled physics
- Reinforcement learning is one of the attractive approach

- Learning to maximize a **reward** while **interacting** with an **environment**.

Ride safe & have fun by controlling steer, brake, pedal on the road.

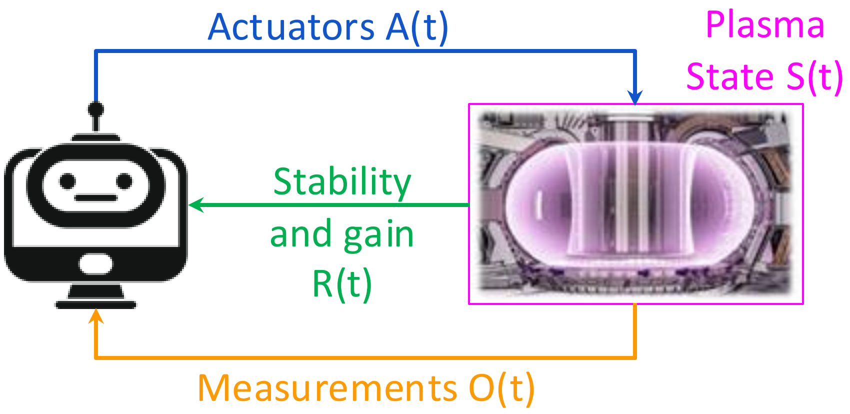


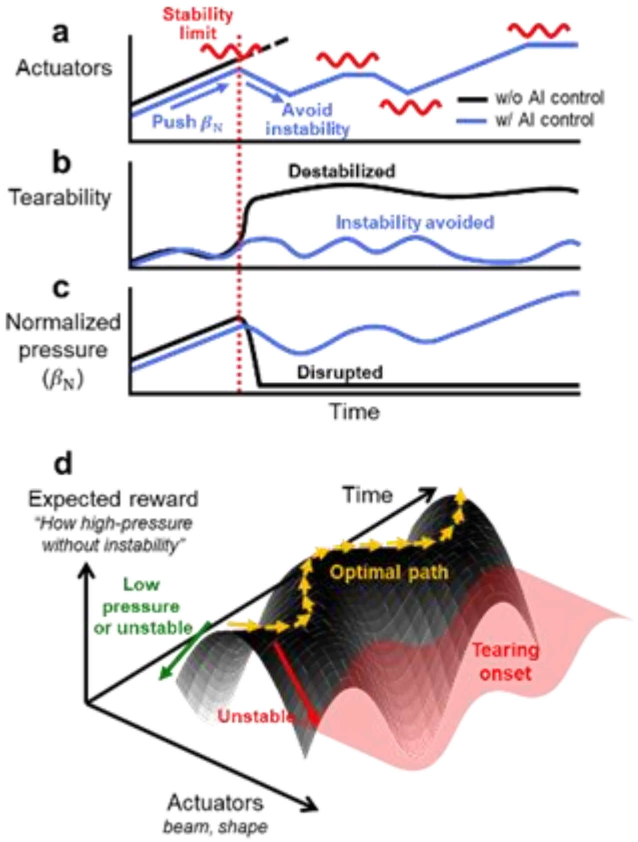
Key components of RL agent:

- **Policy**: It is a map from state s to action a
  - The rider's strategy for choosing actions (steering, pedaling, balancing) based on the current state of the bicycle to maintain balance and forward motion.
- **Value function**: is a predictor of future reward
  - The rider's assessment of how favorable a certain state is, considering the long-term goal of riding successfully without falling.
- **Model**: predicts what the environment will do next
  - The rider's understanding of the cause-and-effect relationships in bicycle dynamics that predicts how actions will change the state of the bicycle.

Avoiding tearing mode instabilities with RL at DIII-D

- Given the plasma state, S(t), which is observed as O(t) by the controller, which action A(t) should be taken to maximize the cumulative reward R(t+1) i.e. minimize instability & maximize gain.

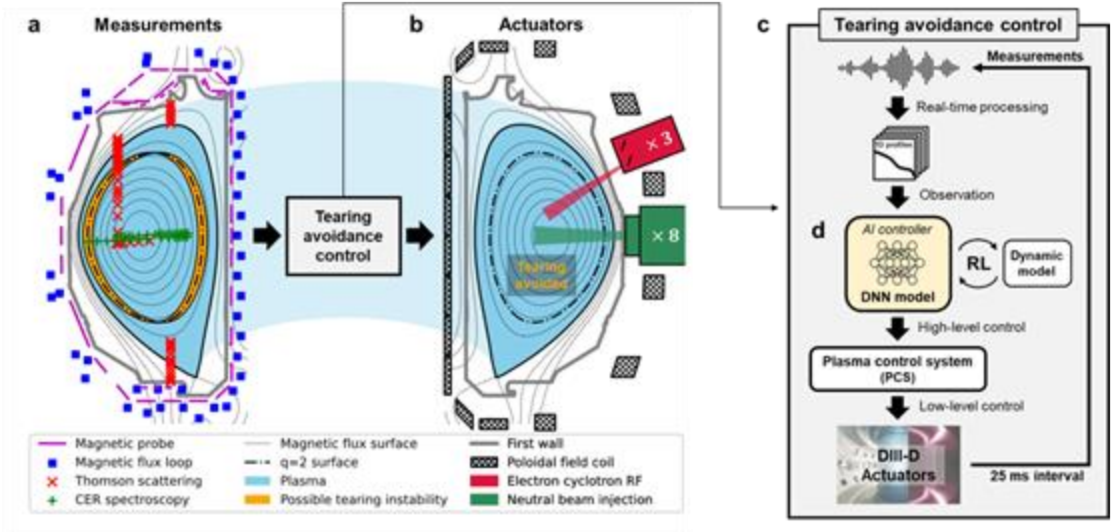


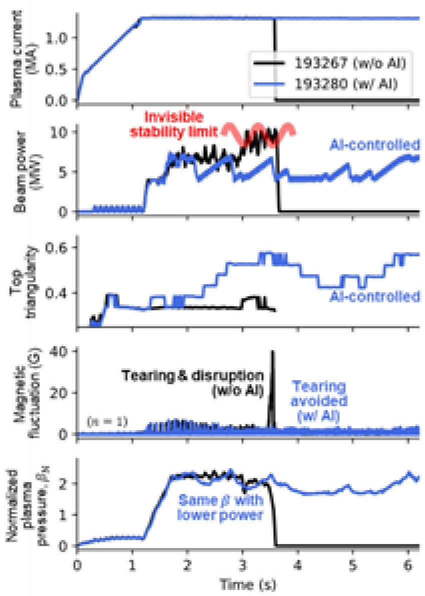


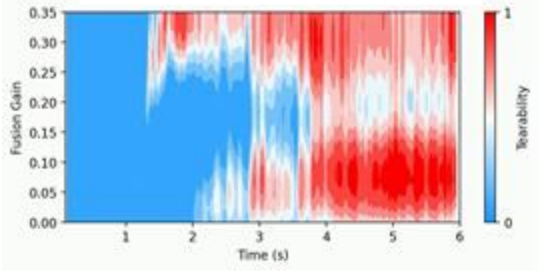
[J. Seo Nature 24]

Avoiding tearing mode instabilities with RL at DIII-D

- Design AI control: Objective is to avoid instability while pushing up performance.
- Preemptive control of beam power and plasma shape can avoid the onset of tearing modes.







[J. Seo Nature 24]

Define objectives, explore patterns, develop model, and apply

- Control is becoming more important as plasma physics advances
- **Adaptive** control is an effective approach to handle the plasma system
- **Predictive model** is key for advancing the scheme
- However, it is difficult due to **complexity and nonlinearity**
- **Exploring pattern** is a good starting point
- **ML/AI is bringing new insight** and predictive capabilities to plasma control

  - Scalability will be important aspect

Thank you