Offline Automated Model Predictive Control of SOLPS-ITER Plasma Edge Simulations

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Connecting Two Key Ideas for ITER and Fusion Pilot Plant

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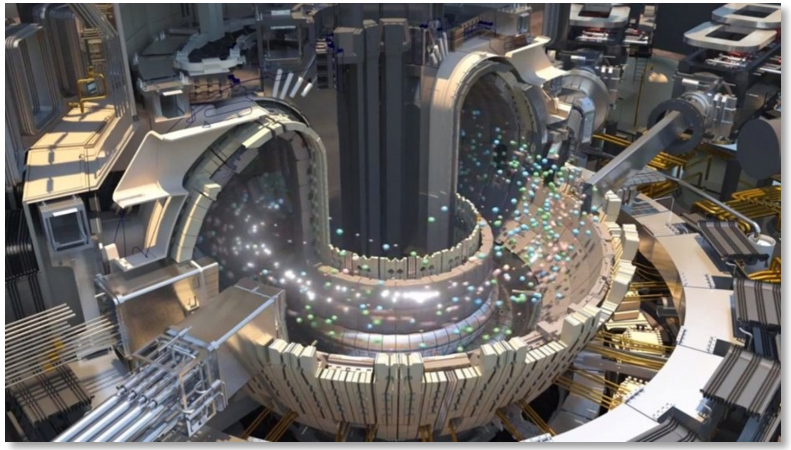
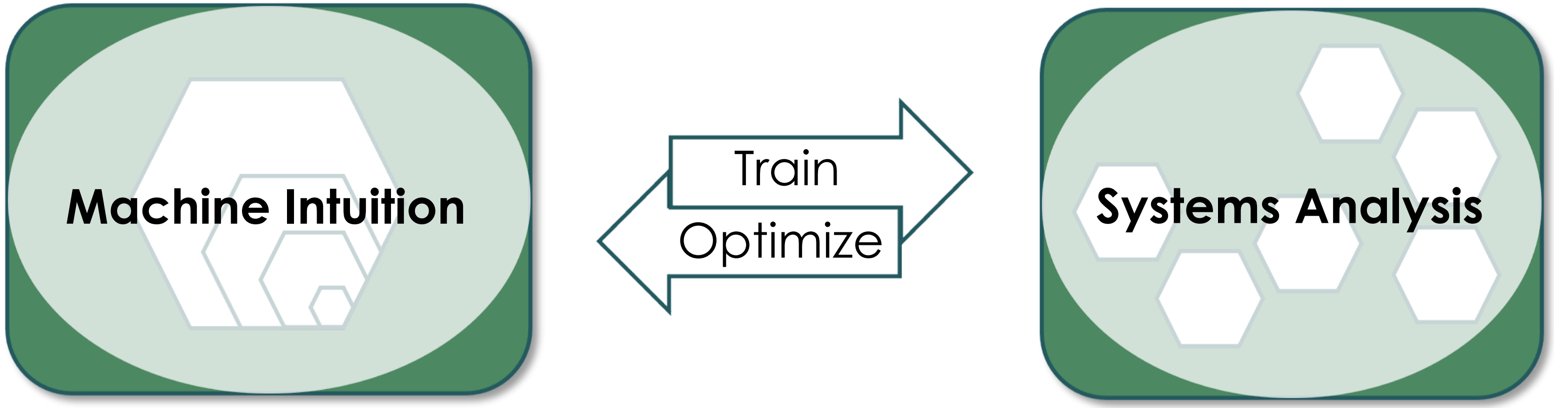


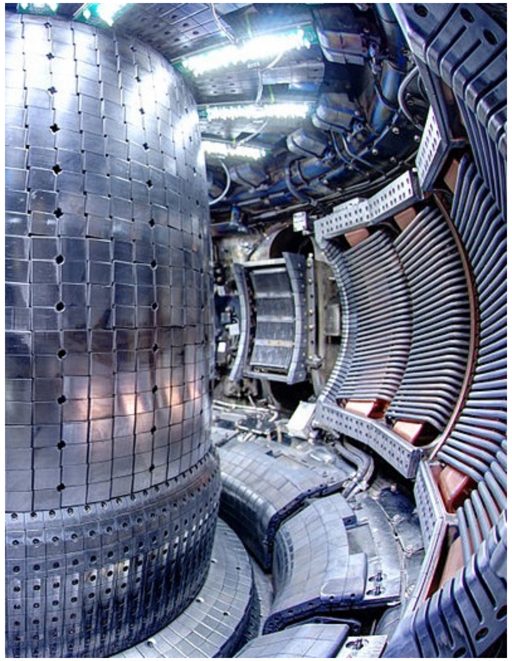
Buildable through "experience"

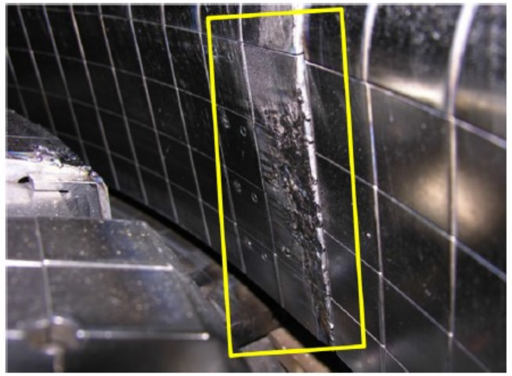


Transferable across "designs"

*Visualization by J. Daniel, Oak Ridge Leadership Computing Facility

How Can We Ensure the Survival of Divertor Components At the Extreme Scale of Fusion Reactor Devices?





- Plasma facing components in a fusion reactor will be **destroyed** by unmitigated power and particle fluxes
- Neutral gas puff can dissipate excess fluxes by **detaching** the divertor plasma
- Actuation strategies must manage scrape-off-layer dynamics while upholding core **performance**

❖ Present devices employ simple controllers that are tuned on forgiving short pulses

OAK RIDGE National Laboratory [1]Alcator C-Mod

How Can We Ensure the Survival of Divertor Components At the Extreme Scale of Fusion Reactor Devices?

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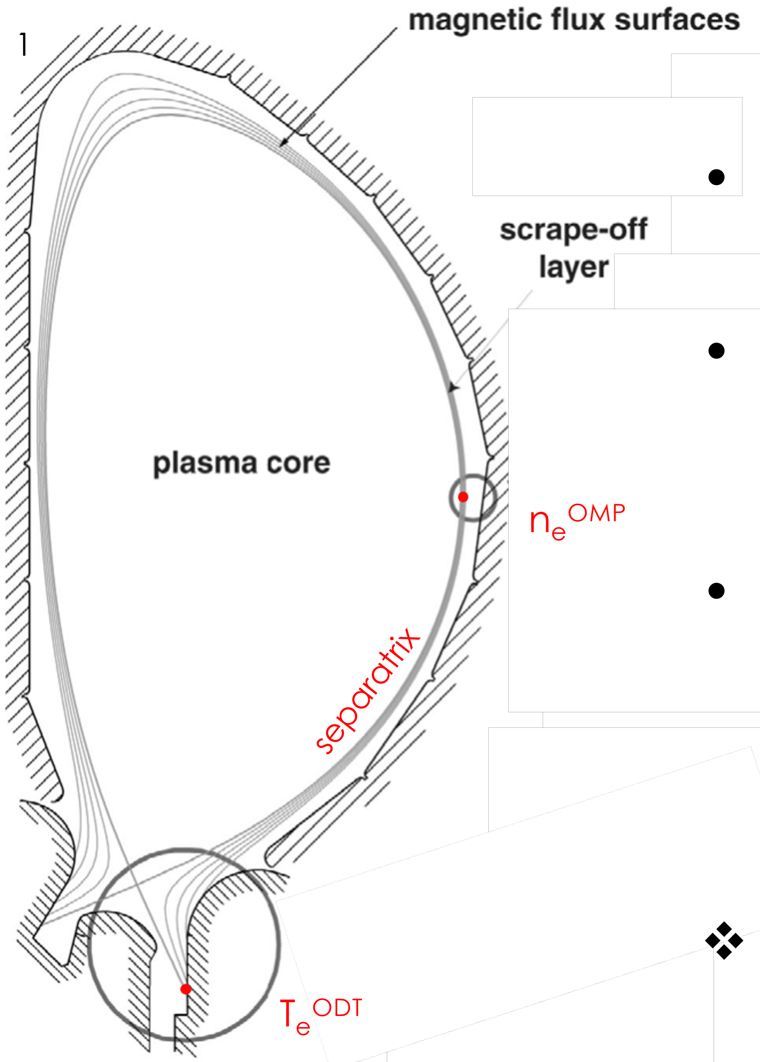


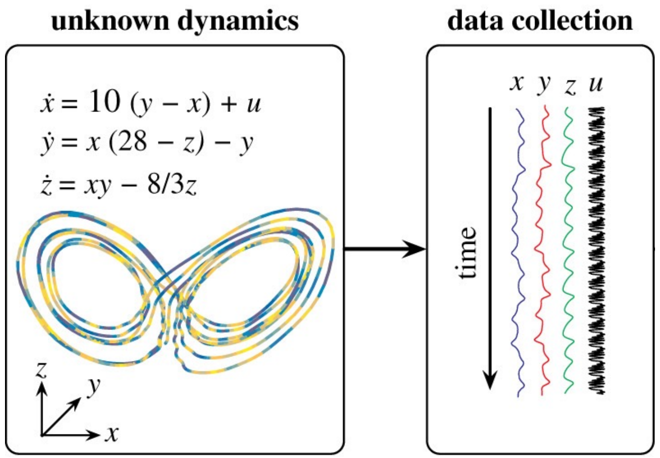
- **SOLPS-ITER** is the state-of-the-art tool for simulating the reduction of heatflux loads due to gas puff detachment[2]
- Tokamak edge plasma simulations are expensive, requiring upwards of **days-weeks-months** wall clock time to converge towards a steady-state solution[3]
- Data-driven sparse identification of nonlinear dynamics (**SINDy**)[4] provides a scheme for **real-time** reduced modeling of tokamak edge physics

❖ Data-driven model predictive control can be deployed on experiments to handle nonlinear dynamics

[1]Adapted [Federici et al., 2001], [2][Bonnin et al., 2016], [3][Kaveeva et al., 2018], [4][Brunton et al., 2016]

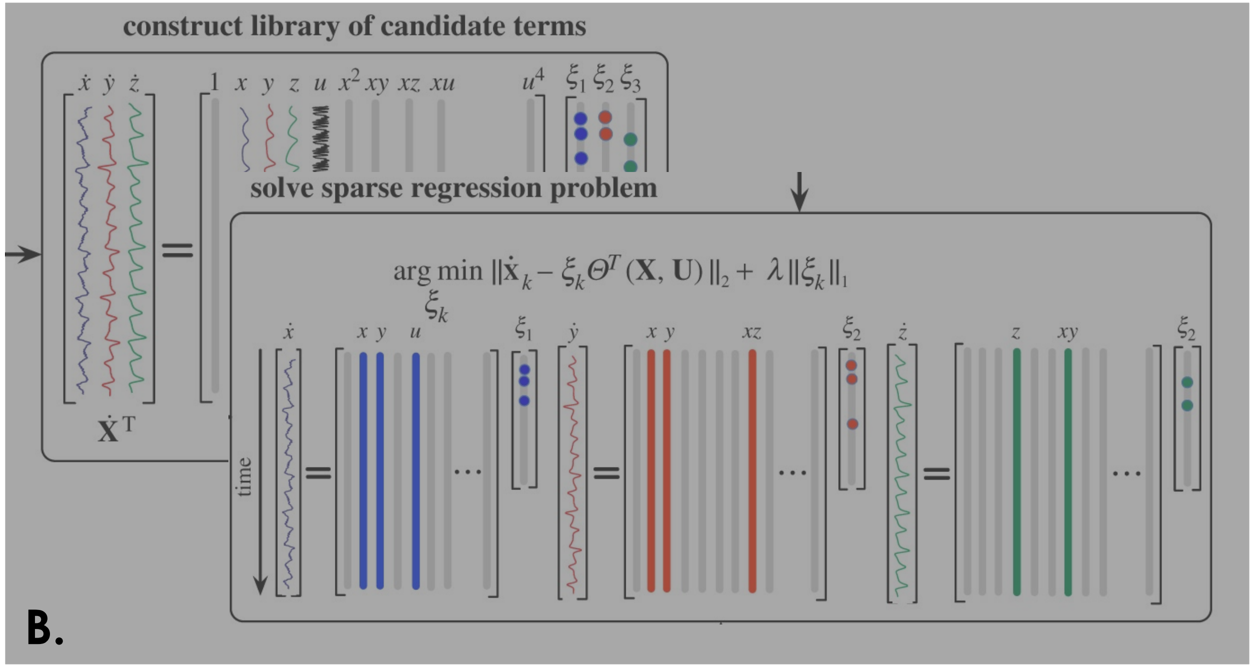
The SINDy Gray Box Approach to Machine Learning

A. [5]

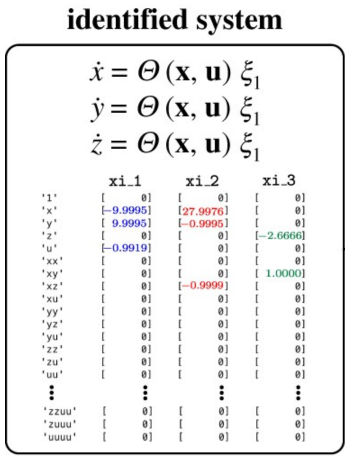


Input

Reduced Model



C.



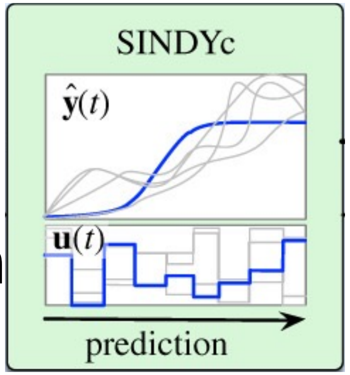
Output

[5] Adapted from [Kaiser et al., 2018]

SINDy Enables Efficient Application of Model Predictive Control Paradigm to SOLPS-ITER

A. **Fixed Point Steady-state**

A. Perturb dynamics around equilibrium through actuation and response



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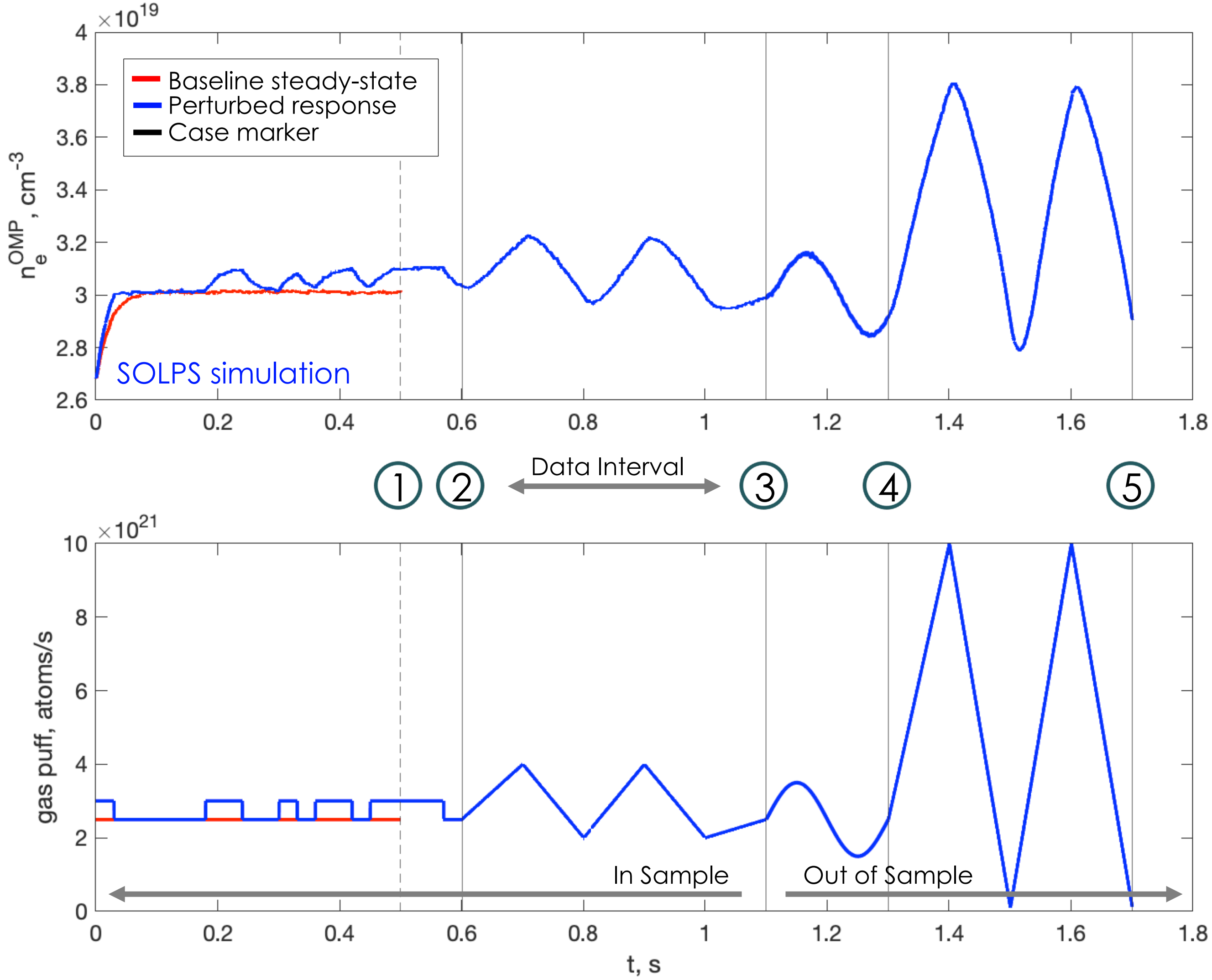
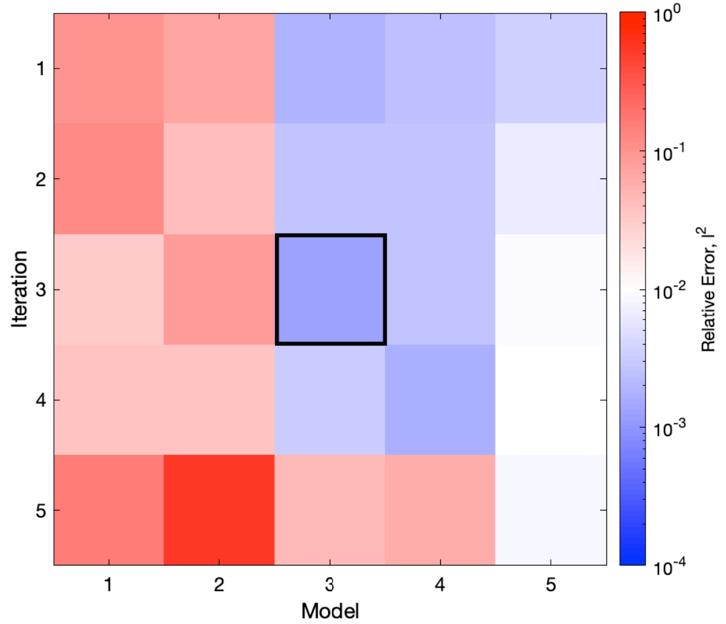
[5] Adapted from [Kaiser et al., 2018]

A. Simulation Cases of Scrape-off-layer Dynamics Probe a Range of Actuation Rates and Output Variables



5-Fold Cross-Validation

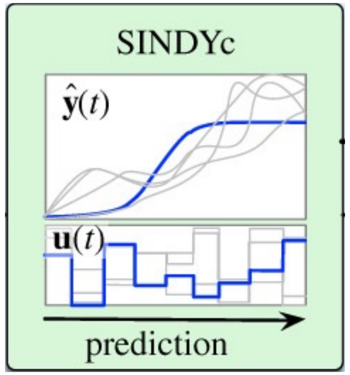


Extracted Linear Model

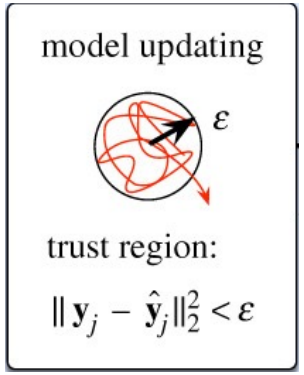
$$\frac{\partial n_e}{\partial t} = -An_e + Bu + C$$

Partition database into independent training and testing intervals

SINDy Enables Efficient Application of Model Predictive Control Paradigm to SOLPS-ITER



[5]

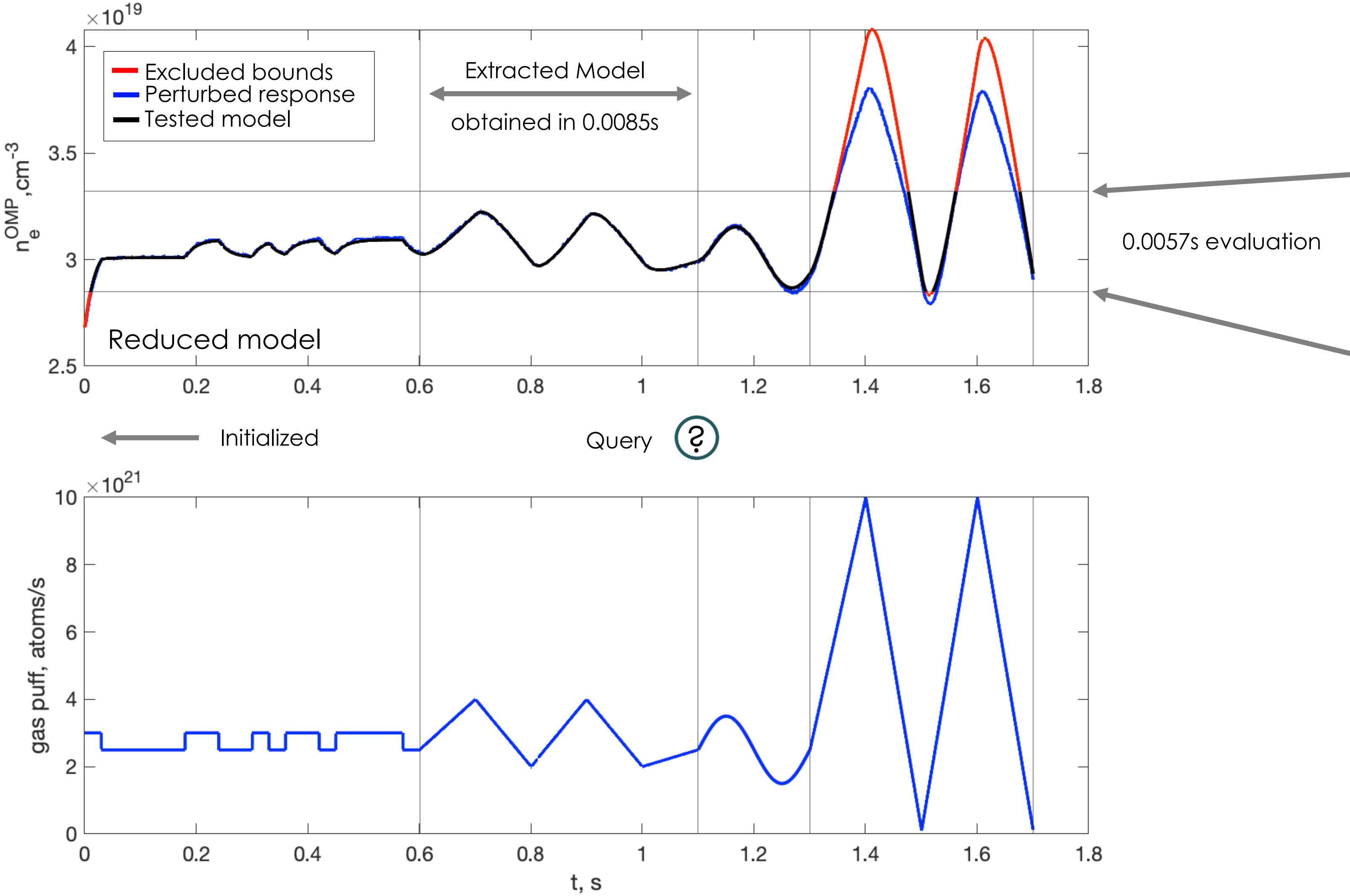


A. Fixed Point Steady-state
   - Perturb dynamics around equilibrium through actuation and response

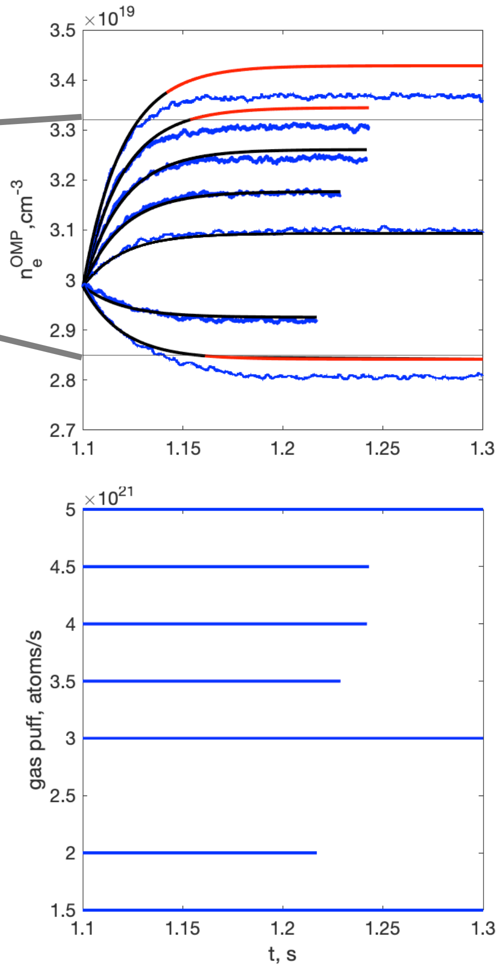
B. Bimodal Automated Algorithm
   - Prediction of timeseries evolution and confidence
   - Exploration of reference runs to provide bounds

[5] Adapted from [Kaiser et al., 2018]

B. Automated Algorithm Identifies Operable Limits of Extracted Model for **Out of Sample** Predictions

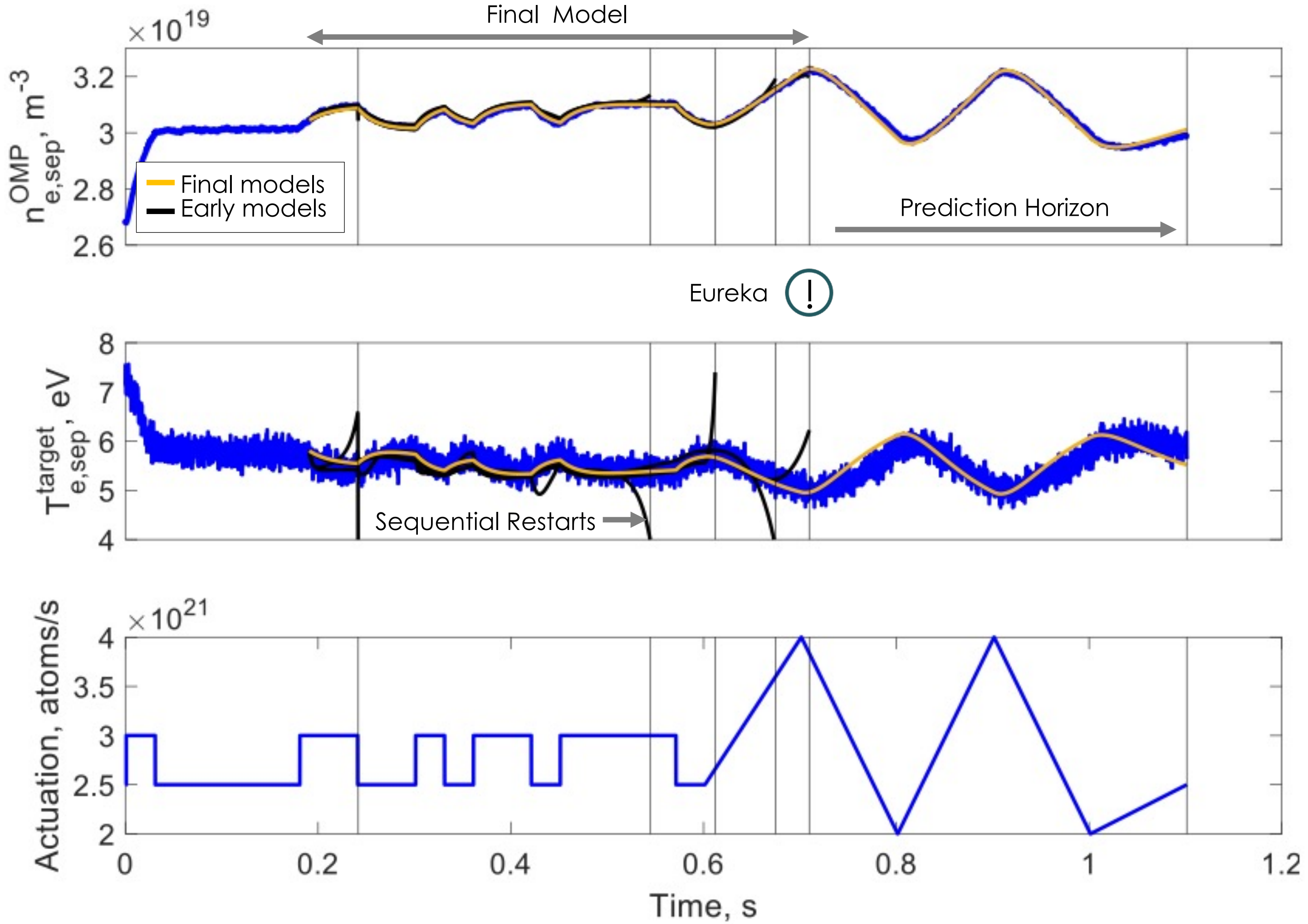


Library Cross-Reference

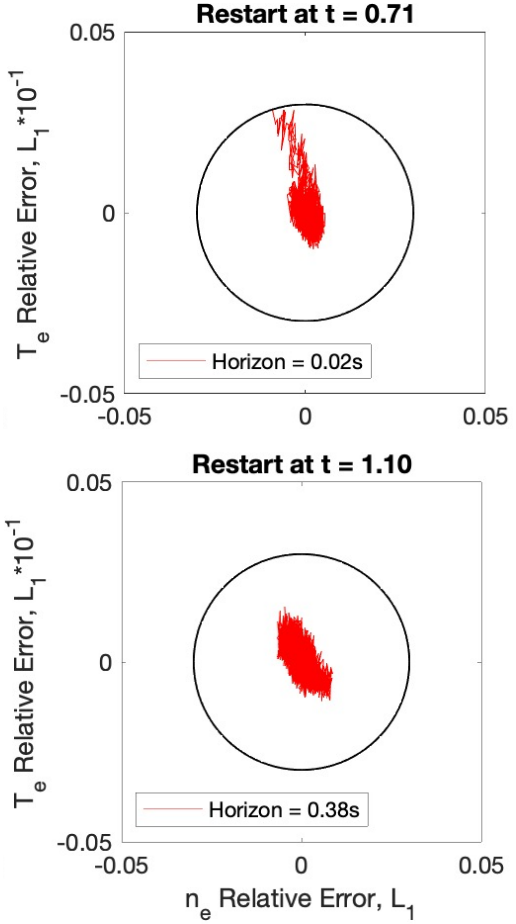


*Poll pre-selected cases for **a priori** detection of model deviations*

B. Automated Algorithm Applies a Rolling Time Horizon to Update Model Progressively for **In Sample** Data

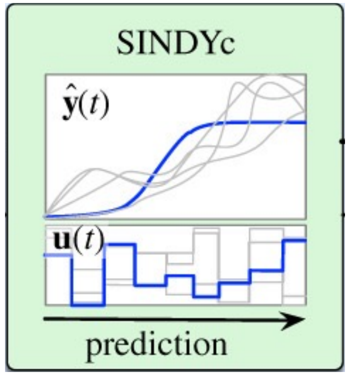


Rolling Cross-Validation



*Chain together observed timeseries for **a posteriori** model updating*

SINDy Enables Efficient Application of Model Predictive Control Paradigm to SOLPS-ITER



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A. Fixed Point Steady-state
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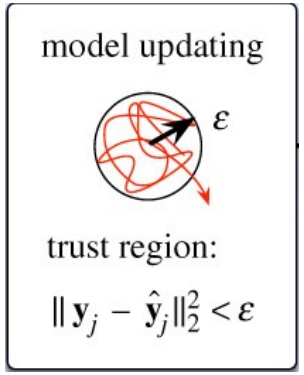
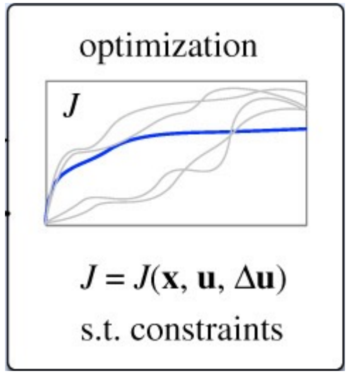
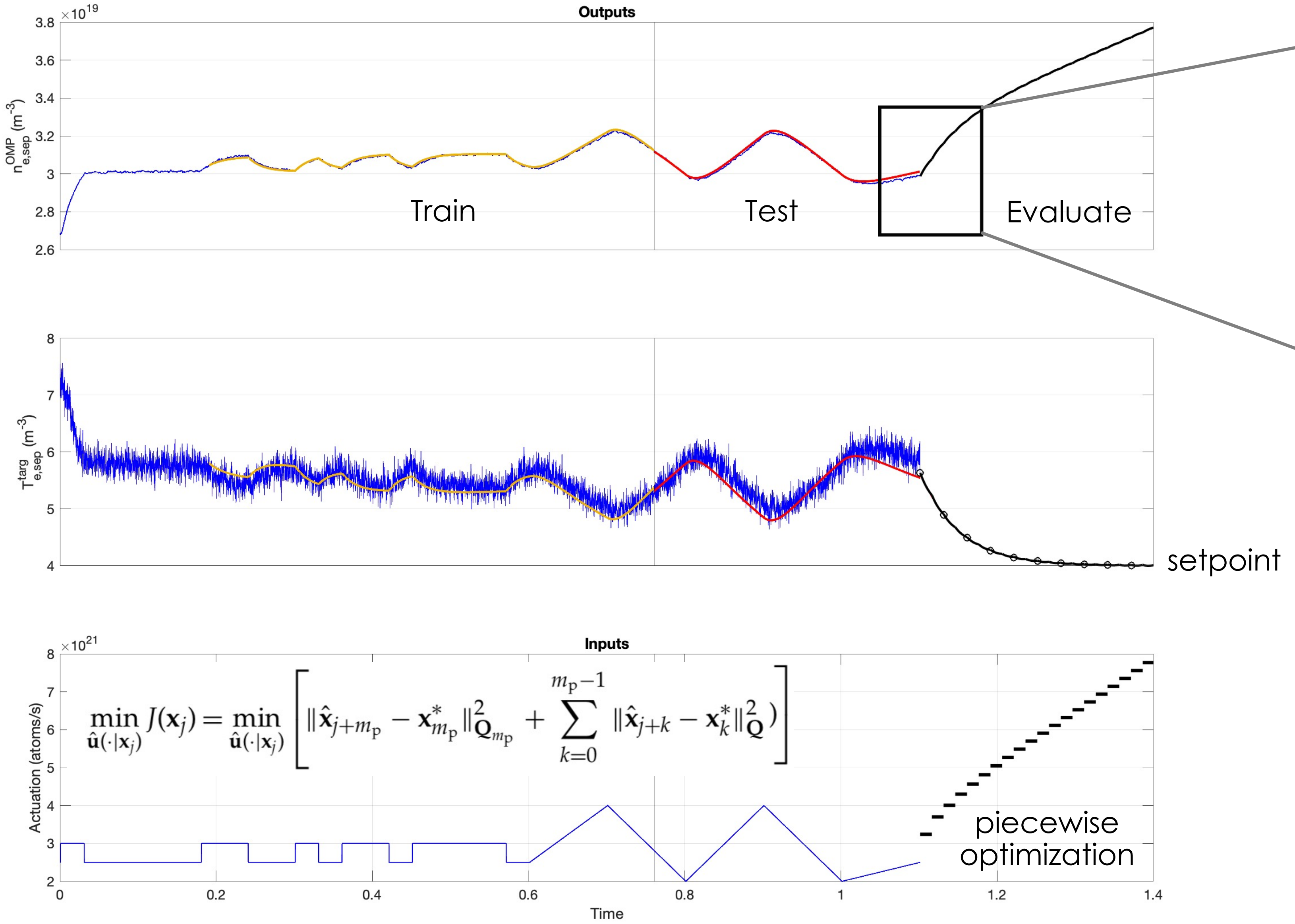


C. **Set Point Trajectory**
   - Control divertor target temperatures through reduced model
   - Maintain fast evaluations through discretized cost function
   - Evaluate performance through direct application to SOLPS-ITER



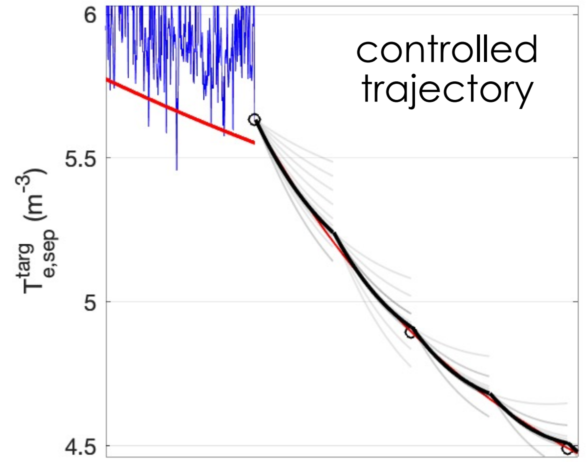
[5] Adapted from [Kaiser et al., 2018]

C. Model Captures Dynamics for Target Setpoint Control



$$\min_{\hat{\mathbf{u}}(\cdot|\mathbf{x}_j)} J(\mathbf{x}_j) = \min_{\hat{\mathbf{u}}(\cdot|\mathbf{x}_j)} \left[\|\hat{\mathbf{x}}_{j+m_p} - \mathbf{x}^*_{m_p}\|^2_{\mathbf{Q}_{m_p}} + \sum_{k=0}^{m_p-1} \|\hat{\mathbf{x}}_{j+k} - \mathbf{x}^*_k\|^2_{\mathbf{Q}}) \right]$$

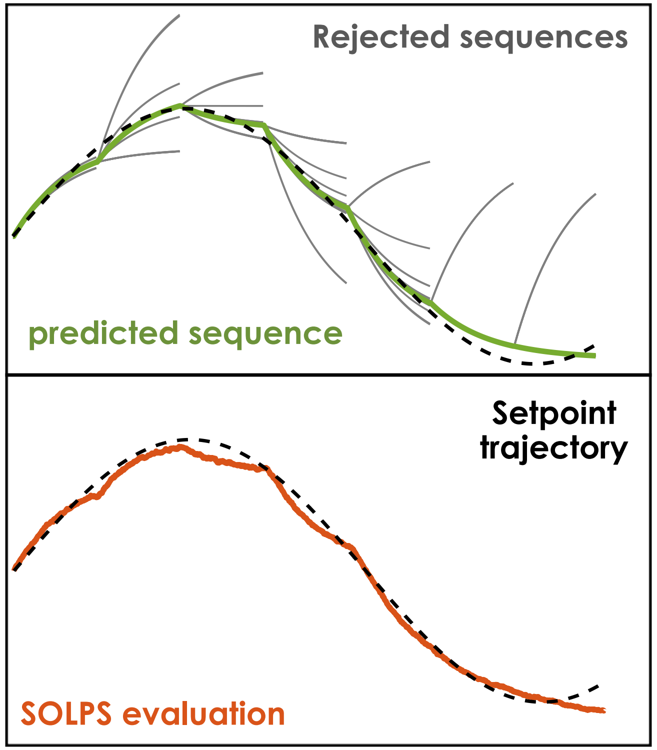
$$\frac{\partial n_e}{\partial t} = -A_1 n_e - A_2 T_e + A_3 u + A_4$$
$$\frac{\partial T_e}{\partial t} = B_1 n_e + B_2 T_e - B_3 u - B_4$$



*Evaluate reduced model by **minimizing** cost-function on the prediction*

Evaluating Offline Automated MPC for SOLPS Simulation

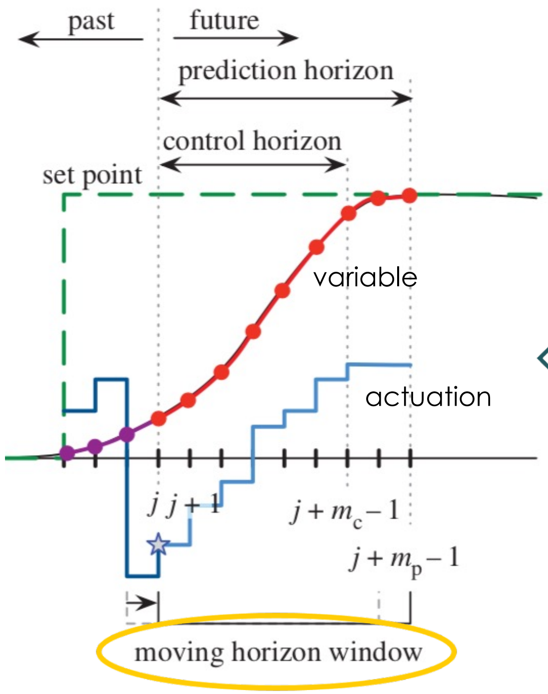
Trained in under **8 ms**

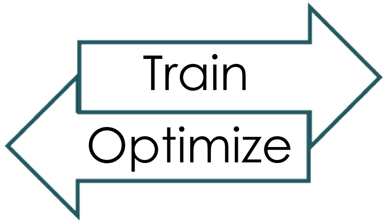


Tested in under **8 hours**

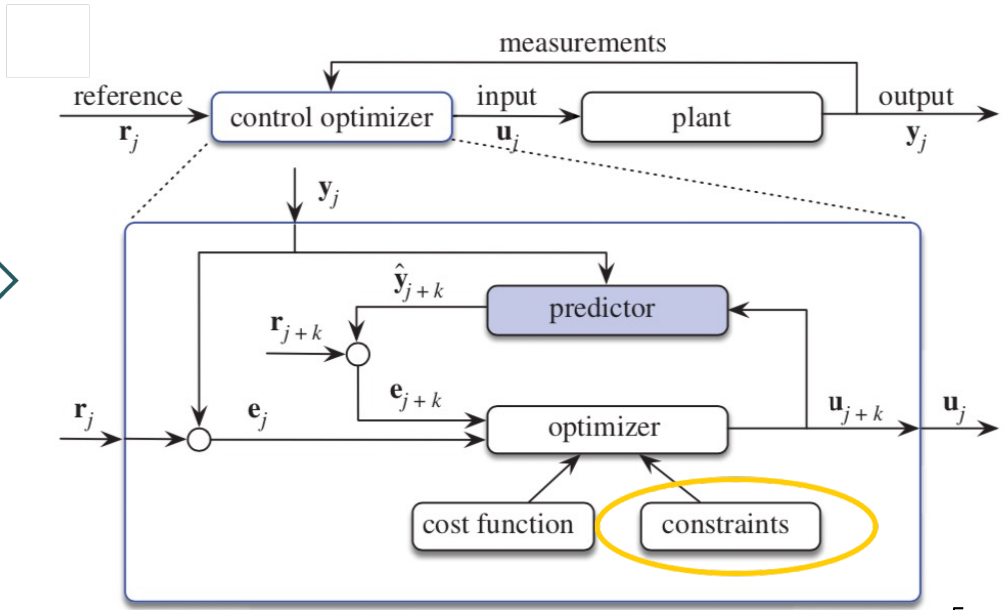
Connecting Two Key Ideas for Model Predictive Control

Machine Intuition





Systems Analysis



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Data reliant
variable horizon

Device specific
replaceable constraints

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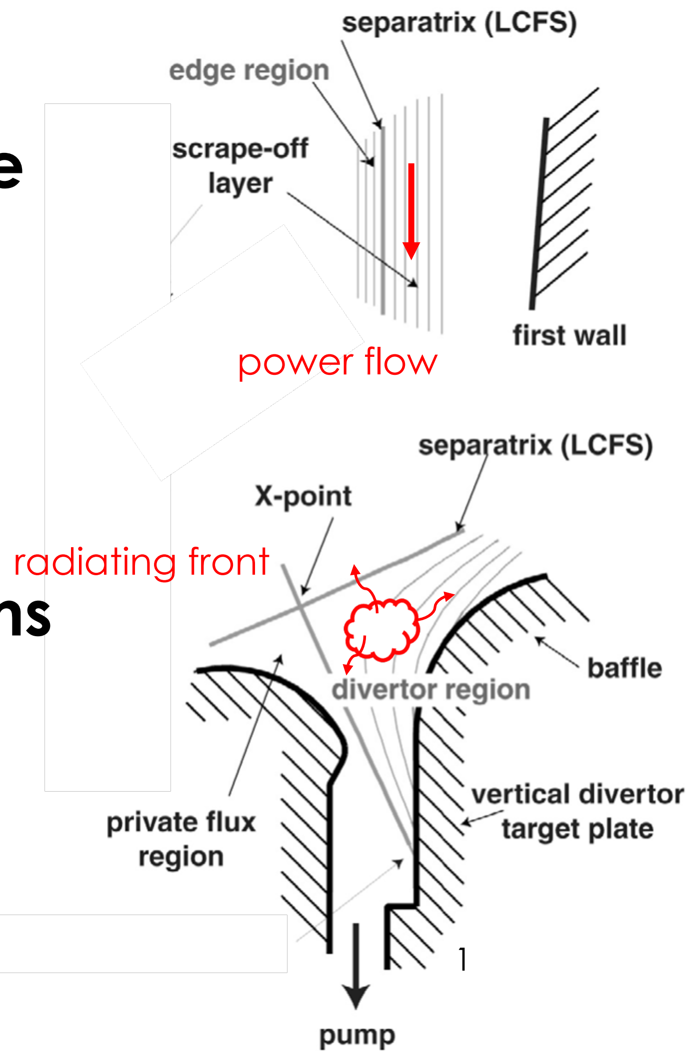
[5] Adapted from [Kaiser et al., 2018], target DIII-D Plasma Control System (PCS)

Summary – Automated Reduced Modeling is Capable of Offline Predictive Control of Divertor Target Temperatures

- Bimodal Paradigm
  - Cross-validation in and out of sample for **predictive** and **explorative** metrics of model deviation
  - Demonstrated automated algorithm over **heterogeneous** system response to actuation
- Remaining Challenges
  - Extend steady-state results to analysis of **bifurcations** and **nonlinear** parameter-sensitive regimes
  - Incorporate **impurity** seeding and divertor **detachment** physics into system identification
  - Utilize device **component** physical constraints in optimization and **experimental systems**



[1]Adapted from [Federici et al., 2001]

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