INL/MIS-23-73304-Revision-1

Adaptive Data-Driven Model Predictive Control for Heat Pipe Microreactors

August 2023

Changing the World's Energy Future

Linyu Lin, Joseph Eugene Oncken, Vivek Agarwal, Benjamin Zastrow

Idaho National Laboratory

INL/MIS-23-73304-Revision-1

Adaptive Data-Driven Model Predictive Control for Heat Pipe Microreactors

Linyu Lin, Joseph Eugene Oncken, Vivek Agarwal, Benjamin Zastrow

August 2023

Idaho National Laboratory
Idaho Falls, Idaho 83415

http://www.inl.gov

Prepared for the
U.S. Department of Energy
Under DOE Idaho Operations Office
Contract DE-AC07-05ID14517

NPIC HMIT 2023

PSA 2023
18th International Probabilistic Safety Assessment and Analysis

Adaptable Data-Driven Model Predictive Control for Heat Pipe Microreactors

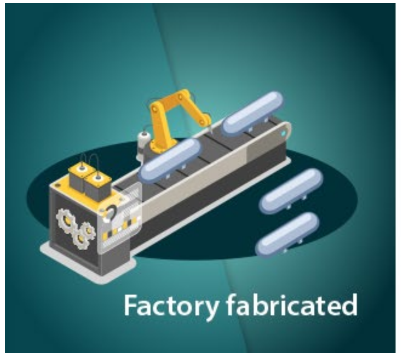
Linyu Lin
Idaho National Laboratory

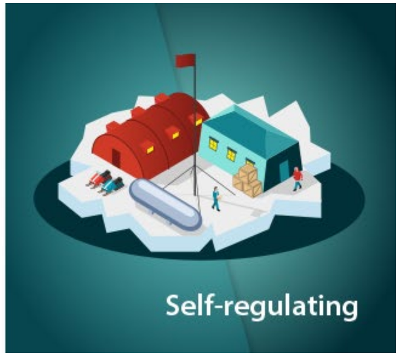
ANS

Idaho National Laboratory

Self-Regulating Microreactor

- Very small (<50MWe) reactors for non-conventional nuclear markets





- Self-regulating requires remote and semi-autonomous microreactor operations
  - Reduced number of specialized operators onsite
  - Load following capability

There are significant needs for research and development support for transferring from operator-centric to autonomous-enabled control room

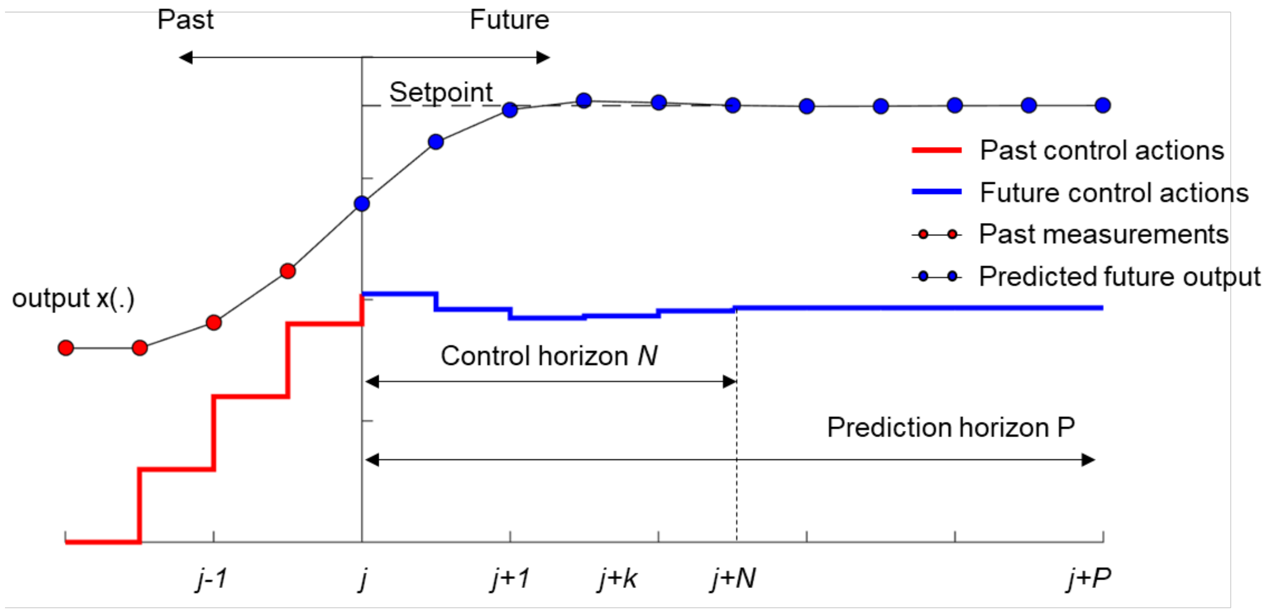
Idaho National Laboratory

ANS

Anticipatory Control

- Anticipatory control strategy for establishing technical basis of self-regulating microreactors
  - Proactively respond to disturbances and find optimal control actions to meet operational goals.
  - Explicitly incorporate and handle constraints by system dynamics, operational and safety requirements.

- Data-driven approaches for adapting systems to different testing systems and operational features
  - Expressive power: representing complex systems with nonlinear dynamics.
  - Modularity: system components can be separated and recombined.
  - Adaptability: flexible model forms and parameters

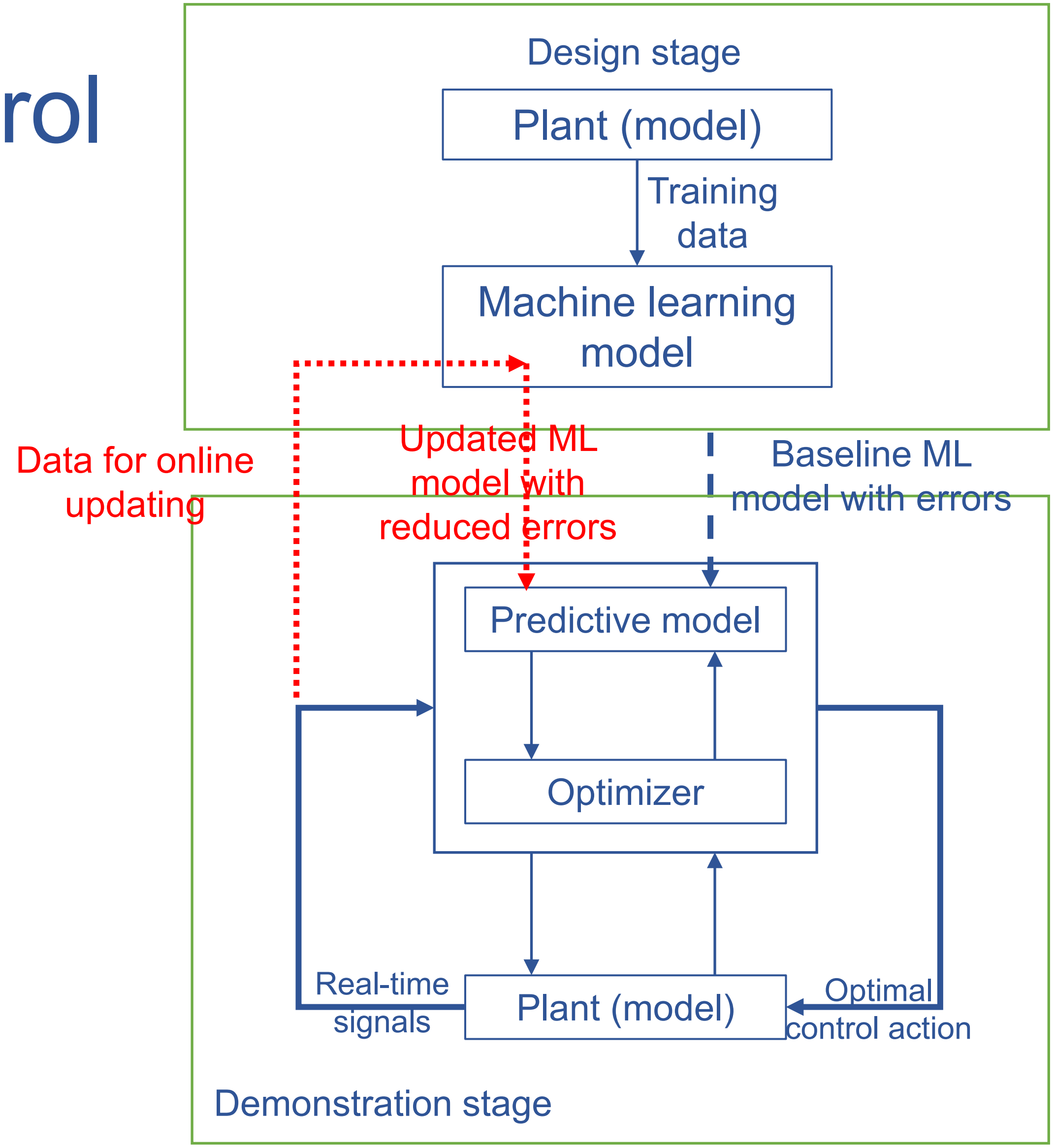


Given the complexity of nuclear energy systems, anticipatory control strategy shows better capabilities in efficiently and safely achieving (semi-) autonomous operations for microreactors

Data-Driven Anticipatory Control

- Uncertainty in representing dynamics of complex systems
  - Gaps between modeled and actual system dynamics
  - Problem-dependent with varying design details among different systems

- Anticipatory control with machine learning surrogates for
  - Model developed based on data from high-fidelity simulations, experiments, and prototype facilities
  - Neural network (shallow) models for highly expressive power and fast computing
  - Online updating and transfer learning based on real-time data



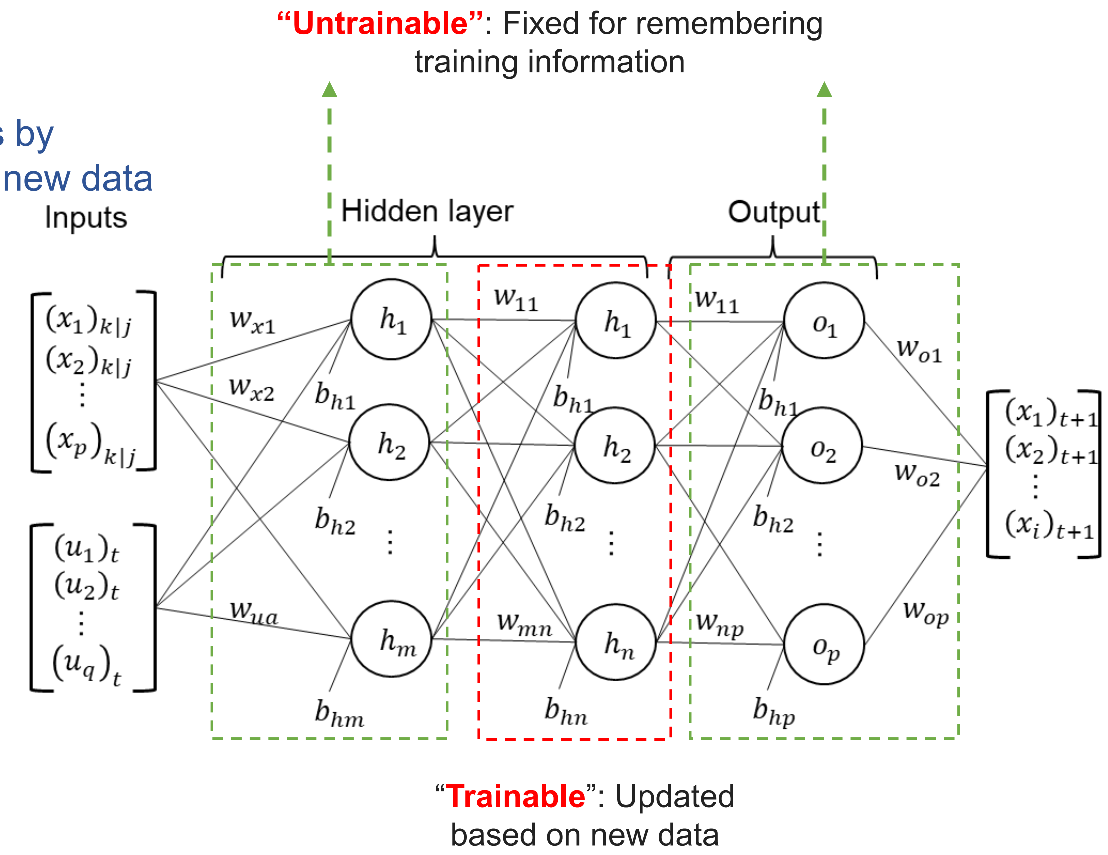
Online Updating and Transfer Learning

- Adaptable process model through online updating

$$x_{k+1|j} = f\left(x_{k|j}, u_{k|j}, w_j\right) \pm \delta$$

Reduce model errors by continuously learning from new data

- Most common incarnation of transfer learning in deep learning:
  - Take layers from a trained model
  - Freeze layers to avoid destroying trained information
  - add new layers or free selected layers
  - Train new layers or selected layers



- Only necessary updates:
  - Update only when large discrepancy is detected.
  - Update only when a sufficient amount of data is collected.

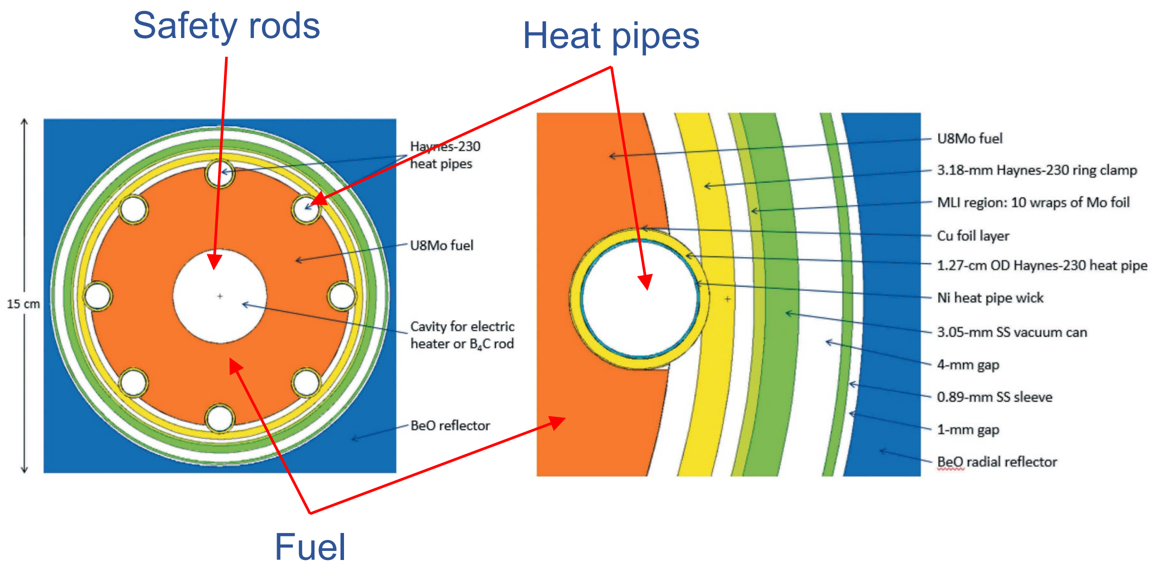
Instead of a "frozen" model, AI/ML models also offer opportunities in adapting to new (sensor) data.

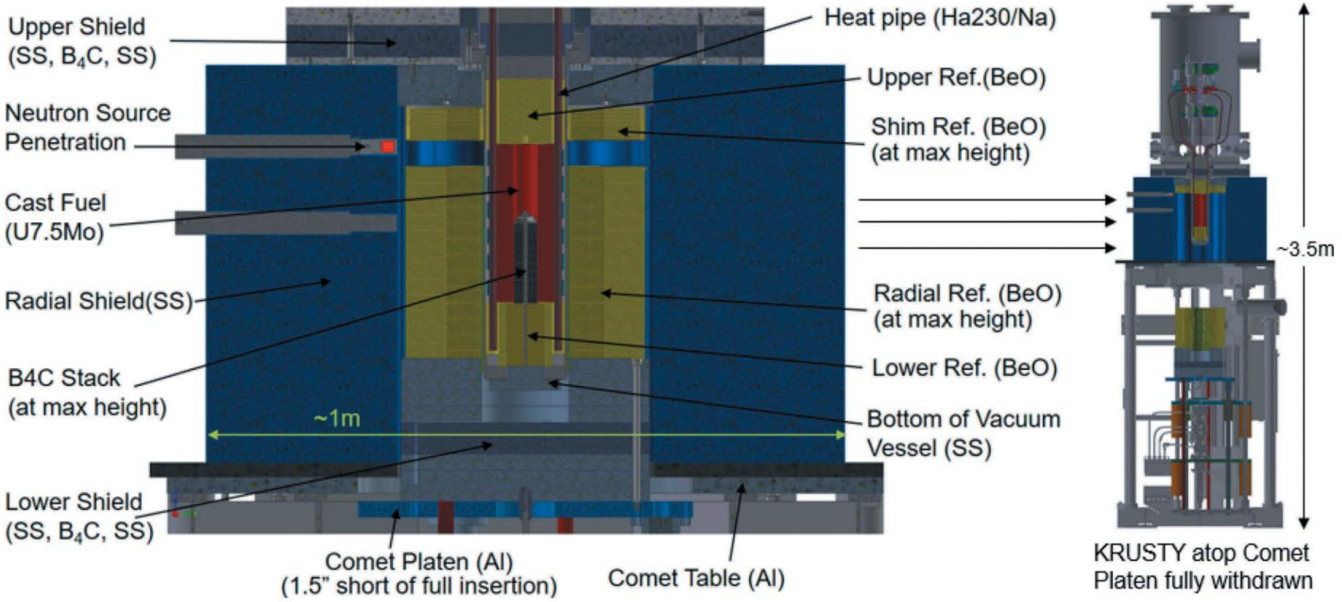
Idaho National Laboratory

ANS

KRUSTY Microreactor

- Kilowatt Reactor Using Stirling TechnologY (KRUSTY) for space fission power development
  - 5kW thermal for 1 kW electric
  - Highly enriched uranium (HEU) U-8Mo
  - Haynes 230 heat pipes with nickel wick and sodium working fluid
  - Three neutron reflector regions

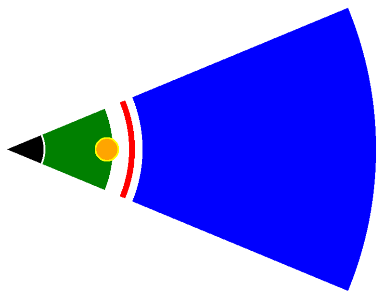




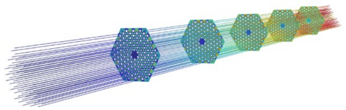
D.I. Poston, et al., “KRUSTY reactor design”, Nuclear Technology, vol. 206, 2020

Heat Pipe Microreactor Simulator

1/8 microreactor core



Cardinal



Driving and interfacing

Geometry

Gmsh

Mesh tool for finite element simulations

Multiphysics Object-Oriented Simulation Environment (MOOSE) Mesh

Neutron transport code

OpenMC

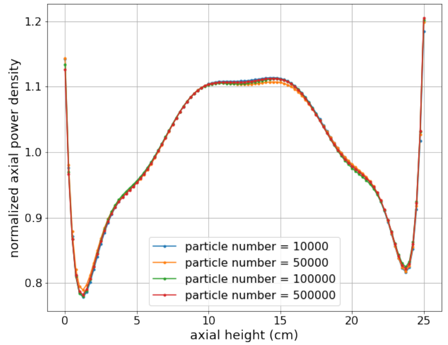
Power distribution

Temperature distribution

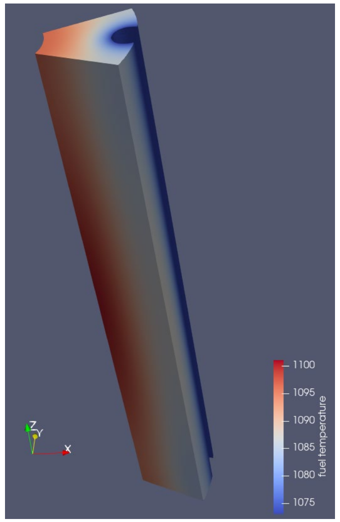
MOOSE

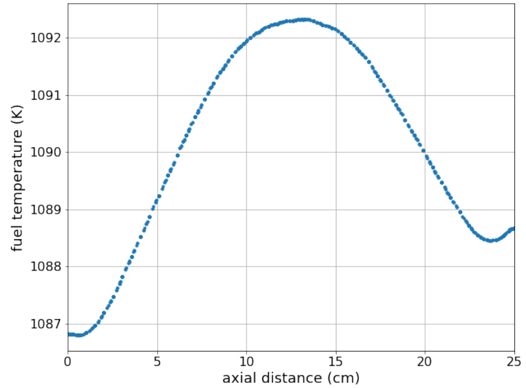
Until converged

Normalized power distribution by Monte Carlo simulation



Temperature distributions by MOOSE





Idaho National Laboratory

ANS

Point Kinetic Model

Inputs $\mathbf{u} = [z_r]$

States $\mathbf{x} = [n_r, c_{r,1}, \cdots, c_{r,6}, T_f, T_e]$

Outputs $\mathbf{y} = [P_a]$

$$z_r = \text{Control rod position}$$
$$n_r = \text{Total relative neutron density (prompt and delayed)}$$
$$c_{r,i} = \text{Delayed relative neutron densities } (i = 1, \ldots, 6)$$
$$T_f = \text{Fuel temperature}$$
$$T_e = \text{Evaporator temperature}$$
$$P_a = \text{Reactor power}$$

Idaho National Laboratory

Point Kinetic Model

Reactivity with temperature feedback terms

$$\rho_r = G_r * z_r + G_0$$

$$\rho = \rho_r + \alpha_f(T_f - T_{f0}) + \alpha_c\left(\frac{T_e + T_c}{2} - T_{avg0}\right)$$

Point kinetics with six delayed neutron groups

$$\frac{\mathrm{d}n_r}{\mathrm{d}t} = \frac{\rho - B}{\Lambda}n_r + \sum_{i=1}^{6}\frac{\beta_i}{\Lambda}c_{r,i}$$

$$\frac{\mathrm{d}c_{r,i}}{\mathrm{d}t} = \lambda_i n_r - \lambda_i c_{r,i}$$

Heat transfer

$$\frac{\mathrm{d}T_f}{\mathrm{d}t} = \frac{f_f P_a - P_c}{\mu_f}$$

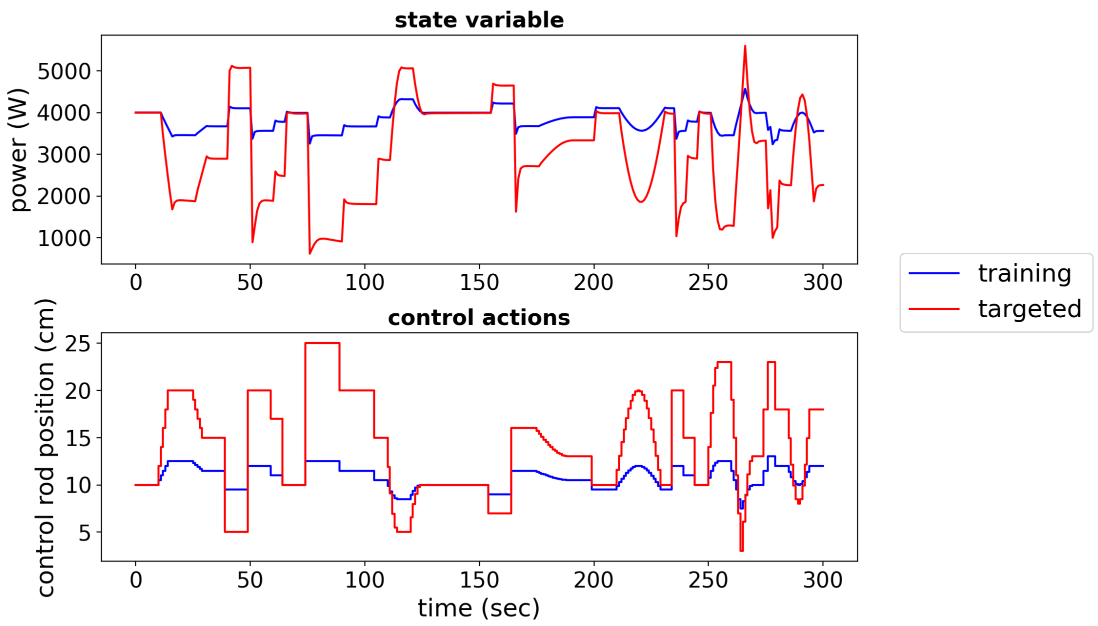
$$\frac{\mathrm{d}T_e}{\mathrm{d}t} = \frac{(1 - f_f)P_a + P_c - P_e}{\mu_c}$$

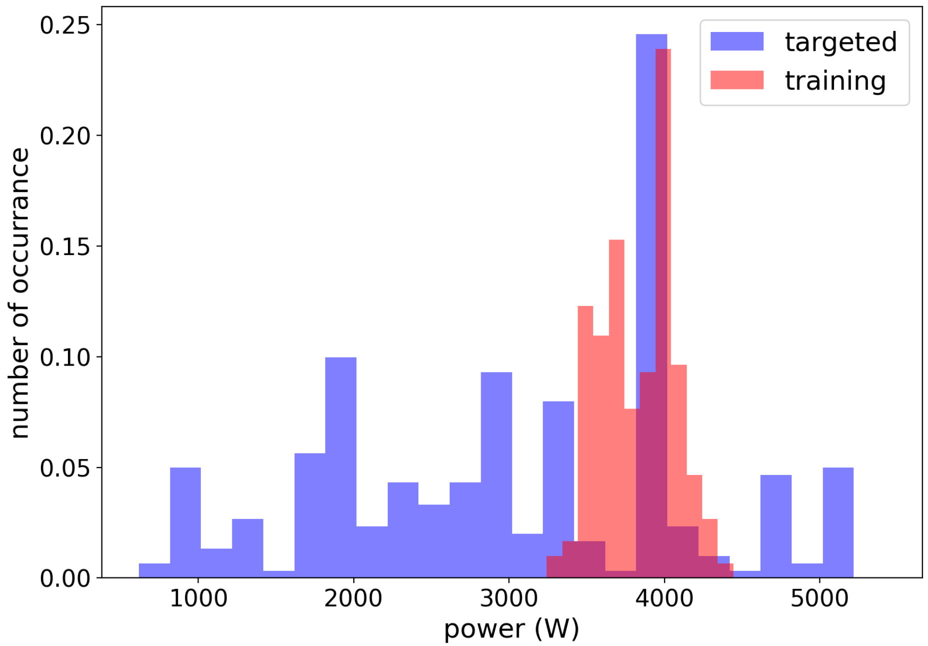
Transient Data

- Multiple transients of reactor power rates P_{t+1} are generated by perturbing the position of control rods u_t

$$P_{t+1} = f(u_t, P_t)$$

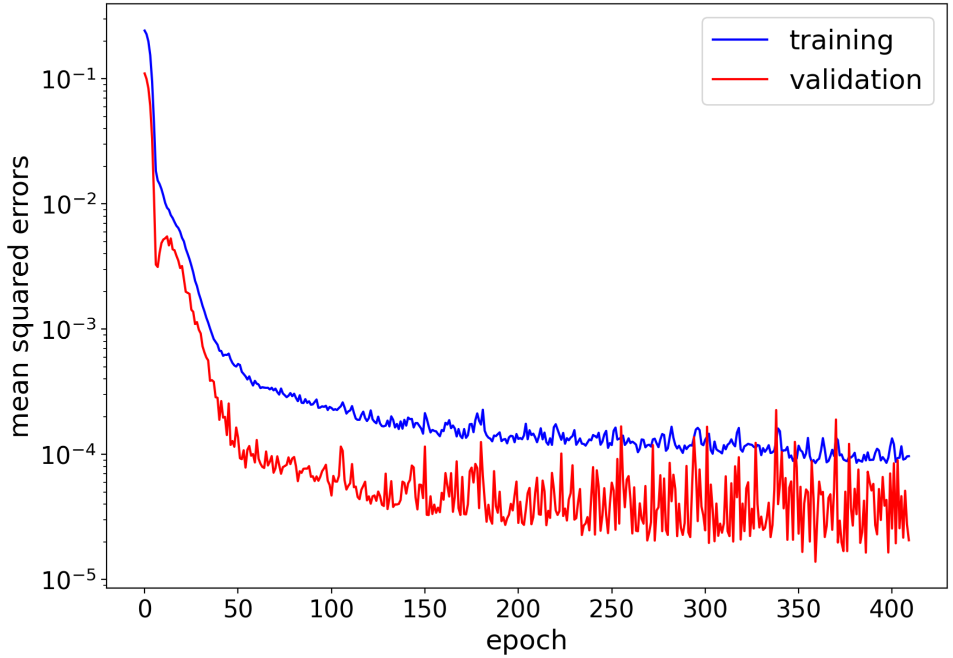
- A gap between training and targeted data
  - Intentionally created to demonstrate online updating
  - Less power variations because of smaller control rod movements

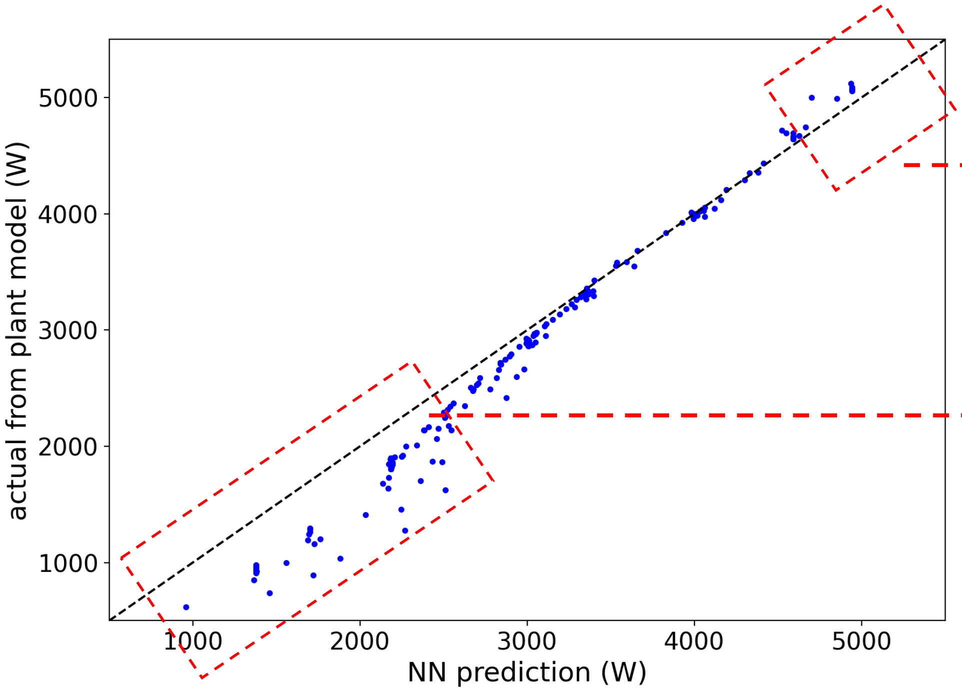




Process Model Validation

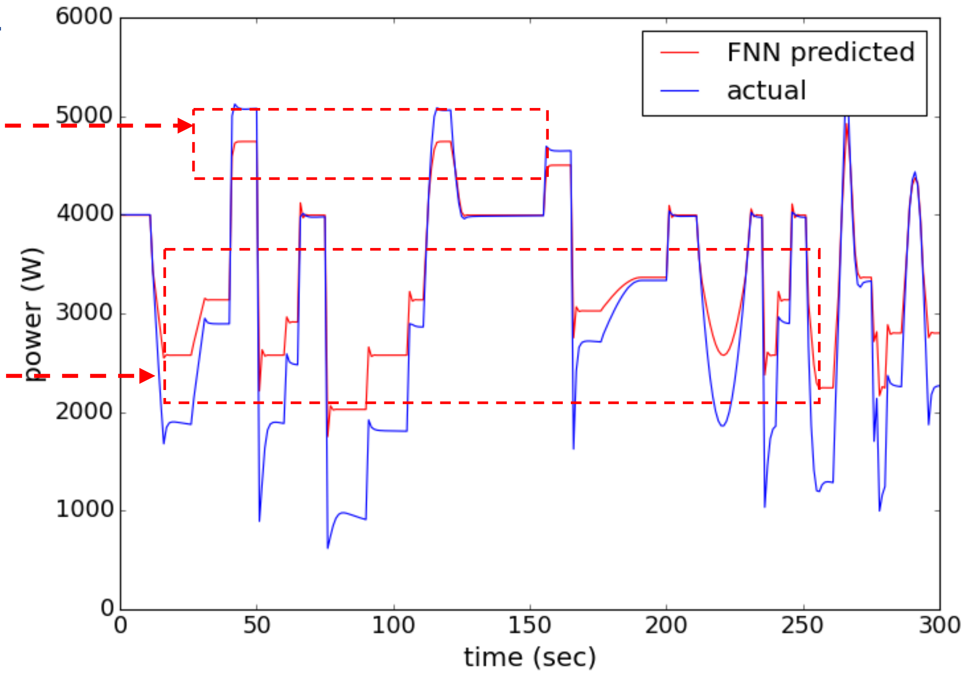
- Model errors due to data gaps
  - Large errors in low- and high-power regions



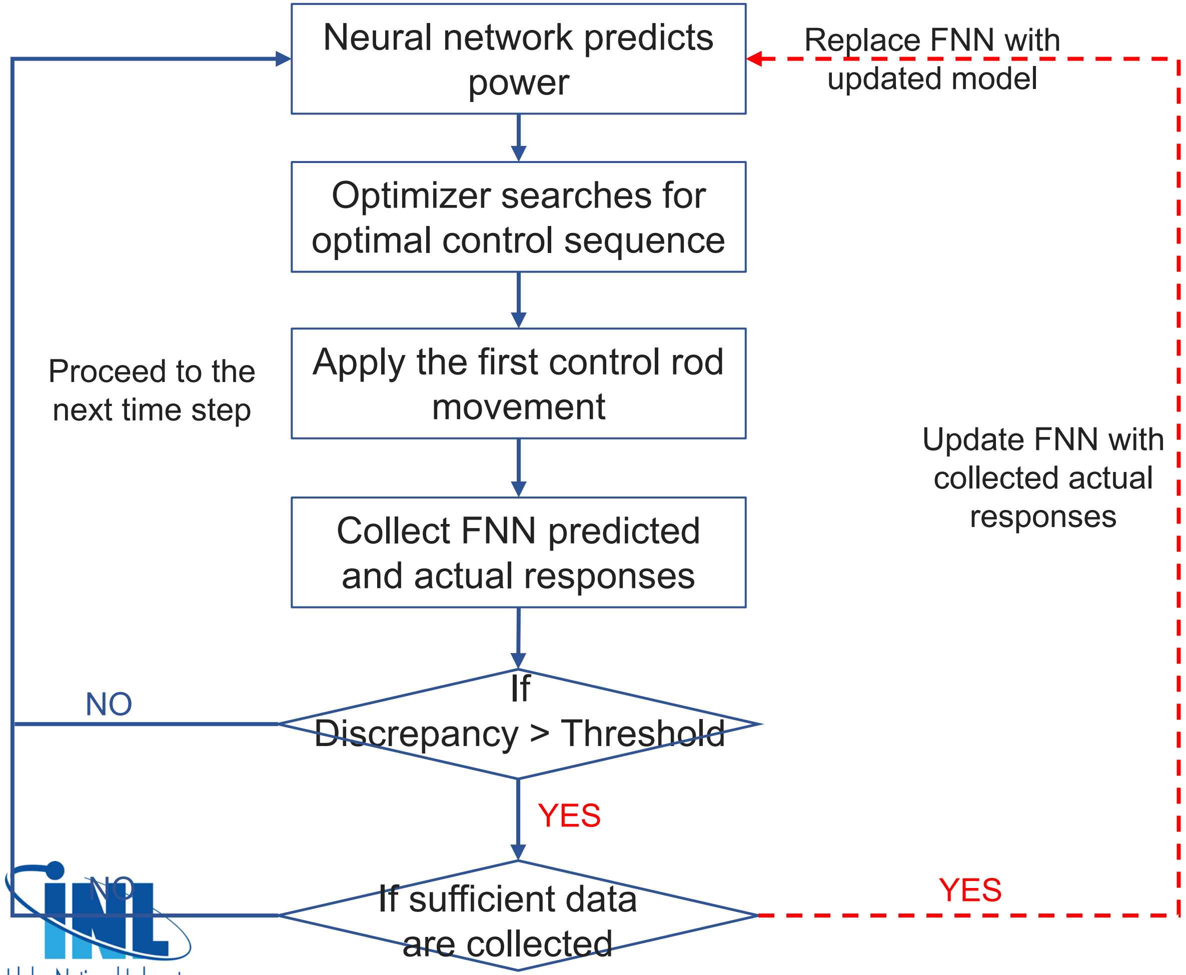


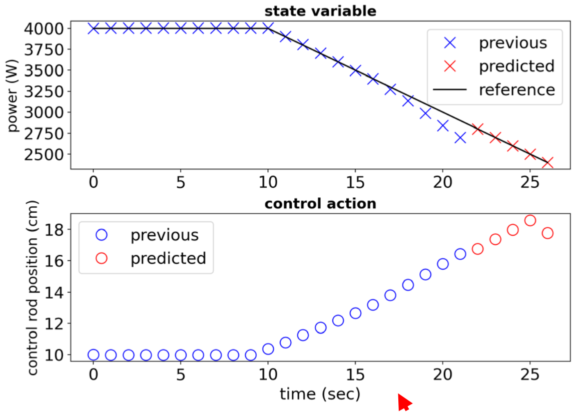
Deviations at high-power regions

Deviations at low-power regions



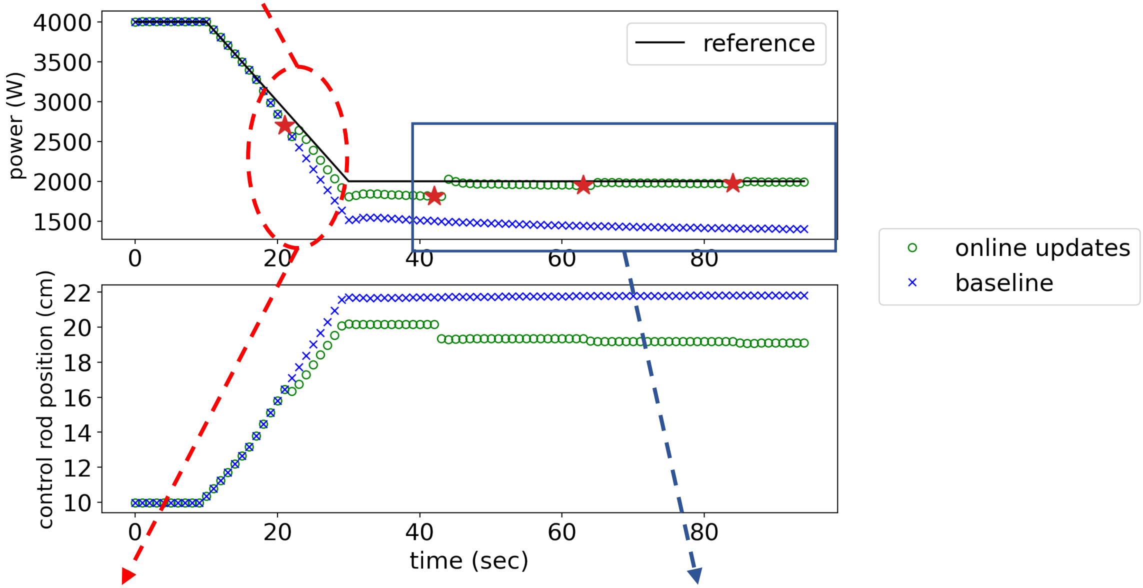
Online Updating





Surrogate overpredicts power and causes biased control actions

Preliminary results given a linear ramp change in power setpoints



Large discrepancy identified

Improved performance with a better surrogate:
Root mean squared error is reduced: 464 W → 87 W

Idaho National Laboratory

ANS

Computational Speed

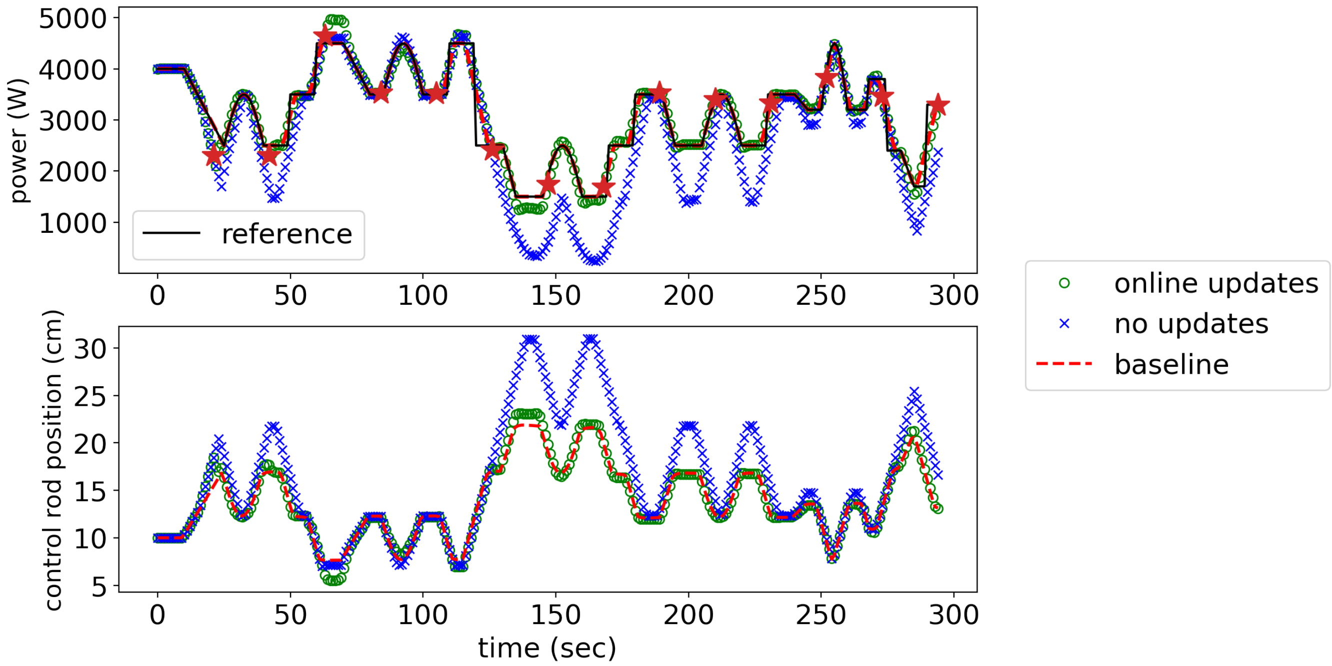
- No updates
  - The entire simulations take 131.3 seconds to finish

- Two updates
  - The entire simulation takes 371.52 seconds to finish
    - The first update takes 97.31 seconds to finish
    - The second update takes 138.5 seconds to finish
  - No major computational burdens given the limited number of updates

Idaho National Laboratory

Online Updating

- Using a two-layer FNN as the surrogate of the baseline point kinetic models
  - Freeze first layer and update second layer
  - 20 neurons each layer

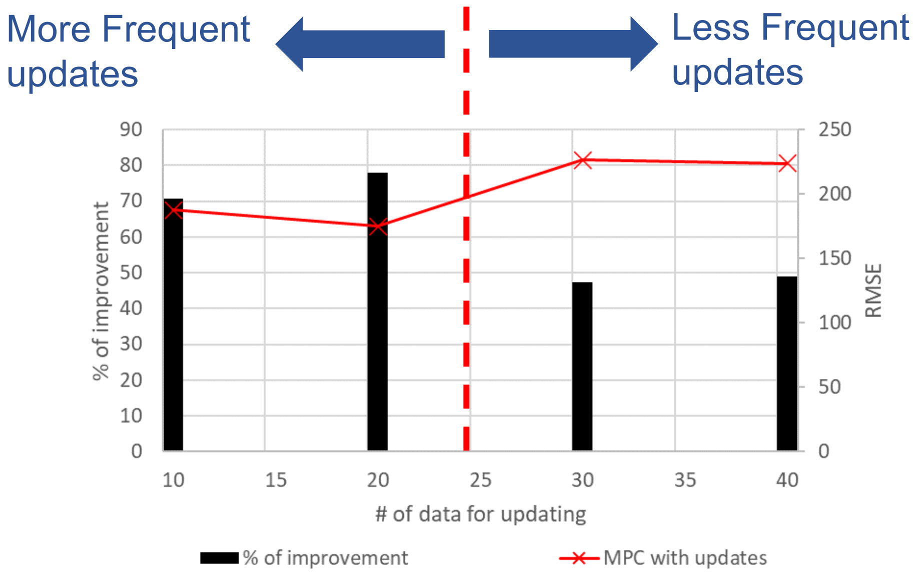


- Demonstrations with a longer transient
  - Prediction accuracy is improved by 74%
  - Controller’s tracking capability is improved by 70%

		Overall Root Mean Squared Errors	Discrepancy in control-rod movements
Prediction errors	No update	510 W	
	With update	133 W	
Tracking errors	No update	649.9 W	3.39 cm
	With update	214.7 W	0.58 cm

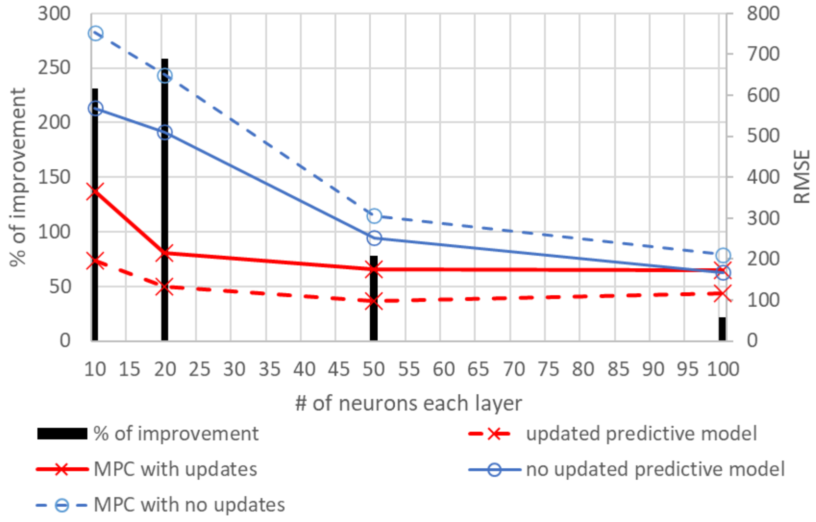
Idaho National Laboratory

Sensitivity Analysis

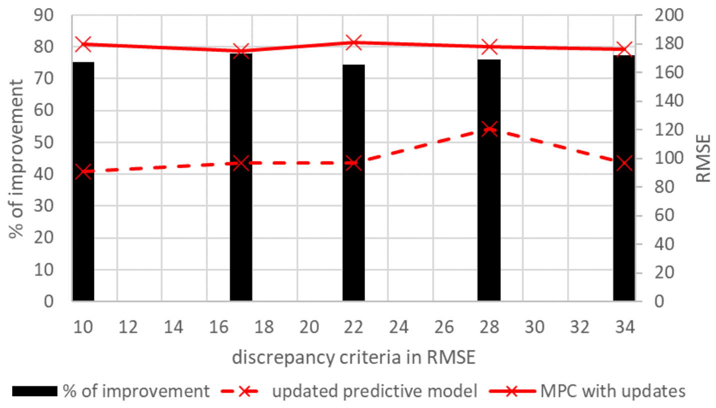


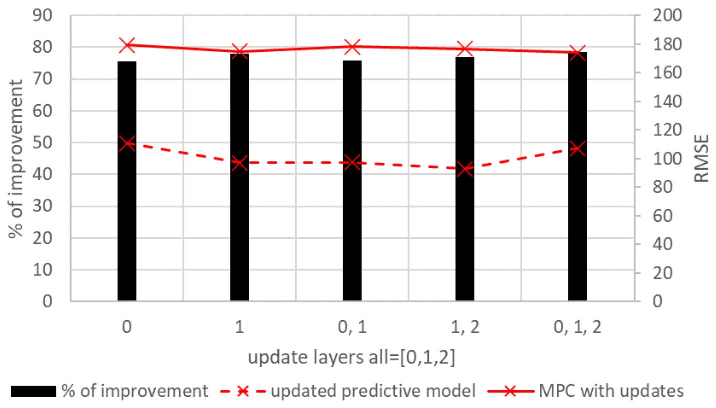
- Given the same testing scenario, the improvement depends on
  - Expressive and generalization capability of neural network
  - Update strategy (threshold, number of data, and layers to update)

- More frequent updates are preferred for smaller errors



- Test online updates with shallow to deep neural network
  - More improvements with shallow (underfitted) networks.
  - Most significant improvements when starting from 20 neurons each layer





- No significant impacts by discrepancy threshold or selections of layers for updates

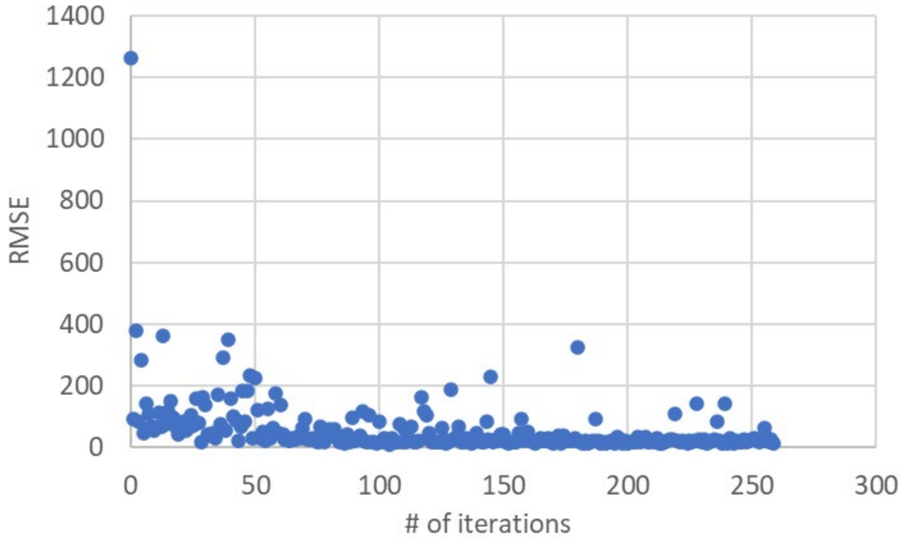
Idaho National Laboratory

Hyperparameter Optimization

- The update strategy includes multiple hyperparameters
  - Layers to update (six possible combinations of any layer index)
  - Error thresholds: [3, 45] W
  - Number of data for updating: [5, 40]
  - Learning rate discount: [0.01, 1]

Hyperparameter	Optimal Values
Layers to update	1st and 2nd layer
Error thresholds	36.9 W
Number of data for updating	10
Learning rate discount	0.98

		Overall RMSE	
Prediction errors	No update	510.0 W	
	With update	130.5 W	
	Baseline	0 W	
Tracking errors	No update	649.9 W	3.39 cm
	With update	178.7 W	0.26 cm
	Baseline	168.2 W	



Idaho National Laboratory

Summary Remarks

- The accuracy of data-driven models and data-driven anticipatory controller are limited by the gaps between training data and targeted applications

- This work proposes an online updating strategy for continuously updating a neural network model when unseen data are detected
    - The goal is to reduce discrepancy between predicted and actual data through continuous learning
    - Transfer learning: Update part of network while freezing the rest
    - Learning is activated when a sufficient amount of data is collected, and a large discrepancy is detected

- Results show that the proposed strategy could significantly improve the accuracy of an “underfitted” process model and controller performance when there are data gaps
    - Deep networks show better initial performance
    - Optimal update strategy can be found through hyperparameter optimizations

Idaho National Laboratory

linyu.lin@inl.gov