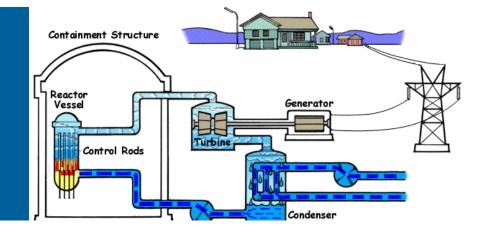


DATA-DRIVEN CONTROL IN THE EXISTING FLEET



HAOYU WANG Principal Nuclear Engineer Argonne National Laboratory

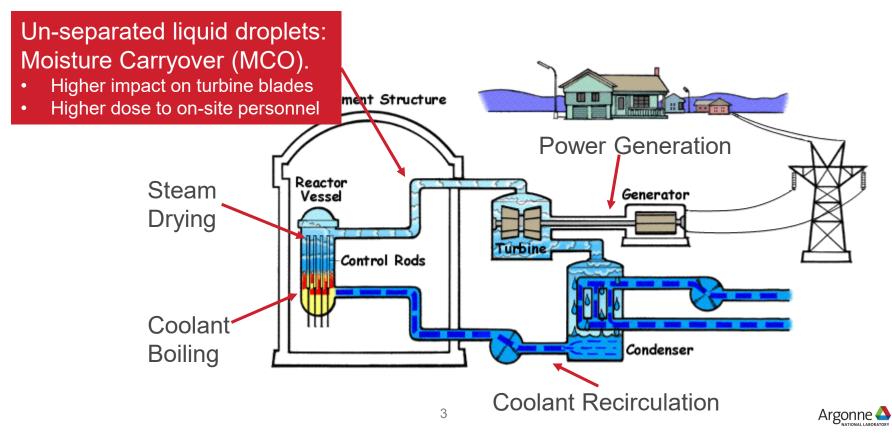
Advanced Reactor Controls Workshop July 12-14, 2023, Argonne National Laboratory, Lemont IL

OBJECTIVES

- Develop a Data-Driven Digital Twin to aid in-cycle control of existing BWR fleet;
- Optimize the efficiency of operation during the planning stage of generation cycle:
 - Reduce the tear and worn of turbine components;
 - Reduce the radiation exposure of on-site personnel;
 - Increase the profitability of nuclear generation.

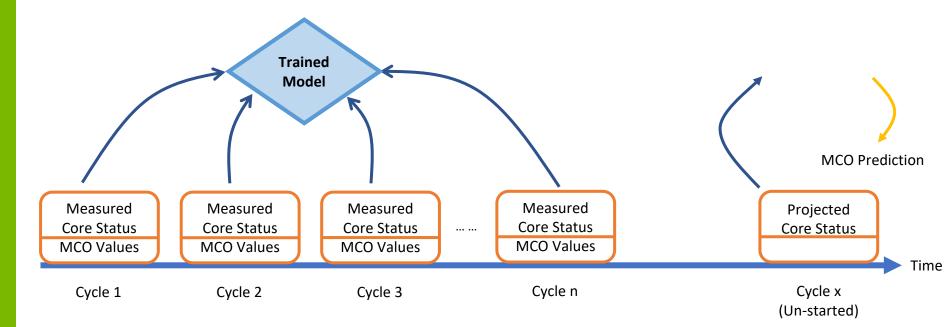


PROBLEM TO SOLVE: MCO PREDICTION



PROBLEM TO SOLVE: MCO PREDICTION

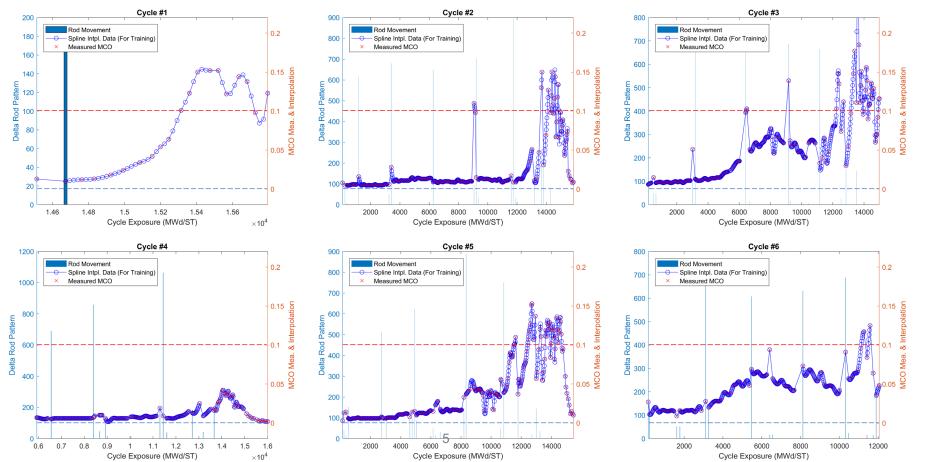
Un-started cycle prediction: Evaluate MCO using the projected core status.





Higher MCO at the end of each cycle; 7,000+ core variables behind each measurement

TRAINING DATA



FEATURES AND TRAINING METHODOLOGY

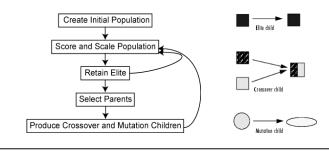
Engineering analysis to determine the feature:

• Steam quality(**Q**) and Coolant flow rate (**V**_L)

$$MCO \sim \frac{1}{Q^m} \left(\frac{1}{V_L^{n1}} + V_L^{n2} \right) \quad (m, n1, n2 > 0)$$

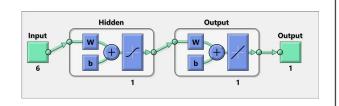
Hyper-parameter optimization:

Genetic Algorithm (Elite Survives)



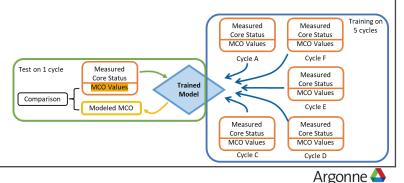
Physics-informed Model Selection:

- Single-layer Neural Network with non-linear addition
- Mimic the nature of MCO (Aggregation of liquid droplets)



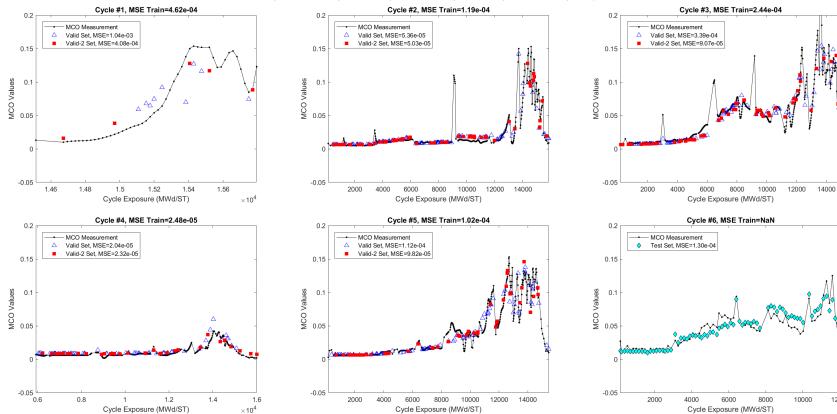
Avoid Overfitting:

· Leave-out one cycle, and cross-validation



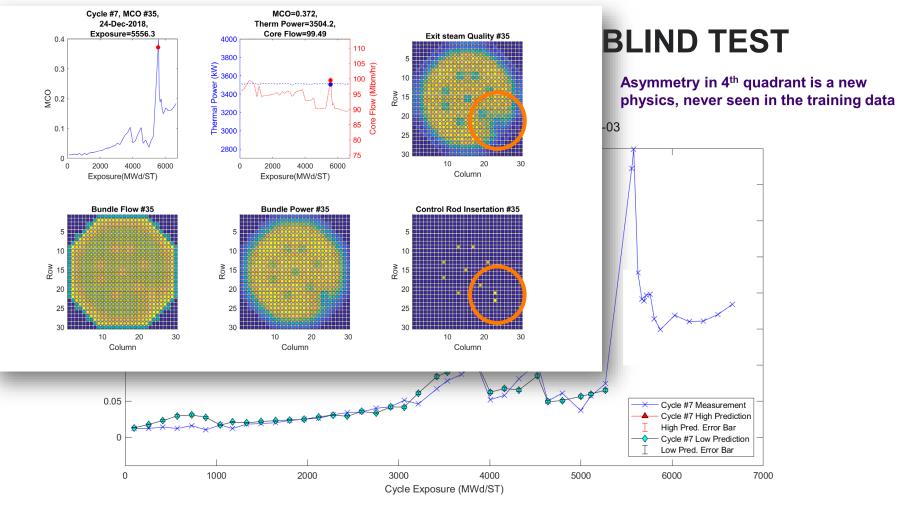
MODEL PERFORMANCE: GENERALIZATION

00% MovHrz Cycle #6, Model #35, Result, 01 Neuron 70% Train(MSE=1.65e-04), 10% Valid(MSE=1.92e-04), 20% Val2(MSE=9.24e-05), Independent Test



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CONCLUSION

- BWR MCO was modeled using machine learning technique, which was never achieved by any other trivial methods;
- Collaborating nuclear facility is using this model for performance optimization;
- This model could be included in a feedback loop, to provide the feasibility to:
 - Automatic operation based on MCO prediction;
 - On-line learning and updating of the machine learning model for better accuracy.



THANK YOU



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BACK-UP SLIDES



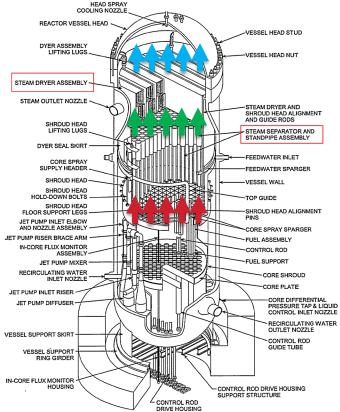
STEAM DRYING PROCESS

Steam drying in GE BWR/4 reactor :

(1)Steam Separator, upgrading the steam quality from ~30% to ~90%;

(2)Steam Dryer, upgrading the steam quality from ~90% to ~99.9%.

Saturated Steam Separators will elevate the Moisture Carryover

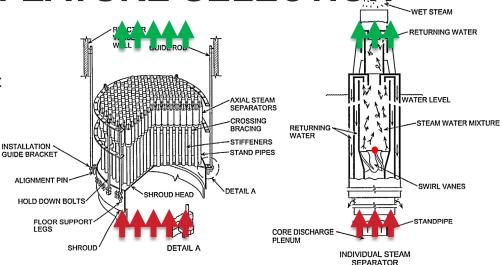




ENGINEERING FEATURE SELECTION

Before Entering the Separator: Lower initial steam quality (*Q*), Higher *MCO* :

$$MCO \sim \frac{1}{Q^m} \ (m > 0)$$



In Steam Separator : Mixture passes swirl vanes, Liquid Drops hit the wall and get separated. Too low or too high Coolant flow rate (V_L), Higher *MCO* :

$$MCO \sim \frac{1}{V_L^{n_1}} + V_L^{n_2}(n_1, n_2 > 0)$$



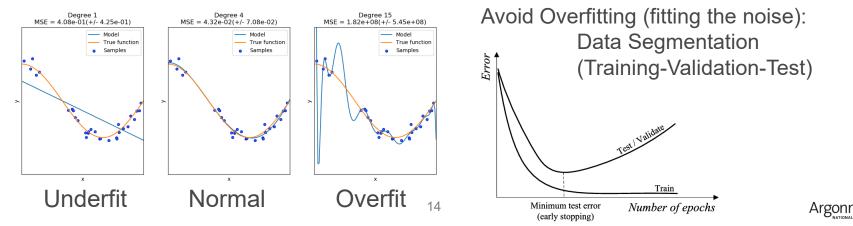
ML STRUCTURE

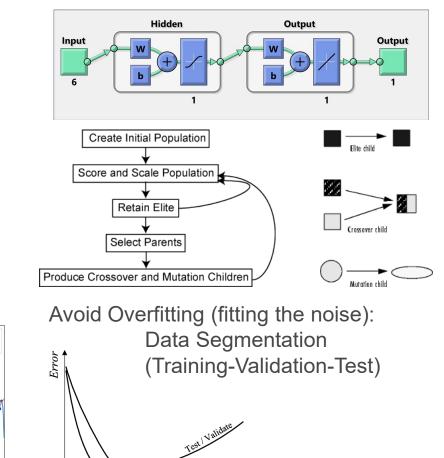
Nature of MCO:

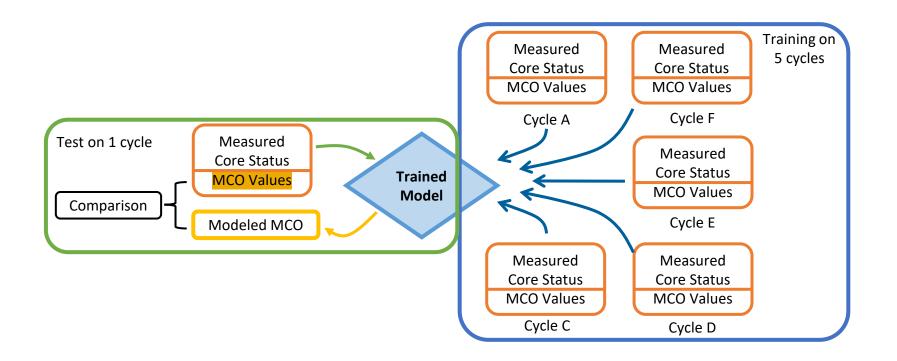
Aggregation of liquid droplets Model Selected:

Single-layer Neural Network (non-linear addition included) Hyper-parameter optimization:

Genetic Algorithm (Elite Survives)









WHY? NEW-PHYSICS AND DATA <u>PIVERSITY</u>

1. A machine learning model can only interpolates the points it sees.

2. Extrapolation is unreliable.

3. In order to get accurate interpolation, adequate sampling density of the input space must exist.

