NS&T ML-AI

*Big Data* *Machine Learning* *Artificial Intelligence*

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**Webinar will begin at 11:00 am MST**

*Welcome to the*

# Artificial Intelligence and Machine Learning Symposium 11.0

**April 27, 2023**

IDAHO NATIONAL LABORATORY

April 27th, 2023

**Dr. Nancy Lybeck**

**Department Manager**
Instrumentation, Controls, & Data Science

# Welcome to the AI/ML Symposium 11.0

## “AI/ML in Instrumentation, Control, and Automation”

Idaho National Laboratory

# AI/ML in Instrumentation, Control, and Automation


"Imagine a wizard buying a rusty old car and telling his wife all he wanted to do with it was take it apart to see how it worked, while really he was enchanting it to make it fly." – Molly Weasley, *Harry Potter and the Chamber of Secrets*

Big Data, Machine Learning, Artificial Intelligence

# "AI/ML in Instrumentation, Control, and Automation"

## Agenda – ML/AI Symposium 11.0

## April 27, 2023 - 11:00 am to 1:00 pm MDT

| Time | Subject | Speaker |
|---|---|---|
| 11:00 – 11:05 | Welcome, Introductions, and Agenda | **Nancy Lybeck**<br>Department Manager, Instrumentation, Controls, & Data Science<br>INL |
| 11:05 – 11:20 | Experimental demonstration of a data-driven control system for the MIT Graphite Exponential Pile | **Jiankai Yu**, MIT |
| 11:20 – 11:35 | Can we use machine learning to control nuclear power plants? | **Jake Farber**, INL |
| 11:35 – 11:50 | AI for Modeling, Optimizing, and Controlling Complex Systems in Science Domains | **Prasanna Balaprakash**, ANL/ORNL |
| 11:50 – 12:05 | Remote Operations and Monitoring of Microreactors and the Opportunity for ML/AI | **Joe Oncken**, INL |
| 12:05 – 12:20 | Machine Learning techniques for enhanced model-based control | **Brendan Kochunas**, U of Michigan |
| 12:20 – 12:35 | Autonomous Control with ML/AI for Microreactors: Opportunity and Challenge | **Linyu Lin,** INL |
| 12:35 – 12:50 | Unattended Operation of Fission Batteries | **Vivek Agarwal**, INL |
| 12:50 – 1:00 | Wrap-up | **Nancy Lybeck** |

Idaho National Laboratory

Battelle Energy Alliance manages INL for the U.S. Department of Energy's Office of Nuclear Energy. INL is the nation's center for nuclear energy research and development, and also performs research in each of DOE's strategic goal areas: energy, national security, science and the environment.

# Experimental Demonstration of a Data-Driven Control System for MIT Graphite Exponential Pile

Jiankai Yu[1], Jarod C. Wilson[2], Akshay Dave[3], Kaichao Sun[4] and Bren Phillips[1*]

[1] Nuclear Science and Engineering

[2] Nuclear Reactor Laboratory

[3] Argonne National Laboratory

[4] International Atomic Energy Administration

MIT Nuclear Reactor Laboratory

Massachusetts Institute of Technology

# Acknowledgments

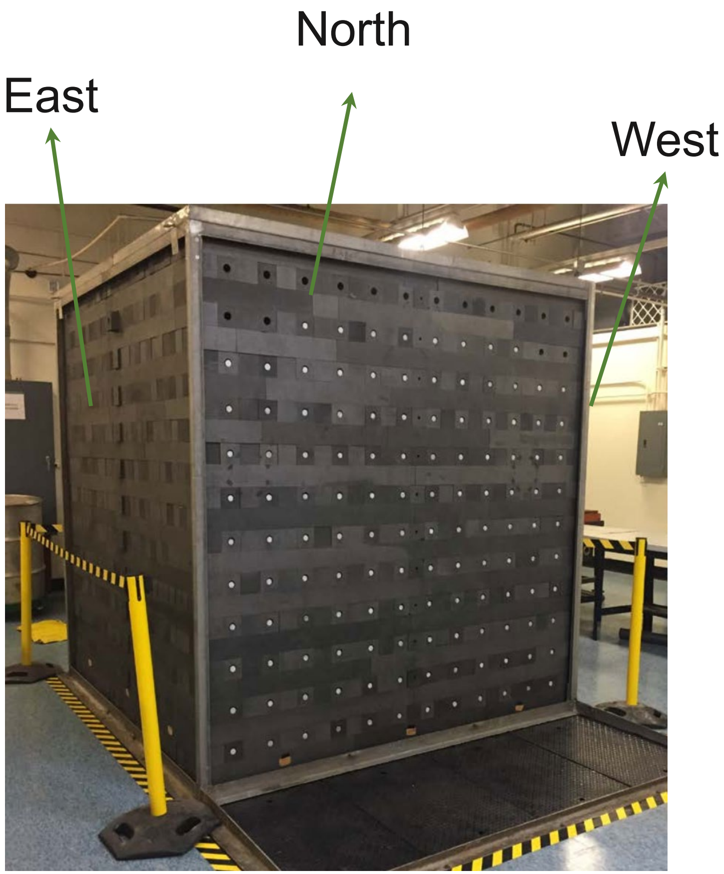
- This work is supported by DOE NEUP Award Number:DE-NE0008872.

# Presentation Outline

- Background
  - Core motivation
  - MIT Graphite Exponential Pile (MGEP)
- Methodologies
  - Control system overview and constraints
  - In-pile control components
  - Machine Learning Methodology
- Experimental Demonstration
  - Performance summary
  - Fault Tolerance
- Conclusions/Future Work

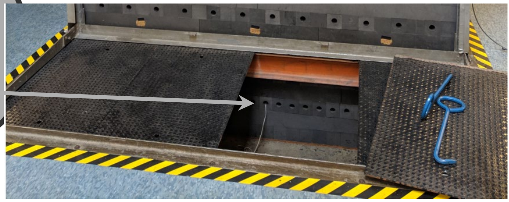
# Research Objectives

- **Experimental Demonstration of Autonomous Control of a Fission System (MGEP)**
  - Virtual control system
    - Neural network surrogate model for detector signal generation
    - Neural network regression model for control rod prediction
  - Experimental data calibration
    - Neural network trained by experimental data
  - Autonomous control system
    - Hardware integration
    - LabVIEW interface
    - In-pile experimental demonstration
    - Fault Tolerance



# Background - MGEP

- **MIT Graphite Exponential Pile (MGEP)**
- **Constructed in 1950s with surplus nuclear-grade graphite from MITR construction.**
  - Fell out of use sometime circa 1970.
  - ‘Rebooted’ in 2016,
  - Excellent facility for demonstration
- 90”×90”×90” (plus underground pedestal)
- Pu-Be / Cf-252 neutron source operation
- 1,288 natural uranium slugs
- **Subcritical ($k_{eff} \approx 0.8$)**

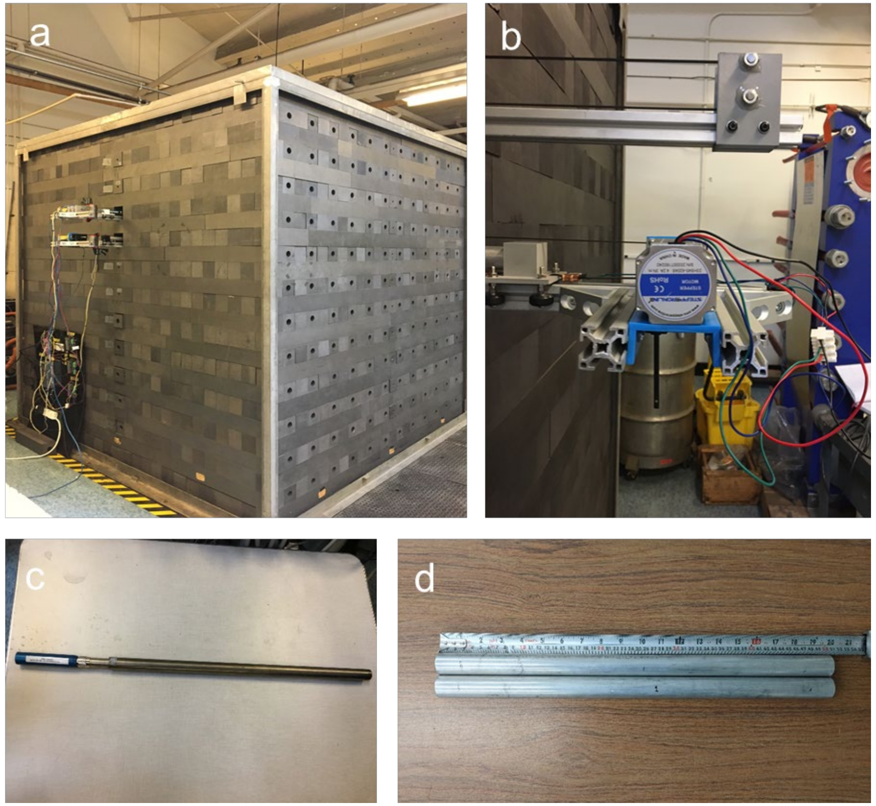


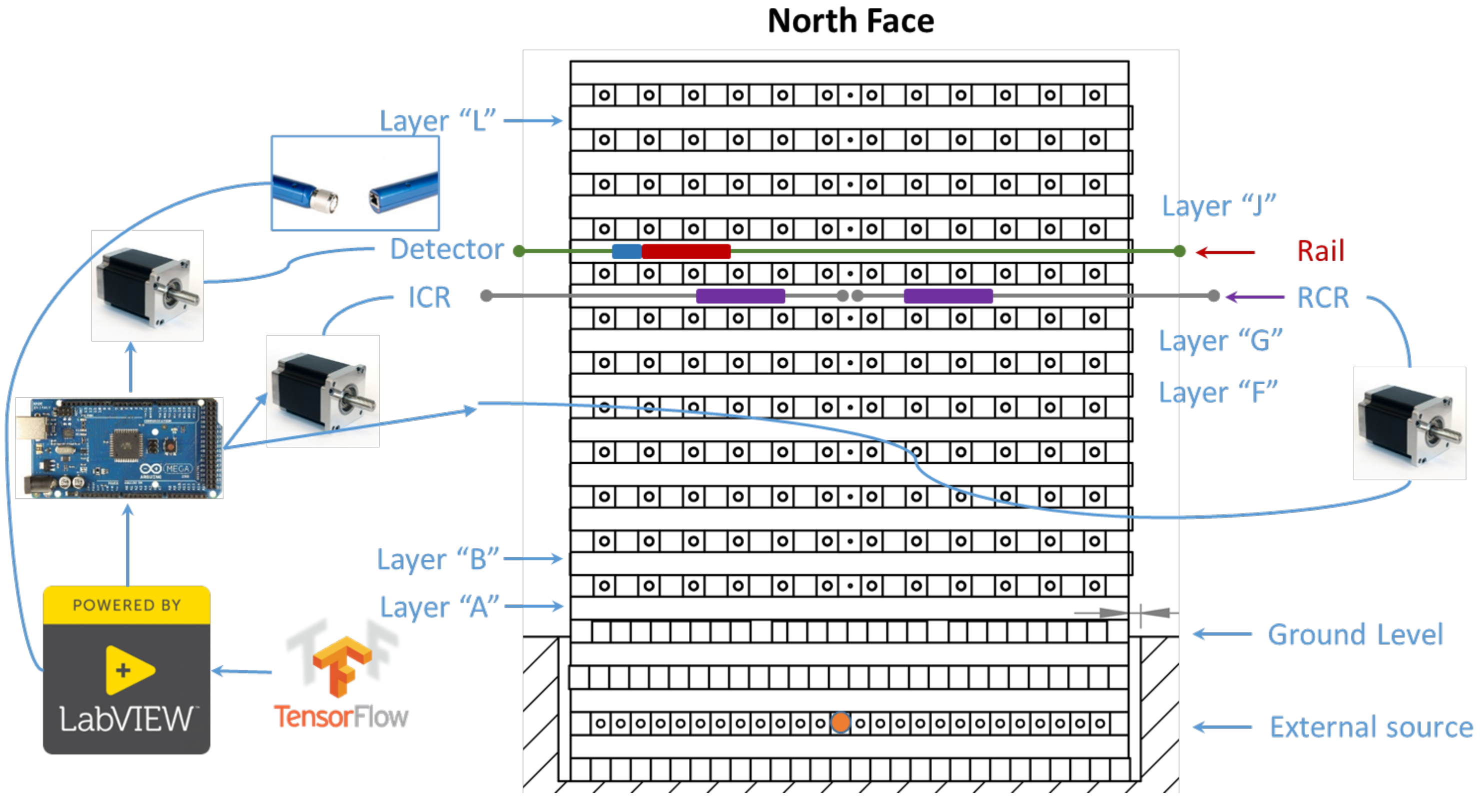
# Development of Data-driven Control System (DCS)

- Perfect candidate to serve as testbed for ML-based system.
  - Subcritical => experimental systems can operate safely.
  - Existing body of work (internal) for pile characterization, modelling, instrumentation and controls, and applicability of ML.
  - Physical construction allows high configurability.
- High-level system design informed by MGEP characteristics, constraints.
  - Measurement and perturbation of neutron flux based on 2D axial sinusoidal profile around neutron source.
  - Actuation of instrumentation and control devices limited geometrically to accessible channels.

# Hardware Integration

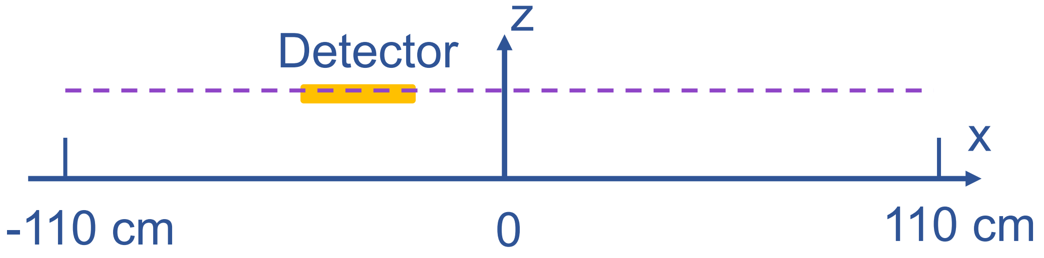
- **Experiment setup**

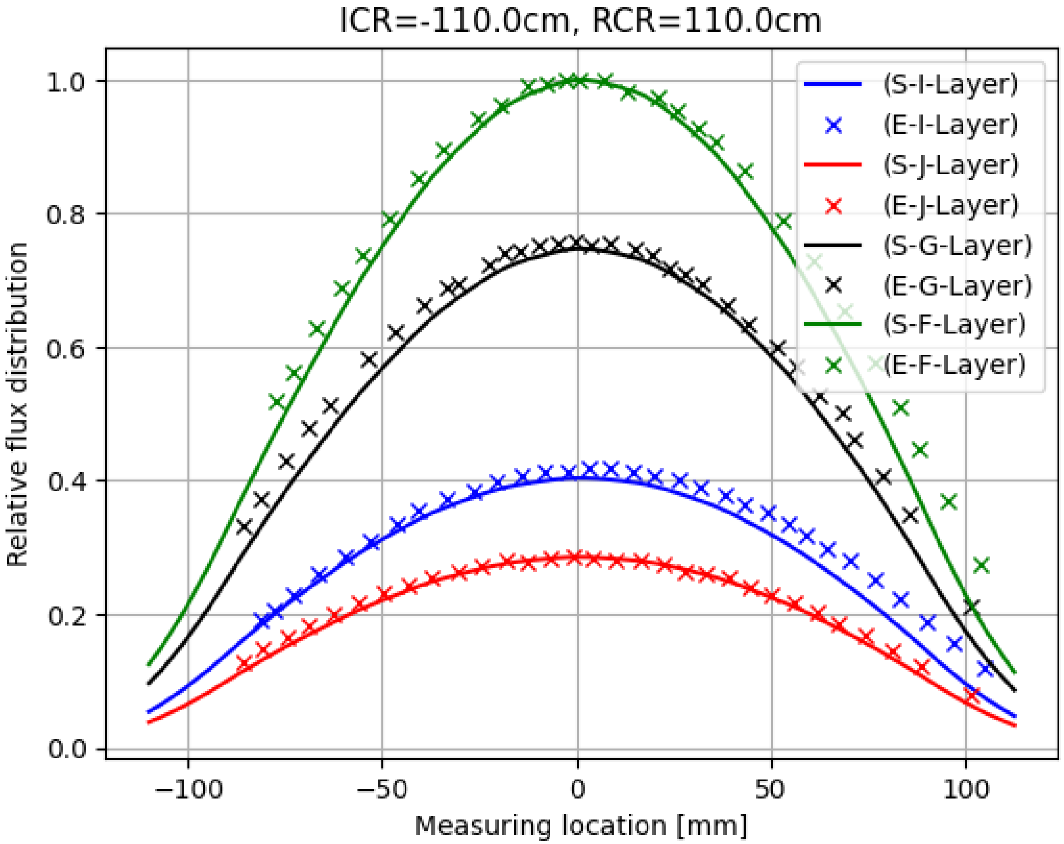


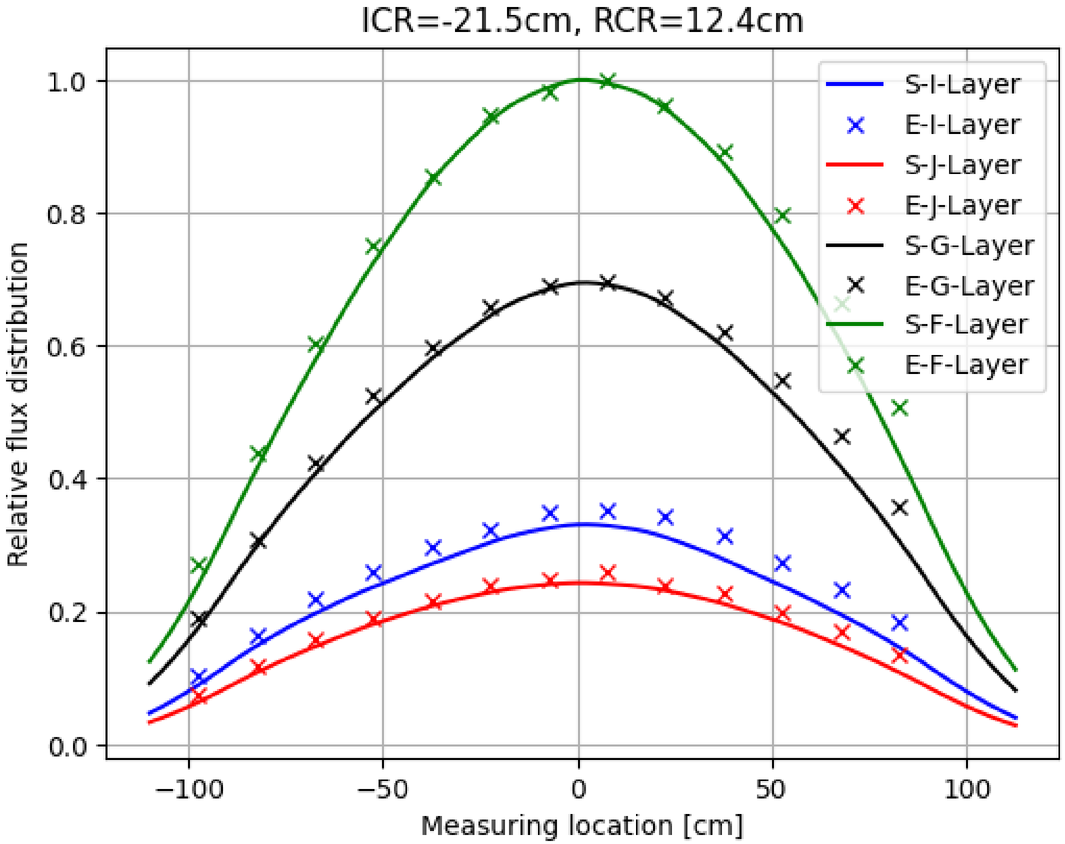



# Numerical Modeling of MGEP

- **Comparison w/ experimental data**
  - CRDs in H layer
  - Detector in F, G, I, J layers



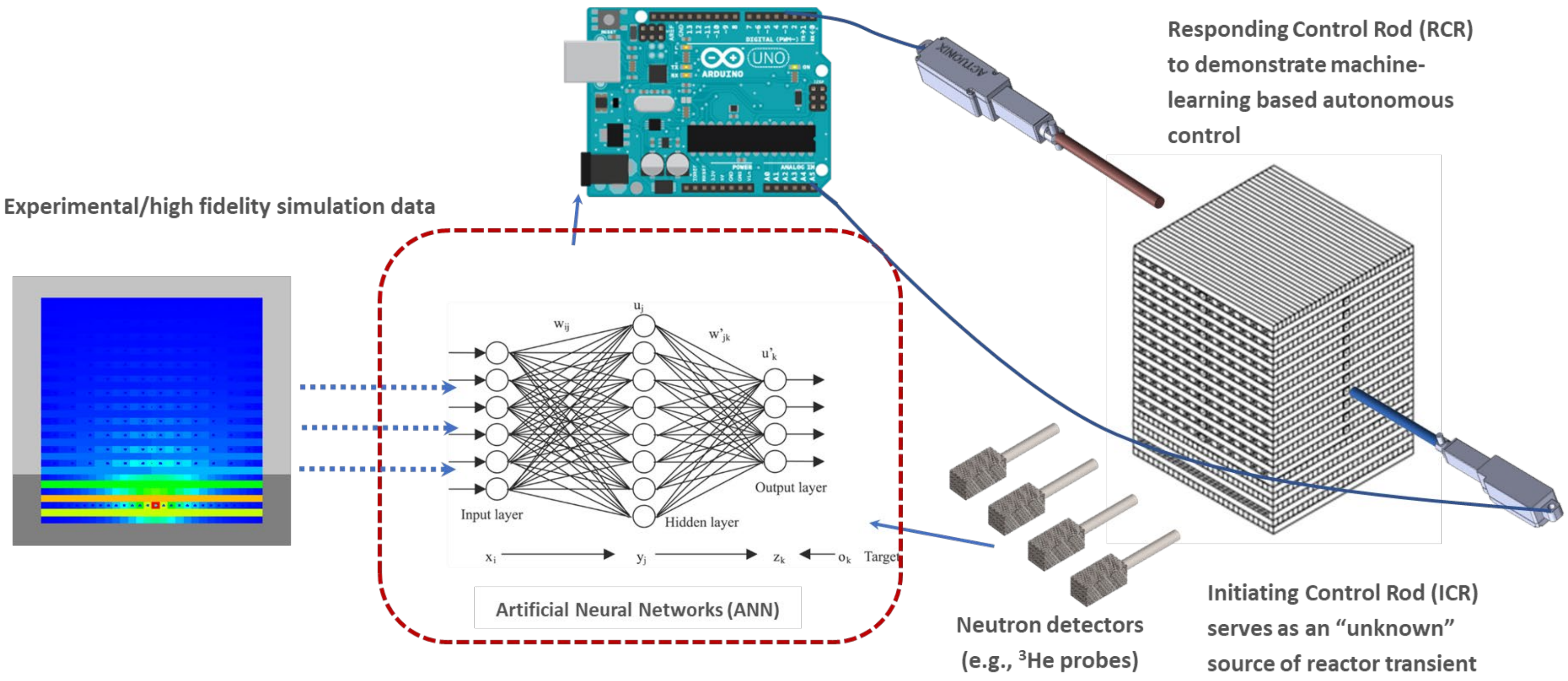




Comparison results verifies the accuracy of numerical modeling of MGEP.

# Project Overview

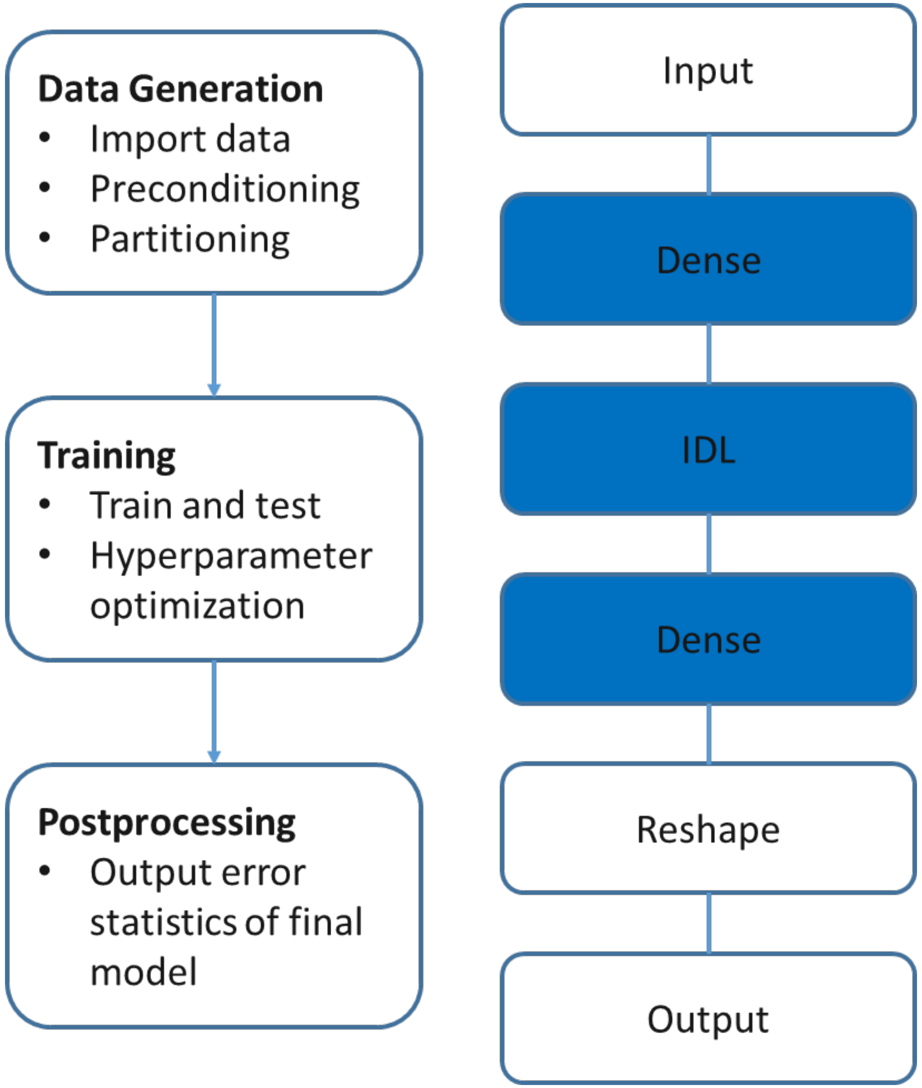
➢ **First-of-a-kind engineering demonstration of reactor autonomous control supported by machine-learning aided real-time prediction***

1. *Detectors: periodic move*
2. *ICR: random move*
3. *RCR: supervised move*
4. *Physics model*
5. *Neural Network*
6. *Decision Making*



# Artificial Neural Network

- **Toolkit**
  - TensorFlow (Keras)
  - NPSN (https://github.com/a-jd/npsn)
- **Data sets**
  - Simulation data
  - Experimental data
- **Neural networks**
  - NN-S (Surrogate model)
    - Input: Control rods positions
    - Output: Flux map
    - Only in virtual control system
  - NN-CR (Control rod regression model)
    - Input: Perturbated flux map
    - Output: Control rod positions



# Figure of Merit

- **Two Neural Networks**
  - NN-S (Surrogate model)
  - NN-CR (Control rod regression model)

$$f_{NN-S} = f\left(x_{RCR}, x_{ICR}^{actual}\right) = \varphi(d_1, \cdots, d_M)$$

$$f_{NN-CR} = x_{ICR}^{predicted}(\varphi(d_1, \cdots, d_M), x_{RCR})$$

  - Figure of Merit

$$\delta_{NN-S} = \frac{\varphi(d_1, \cdots, d_M)^{predicted} - \varphi(d_1, \cdots, d_M)^{actual}}{\varphi(d_1, \cdots, d_M)^{actual}}$$

$$\delta_{NN-CR} = x_{ICR}^{predicted} - x_{ICR}^{actual}$$

# Neural Network Optimization

| Hyperparameters | Search Space | Best Values |
|---|---|---|
| Number of intermediate dense layer | [1~5] | 3 |
| Activation function | ELU, ReLU, Sigmoid, Softsign, Softplus, Tanh | ReLU |
| Shape of intermediate dense layer | [256, 512, 1024] | 1024 |
| Loss function | LogCosh, MSE, MAPE, MSLE | LogCosh |
| Optimizer | [Adam, SGD] | Adam |
| Batch size per epoch | [4, 8, 16, 32] | 8 |

# Interface of Virtual Control System

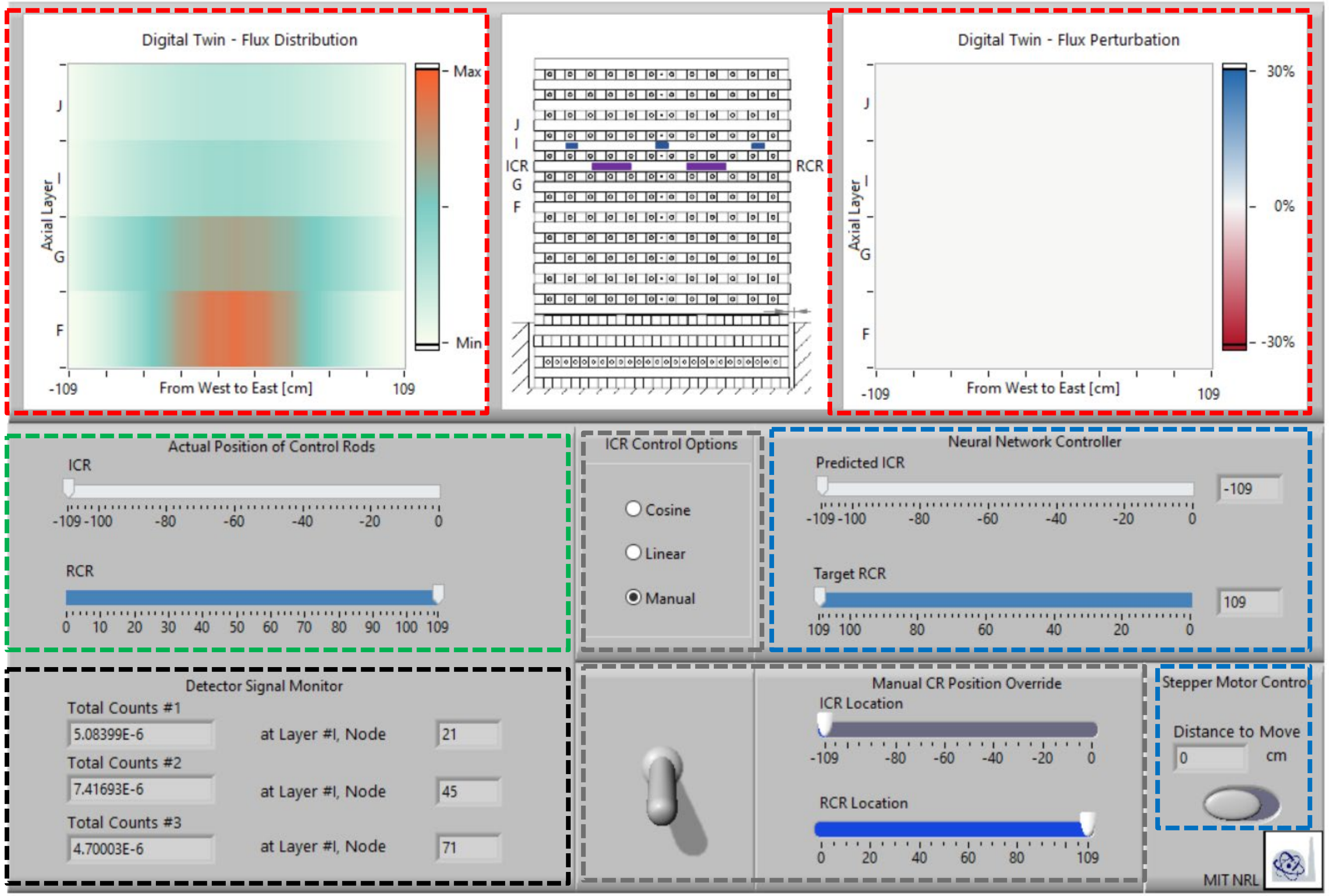
CR Position
Display: $x_I, x_R$

CR Manipulation
Controls: $x_I$ or $x_I,\ x_R$

NN: Digital twin
Input: $x_I,\ x_R$
Output: $\phi(x)$

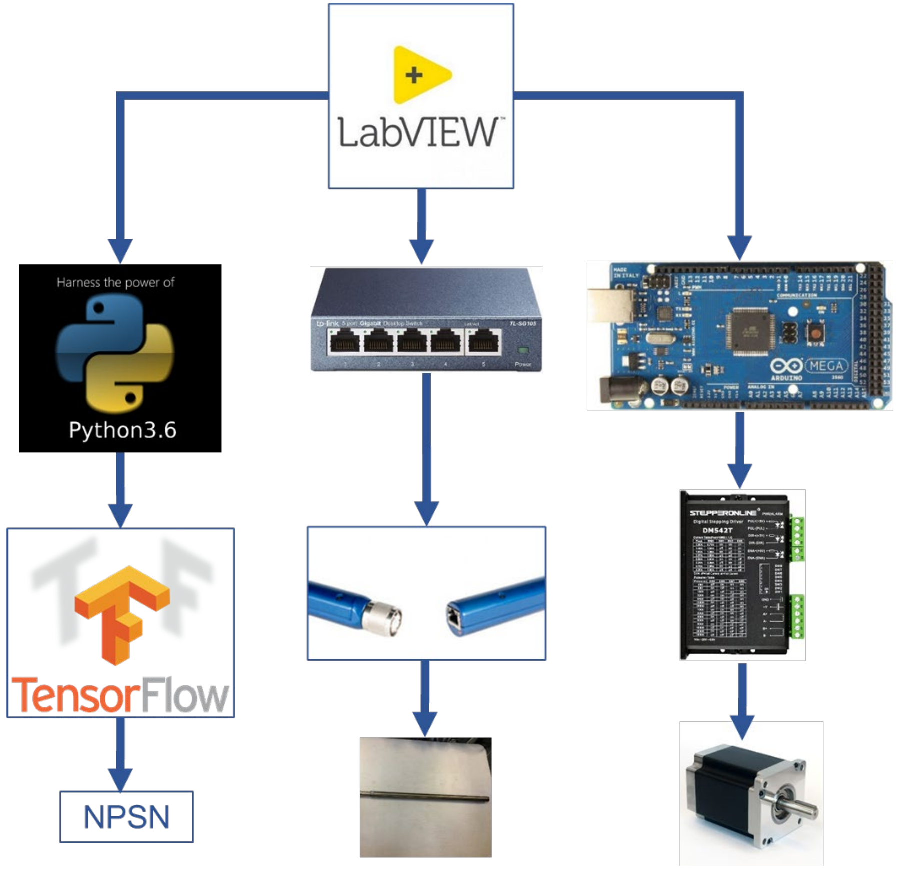
Detector signals
Displays: $\phi_1$, ..., $\phi_M$

RCR Controller
Inputs: $\phi_1$, ..., $\phi_M$, $x_R$
Controls: $x_R$

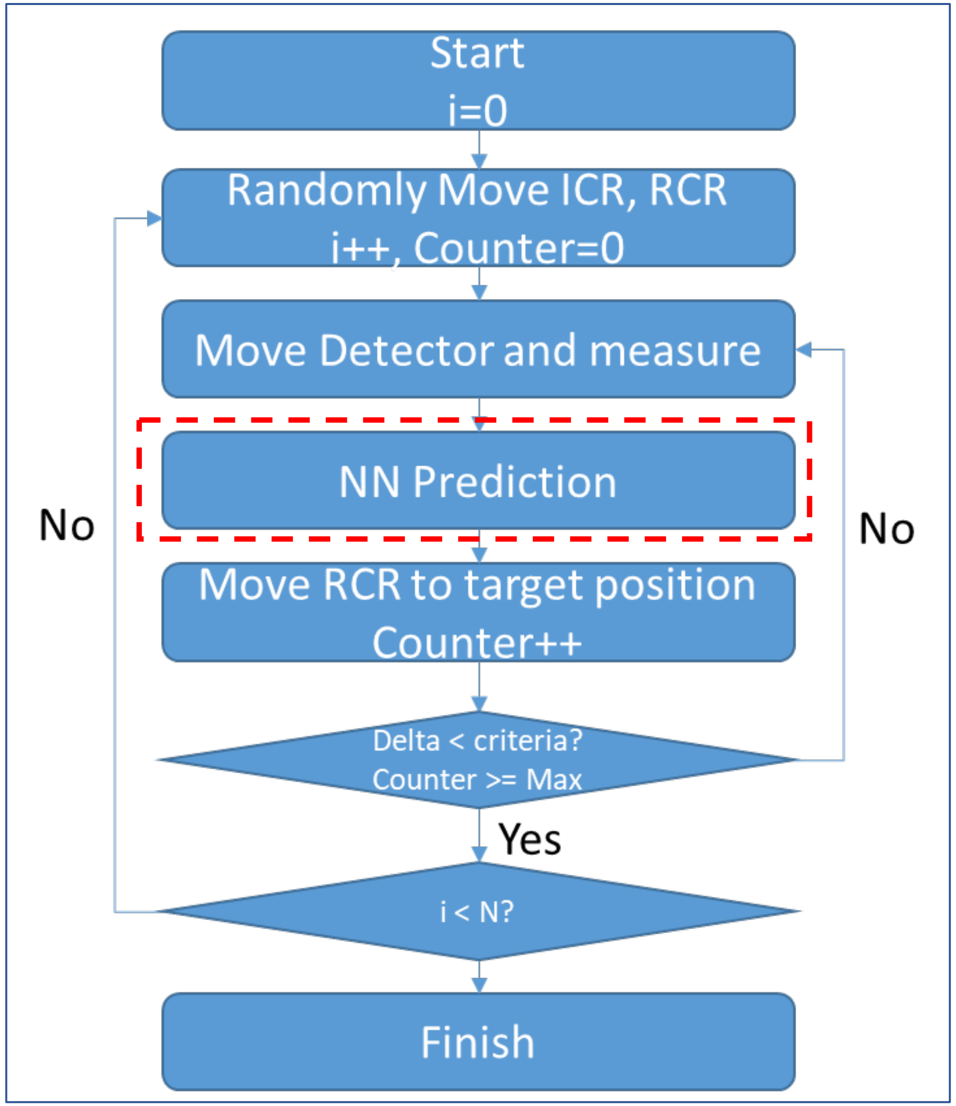


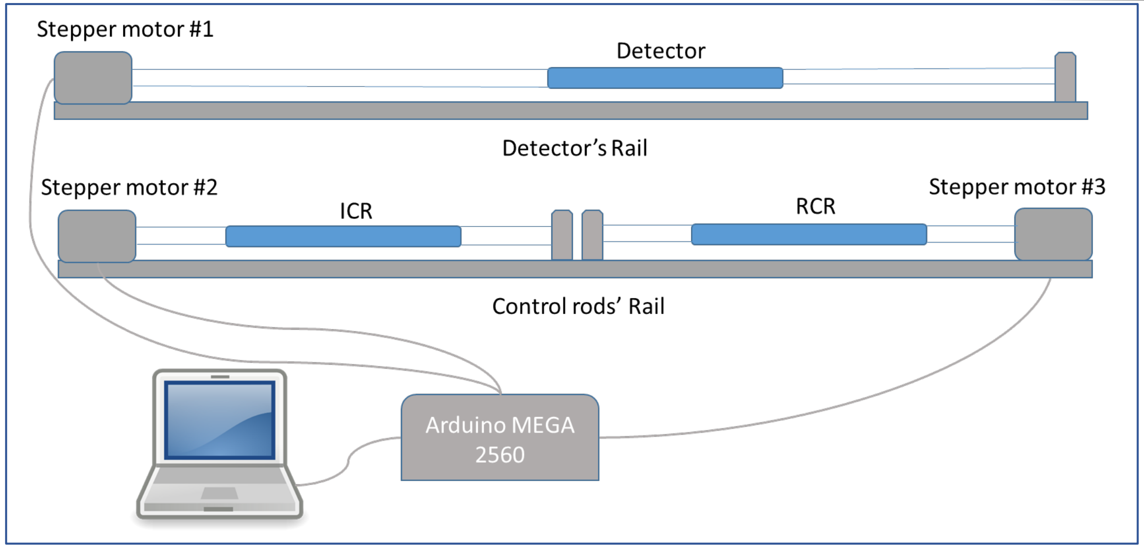
# LabVIEW Interface

- **TCP/IP Interface**
  - Detectors' data collection
- **Python Interface**
  - TensorFlow execution
  - Pre-trained NN-S and NN-CR
- **Arduino Interface**
  - Arduino board to control stepper motors
  - Stepper motor-based control rod moving system
- **Hardware integration**
  - Hardware development
  - Detector moving system
  - Dual control rods moving system



# Experiment Workflow



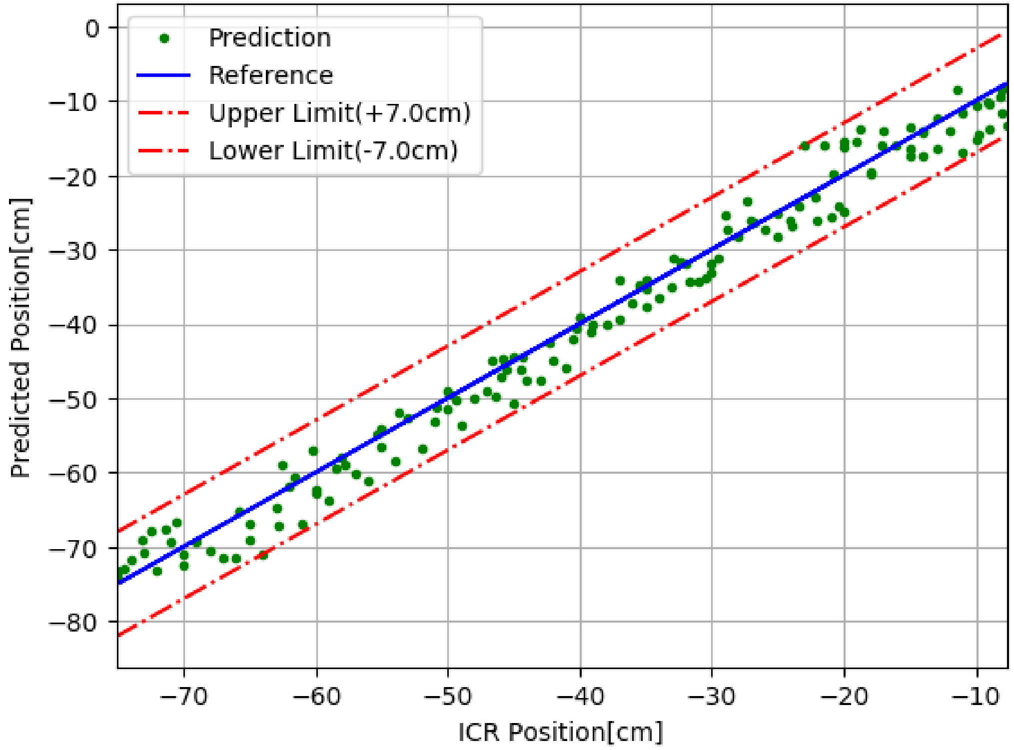

Convergence criteria:

$$\delta = \left| x_{RCR}^{prediction} - x_{RCR}^{last} \right|$$

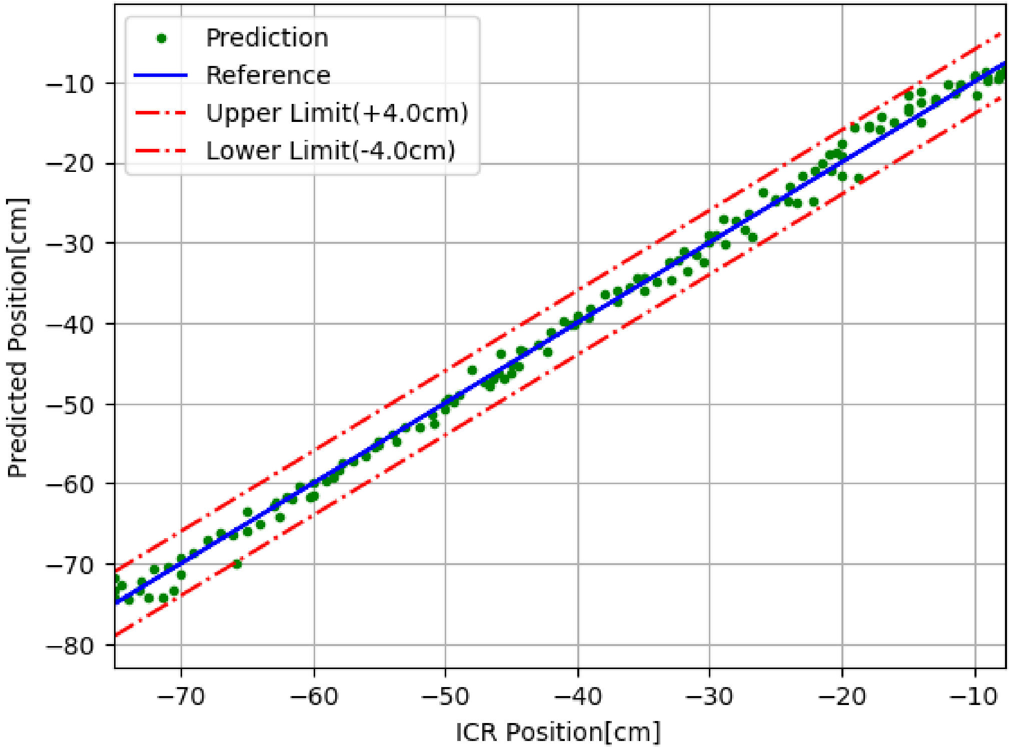
1. Take ICR to specific positions
2. Scan detector
3. Get RCR position → Move RCR
4. Scan detector again → Move RCR position
5. Repeat 3 & 4 until converge or hit iteration limit
6. Move to next ICR position

# Temporal Resolution

- Benefit from high-resolution data
  - Low resolution data set (60s measuring time)
  - High resolution data set (120s measuring time)



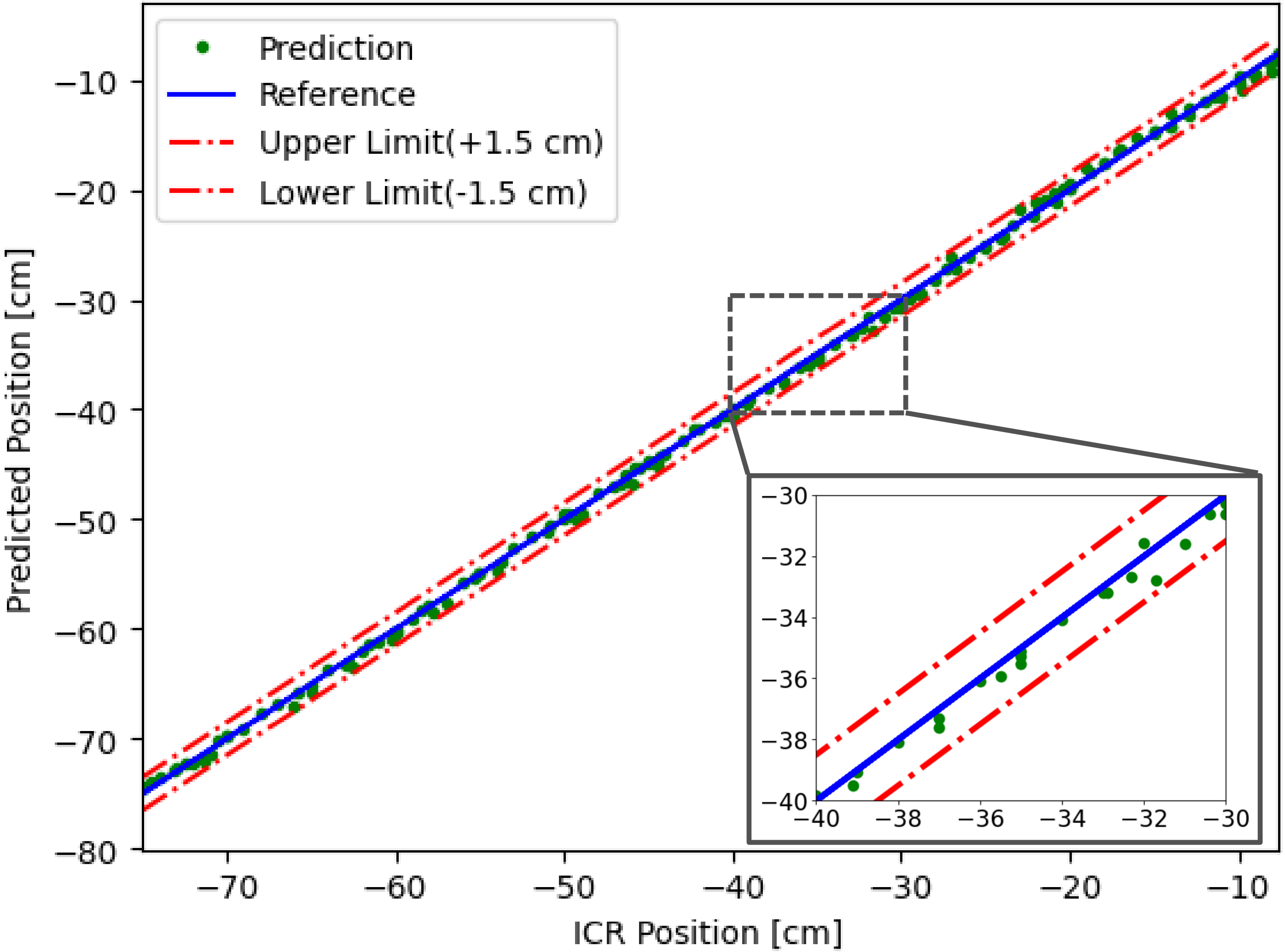

Low-resolution data




High-resolution data

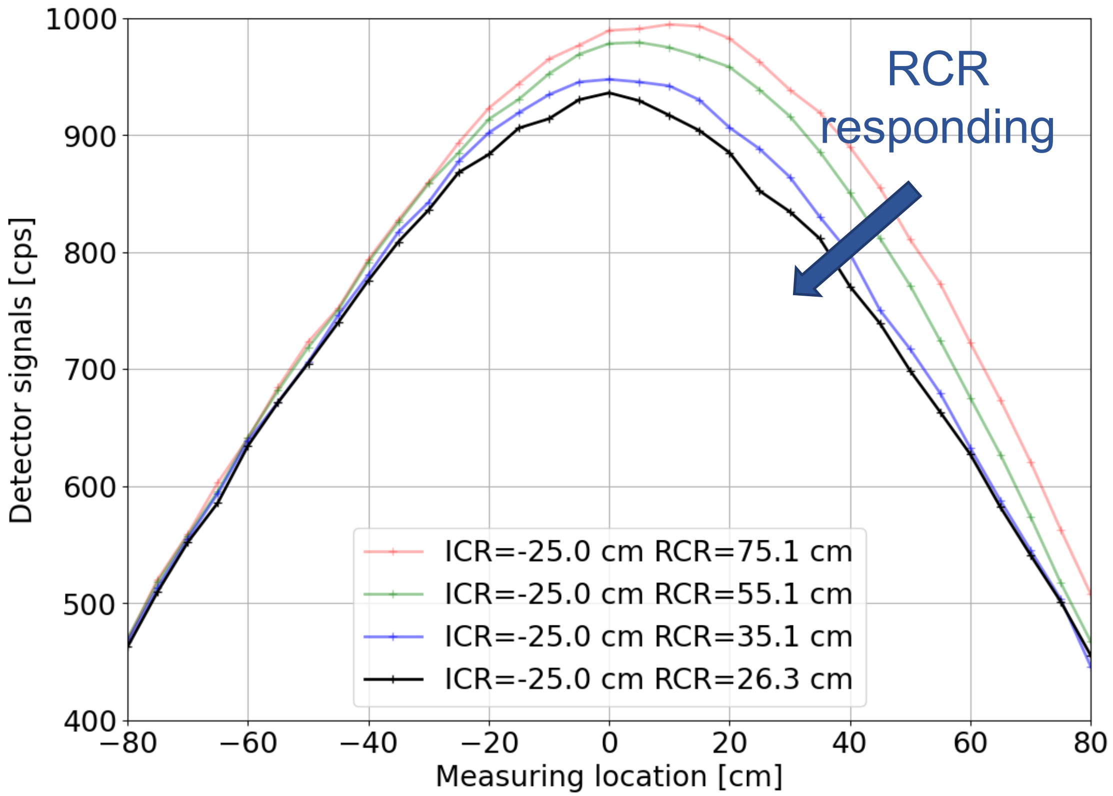
# Optimized Results

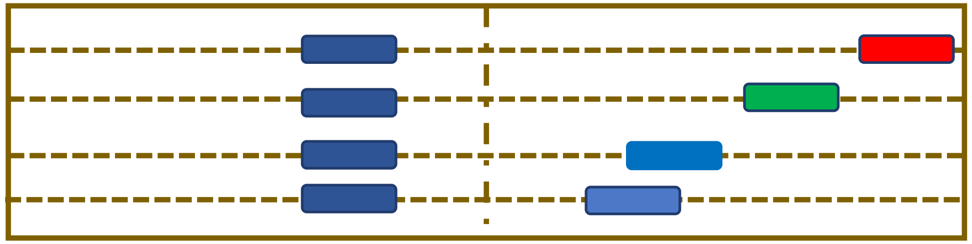
- Using high temporal resolution data (120 s)
  - Low enough error to make further counting not beneficial given other experimental errors
- >140 cases for ICR and RCR position
- ICR control rod position predicted with +/- 1.5 cm accuracy.



# Example Pile Response

- Movement of RCR based on initial ICR position
- After neural network prediction, RCR moves to location symmetric to that predicted by the ICR
- Goal is to achieve a symmetric flux profile
- Upon arrival at the predicted position the detector scans the channel again and will update prediction
- RCR moves to new predicted location



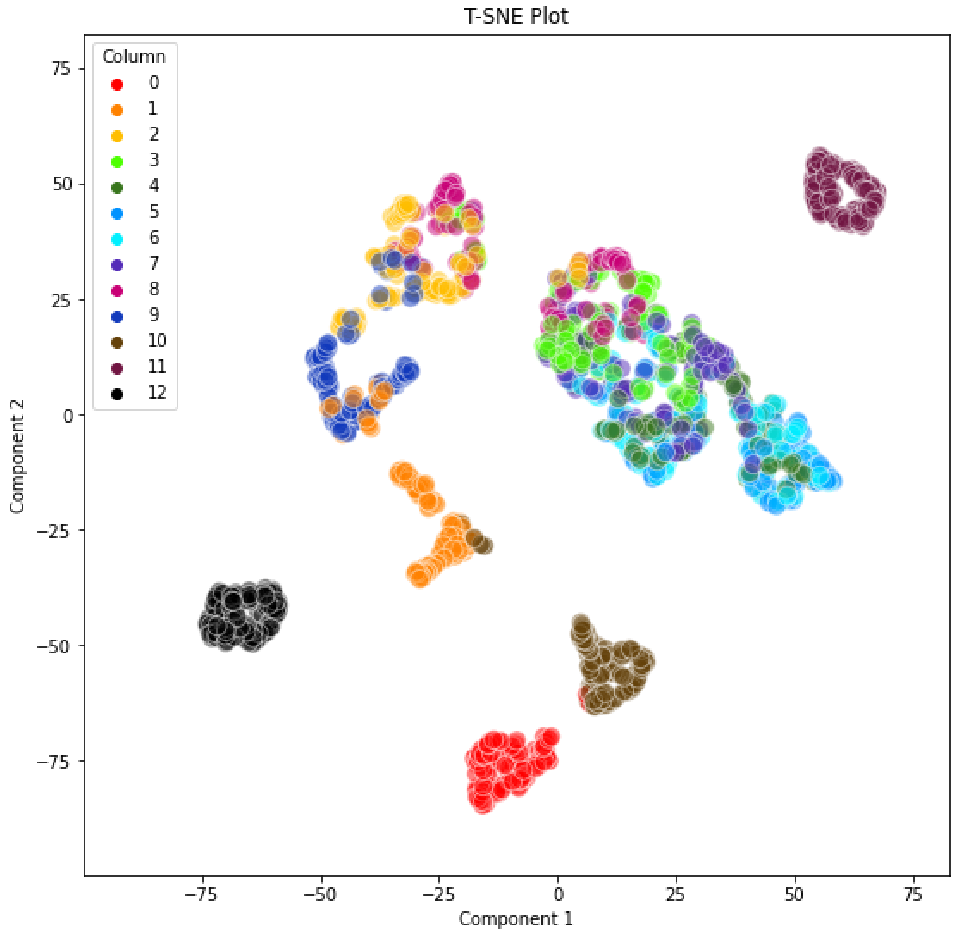
ICR perturbation RCR responding

# Fault Tolerance

- Number of fault tolerance methods explored
  - Principal component analysis (PCA)
  - Interquartile range (IQR)
  - K Nearest Neighbors (kNN)
  - t-Distributed Stochastic Neighbor Embedding (t-SNE)
  - Convolutional neural networks

Method Accuracy

| Method of Evaluating Fault | Fault Detection Accuracy |
| --- | --- |
| PCA + IQR | 95% |
| T-SNE + KNN | 68.5% |
| T-SNE + CNN | 75% |



# Conclusions

- **Digital twin and autonomous control system developed for MGEP**
  - Two movable control rods & single moveable detector system
- **Experimental Autonomous control system successfully developed for the MGEP**
  - Autonomous system can respond to flux perturbations in the profile from unknown control rod movement
- **Fault Tolerance methods shown to be capable to reject bad data points from the system.**
  - PCA + IRQ found to be the best combination of methods

# Future Work

- Additional improvements on MGEP control system
  - Higher work and more control rods
  - Using different detector setups to more closely mimic critical system.
  - Use flux as objective function

- Applications to microreactor
  - First step would be a digital twin of the microreactor and building a digital twin control system to test ANN control systems

- Apply methods to a critical system such as a research reactor
  - More regulatory impediments, but something such as an ANN controlling the regulating rod would be a logical first step.

April 27, 2023

**Jake Farber, Ph.D.**
Research Scientist

# Can We Use Machine Learning to Control Nuclear Power Plants?

# Acknowledgements


**Idaho National Laboratory**

Ahmad Al Rashdan

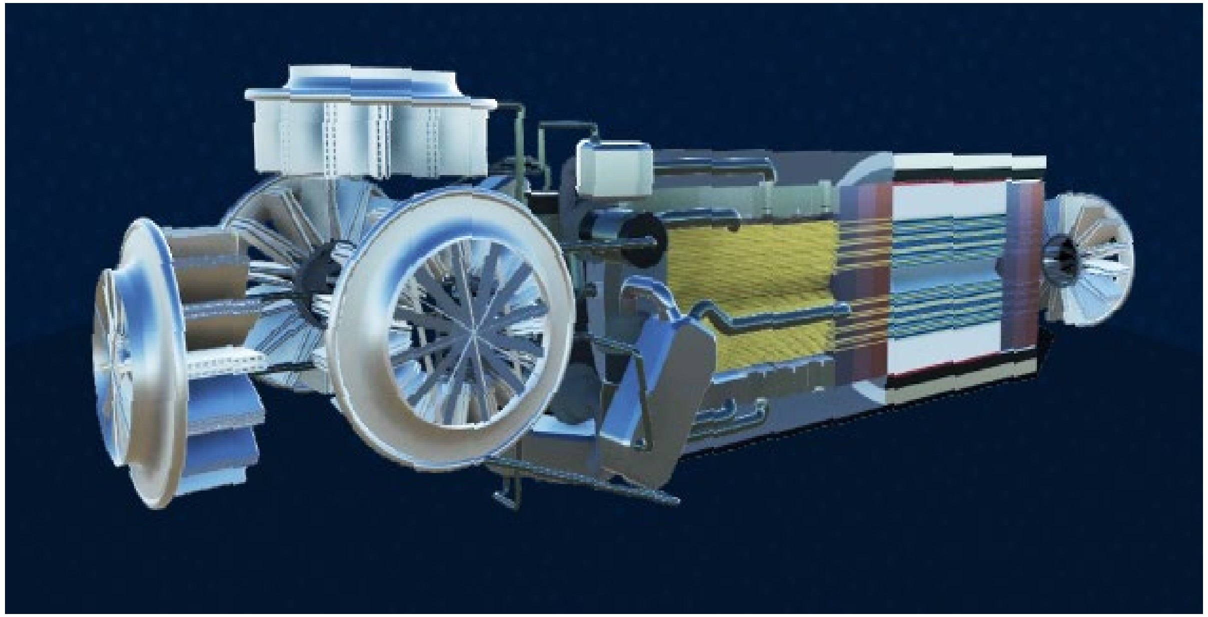
Craig Primer

Maria Coelho

Vaibhav Yadav


ASI | Advanced Sensors and Instrumentation

# Advanced reactors will be highly autonomous and remotely controlled, and will operate at variable power ratings and in rural locations

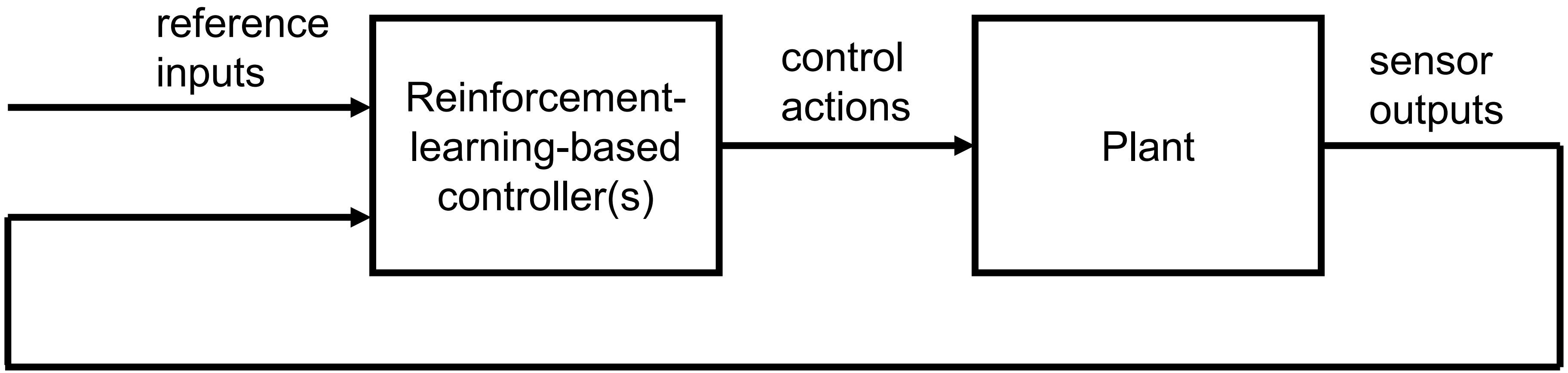


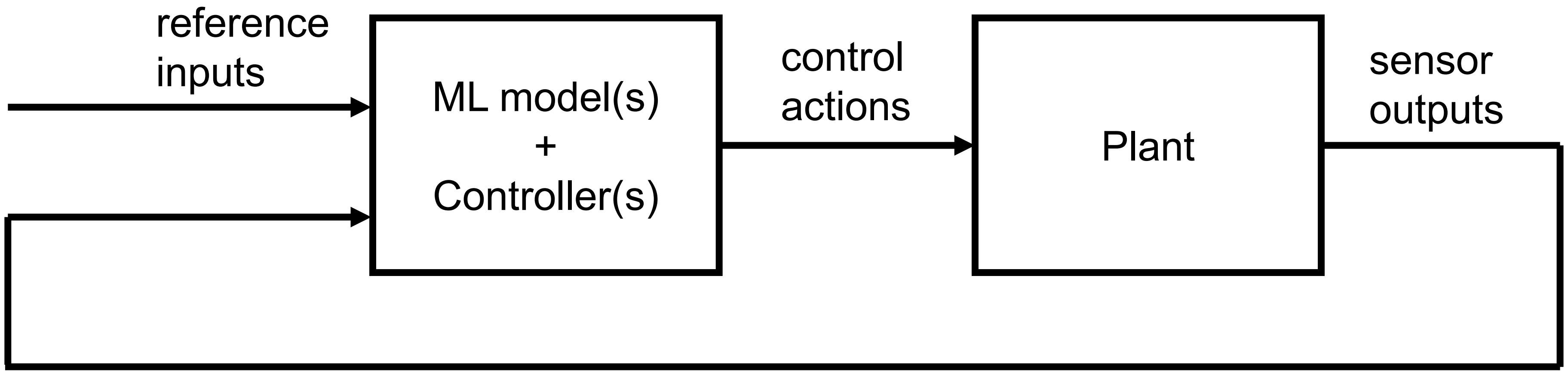
https://www.energy.gov/ne/articles/what-nuclear-microreactor

https://www.energy.gov/ne/articles/infographic-advanced-reactor-development

*These characteristics necessitate more intelligent means of control*

# Typical methods of ML-based intelligent control either use reinforcement learning as a controller or use ML to model the plant

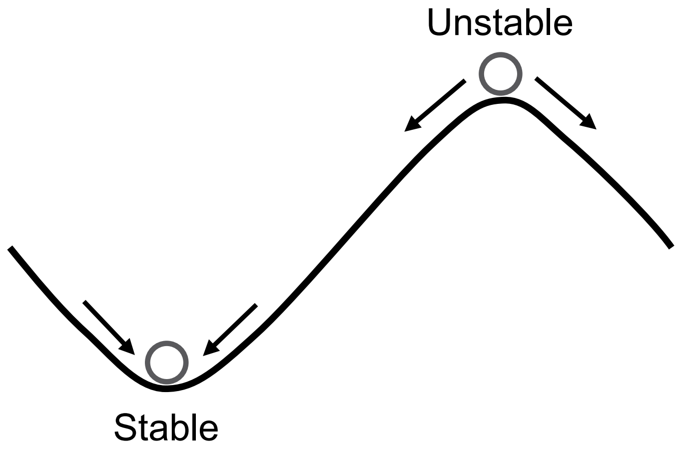


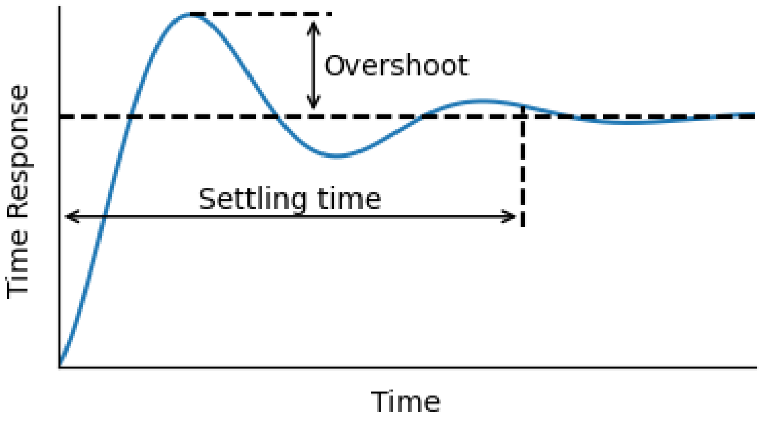



# Regulatory requirements consider the determinism, simplicity, explainability, and verifiability of NPP control systems

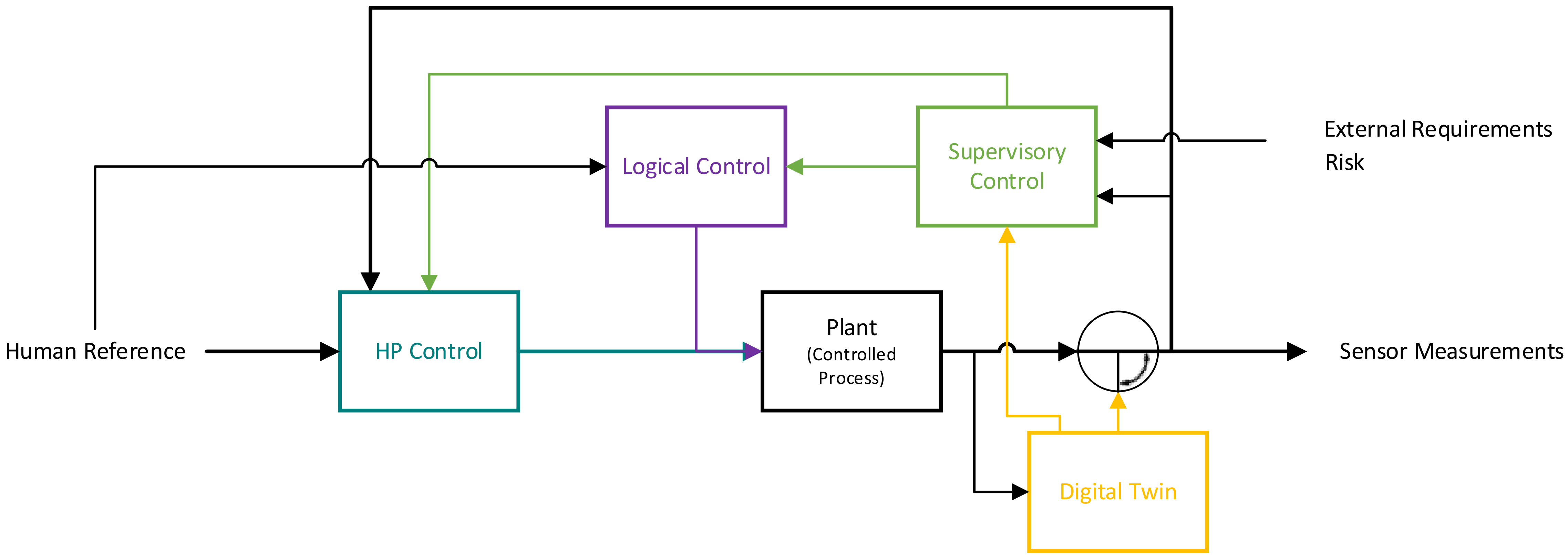
- Example general considerations
  - Many ML algorithms are stochastic
  - Many ML algorithms are black box in nature
- Example control-specific consideration
  - ML-based control lacks history of verifiable stability and performance

*New solutions may be necessary to overcome these barriers in using ML to directly control NPPs*

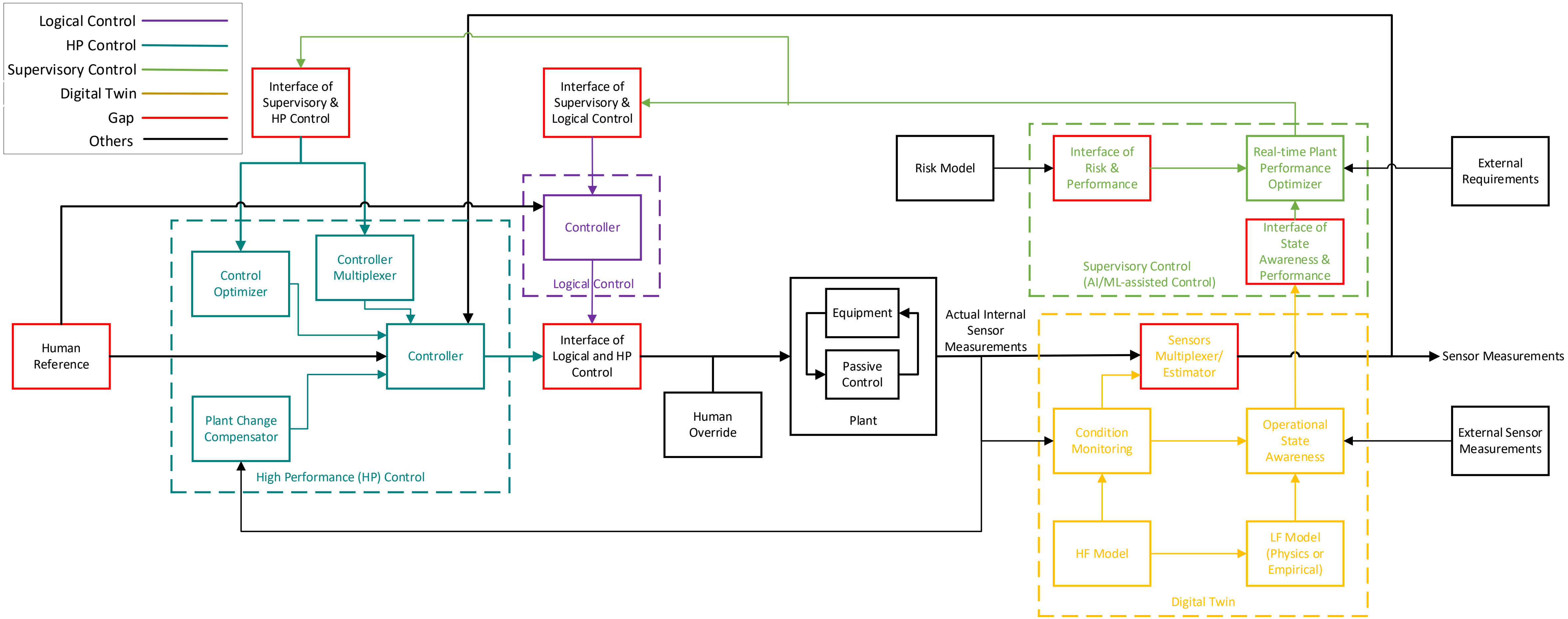


# Alternatively, high-performance control could be employed for direct control, with ML implemented via supervisory control and digital twins



# These systems can be expanded to show research gaps that need to be closed before implementing this hierarchical approach



# Conclusions

- Using ML to directly control NPPs may necessitate new solutions that consider determinism, simplicity, explainability, and verifiability
- Our hierarchical solution can be broken into two parts:
  - Perform direct control using high-performance methods that possess these important characteristics
  - Provide control support and analysis by using digital-twin-assisted supervisory control that can benefit from ML and conveys less risk
- Many open research questions remain to be answered before this hierarchical solution can be implemented

Questions?

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Idaho National Laboratory

# AI for Modeling, Optimizing, and Controlling Complex Systems


**Prasanna Balaprakash**

Director of AI Programs

Oak Ridge National Laboratory

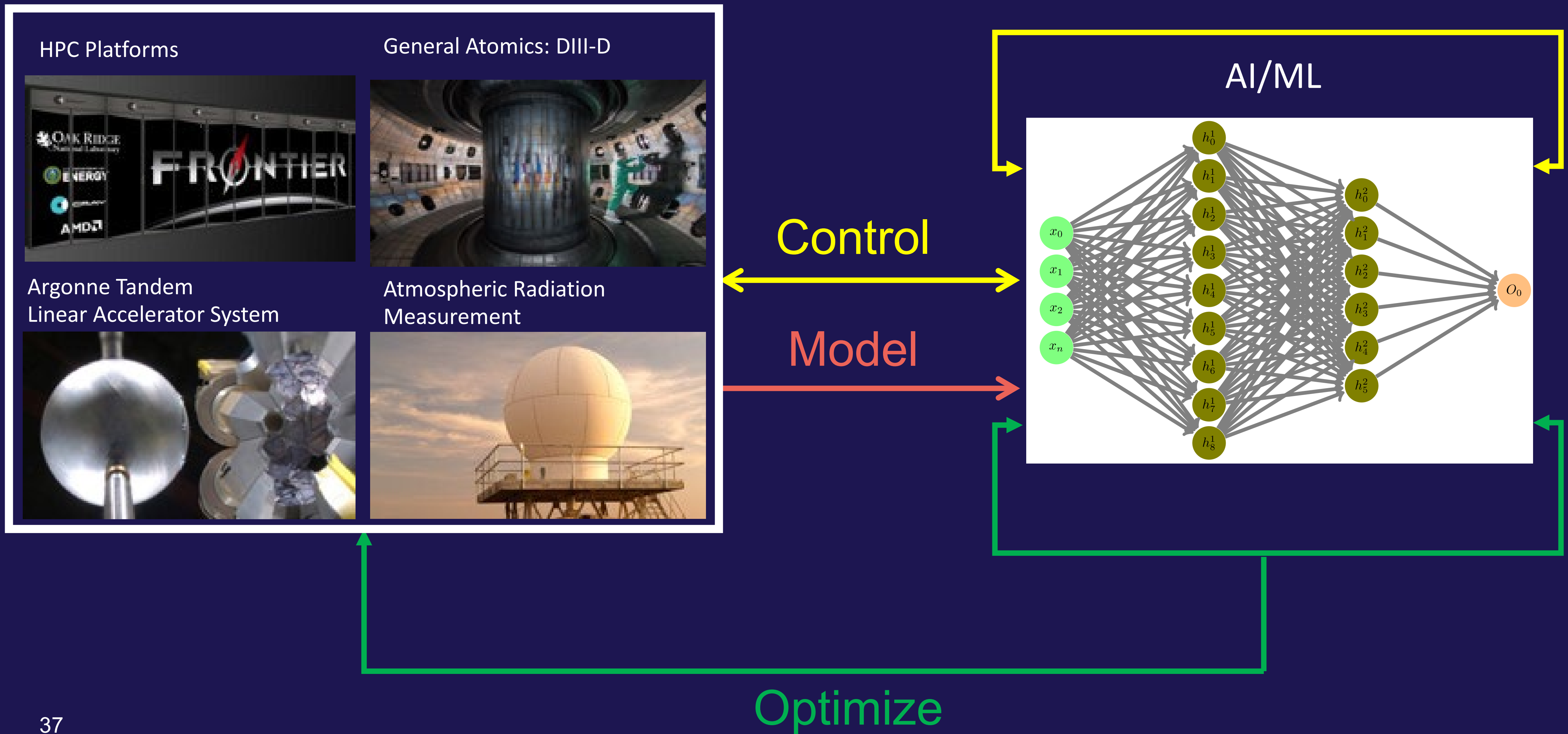

April 27, 2023

https://deephyper.readthedocs.io/

Joint work with Yixuan Sun, Sami Khairy, Rui Hu, Akshay J. Dave, ANL

AI/ML Symposium 11.0 – AI/ML in Instrumentation, Control, and Automation

# AI for Modeling, Optimizing, and Controlling Complex Systems



# Nuclear Power Plant Control

- Nuclear power: carbon-free baseload energy source that suffers from high upfront capital and operating costs
- Autonomous operation of nuclear power plant
  - drastically reduce variable O&M costs
- Autonomous agents provide other indirect benefits:
  - reducing errors (risk)
  - improving scalability of deploying multiple reactors of the same design

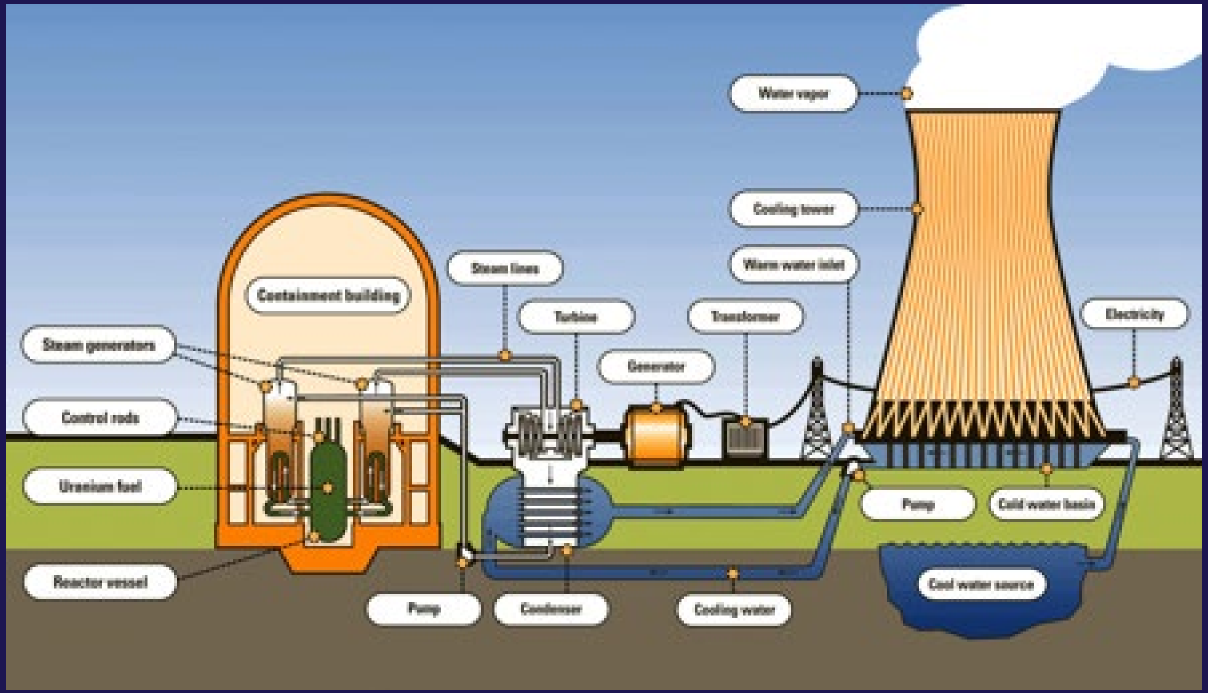
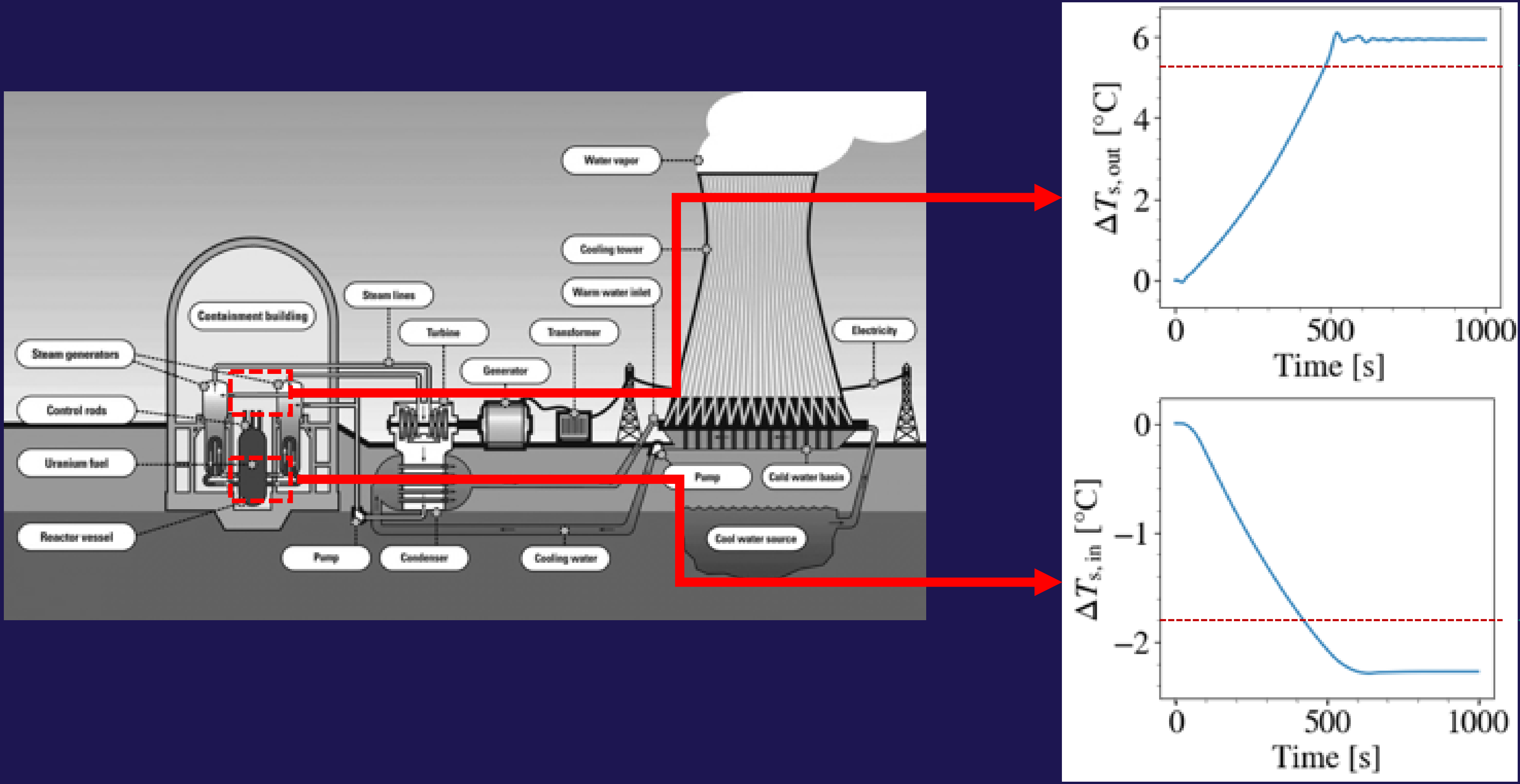





Image credit: https://www.foronuclear.org/en/updates/in-depth/what-are-the-different-components-of-a-nuclear-power-plant/

# Nuclear Power Plant Control

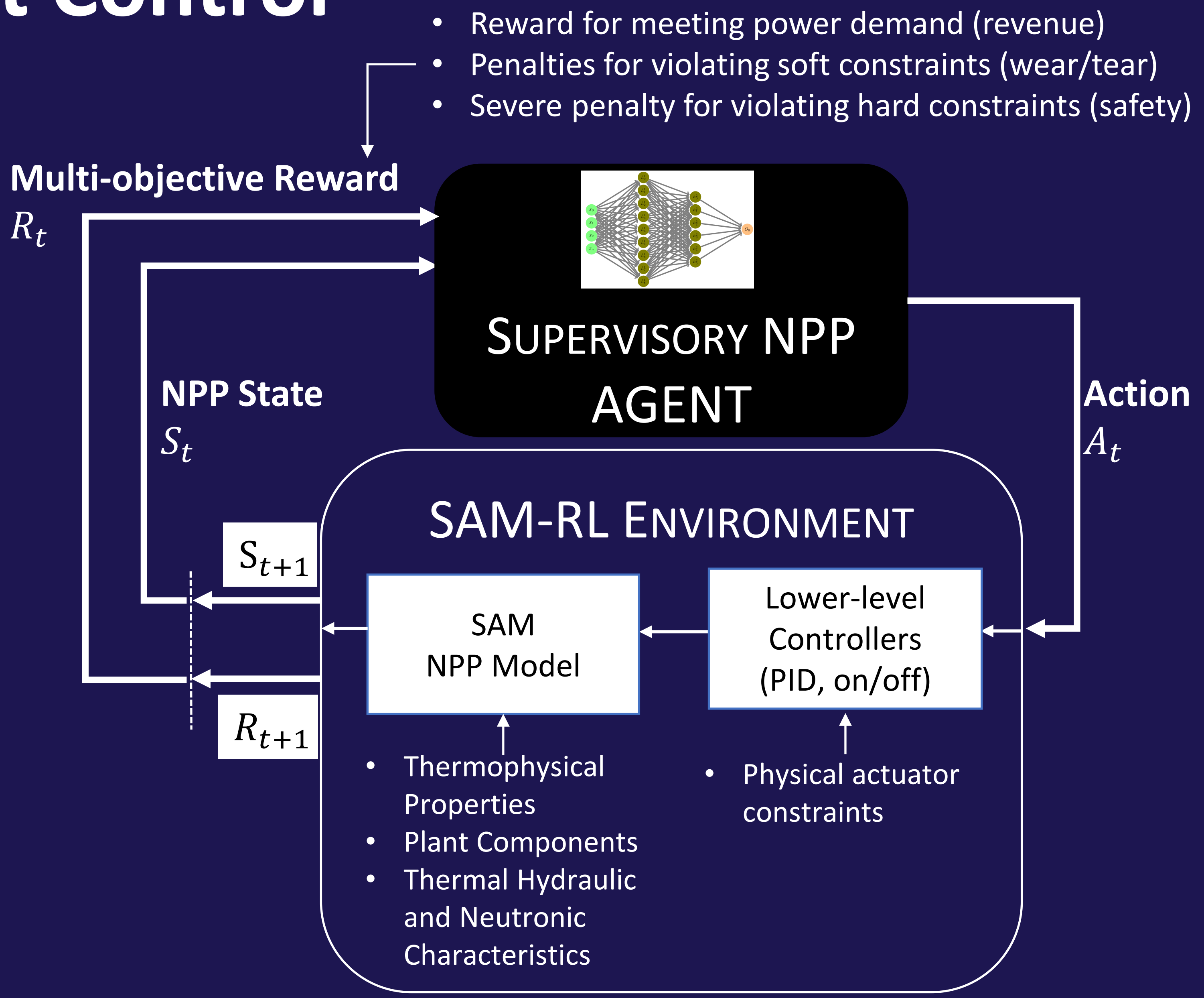
Load-follow transient: important for advanced reactors to adopt due to the increasing proportion of intermittent energy sources




accept the requested change in power, as far as no constraints on system states are violated

# Safe Reinforcement Learning for Nuclear Power Plant Control

- System Analysis Module (SAM)
  - high-fidelity physics-based simulator of nuclear power plants
  - model multiple reactor designs (molten-salt, lead-cooled, fluoride-cooled)
  - enforce physical constraints on state of system or actuators



# Reinforcement Learning for Nuclear Power Plant Control

Reward

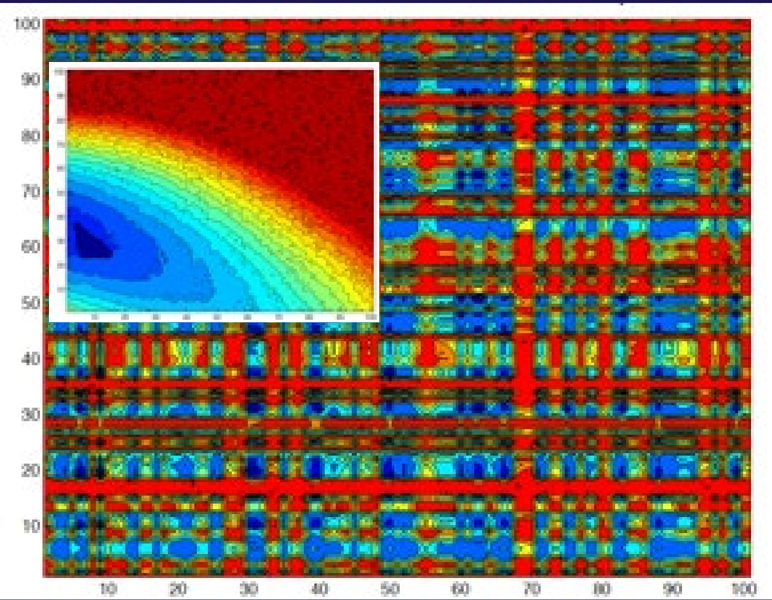
- Chance-constrained optimization:

$$\max_{\pi} \mathbb{E}_{a_n\sim\pi, s_n\sim D_s}\left[\sum_{n=0}^{H-1} r_0(s_n, a_n)\right]$$

$$s.t.\ \ \Pr\left\{\bigcap_{n=0}^{H-1}(s_n \in \mathcal{X}_{safe})\right\} \geq 1 - K\delta$$

Safe state

#constraints X violation probability



- Intractable, reformulate by applying Boolean Algebra and DeMorgan's law

$$\max_{\pi} \mathbb{E}\left[\sum_{n=0}^{H-1} r_0(s_n, a_n)\right]$$

$$s.t. \sum_{n=0}^{H-1} \Pr\left(s_n \notin \mathcal{X}_{safe}\right) \leq \sum_{n=0}^{H-1}\sum_{i\in[K]} \Pr(Ci(s_n) = 1) \leq K\delta$$

indicator function to track if the $i^{th}$ safety constraint is satisfied at $s_n$

- $\mathbb{E}[\sum_{n=0}^{H-1} r_i(s_n, a_n)] \leq \delta, \forall i \in [K] \Rightarrow \sum_{n=0}^{H-1}\sum_{i\in[K]} \Pr(r_i(s_n, a_n) \geq c_i) \leq K\delta$

Easy to optimize

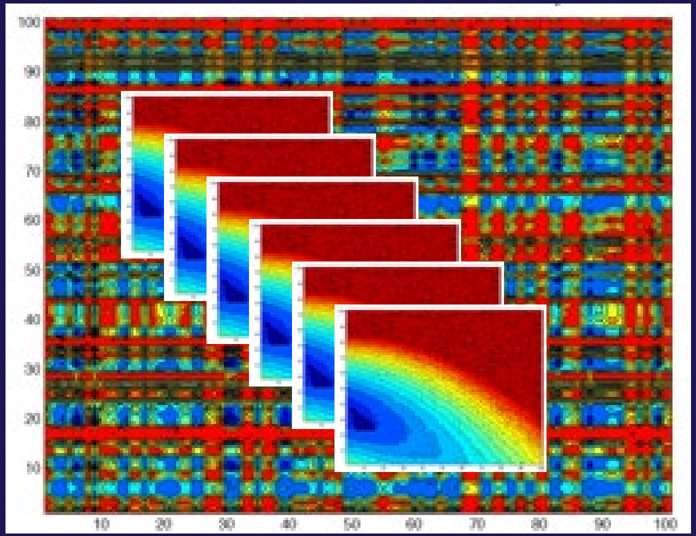
# Reinforcement Learning for Nuclear Power Plant Control

Lagrange multiplier for the $i^{th}$ constraint

- Reward-constrained optimization:

$$\max_{\pi} \min_{\lambda_i \geq 0} \mathbb{E}\left[\sum_{n=0}^{H-1} r_0(s_n, a_n) - \lambda_i r_i(s_n, a_n)\right]$$

- Optimize policy parameters using gradient ascent to maximize rewards assuming $\lambda_i, \forall i$ are fixed.
- On a slower timescale, optimize $\lambda_i, \forall i$ using gradient descent on the original constraints
- Converges to a *local saddle point*



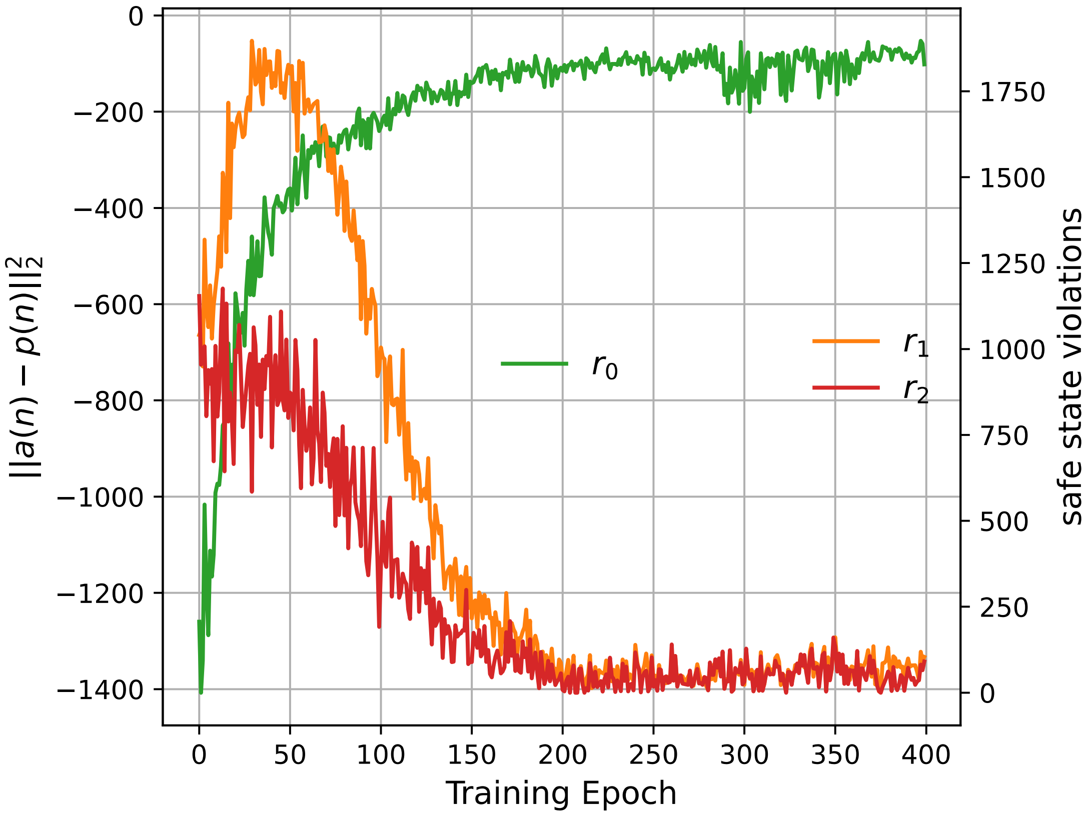
- Actor-critic RL agent design
  - Value network:

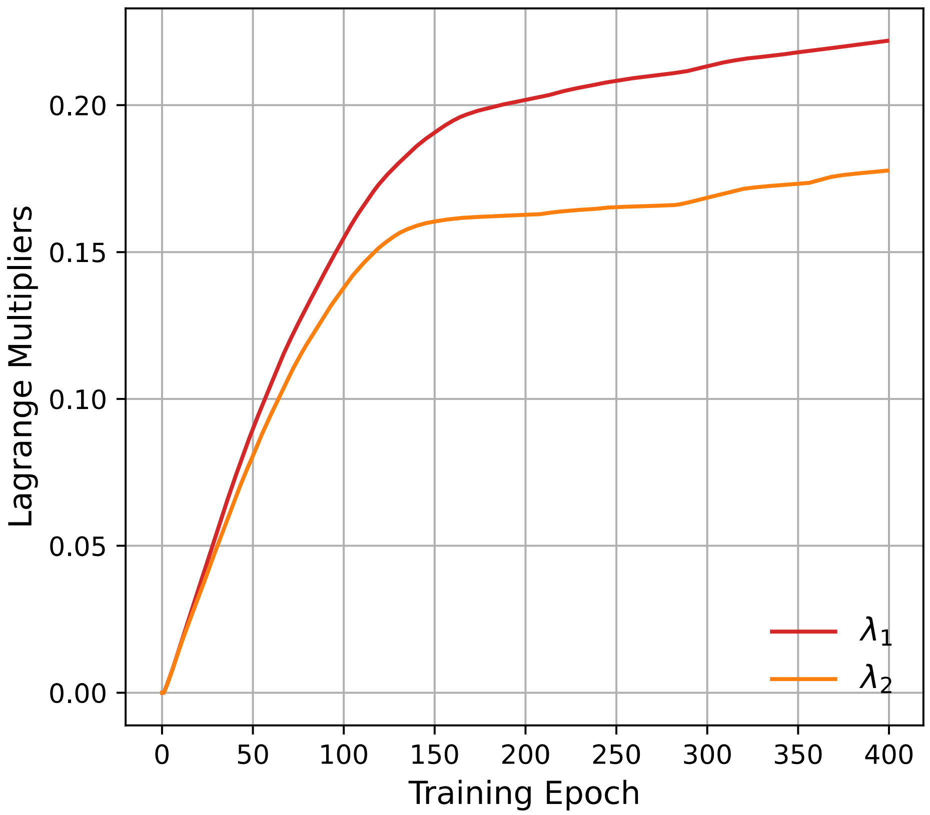
$s \rightarrow$ LSTM → MLP → MLP $r_0(s)$, MLP $r_1(s)$, MLP $r_2(s)$

  - Policy network:

$s \rightarrow$ LSTM → MLP $\mathcal{N}(\mu(s), \sigma(s))$

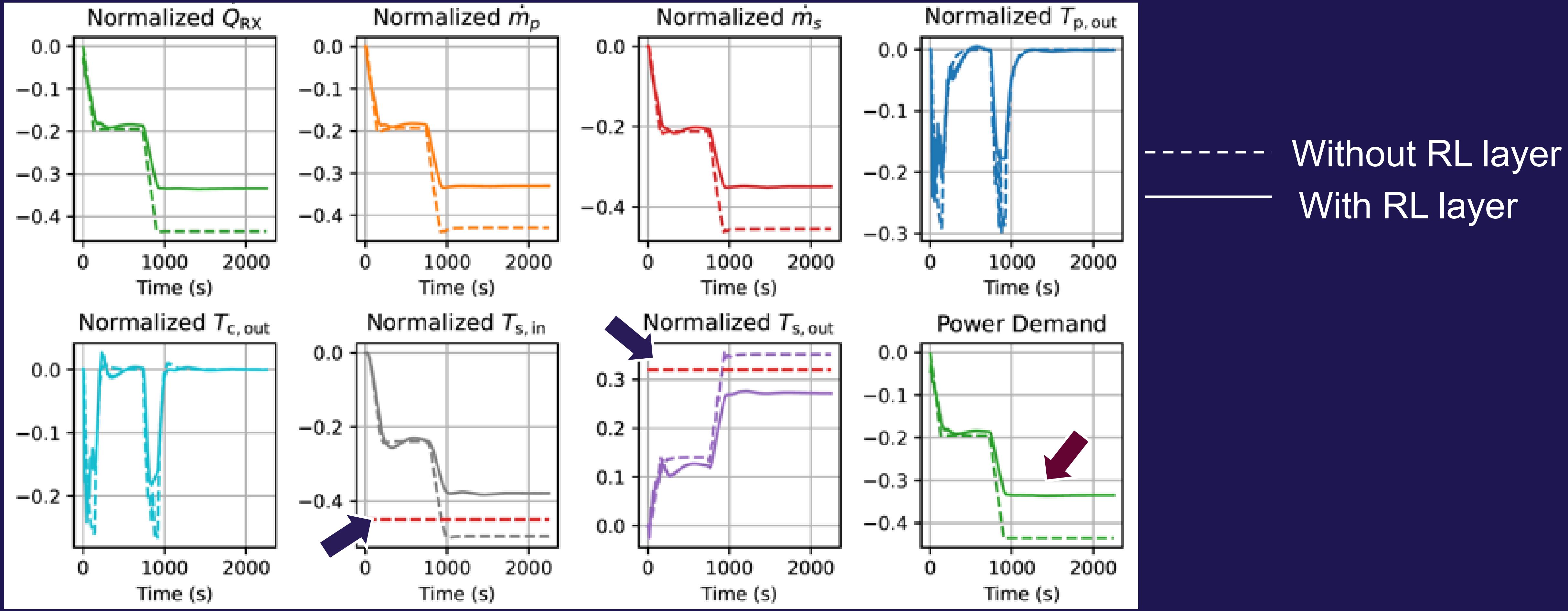
# Reinforcement Learning for Nuclear Power Plant Control



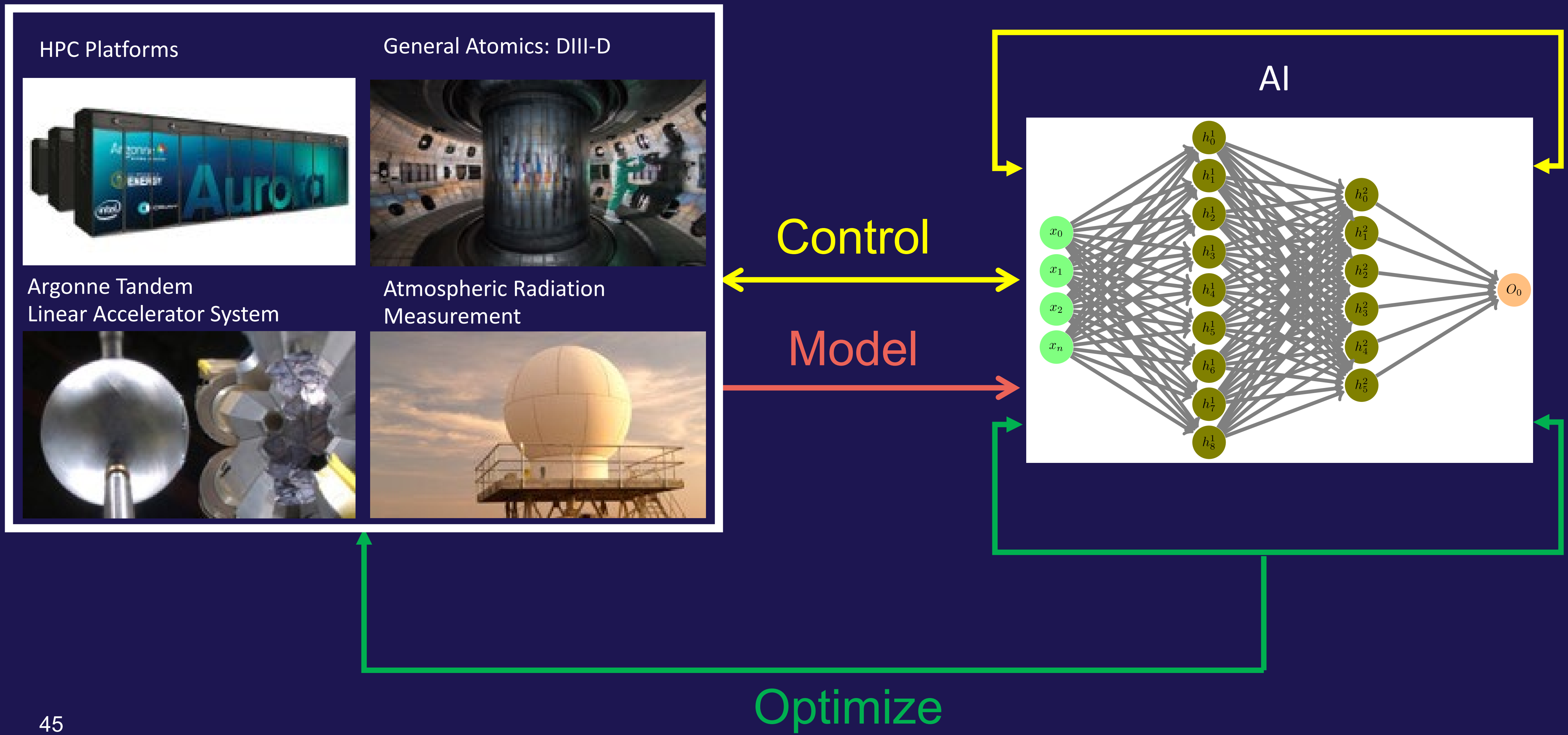



# Reinforcement Learning for Nuclear Power Plant Control

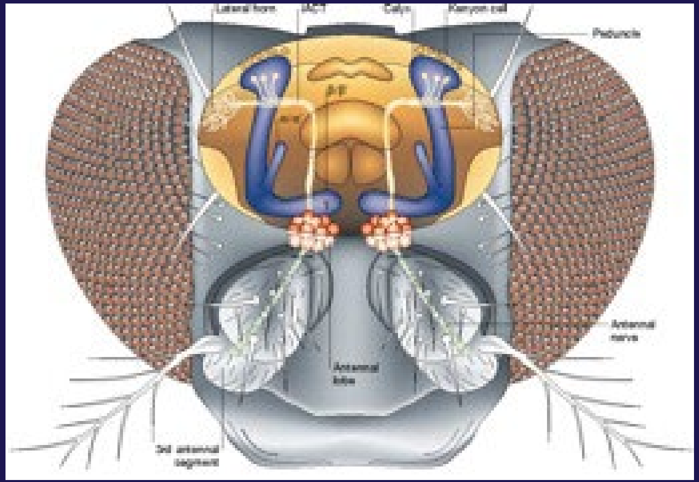
- Unseen power demand curve
- Constraints are imposed on the secondary loop (inlet and outlet temperatures at heat exchanger)

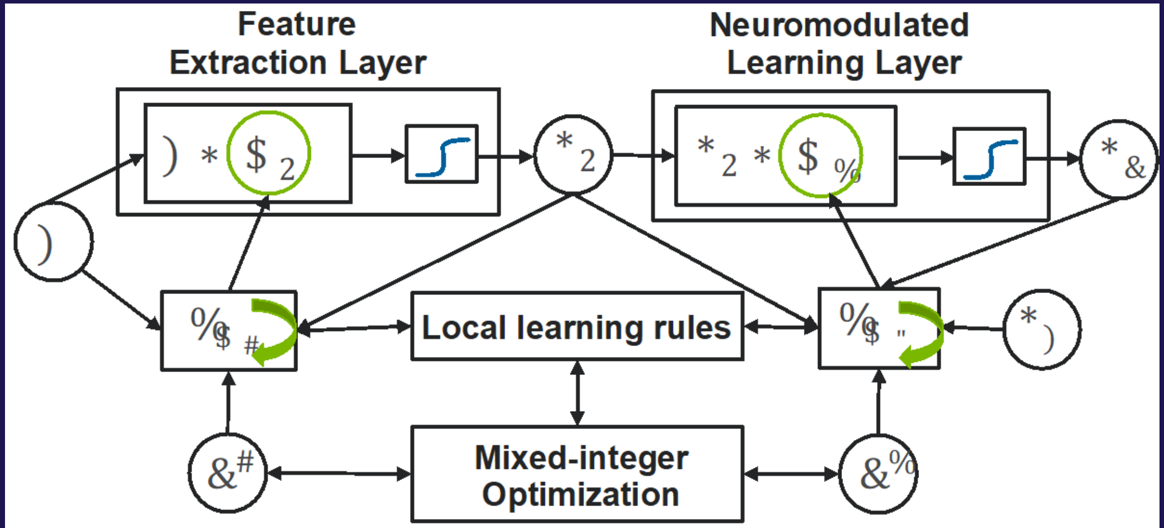


# AI for Modeling, Optimizing, and Controlling Complex Systems



# Neuromorphic Hardware and Algorithms

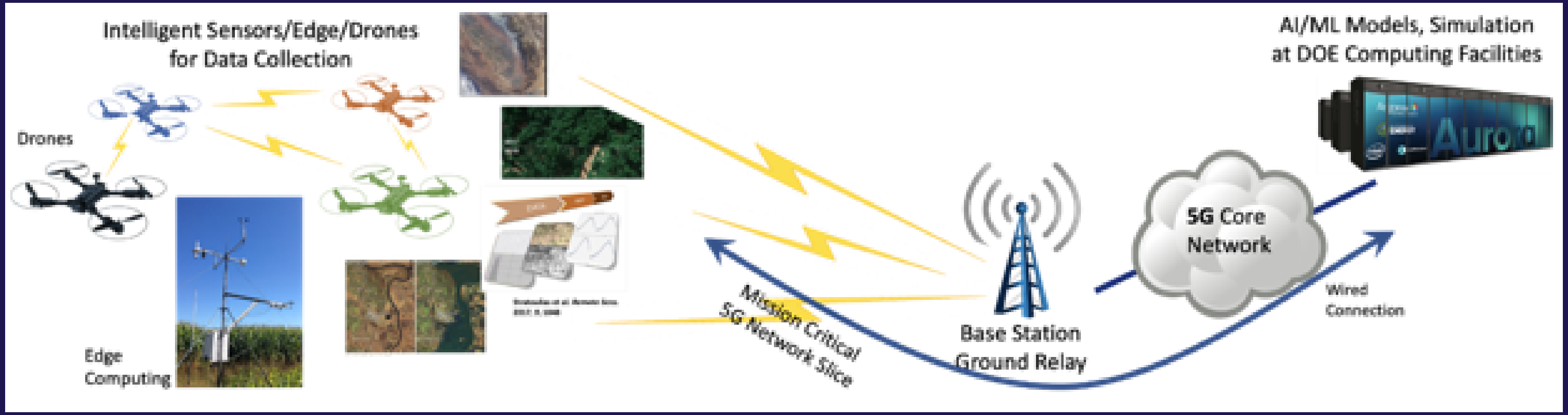


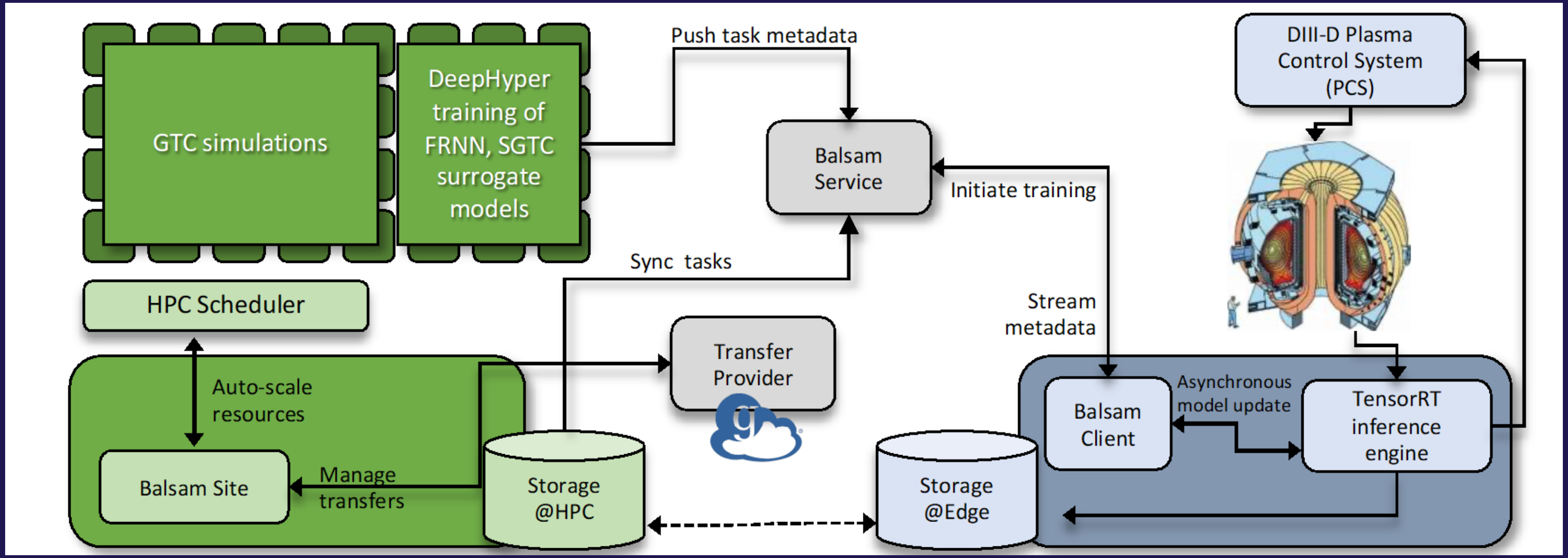



Advanced photon source – Argonne

A. Yanguas-Gil, J. Koo, S. Madireddy, P. Balaprakash, J. W. Elam, and A. U. Mane. "Neuromorphic architectures for edge computing under extreme environments." In 2021 IEEE Space Computing Conference (SCC), pp. 39-45. IEEE, 2021.

# Computing Continuum



# Acknowledgements


DOE Early Career Research Program, ASCR

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RAPIDS: A SciDAC Institute for Computer Science and Data

Laboratory Directed Research and Development (LDRD)

Date: 04/27/2023

# Remote Operations and Monitoring of Microreactors and the Opportunity for Machine Learning and Artificial Intelligence

Dr. Joe Oncken, NS&T, C220

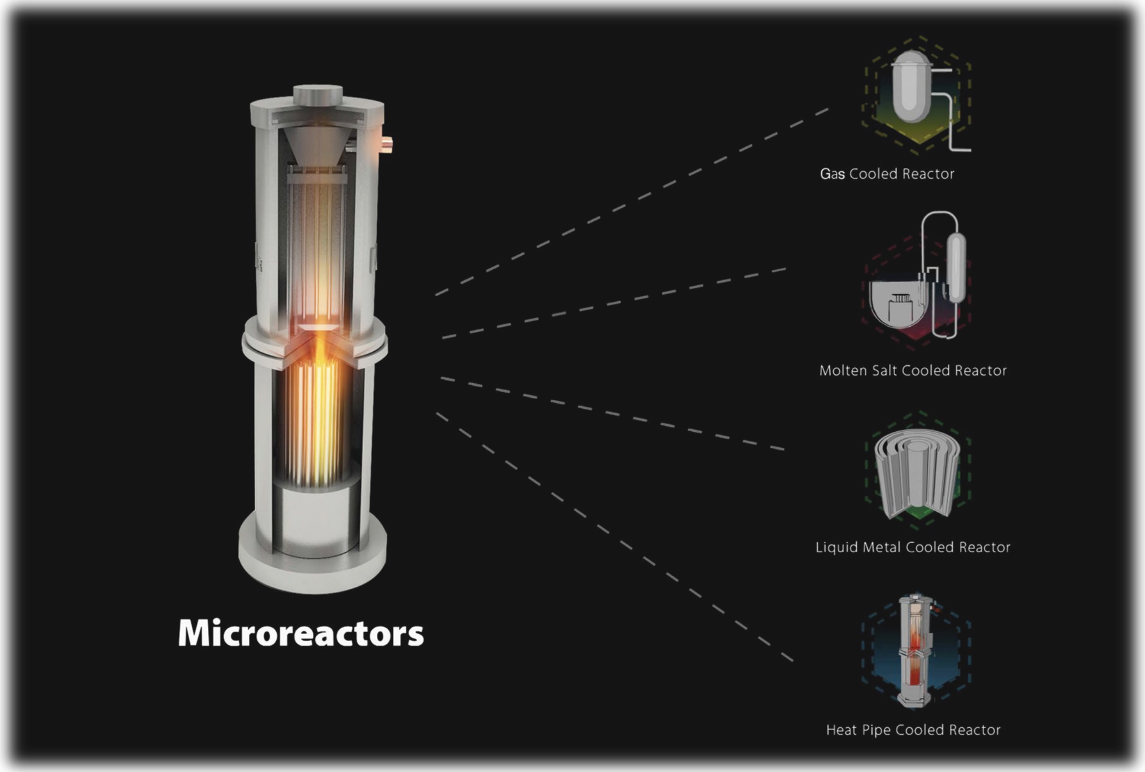
Idaho National Laboratory

# Remote Operations and Monitoring of Microreactors and the Opportunity for ML/AI

- What is a microreactor and what are the primary use cases?
- Why remote monitoring and operation may be needed.
- What challenges are introduced by remote operations and monitoring?
- How can AI/ML help solve these challenges and what is INL pursuing to address these challenges?

# What are Microreactors?

- Small size and power level: ~0.1 - 50 $MW_e$*
- Factory fabricated
- Easily transportable to and from site
- Minimum site preparation
- Flexible operation
- High-degree of passive safety
- Operational lifetime: 5 – 20 yrs
- Technologies evolving from advances in materials, space reactor technologies, advanced nuclear fuels, and modeling & simulation
- Well suited for remote areas and applications:
  - Remote communities
  - Isolated microgrids
  - Mining sites
  - DOD applications
- Broadly distributed, reliable, energy sources

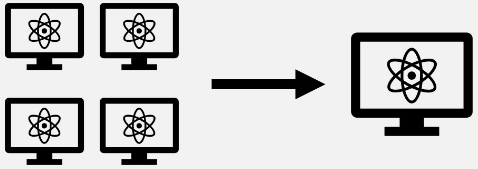



Microreactors are integrated systems that can be based on a range of reactor technologies

*Infrastructure and Jobs Act of 2021

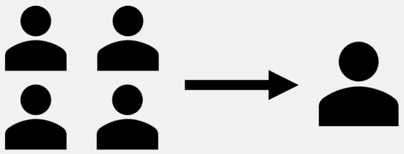
# Economics of Remote Operation and Monitoring

## Control Room Centralization



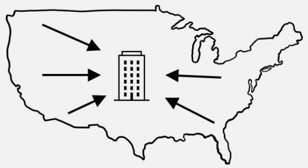
Many individual, small, onsite control rooms can be replaced by a centralized, large, offsite control room that remotely controls microreactors around the country. Economies of scale will result in reductions to capital costs.

## Reactor Operator Regulations



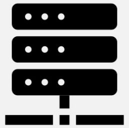
Economies of scale, when combined with updated regulations regarding the number of reactor operators required for microreactors, can significantly reduce staffing requirements across a large system of many centrally-operated reactors.

## Strategic Siting



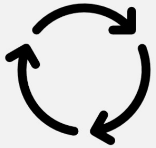
The centralized control room can be sited in an area with low construction costs, a strong labor pipeline, and other amenable qualities: reducing both capital and operational expenditures.

## Semi-Autonomous Control



The cost reduction opportunities from semi-autonomous monitoring and control increase with the number of co-managed reactors. The combination of remote operation and semi-autonomous control allows for significant cost reductions.

## Microreactor Adoption



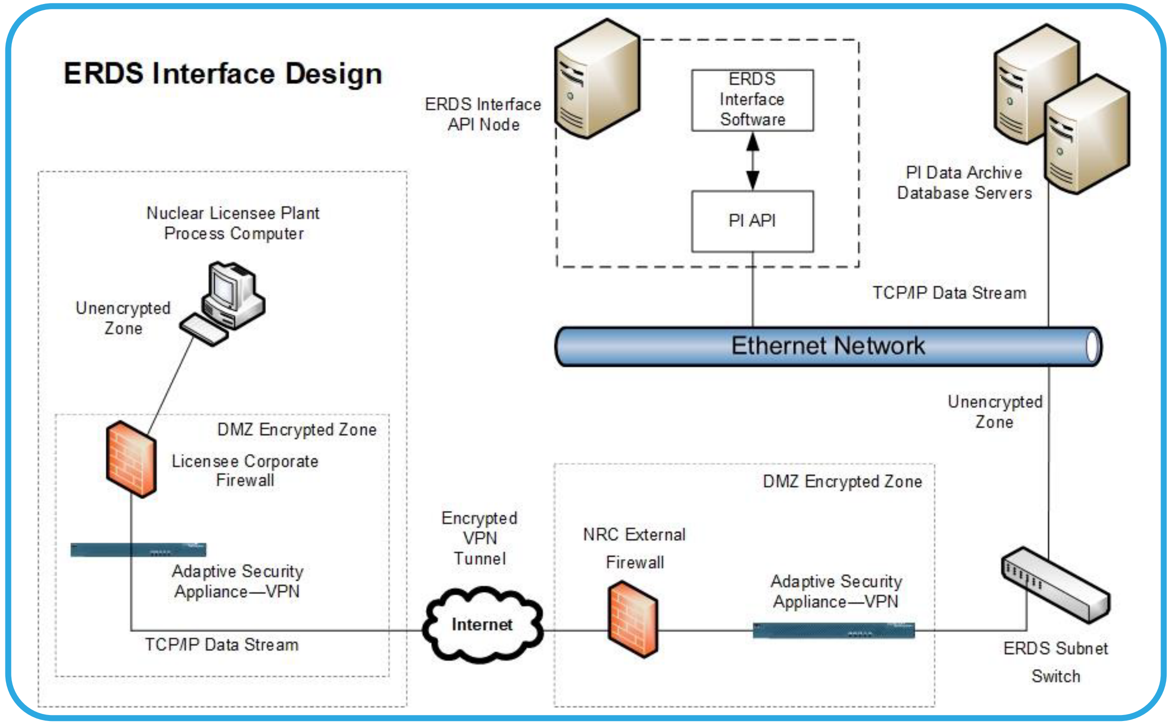
The combined economic benefits of remote operation increases microreactor competitiveness against alternatives – allowing for greater adoption.

As microreactor deployment increases, costs are reduced through economies of learning – creating a compounding effect as the cycle repeats.

Many early adopters are expected to be those who would also benefit the most from remote operation, meaning that the capability could have considerable effects on the critical early adoption stage of the technology.

# Is there precedence for remote operations and monitoring of nuclear reactors?

- Emergency Response Data System (ERDS) is one US nuclear specific precedence
  - Direct real-time transfer of data from licensee plant computers to the Nuclear Regulatory Commission (NRC) Operations Center
  - Does not afford control as it is intended to support emergency response planning and reporting




**NUREG-1394, Revision 2**

# Is there precedence for remote operations and monitoring of nuclear reactors?

Extensive analogous industries with geographically distributed control systems.

- Electric grid (existing methods, smart grid communication, advanced modelling)
- Distributed Energy Resources (DER)
- Oil and gas
- Aerospace
- Military unmanned vehicles (aerial and land based)

Architecture of Distributed Wind integrated into larger DER plants and facilities

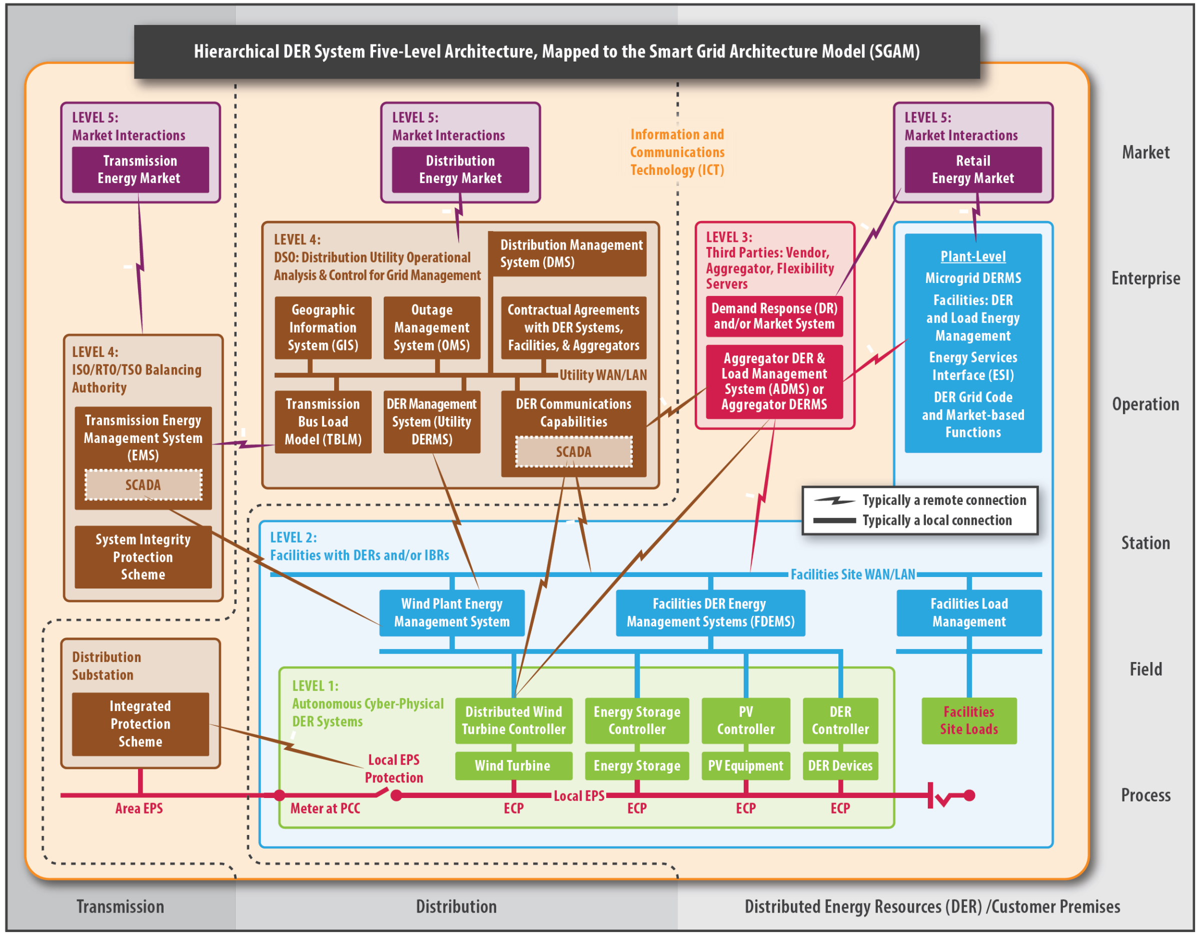



Image Source: INL/EXT-21-62264 Revision 0

# Remote operations and monitoring challenges

Ground Rules for Regulatory Feasibility of Remote Operations of Nuclear Power Plants

- Nuclear Regulator Research Initiative Report
- Identified 8 Focus Areas
    1. Human Factors
    2. Operations
    3. Inspections
    4. Risk
    5. Information Exchange
    6. Cybersecurity
    7. Physical Security
    8. Legal
- Within these 8 focus areas the NRC has identified high-level items that are crucial for feasible remote operations – “Ground Rules”
- Items important for achieving ground rules – “Key Attributes”
- Summarized as 11 Key findings which are expressed from the NRC’s perspective

# NRC Key Findings

1. Remote operations criteria should be part of the **design and development process from the beginning.**
2. The **public's risk perception** must be addressed by appropriately conveying societal impacts and **accurate safety precautions** that ensure public safety.
3. Changes to regulations are expected and must be addressed as needed (**Part 53** will address some aspects, but others **may require additional or altered regulations**).
4. Guidance on acceptable approaches to meet regulations shall use **technology-neutral** and **performance-based** acceptance criteria.
5. "Minimal risk conditions" representing safe plant conditions following a credible initiating event must be identified with **safe and stable shutdown** being the predominately expected outcome.

# NRC Key Findings continued

Opportunity for AI/ML

6. Data and voice **communication infrastructure and security are critical** for remote operations and should be central during the design and development process.
7. Remote operator responsibilities should be based **on automation levels** and "minimal risk conditions" human intervention and time requirements.
8. Operator licensing will be necessary, but due to high levels of automation and inherent safety functions the **level of training and licensing oversight is expected to be reduced**.
9. A **local crew** based onsite or nearby to sever emergency quick response functions has been deemed **unavoidable**.
10. **Physical and cybersecurity inspections are necessary** for both the site and control room facilities, with anticipated possible shifts towards remote inspection capabilities.
11. **Physical security will be required** at both the site and remote control room facilities.

# Remote Operation Enabling Technologies: Automated Operation

- For remote operation and monitoring of reactors to be possible, it is envisioned that full automation of the reactor control system will be required.
- Full automation of a reactor control system is a complex task, as detailed models of the reactor system are required.
- AI/ML has significant potential to supplement this modeling and control system development required for automated control.
  - Data-based control
  - Surrogate modeling

Proposed levels of automation for nuclear reactor operations [1]

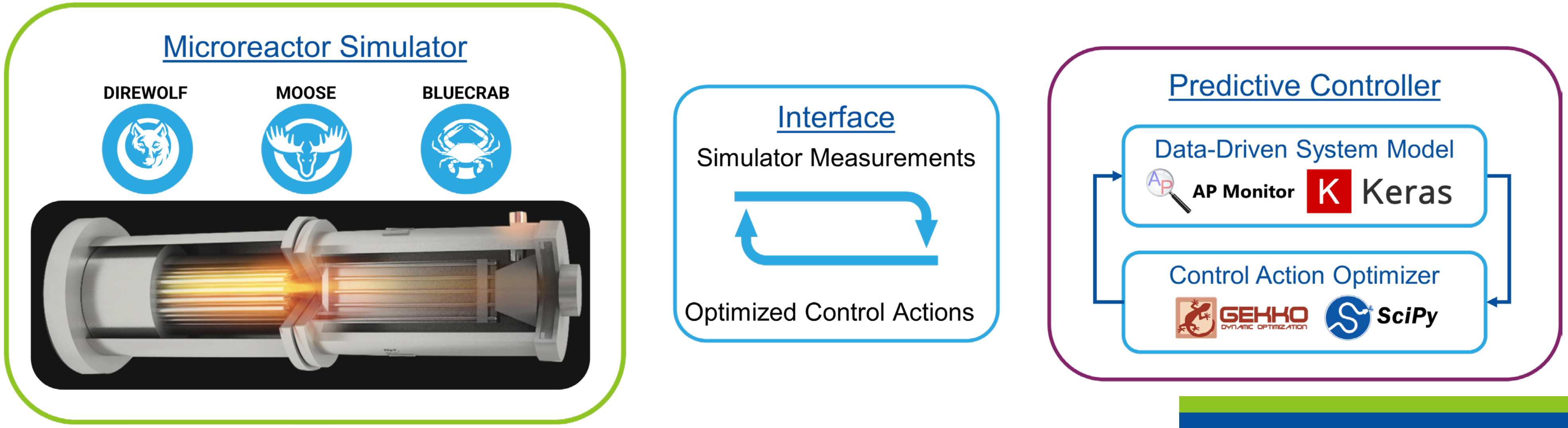
| | Level | Human/Machine Interoperability |
|---|---|---|
| 0 | No Automation | Manual control: the operator makes all decisions and performs all actions |
| 1 | Operator Assistance | Operator sets the desired state for a given component. The automated system maintains the given state until directed otherwise. |
| 2 | Automation by Consent | Operator defines optimal conditions for a system of multiple components. The automated system operates within the conditions. The system is closely monitored by operators; they approve actions when requested, provide fallback, and can intervene with commands. |
| 3 | Automation by Exception | Automated reactor operation system (AROS) performs tactical and operational tasks in specific and limited operational domains. Upon request, an operator must approve tactical and operational decisions and provide fallback |
| 4 | High Automation | AROS provides sustained operational and tactical control and fallback in semi-limited operational domains. A fallback-ready reactor supervisor familiar with AROS is required on-site. |
| 5 | Full Automation | AROS provides sustained operational and tactical control and fallback in all operational domains:<br>One-way communication: remote reactor supervisor monitors operations<br>Two-way communication: remote reactor supervisor monitors operations and provides strategic commands as necessary |

[1] A. Alberti, V. Agarwal, I. Gutowska, C. Palmer, C. de Oliveira, "Automation Levels for Nuclear Reactor Operations: A Revised Perspective," *Progress in Nuclear Energy*, **157**, pp.1-12 (2022).

# Remote Operation Enabling Technologies: Automated Operation

## Autonomous Control for Reactor Technologies

- A data-driven model predictive control (MPC) system was developed by INL researchers to enable the self-regulating capability of nuclear microreactors.
- **Data-riven modeling methods** allow us to create models the complex physics of a reactor suitable for running **real-time controllers**.
- More details will be provided by Dr. Linyu Lin in a later session.



# Remote Operation Enabling Technologies: Security and Operator Augmentation

- How does the remote operator know that data they are seeing on the screen is the true state of the reactor.
- How does the reactor know that a command received from the remote operator is authentic and safe?

Proposed levels of automation for nuclear reactor operations [1]

| | Level | Human/Machine Interoperability |
|---|---|---|
| 5 | Full Automation | AROS provides sustained operational and tactical control and fallback in all operational domains:<br>One-way communication: remote reactor supervisor monitors operations<br>Two-way communication: remote reactor supervisor monitors operations and provides strategic commands as necessary |

[1] A. Alberti, V. Agarwal, I. Gutowska, C. Palmer, C. de Oliveira, "Automation Levels for Nuclear Reactor Operations: A Revised Perspective," *Progress in Nuclear Energy*, **157**, pp.1-12 (2022).

- Option 1: Rely on existing cybersecurity, encryption and communication protocol to ensure integrity of data transmitted.
- Option 2: Leverage AI/ML-enhanced digital twins of the reactor to evaluate reactor commands and measurements for authenticity and safety.

## Resilient Remote Operation of Microreactors and Fission Batteries

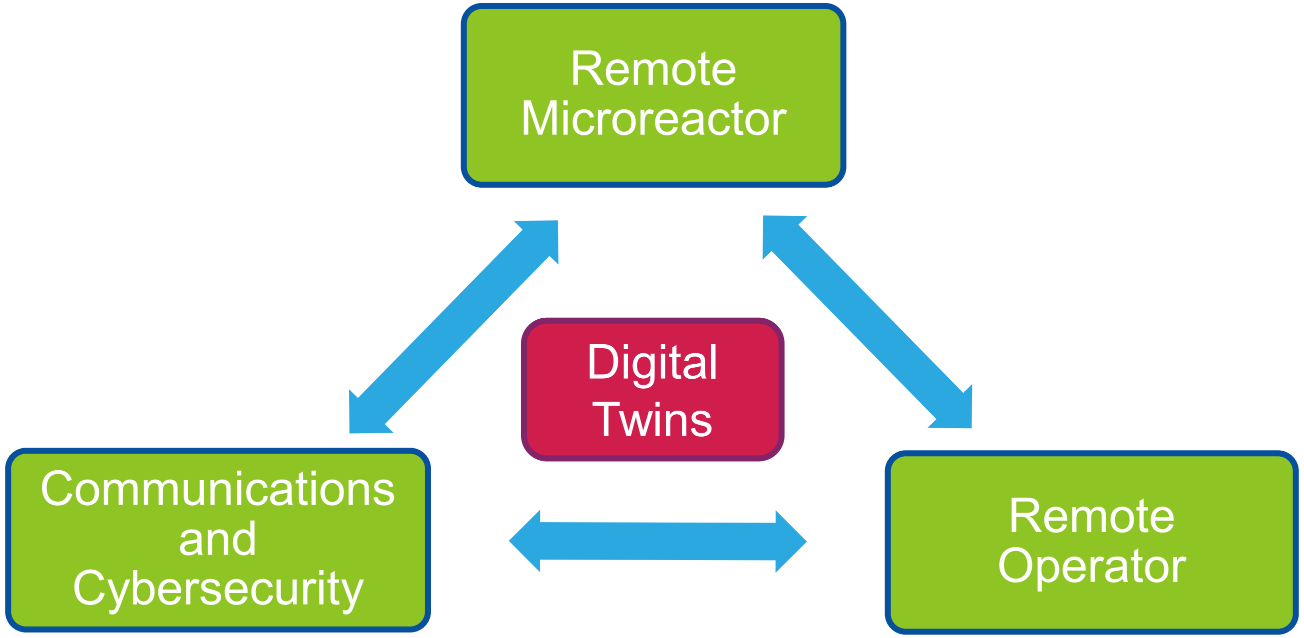
- Construct a digital twin-based measurement and command verification system.

# Resilient Remote Operation of Microreactors and Fission Batteries

Can we leverage AI/ML-informed digital twins to enhance the resiliency of remote monitoring and operations?

## Project Hypothesis

A major unresolved technical challenge to the full deployment of microreactors and fission batteries is a reliable, resilient, and secure remote operations and monitoring capability.




## Proposed Work Tasks

1. Identify operator, control, and signal monitoring and verification needs *unique to remote operation* and monitoring.
2. Define a safe, secure, and resilient communications architecture that meets the needs of remote operation.
3. Develop a digital twin-based cybersecurity and operator augmentation system to enhance operational resilience.
4. Provide simulation and physical demonstrations of remote operation capabilities.

# Concluding thoughts on the remote operation and monitoring of microreactors and the opportunity for AI/ML

- The primary application of microreactors is in remote locations with limited infrastructure.
- The remote nature of these sites makes traditional on-site operation and monitoring of these reactors expensive and difficult.
- Remote monitoring and operation creates a number of technical challenges, some of which could see their solution reside in the application of AI and ML, primarily in the development of data driven reactor models.
  - Reactor Control Automation
  - Security and Operator Augmentation

# Machine Learning Techniques for Enhanced Model Based Control

Prof. Brendan Kochunas

AI/ML Symposium 11.0 – AI/ML in Instrumentation, Control, and Automation

April 27th, 2023

COLLEGE OF ENGINEERING
NUCLEAR ENGINEERING & RADIOLOGICAL SCIENCES
UNIVERSITY OF MICHIGAN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# Outline

- Underlying Philosophy
- Model Based Control
- Applications
  - Basic approach
  - Enhancing Linear Time Invariant Models
  - Hybrid Control Drum Reactivity Worth Model
- Summary

# Underlying Philosophy

This establishes the “world-view” from which we approach problem solving

# Reduced Order Model Methods for Real-Time Applications

KNOWLEDGE OF PHYSICS

COMPLEXITY

| Physics Based | Statistical | Data-Driven Mathematical Machine "Learning" | Artificial Intelligence |
|---|---|---|---|
| Have full knowledge of nicely behaved PDE | Coefficients are Hard | Here's a bunch of numbers | What's the equation for "is this a cat?" |
| • Analytic Models<br>• Approximate Models<br>• High-fidelity | • Empirical/ Surrogate Models<br>• Monte Carlo methods<br>• Bayesian Calibration | • Regression<br>• Principal Component Analysis<br>  • SVD<br>• Dynamic Mode Decomposition | • Neural Networks<br>• Autoencoders<br>• Bayesian Networks |

# Guiding Principles

Don’t be stupid

Don’t be lazy

Use the equations you have

(only use ML judiciously, and as a last option)

# All the hammers in the toolbox

KNOWLEDGE OF PHYSICS

COMPLEXITY

| Physics Based | Statistical | Data-Driven Mathematical Machine "Learning" | Artificial Intelligence |
| --- | --- | --- | --- |
| Have full knowledge of nicely behaved PDE | Coefficients are Hard | Here's a bunch of numbers | What's the equation for "is this a cat?" |
| • Analytic Models<br>• Approximate Models<br>• High-fidelity | • Empirical/ Surrogate Models<br>• Monte Carlo methods<br>• Bayesian Calibration | • Regression<br>• Principal Component Analysis<br>• SVD<br>• Dynamic Mode Decomposition | • Neural Networks<br>• Autoencoder<br>• Bayesian Networks |

# Model Based Control

(Warning math ahead!)

# Model Based vs Model Free

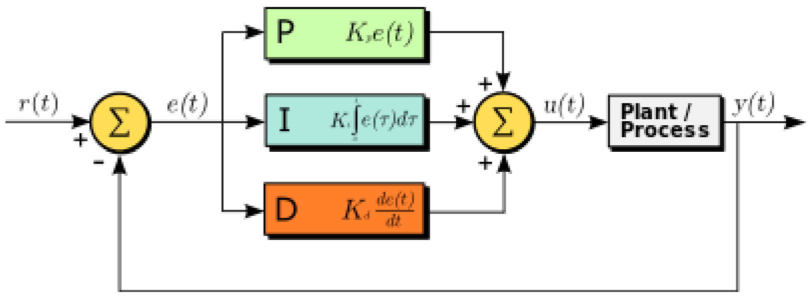
## Model Based

- Some representation of the physics
  - Most model based controllers use a state-space representation
  - $\dot{x}(t) = Ax(t) + Bu(t)$
- Differences in model based control involve how model is used and definition of the optimization problem
  - Model predictive control, Linear Quadratic Regulators, $H_\infty$

## Model Free

- No (direct) physics in the model/controller
- Example proportional-integral-derivative

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau)d\tau + K_d \frac{de(t)}{dt}$$



# State-Space Representations

- $A$ System Matrix
  - Describes time evolution of state-space
  - Example: Point Kinetics equations
- $x$ state-space
  - Describes the unknowns of the system
  - Example: power, reactivity, delayed neutron precursor concentrations
- $u$ input vector
  - Control actions to perform
  - Example: control rod/drum drive position/speed
- $B$ input matrix
  - Maps inputs to state-space
  - Example: control rod/drum reactivity worth curves
- $y$ output vector
  - What you measure in your system
  - Example: core average temperature
- $C$ Output Matrix
  - Relationship between state-space and output vector
  - Example: How core average temperature is computed from
    point reactor model unknowns (e.g., power or moderator temperature)
- $D$ Feedthrough Matrix
  - doesn't apply to reactor control problems (it's 0)
- Lots of variations
  - Continuous ($x(t)$,$\dot{x}(t)$) vs Discrete ($x(k)$,$x(k+1)$)
  - Time invariant ($A$) vs Time varying ($A(x)$)
  - Linear and nonlinear ($A(u,x)$, $A(u)$, $A(x)$)

<u>Continuous Linear Time Invariant</u>

$$\dot{x}(t) = Ax(t) + Bu(t)$$
$$y(t) = Cx(t) + Du(t)$$

<u>Discrete Linear Parameter varying</u>

$$x(k+1) = A(p)x(k) + B(p)u(k)$$
$$y(k) = C(p)x(k)$$

# Point-Reactor State-Space Representations

## Point Kinetics

$$\frac{dn(t)}{dt} = \frac{\rho(t)-\beta}{\Lambda}n(t) + \sum_{i=1}^{6}\lambda_i C_i(t) ,$$

$$\frac{dC_i(t)}{dt} = \frac{\beta_i}{\Lambda}n(t) - \lambda_i C_i(t) , \quad i = 1 \ldots 6 ,$$

## Two-Temperature

$$m_f c_f \frac{dT_f(t)}{dt} = q\kappa n(t) - K_{fc}\left(T_f(t) - T_c(t)\right) ,$$

$$m_c c_c \frac{dT_c(t)}{dt} = (1-q)\kappa n(t) + K_{fc}\left(T_f(t) - T_c(t)\right) - 2\dot{m}_c c_c (T_c(t) - T_i)$$

## Xenon/Iodine

$$\frac{dI(t)}{dt} = \gamma_I \Sigma_f v n(t) - \lambda_I I(t) ,$$

$$\frac{dX(t)}{dt} = \gamma_X \Sigma_f v n(t) + \lambda_I I(t) - \lambda_X X(t) - \sigma_X v n(t) X(t) ,$$

## Reactivity

$$\begin{aligned}\rho(t) &= \rho_f(t) + \rho_c(t) + \rho_X(t) + \rho_r(t)\\ &= \alpha_f\left(T_f(t) - T_f(0)\right) + \alpha_c\left(T_c(t) - T_f(0)\right) - \frac{\sigma_X}{\nu\Sigma_f}\left(X(t) - X(0)\right) + \rho_r(t) ,\end{aligned}$$

## Control Rod Worth

$$\rho_r(t) = \frac{W}{\left(1.0 + exp\left(\frac{r(t)-76.053}{-36.967}\right)\right.} - \frac{W}{\left(1.0 + exp\left(\frac{r(0)-76.053}{-36.967}\right)\right.}$$

# Point-Reactor State-Space Representations

## Point Kinetics

$$\frac{dn(t)}{dt} = \frac{\rho(t) - \beta}{\Lambda} n(t) + \sum_{i=1}^{6} \lambda_i C_i(t),$$

$$\frac{dC_i(t)}{dt} = \frac{\beta_i}{\Lambda} n(t) - \lambda_i C_i(t) \ , \quad i = 1 \ldots 6 \ ,$$

$$P_r(t) = \kappa n(t)$$

## Two-Temperature

$$m_f c_f \frac{dT_f(t)}{dt} = q\kappa n(t) - K_{fc} \left( T_f(t) - T_c(t) \right),$$

$$m_c c_c \frac{dT_c(t)}{dt} = (1-q)\kappa n(t) + K_{fc} \left( T_f(t) - T_c(t) \right) - 2\dot{m}_c c_c \left( T_c(t) - T_i \right)$$

## Xenon/Iodine

$$\frac{dI(t)}{dt} = \gamma_I \Sigma_f v n(t) - \lambda_I I(t),$$

$$\frac{dX(t)}{dt} = \gamma_X \Sigma_f v n(t) + \lambda_I I(t) - \lambda_X X(t) - \sigma_X v n(t) X(t),$$

## Reactivity

$$\begin{aligned} \rho(t) &= \rho_f(t) + \rho_c(t) + \rho_X(t) + \rho_r(t) \\ &= \alpha_f \left( T_f(t) - T_f(0) \right) + \alpha_c \left( T_c(t) - T_f(0) \right) - \frac{\sigma_X}{\nu \Sigma_f} \left( X(t) - X(0) \right) + \rho_r(t), \end{aligned}$$

## Control Rod Worth

$$\rho_r(t) = \frac{W}{\left(1.0 + exp\left(\frac{r(t) - 76.053}{-36.967}\right)\right)} - \frac{W}{\left(1.0 + exp\left(\frac{r(0) - 76.053}{-36.967}\right)\right)}$$

$$x(k+1) = Ax(k) + Bu(k)$$
$$y(k) = Cx(k)$$

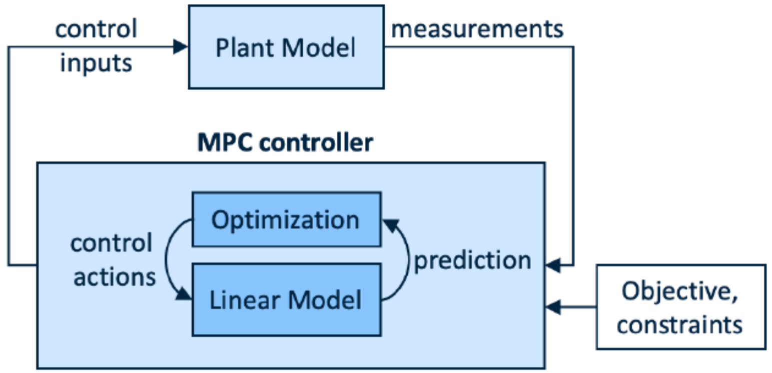
# Applications

# The Basic Approach

- Use ML to create nonlinear corrections to simplified, linearized models
  - Real problems are nonlinear (to varying degrees)
  - Most numerical methods for nonlinear problems make use of linearizations (but can lack robustness or are too expensive for real-time)
  - Linear models are well understood (mathematically, physically, etc.) and are simple enough to be "textbook" examples in many cases. They also facilitate real-time calculations and can be used by controllers

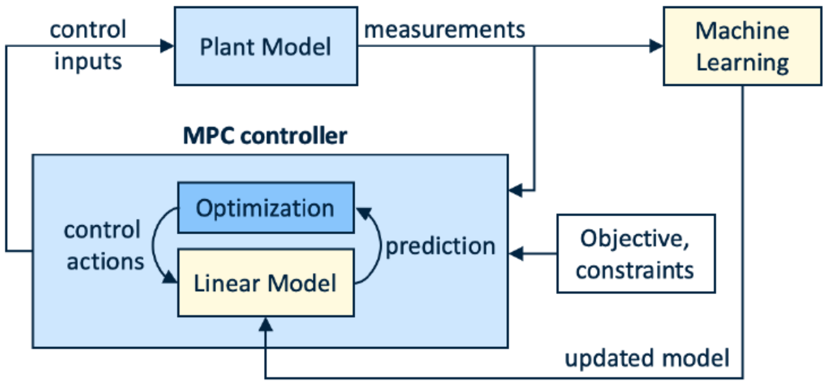
# Enhanced Linear Time Invariant Models (Point-Reactor Model with Model Predictive Control)

- What is the problem?
  - Model is linear time invariant
    - and it is linearized about the initial condition
    - parameters change
  - Model has no spatial dependence




- Let us use ML to intentionally ***correct the known limitations*** of the model

$$x(k+1) = Ax(k) + Bu(k) + ?$$
$$y(k) = Cx(k)$$



# Enhanced Model Based Control
# (Point-Reactor Model with Model Predictive Control)

- Look at elements of A and see how they change as function of time

$$\mathbf{z} = \begin{bmatrix} \frac{\partial f_n}{\partial n} & \frac{\partial f_n}{\partial T_f} & \frac{\partial f_n}{\partial T_c} & \frac{\partial f_n}{\partial X} & \frac{\partial f_n}{\partial r} & \frac{\partial f_X}{\partial n} & \frac{\partial f_X}{\partial X} \end{bmatrix}$$

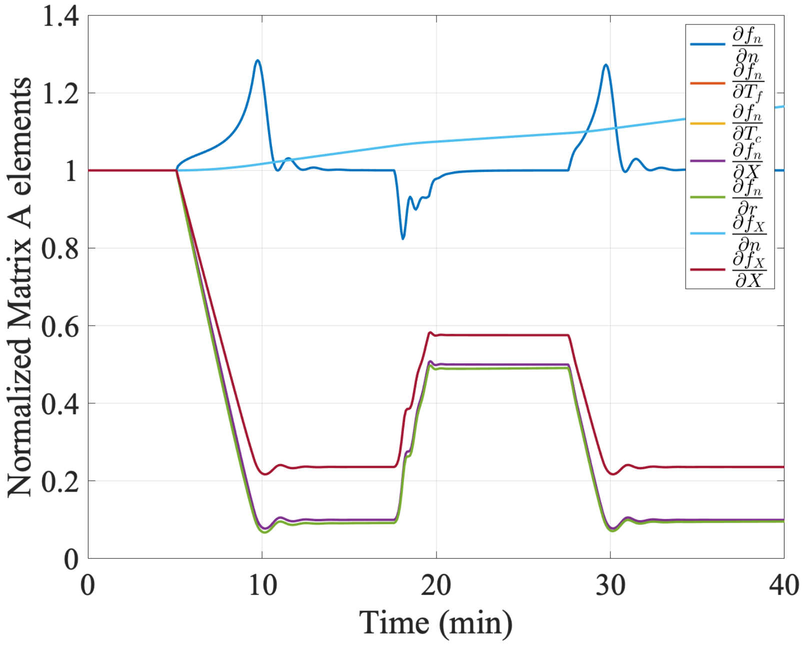
  - Use Gaussian Process Regression to learn elements of $A$ that are nonlinear

$$\mathbf{w} = \begin{bmatrix} n(t) & \rho(t) & r(t) & \frac{dr(t)}{dt} & X(t) \end{bmatrix} \quad P(z^*|w, z, w^*) \approx N(\bar{z}^*, \mathrm{cov}(z^*))$$

- New state-space model with correction

$$x(k+1) = \left(A + \tilde{A}(k)\right)x(k) + Bu(k)$$
$$y(k) = Cx(k)$$

$$\mathbf{A}_s = \left.\frac{\partial \mathbf{f}}{\partial \mathbf{x}}\right|_{t=t_n} = \left.\begin{bmatrix} \frac{\partial \mathbf{f}}{\partial x_1} & \cdots & \frac{\partial \mathbf{f}}{\partial x_m} \end{bmatrix}\right|_{t=t_n} = \left.\begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \cdots & \frac{\partial f_1}{\partial x_m} \\ \vdots & \ddots & \vdots \\ \frac{\partial f_m}{\partial x_1} & \cdots & \frac{\partial f_m}{\partial x_m} \end{bmatrix}\right|_{t=t_n}$$




$$\frac{dn(t)}{dt} = \frac{\rho(t) - \beta}{\Lambda} n(t) + \sum_{i=1}^{6} \lambda_i C_i(t) ,$$
$$\frac{dC_i(t)}{dt} = \frac{\beta_i}{\Lambda} n(t) - \lambda_i C_i(t) , \quad i = 1 \ldots 6 ,$$

$$m_f c_f \frac{dT_f(t)}{dt} = q\kappa n(t) - K_{fc}\left(T_f(t) - T_c(t)\right) ,$$
$$m_c c_c \frac{dT_c(t)}{dt} = (1-q)\kappa n(t) + K_{fc}\left(T_f(t) - T_c(t)\right) - 2\dot{m}_c c_c (T_c(t) - T_i)$$

$$\frac{dI(t)}{dt} = \gamma_I \Sigma_f v n(t) - \lambda_I I(t) ,$$
$$\frac{dX(t)}{dt} = \gamma_X \Sigma_f v n(t) + \lambda_I I(t) - \lambda_X X(t) - \sigma_X v n(t) X(t) ,$$

# Enhanced Model Based Control (Point-Reactor Model with Model Predictive Control)

- Look at elements of A and see how they change as function of time

$$\mathbf{z} = \begin{bmatrix} \frac{\partial f_n}{\partial n} & \frac{\partial f_n}{\partial T_f} & \frac{\partial f_n}{\partial T_c} & \frac{\partial f_n}{\partial X} & \frac{\partial f_n}{\partial r} & \frac{\partial f_X}{\partial n} & \frac{\partial f_X}{\partial X} \end{bmatrix}$$

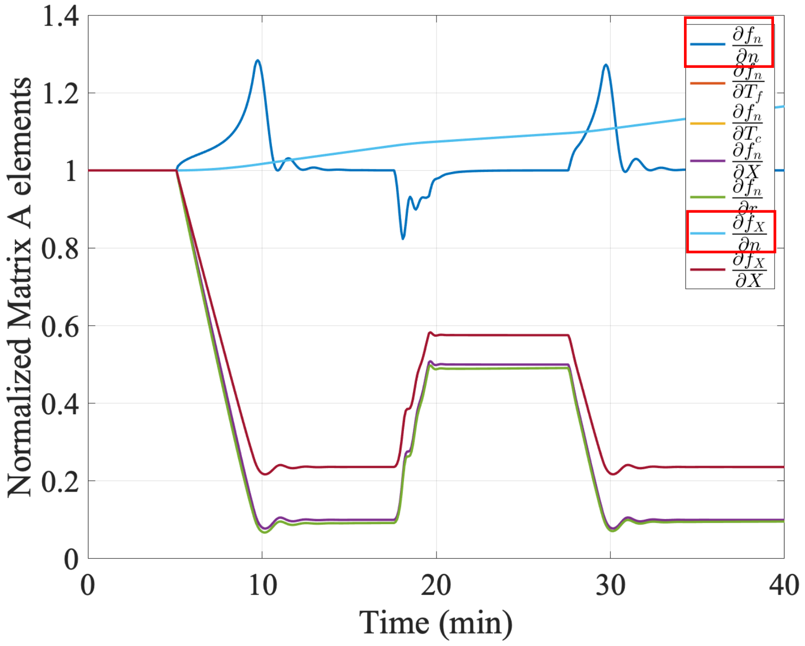
  - Use Gaussian Process Regression to learn elements of $A$ that are nonlinear

$$\mathbf{w} = \begin{bmatrix} n(t) & \rho(t) & r(t) & \frac{dr(t)}{dt} & X(t) \end{bmatrix} \qquad P(z^*|w, z, w^*) \approx N(\bar{z}^*, \mathrm{cov}(z^*))$$

- New state-space model with correction

$$x(k+1) = \left(A + \tilde{A}(k)\right)x(k) + Bu(k)$$
$$y(k) = Cx(k)$$

$$\mathbf{A}_s = \left.\frac{\partial \mathbf{f}}{\partial \mathbf{x}}\right|_{t=t_n} = \left.\begin{bmatrix} \frac{\partial \mathbf{f}}{\partial x_1} & \cdots & \frac{\partial \mathbf{f}}{\partial x_m} \end{bmatrix}\right|_{t=t_n} = \left.\begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \cdots & \frac{\partial f_1}{\partial x_m} \\ \vdots & \ddots & \vdots \\ \frac{\partial f_m}{\partial x_1} & \cdots & \frac{\partial f_m}{\partial x_m} \end{bmatrix}\right|_{t=t_n}$$

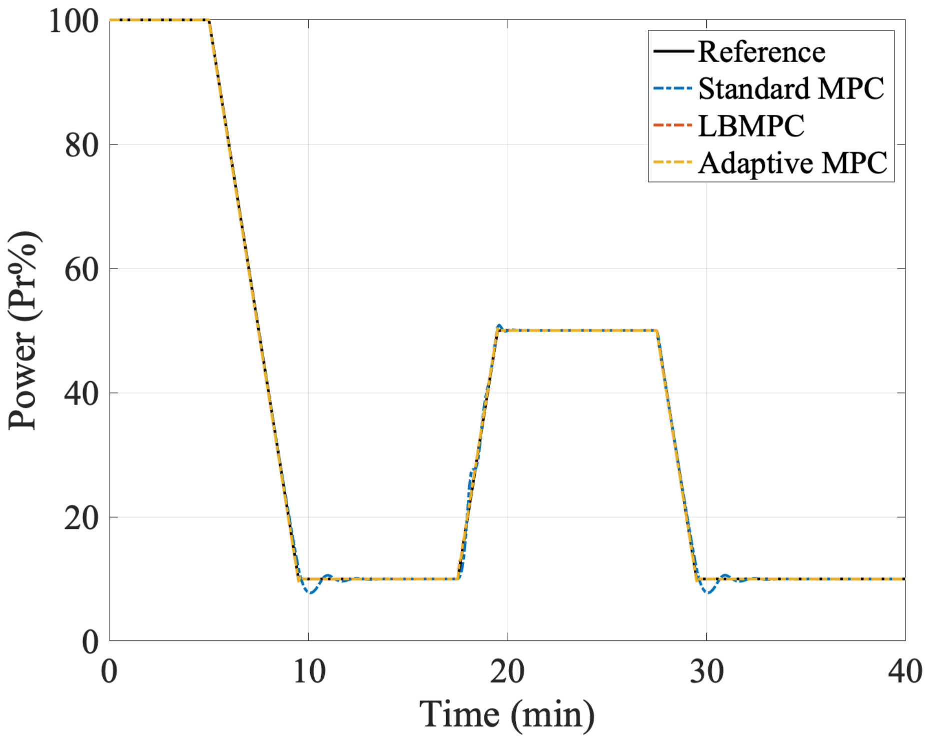


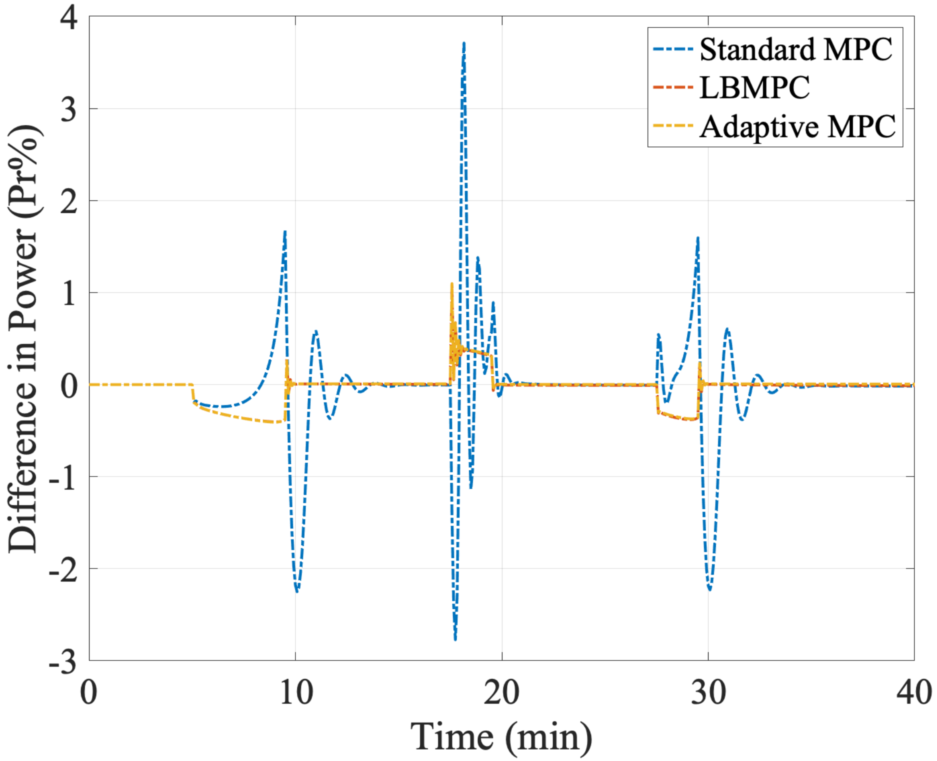

$$\frac{dn(t)}{dt} = \boxed{\frac{\rho(t) - \beta}{\Lambda} n(t)} + \sum_{i=1}^{6} \lambda_i C_i(t) ,$$
$$\frac{dC_i(t)}{dt} = \frac{\beta_i}{\Lambda} n(t) - \lambda_i C_i(t) , \quad i = 1 \ldots 6 ,$$

$$m_f c_f \frac{dT_f(t)}{dt} = q\kappa n(t) - K_{fc}\left(T_f(t) - T_c(t)\right) ,$$
$$m_c c_c \frac{dT_c(t)}{dt} = (1-q)\kappa n(t) + K_{fc}\left(T_f(t) - T_c(t)\right) - 2\dot{m}_c c_c (T_c(t) - T_i)$$

$$\frac{dI(t)}{dt} = \gamma_I \Sigma_f v n(t) - \lambda_I I(t) ,$$
$$\frac{dX(t)}{dt} = \gamma_X \Sigma_f v n(t) + \lambda_I I(t) - \lambda_X X(t) - \boxed{\sigma_X v n(t) X(t)} ,$$

# Enhanced Model Based Control (Point-Reactor Model with Model Predictive Control)



# Hybrid Control Drum Reactivity Worth Model

- Control drums (and rods) have differential reactivity worth that varies with position
  - There are also nonlinear effects between the drums (shadowing effect)
  - More accurate prediction of drum worth will lead to better control action
- We may want to move control drums individually
  - Model Predictive Control supports multiple control inputs
- Challenges
  - A point reactor model neglects the spatial dependence
  - Difficult to capture the nonlinear effects between control drums
    (but these are first order effects!)
  - Calculating all the possibilities directly is time consuming (a little more than 7 cpu years)

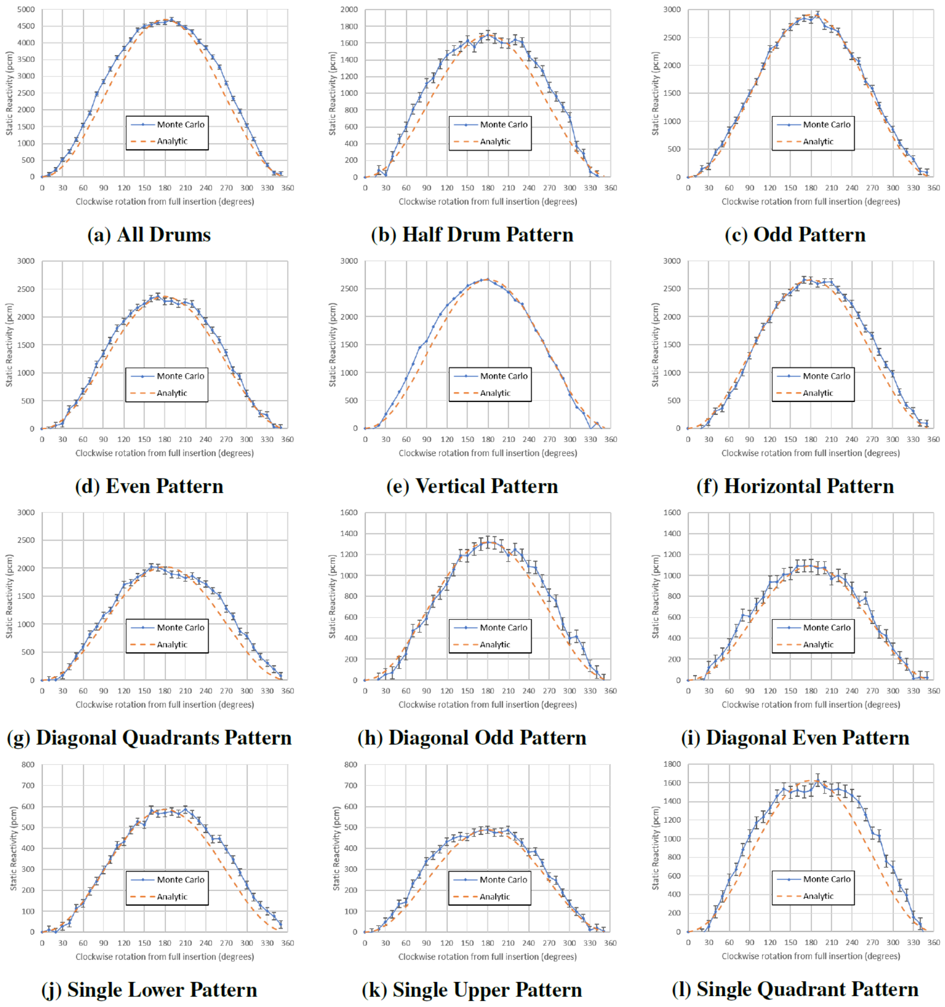



**Figure 6. Integral Control Drum Reactivity Worths**

# Hybrid Control Drum Reactivity Worth Model

https://doi.org/10.1016/j.anucene.2021.108903

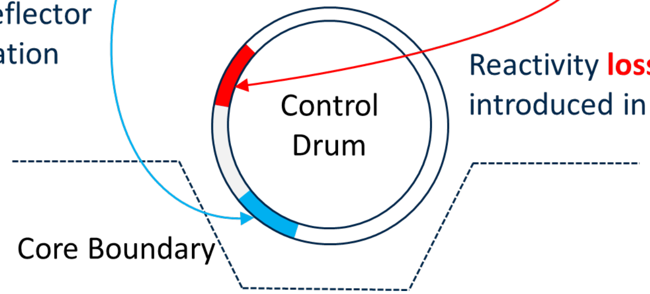
- Use First Order Perturbation Theory as a starting point
  - No spatial dependence
  - Not easy to incorporate effects between drums
  - It ignores higher order effects
- Extend First Order Perturbation Theory with statistical regression
  - Write total core reactivity as a linear combination of first order models
  - Solve for coefficients of linear combination by regression

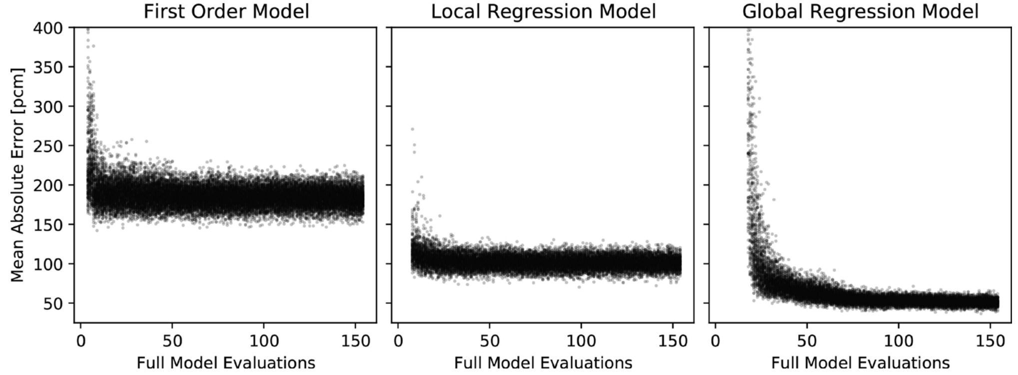
Obtained by **Statistical Regression**

$$\Delta\rho = \boxed{\tilde{\zeta}(\gamma)} \overbrace{\left( \boxed{\int_{\Theta_{A'}\cap\Theta_{A_0}} j^-(\beta)^2 d\beta} - \boxed{\int_{\Theta_{A}\cap\Theta_{A'_0}} j^-(\beta)^2 d\beta} \right)}^{\text{Model from First Order Perturbation Theory}}$$

Reactivity **gain** from reflector introduced in perturbation

Reactivity **loss** from absorber introduced in perturbation



# Summary

# Summary

- Using simple models and ML to correct known approximations/limitations can work well
  - We used it here to capture combinations of nonlinear effects in two different settings
  - This was better than “brute force” (in the case of control drums)
  - Issues of explainability and training bias that are inherent in any AI approach are not present here

- Don’t throw the physics out with Archimedes’s bathwater.

# Summary

- Using simple models and ML to correct known approximations/limitations can work well
  - We used it here to capture combinations of nonlinear effects in two different settings
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AI Generated image by craiyon

# Acknowledgements


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# Questions?

# Backup

# State-Space Model

$$\dot{\mathbf{x}}_\mathbf{c} = \mathbf{A}_\mathbf{c}\mathbf{x}_\mathbf{c} + \mathbf{B}_\mathbf{c}\mathbf{u}$$

$$\mathbf{y} = \mathbf{C}_\mathbf{c}\mathbf{x}_\mathbf{c}$$

$$\mathbf{A}_\mathbf{c} = \begin{bmatrix} -\frac{\beta}{\Lambda} & \frac{\beta_1}{\Lambda} & \cdots & \frac{\beta_m}{\Lambda} & \frac{\alpha_f}{\Lambda} & \frac{\alpha_m}{\Lambda} & \frac{\alpha_c}{\Lambda} & 0 & -\sigma_x v & \frac{1}{\Lambda} \\ \lambda_1 & -\lambda_1 & \cdots & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \lambda_m & 0 & \cdots & -\lambda_m & 0 & 0 & 0 & 0 & 0 & 0 \\ \frac{qP_r}{m_f c_f} & 0 & \cdots & 0 & -\frac{K_{fm}}{m_f c_f} & \frac{K_{fm}}{m_f c_f} & 0 & 0 & 0 & 0 \\ \frac{(1-q)P_r}{m_m c_m} & 0 & \cdots & 0 & \frac{K_{fm}}{m_m c_m} & -\frac{K_{fm}+K_{mc}}{m_m c_m} & \frac{K_{mc}}{m_m c_m} & 0 & 0 & 0 \\ 0 & 0 & \cdots & 0 & 0 & \frac{K_{mc}}{m_c c_c} & -\frac{K_{mc}+2\dot{m}_c c_c}{m_c c_c} & 0 & 0 & 0 \\ \gamma_i \sigma_f v n_0 & 0 & \cdots & 0 & 0 & 0 & 0 & -\lambda_i & 0 & 0 \\ \left(\gamma_x \Sigma_f - \sigma_x X_0\right) v n_0 & 0 & \cdots & 0 & 0 & 0 & 0 & -\lambda_i & -\lambda_x - \sigma_x v n_0 & 0 \\ 0 & 0 & \cdots & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$\mathbf{x}_\mathbf{c} = \begin{bmatrix} \delta\bar{n}(t) & \delta\bar{C}_1(t) & \cdots & \delta\bar{C}_m(t) & \delta T_f(t) & \delta T_m(t) & \delta T_c(t) & \delta I(t) & \delta X(t) & \delta\rho_d(t) \end{bmatrix}^T$$

# Sensitivities on Reduced Order Model Parameters

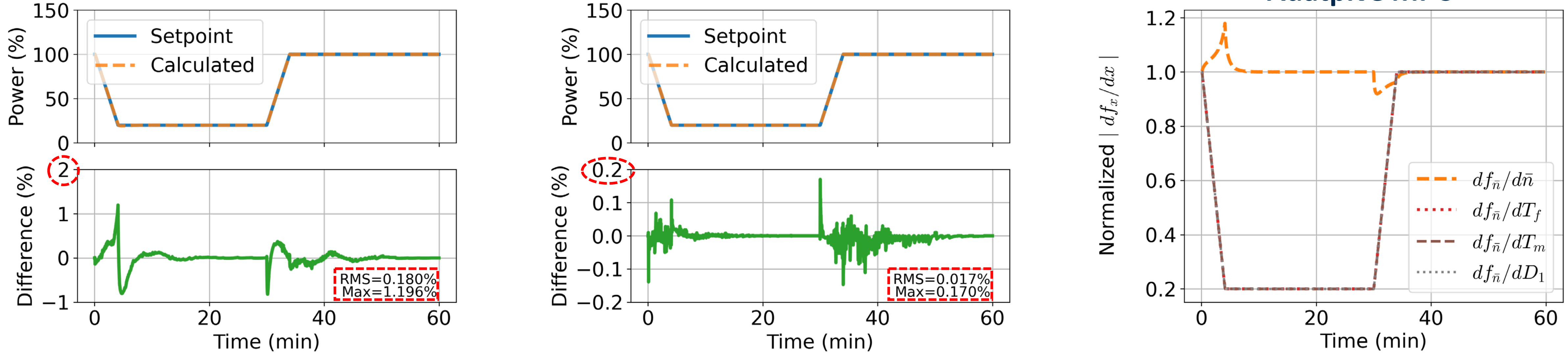
- Even though observer may correct some degree of error, MPC still needs to have a reasonable ROM for accurate and stable simulation results
- Control drum differential worth and $\beta_i$ have larger sensitivities than other parameters
- ROM parameters may have pretty large margin (30%)
- Standard MPC causes large error since it cannot predict time-varying component

| Description | Tracking difference (%) | | Control cost | |
|---|---|---|---|---|
| | RMS | Max | Velocity (deg/s) | Acceleration (deg/s$^2$) |
| 3D core simulation | 0.027 | 0.234 | 2.22E-02 | 5.55E-03 |
| 2D core simulation (Base case) | 0.017 | 0.170 | 2.03E-02 | 5.10E-03 |
| Standard MPC | 0.180 | 1.196 | 1.81E-02 | 2.03E-03 |
| Position-dependent drum worth | 0.019 | 0.166 | 2.03E-02 | 5.26E-03 |
| Drum worth −60% | 0.106 | 0.790 | 9.95E-02 | 1.93E-01 |
| Drum worth −30% | 0.022 | 0.326 | 2.04E-02 | 7.54E-03 |
| Drum worth +30% | 0.031 | 0.172 | 2.03E-02 | 4.49E-03 |
| Drum worth +60% | 0.049 | 0.226 | 2.02E-02 | 4.06E-03 |
| $\beta_i$ −30% | 0.020 | 0.145 | 2.02E-02 | 4.29E-03 |
| $\beta_i$ +30% | 0.019 | 0.267 | 2.03E-02 | 6.31E-03 |
| $\lambda_i$ −30% | 0.021 | 0.176 | 2.05E-02 | 5.66E-03 |
| $\lambda_i$ +30% | 0.016 | 0.165 | 2.04E-02 | 4.79E-03 |
| $\Lambda$ −30% | 0.017 | 0.170 | 2.03E-02 | 5.10E-03 |
| $\Lambda$ +30% | 0.017 | 0.170 | 2.03E-02 | 5.10E-03 |
| $\alpha_f, \alpha_m$ −30% | 0.030 | 0.221 | 2.03E-02 | 5.10E-03 |
| $\alpha_f, \alpha_m$ +30% | 0.019 | 0.170 | 2.03E-02 | 5.11E-03 |
| $c_{p,f}, c_{p,m}, c_{p,c}$ −30% | 0.020 | 0.171 | 2.03E-02 | 5.10E-03 |
| $c_{p,f}, c_{p,m}, c_{p,c}$ +30% | 0.022 | 0.192 | 2.03E-02 | 5.10E-03 |
| Ramp rate 5%/min | 0.012 | 0.097 | 1.23E-02 | 1.65E-03 |
| Ramp rate 10%/min | 0.014 | 0.112 | 1.52E-02 | 2.78E-03 |
| Ramp rate 30%/min | 0.021 | 0.384 | 2.59E-02 | 8.29E-03 |
| Power 100%→140%→100% | 0.015 | 0.140 | 8.14E-03 | 1.21E-03 |

# Adaptive MPC vs. Standard MPC

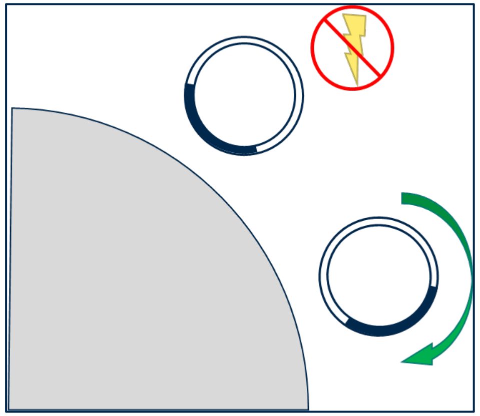
- Ignoring time-varying elements in standard MPC may degrade accuracy
- Successive linearization in adaptive MPC can consider these nonlinearity in ROM

**Standard** **Adaptive** **Time-varying elements from Adatpive MPC**



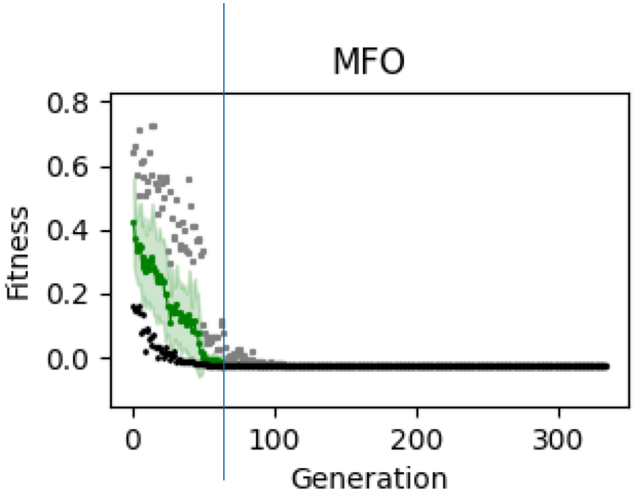
# Multi-Objective Optimization of Microreactor Control Drum Operation

- ***Problem***
  - For real time control how do I accurately determine an optimal control drum configuration to meet reactivity requirements, peaking requirements, and do so robustly?
- ***Our Solution***
  - Multi-objective optimization with scalarization and moth flame optimization
- ***Result***
  - Capable of configuring 8 drums to match a desired reactivity, while satisfying quadrant power tilt ratio, even when you have a struck drum
- ***Value***
  - Near real-time method for robust reactivity control of microreactors



Works with Stuck Drums

Optimal Control Drum Positioning Reached




Optimal solution solved with high-fidelity Monte Carlo (~50 pcm off critical QPTR within 0.001)

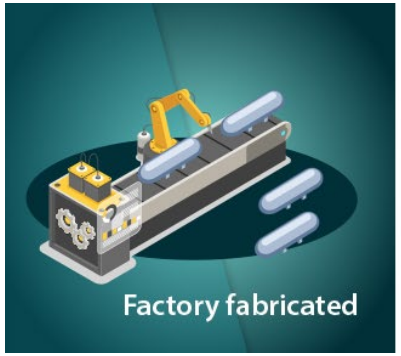
# Autonomous Control with ML/AI for Microreactors: Opportunity and Challenge

Linyu Lin
Joseph Oncken
Vivek Agarwal

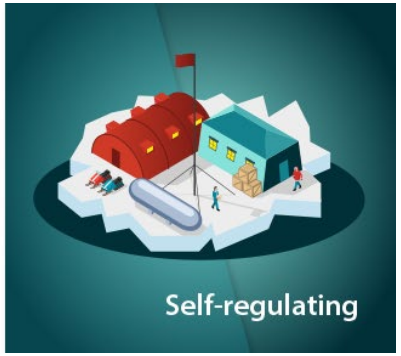
Idaho National Laboratory

# Self-Regulating Microreactor

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







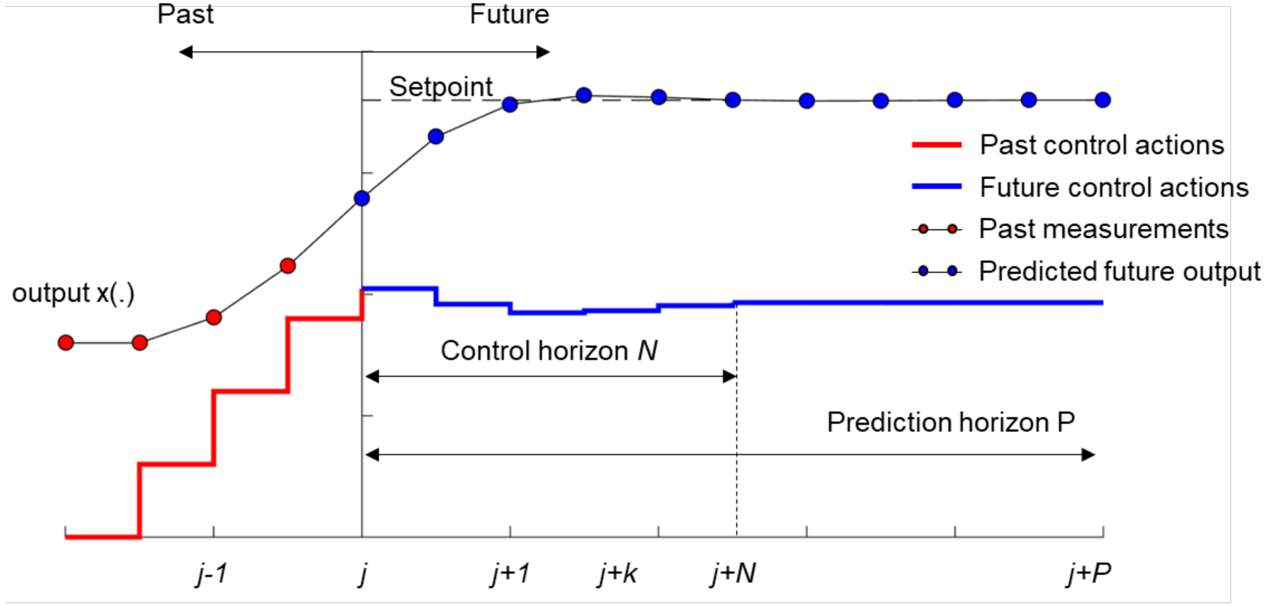

- Self-regulating requires remote and semi-autonomous microreactor operations
  - Reduced number of specialized operators onsite
  - Load following capability

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

# Anticipatory Control

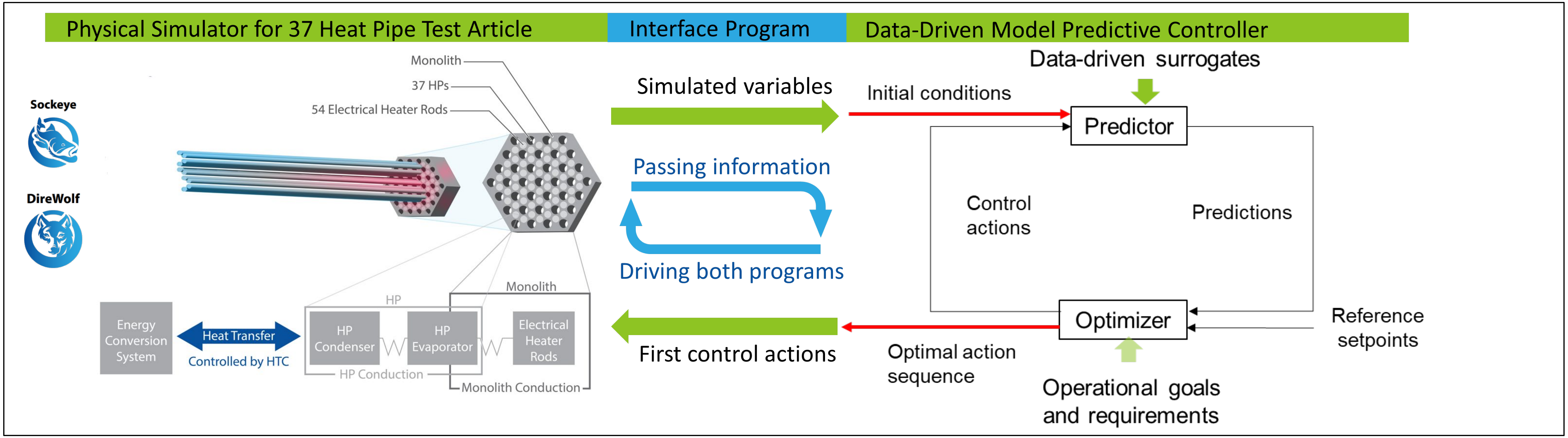
- Anticipatory control strategy for establishing technical basis of self-regulating microreactors
  - Proactively respond to disturbances and find optimal control actions to meet operational goals.
  - Explicitly incorporate and handle constraints by system dynamics, operational and safety requirements.

- 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 achieving (semi-) autonomous operations for microreactors

# Anticipatory Control with Plant Simulator



# Anticipatory Control

- Data-Driven Model Predictive Control (MPC) as an implementation of anticipatory control strategy

| | | |
|---|---|---|
| $J^* = \min_U \left[\sum_{k=1}^{N} l\left(x_{k\|j}, u_{k\|j}\right)\right]$ | | Optimization |
| subject to | $x_{k+1\|j} = f\left(x_{k\|j}, u_{k\|j}\right)$ | Process Model |
| | $U = \left[u_{1\|j}, \ldots, u_{N\|j}\right] \in \mathbf{U}_i$ for all $i = 1, \ldots, n_{c_u}$ | Constraints on range, magnitudes, and derivatives of control actions and state variables |
| | $X = \left[x_{1\|j}, \ldots, x_{N\|j}\right] \in \mathbf{X}_i$ for all $i = 1, \ldots, n_{c_x}$ | |
| | $x_{0\|j} = x_j$ | Initial conditions at every shifted time window |

- Process model with data-driven methods

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

Approximated by

State-space model by SINDYc

AI/ML models

Feedforward neural network (FNN)

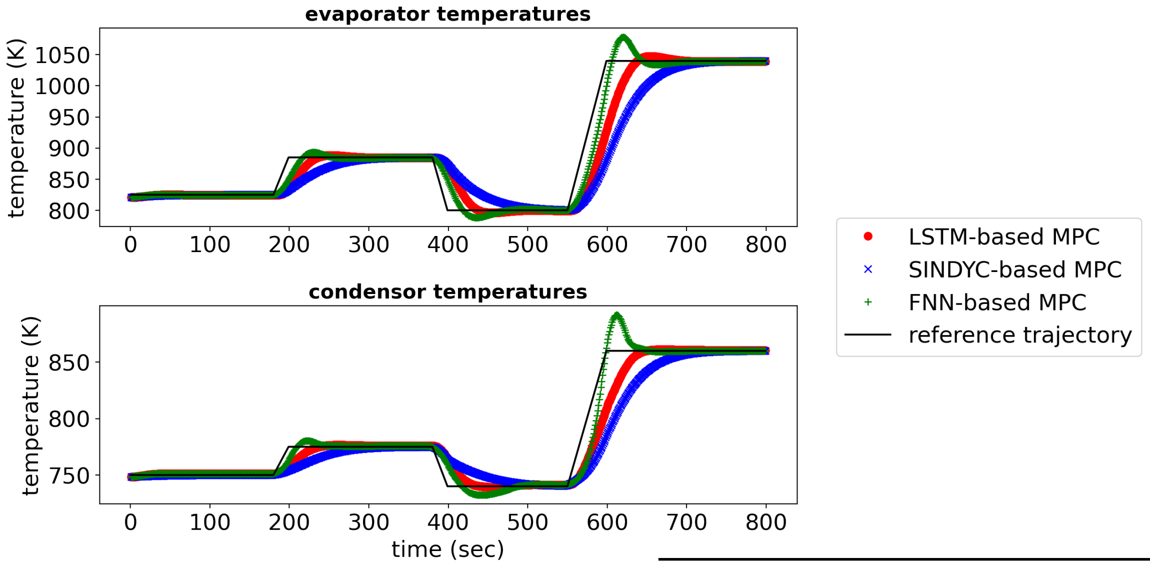
Recurrent neural network (RNN)

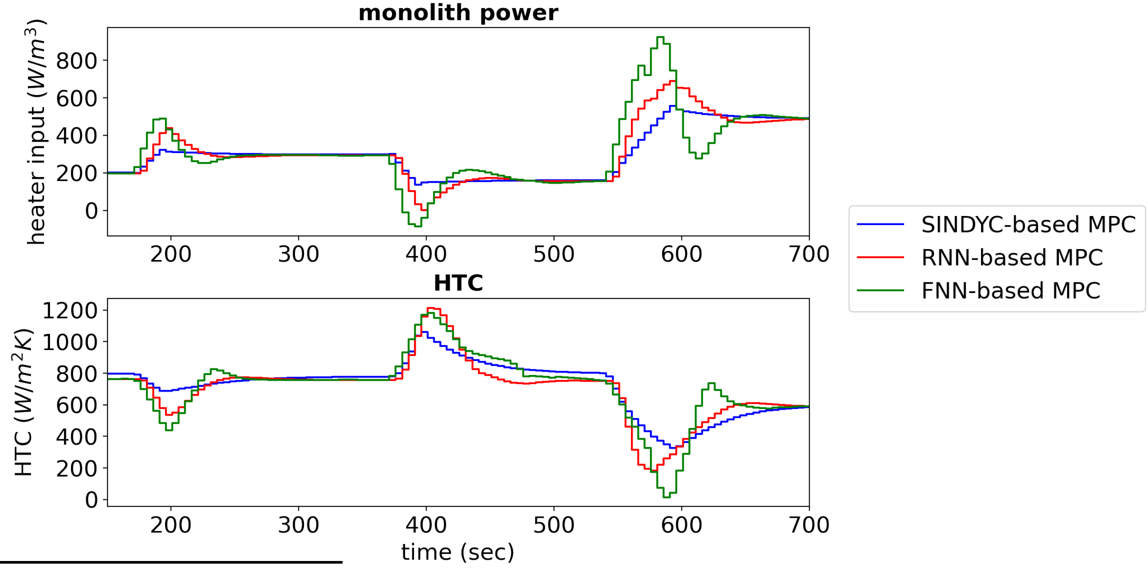
Compared to linear state-space model, AI/ML models offer opportunities of better capturing nonlinear system dynamics

Sparse Identification of Nonlinear Dynamics with Controls (SINDYc) is a data-driven system identification method for nonlinear dynamical system with inputs and forcing using regression methods

# Case Study #1

- All model predictive controllers (MPCs) have the same settings except for different modeling approaches
  - More fluctuated predictions from AI/ML models than the state-space model identified by SINDYc
  - NN-based MPCs better track sharp changes (nonlinear behaviors) in setpoints.




| Models in MPC | Errors in tracking reference setpoints | |
|---|---|---|
| | $T_e$ | $T_c$ |
| SINDYc State-Space | 39.50 | 17.89 |
| Feedforward Neural Net | 27.54 | 11.63 |
| Recurrent Neural Net | 16.03 | 8.56 |

# Online Updating and Transfer Learning

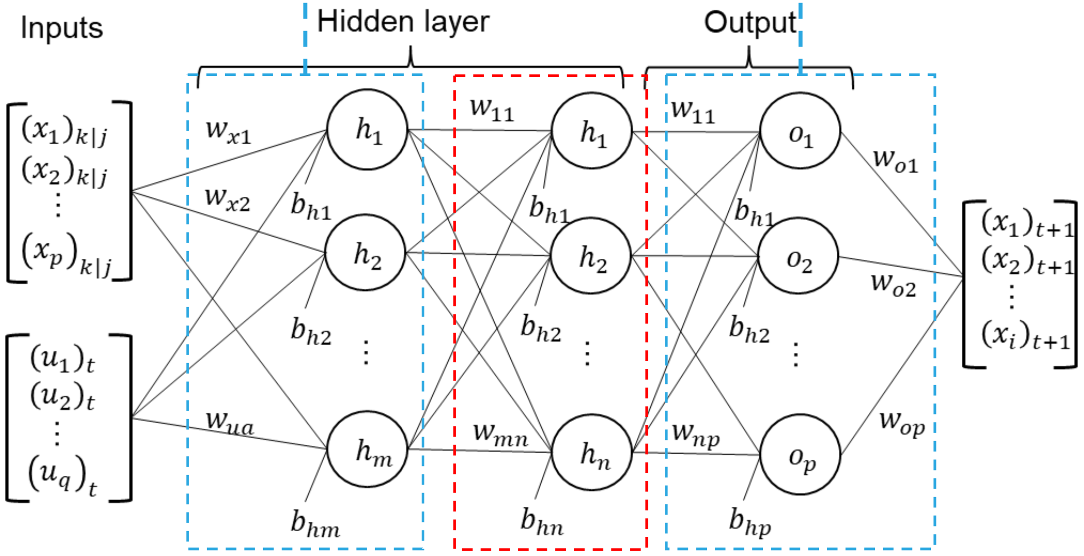
- Adaptable process model through online updating

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

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

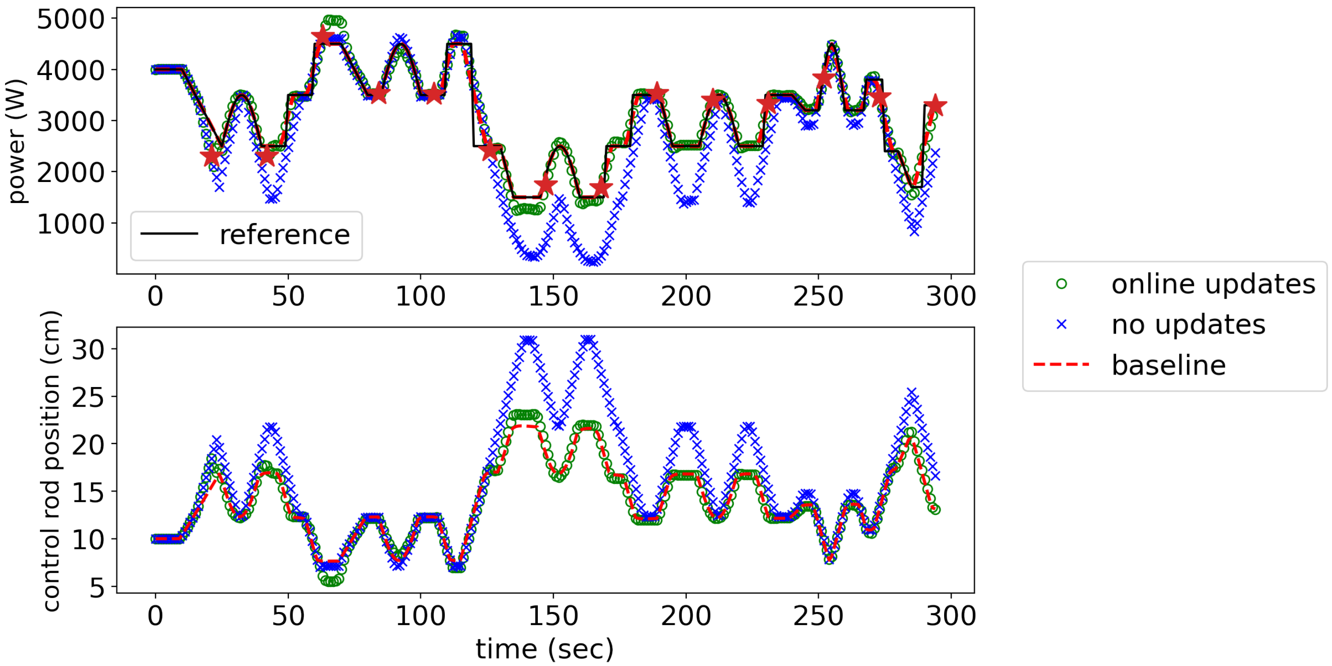
- Only necessary updates:
  - Update only when large discrepancy is detected.
  - Update only when a sufficient amount of data is collected.




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

# Case Study #2

- Used a two-layer Feedforward Neural Net as the surrogate of the baseline reactor model
  - FNN is updated with discrepancy between predicted and measured powers exceeds a limit (marked by ★).
  - Optimize updating strategies for better performance.




| | Surrogate models | RMSE (W) |
|---|---|---|
| Prediction errors | FNN without update | 510 |
| | + FNN with online updates | 223.5 |
| | + Optimized online updating strategy | 130.5 |
| | Target (ground-truth) model | 0.0 |
| Discrepancy between target and achieved power rates | FNN without update | 649.9 |
| | + FNN with online updates | 214.7 |
| | + Optimized online updating strategy | 178.7 |
| | Target (ground-truth) model | 168.2 |

- Improved performance with online updating
  - Prediction accuracy is improved by 74%
  - MPC performance is improved by 70%

# Challenges

- Model validation and uncertainty quantification for autonomous control.
  - Quality of model input data (cyber incidents, sensor biases and noises)
  - Predictive capability of surrogate models (interpolated vs. extrapolated)
  - Solvability of control problems

- Physical tests
  - Prototyping and testing system for control software
  - Real-time processing and computations

Despite the nonlinear and adaptable control capabilities by AI/ML, physical tests and validations are currently the major barriers.

April 05, 2023

**Vivek Agarwal, Ph.D.**
**Distinguished Staff Scientist**
**Lead, Fission Battery Initiative**

# Unattended Operation of Fission Batteries

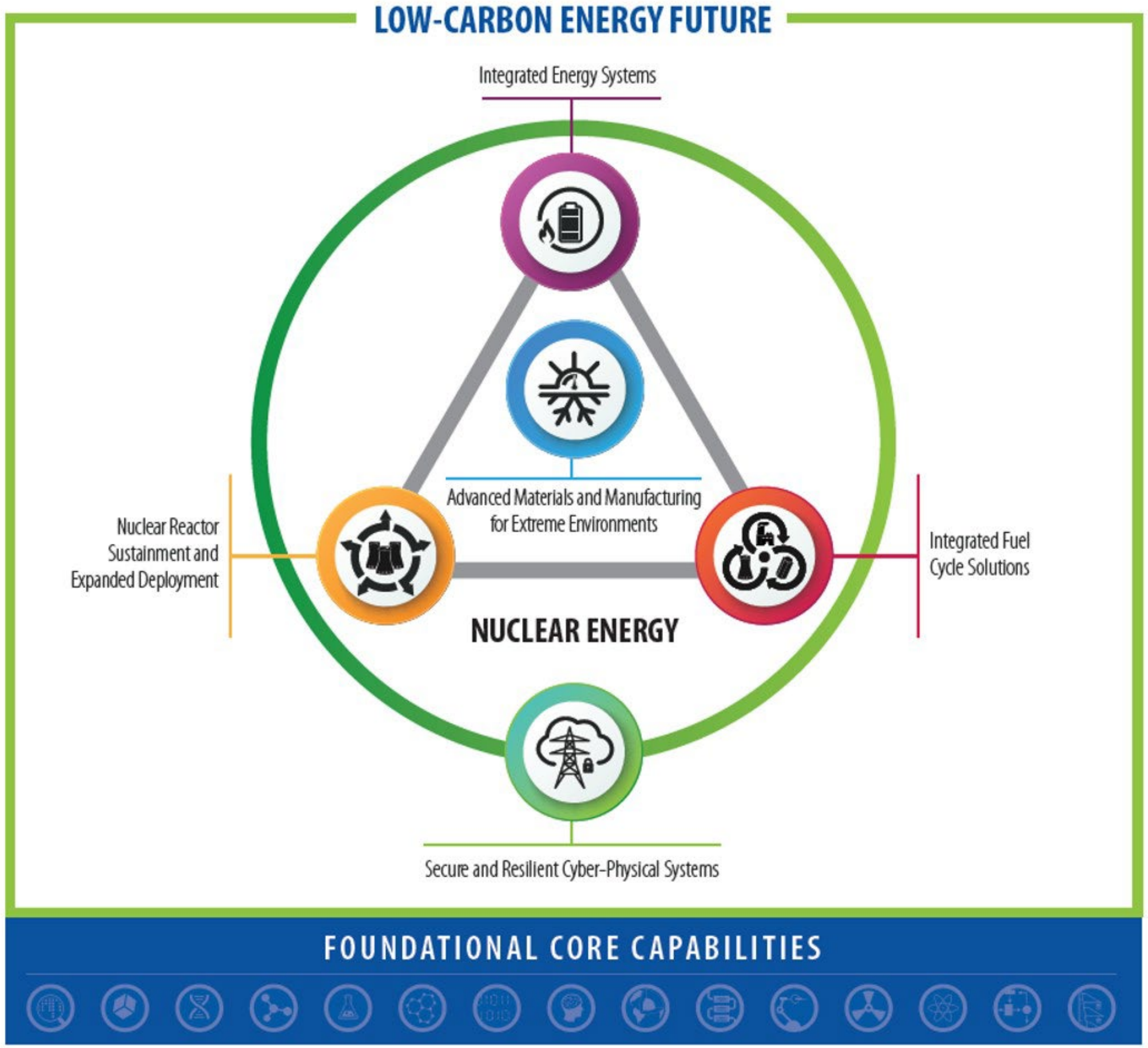
## Artificial Intelligence and Machine Learning Symposium 11.0

Idaho National Laboratory

# INL's Science and Technology (S&T) Initiatives

- These five strategic S&T Initiatives will contribute to changing the world's energy future and securing our critical infrastructure.

- These initiatives build on INL's research, development, and demonstration leadership in nuclear energy to advance a vision of a low-carbon energy future that fully realizes the game-changing potential of nuclear energy.

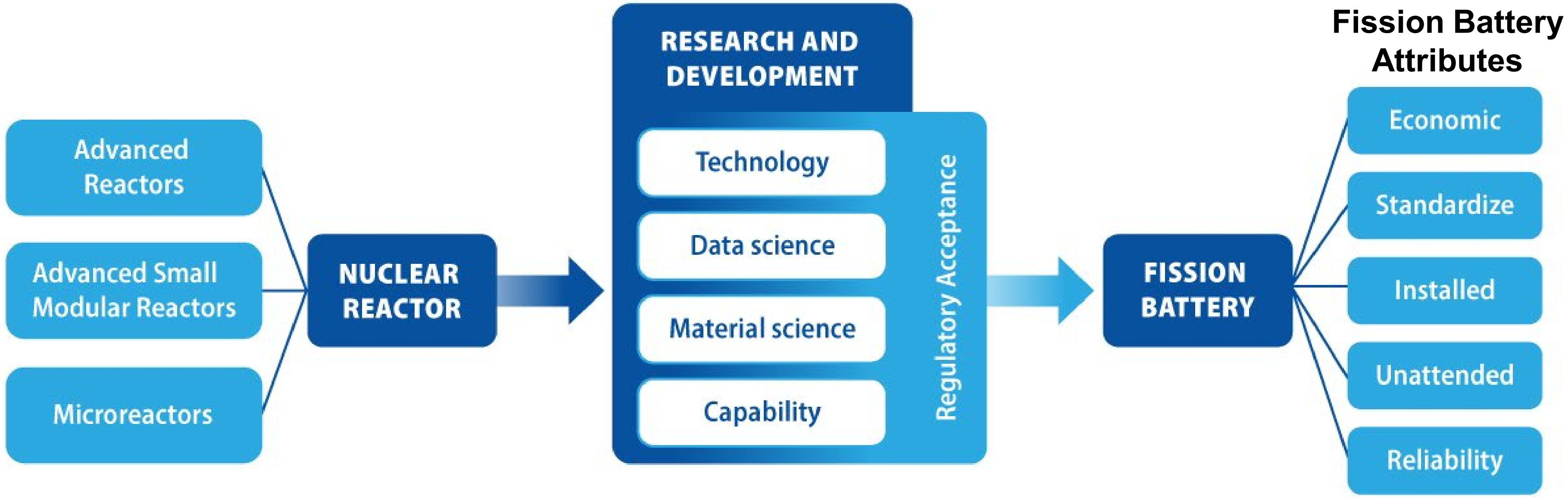


# Fission Battery Initiative

**Nuclear Reactor Sustainment and Expanded Deployment**

**Vision:** Developing technologies that enable nuclear reactor systems to function as batteries.

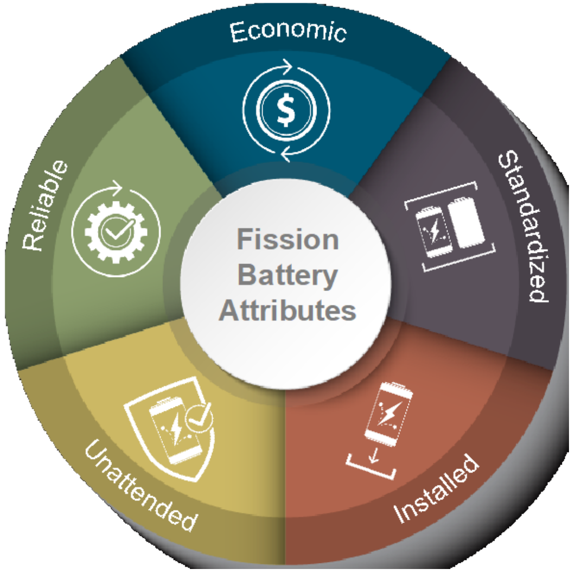
**Outcome:** Deliver on research and development needed to provide technologies that achieve key fission battery attributes and expand applications of nuclear reactors systems beyond concepts that are currently under development.



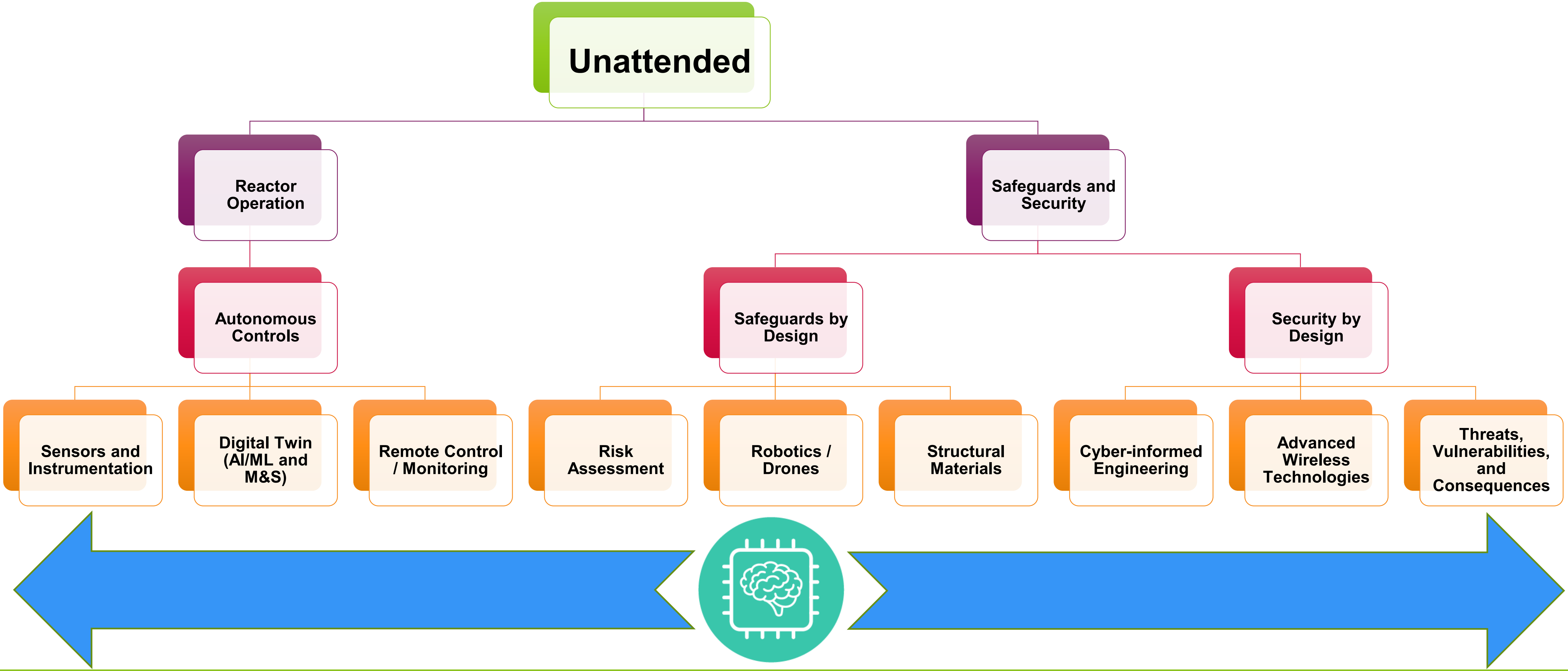

*Research and development to enable nuclear reactor technologies to achieve fission battery attributes*

# Fission Battery Attributes

- **Economic** – Cost competitive with other distributed energy sources (electricity and heat) used for a particular application in a particular domain. This will enable flexible deployment across many applications, integration with other energy sources, and use as distributed energy resources.
- **Standardized** – Developed in standardized sizes, power outputs, and manufacturing processes that enable universal use and factory production, thereby enabling low-cost and reliable systems with faster qualification and lower uncertainty for deployment.
- **Installed** – Readily and easily installed for application-specific use and removal after use. After use, fission batteries can be recycled by recharging with fresh fuel or responsibly dispositioned.
- **Unattended** – Operated securely and safely in an unattended manner to provide demand-driven power.
- **Reliable** – Equipped with systems and technologies that have a high level of reliability to support the mission life and enable deployment for all required applications. They must be robust, resilient, fault tolerant, and durable to achieve fail-safe operation.

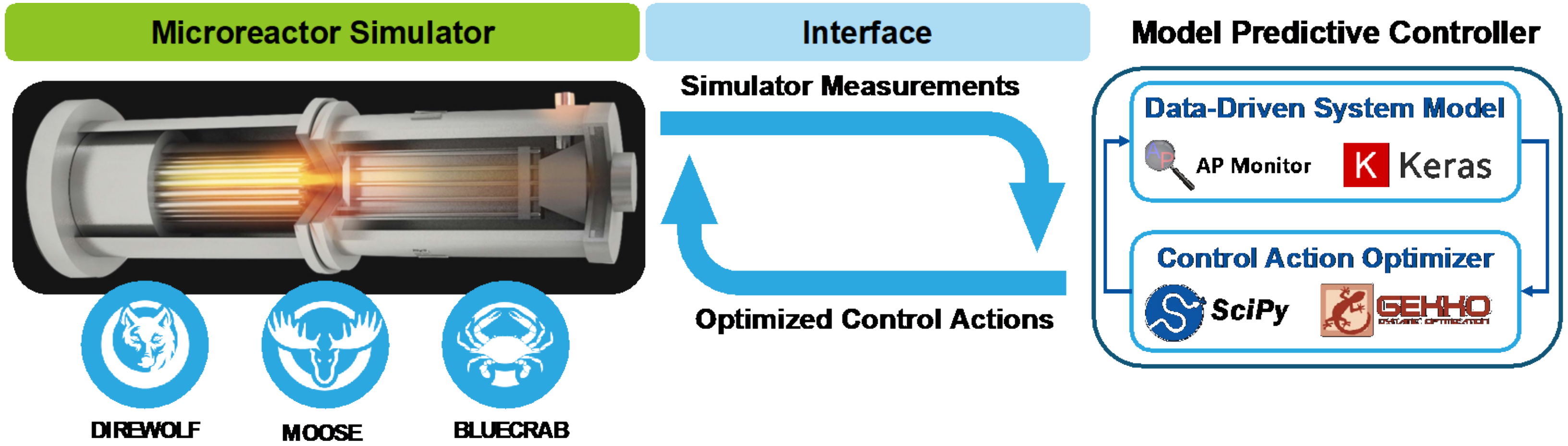


# Unattended Operation of Fission Batteries



# LDRD: Scalable Hybrid Modeling with Anticipatory Control Strategy for Autonomous Operation of Modular and Microreactor

- First-of-a-kind anticipatory controller **Autonomous Control fOr Reactor technology (ACORN)** to achieve autonomous control of microreactors
- Leverages and expands INL's modeling and simulation capabilities like DireWolf and BlueCRAB for capturing microreactor thermal and neutronic performance
- ACORN controller provides optimal control actions for microreactor under different scenarios and external uncertainties
  - Steady state and transient operations
  - Flexible operation (load following)
  - Failure or degraded operation

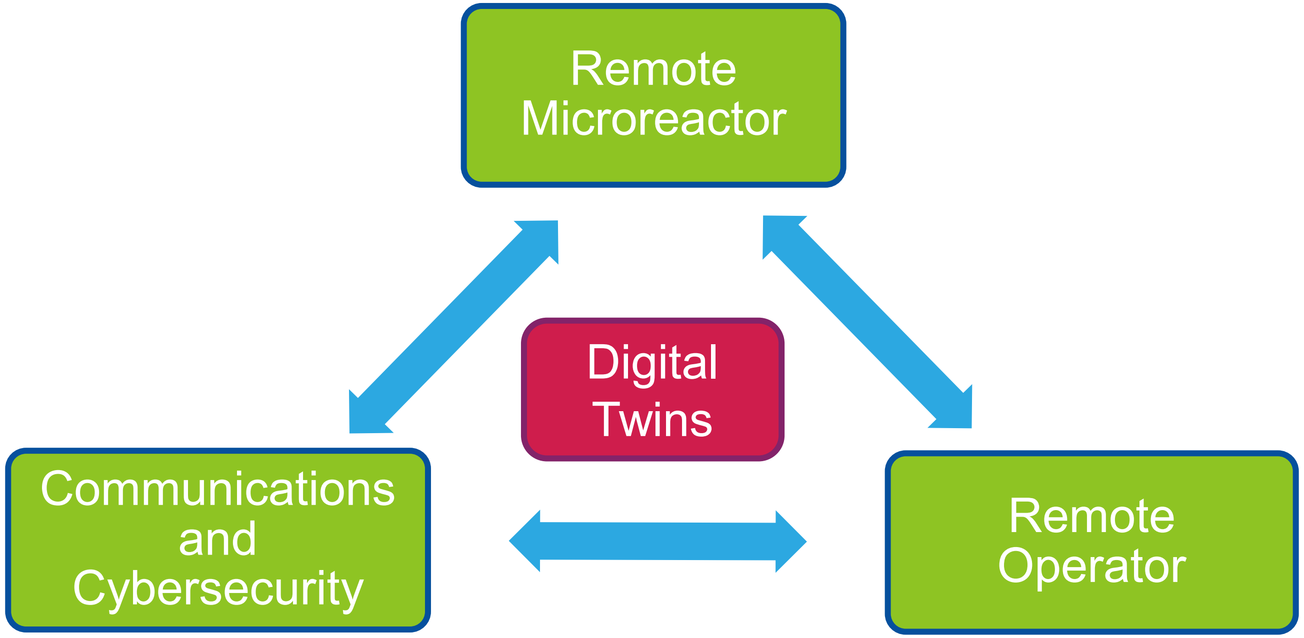



ACORN advances the level of automation to address the unattended attribute of the Fission Battery Initiative. This advancement also accounts for economics of operation of microreactors.

# LDRD: Resilient Remote Operation of Microreactors and Fission Batteries

## Project Hypothesis

A major unresolved technical challenge to the full deployment of microreactors and fission batteries is a reliable, resilient, and secure remote operations and monitoring capability.



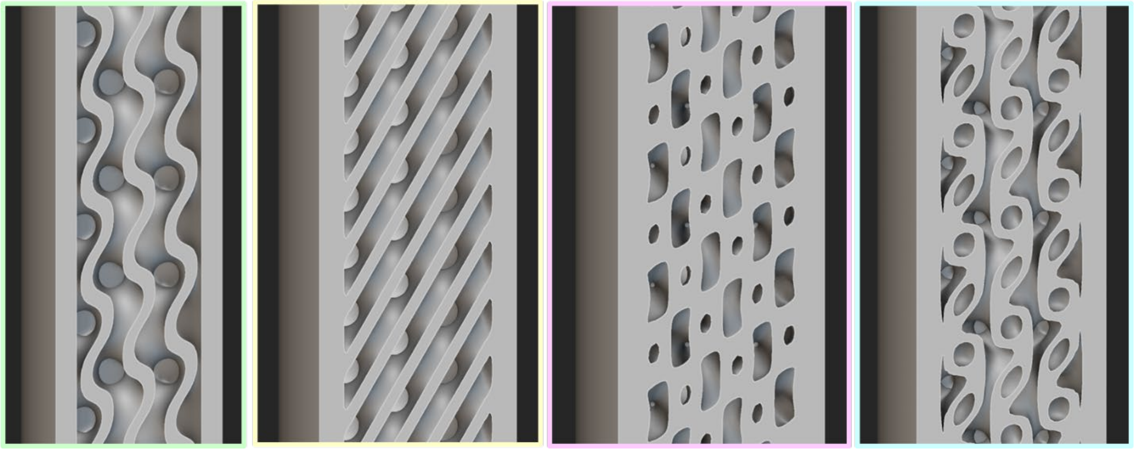

Can we leverage AI/ML-informed digital twins to enhance the resiliency of remote monitoring and operations?

## Proposed Work Tasks

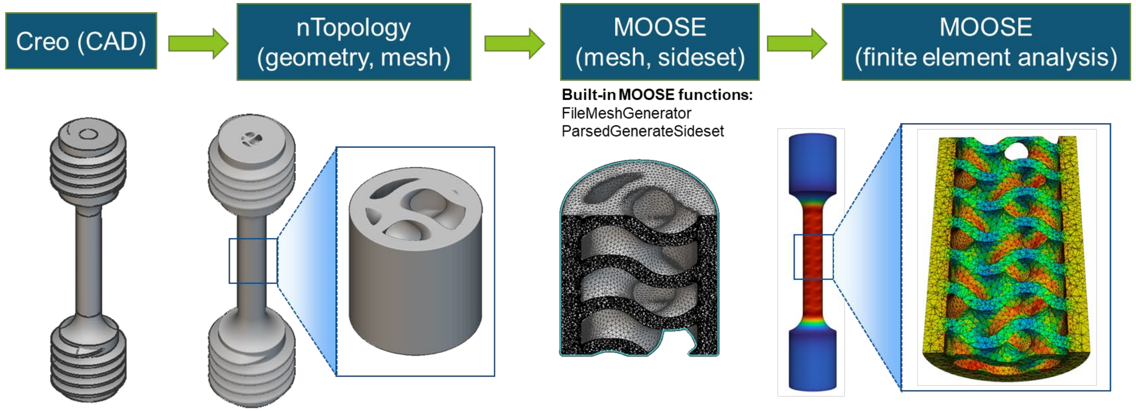
1. Identify operator, control, and signal monitoring and verification needs *unique to remote operation* and monitoring.
2. Define a safe, secure, and resilient communications architecture that meets the needs of remote operation.
3. Develop a digital twin-based cybersecurity and operator augmentation system to enhance operational resilience.
4. Provide simulation and physical demonstrations of remote operation capabilities.

# LDRD: Development of Lightweight Structural Materials with Improved Properties for Fission Batteries

- The geometry of the printed test piece was determined. The printed piece is expected to be able to be directly used for mechanical testing with minimal machining.
- nTopology can successfully mesh the unit cell, cell wall, shell, and lattice type.
- A process was successfully developed for transforming lattice structure data to MOOSE input.
- Simulated macro/engineering scale tensile behavior (Effective elastic modulus/ yield stress):
  - Cell size: minimal effect
  - Smooth radius: has effect
  - Weight saving: obvious effect
- Simulated micro scale mechanical behavior (localized response) needs to be analyzed for different structures under different testing conditions.



**Different lattice type**




**Interface with MOOSE**

Idaho National Laboratory

# INL Summer 2023 AI/ML Symposium (S23S)

- As a continuation of the INL Summer Symposium series, we will host the S23S artificial intelligence (AI) and machine learning (ML) symposium this summer starting in June.
- Participants will have the opportunity to understand and apply concepts related to AI and ML.
- Over seven 1.5-hour sessions, we will explore a variety of current topics within the AI/ML community.
- This exploration will focus on applications but will also investigate the theory behind these topics and provide a framework for demonstrating the concepts.
- This professional development opportunity is available to INL staff and interns. The sessions will be held on Thursdays from 1:00 to 2:30 p.m. MDT from June 1 to July 20 (skipping the 4th of July week).
- We will be capping off the symposium on July 27th with an AI/ML Expo to be held in EIL.

| June 1 | June 8 | June 15 | June 22 | June 29 | July 13 | July 20 |
|---|---|---|---|---|---|---|
| Data Prep – How to clean, filter, and prepare data to be used by a machine learning model. | Review of S21S, including how to request HPC access and how to use Jupyter Notebooks inside of the HPC enclave. | Imbalanced Classification and strategies | Generative Adversarial Networks | ChatGPT | Attention and Transformers | Anomaly Detection |

**S23S is being led by Cody Walker, Jacob Farber, and Shad Staples.**
**For more information or to register please contact Shad Staples.**