Anticipatory Control for Microreactor

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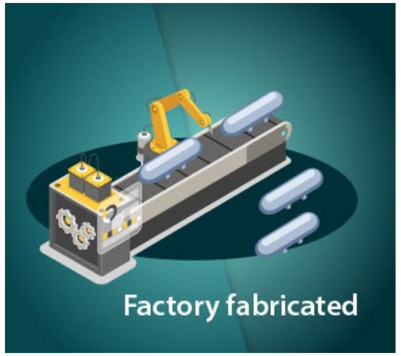
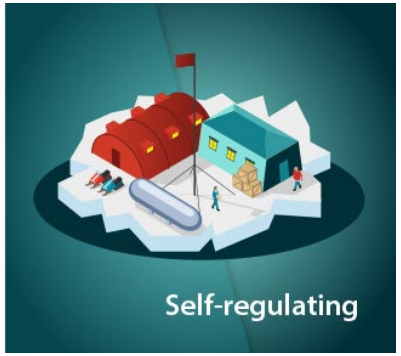
Self-Regulating Microreactor

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





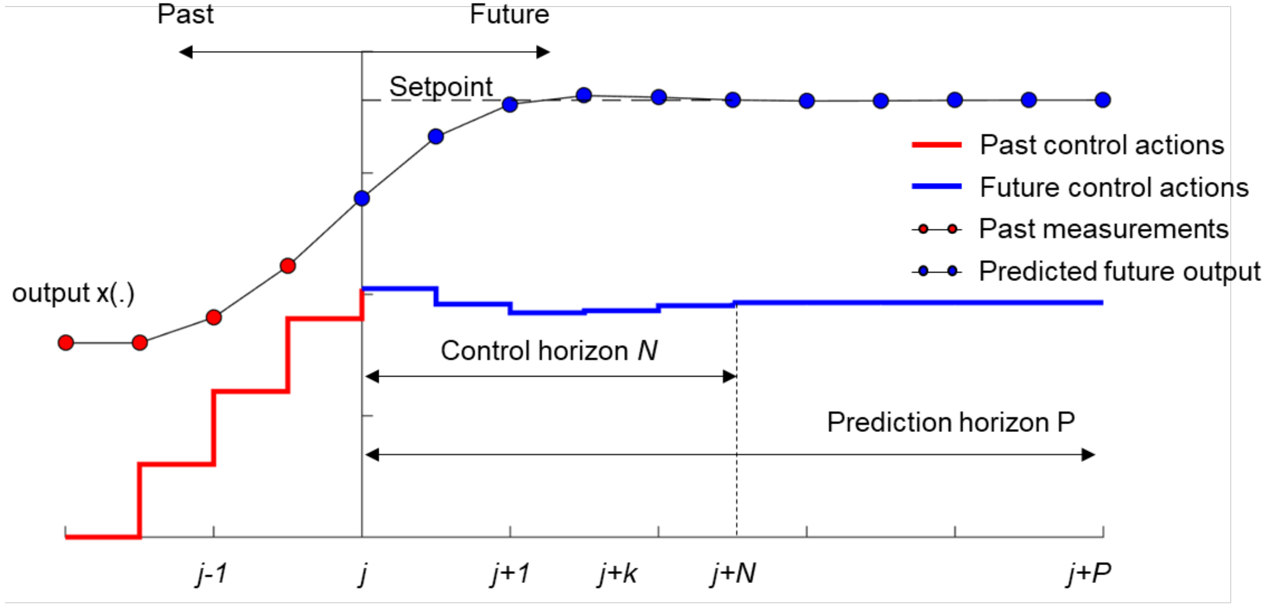
- Self-regulating requires remote and semi-autonomous microreactor operations
  - Reduced number of specialized operators onsite
  - Load following capability

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.

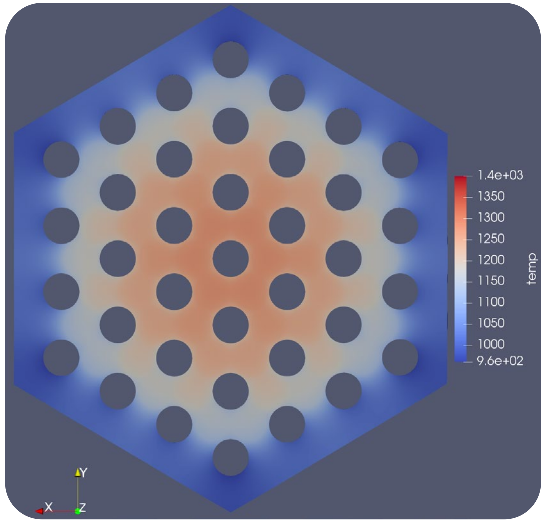
- Data-driven approaches for adapting systems to different testing systems and operational features
  - Expressive power: representing complex systems with nonlinear dynamics.
  - Modularity: system components can be separated and recombined.
  - Adaptability: flexible model forms and parameters

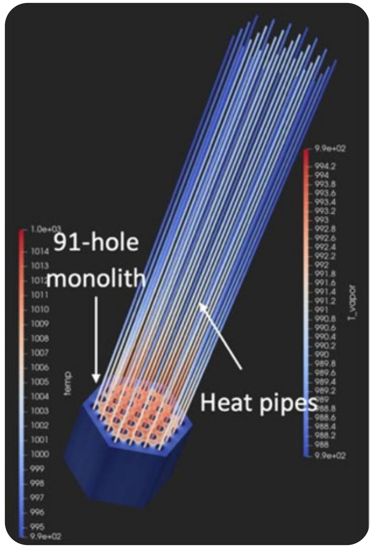


Given the complexity of nuclear energy systems, anticipatory control strategy shows better capabilities in efficiently and safely achieving (semi-) autonomous operations for microreactors

Physics Model Background

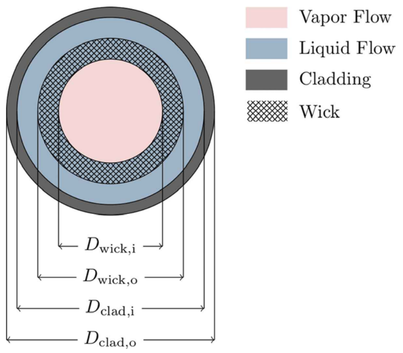
- This work utilizes MOOSE-based tools to create a high-fidelity simulator for a generic design of a 37-HP microreactor test facility.
- The 37-HP system consists of a hexagonal stainless-steel monolith containing 37 HPs and 54 heater rods.
  - MOOSE—Multi-Apps Simulation
  - BISON—Monolith heat transfer
  - SOCKEYE—Heat Pipes

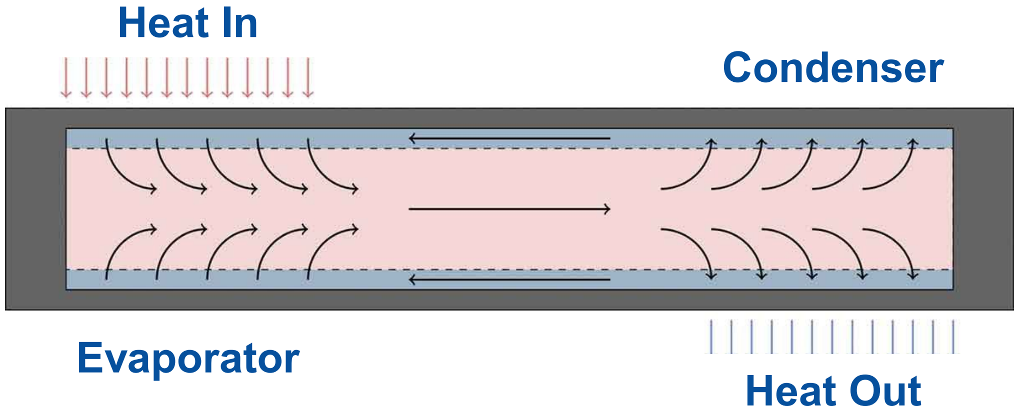




Heat Pipe Overview

- Thermal heat from the fuel pins is absorbed, evaporating the working fluid at the evaporator end.
- The vapor then travels axially through the vapor core, and the working fluid is condensed at the cold end of the HP.
- A wick structure inside the HP then drives the condensed working fluid back to the hot end of the HP via capillary force.

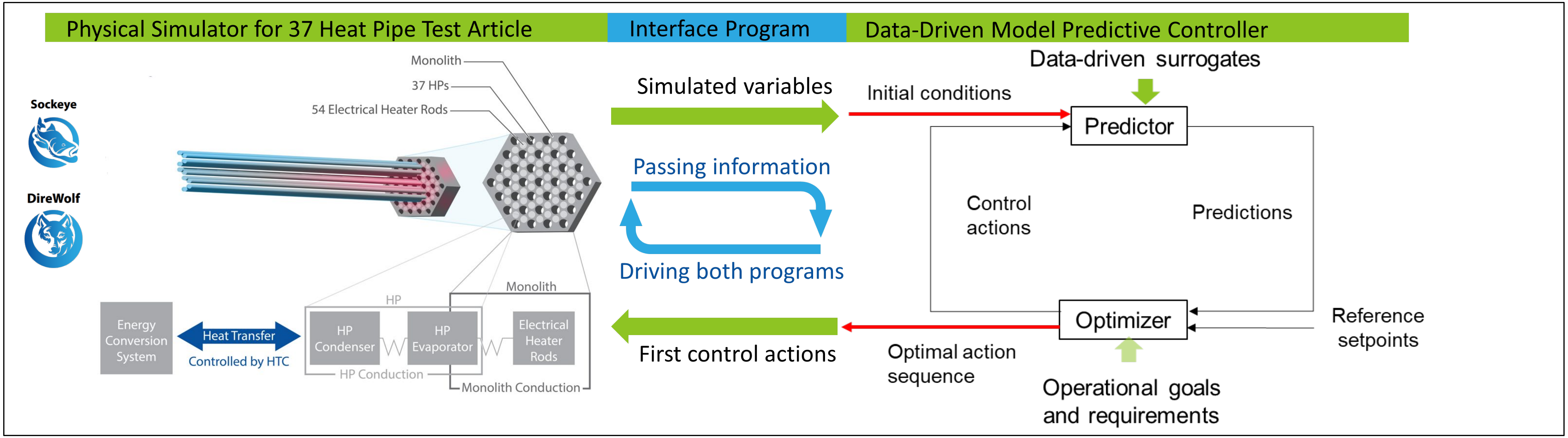




Sockeye: A One-Dimensional, Two-Phase, Compressible Flow Heat Pipe Application, Hansel et al., 2021

Anticipatory Control with Plant Simulator

Autonomous Control fOr Reactor techNologies (ACORN)



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
	$U = \left[u_{1\|j}, \dots, u_{N\|j}\right] \in \mathbf{U}_i$ for all $i = 1, \dots, n_{c_u}$	Constraints on range, magnitudes, and derivatives of control actions and state variables
	$X = \left[x_{1\|j}, \dots, x_{N\|j}\right] \in \mathbf{X}_i$ for all $i = 1, \dots, n_{c_x}$	
	$x_{0\|j} = x_j$	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)

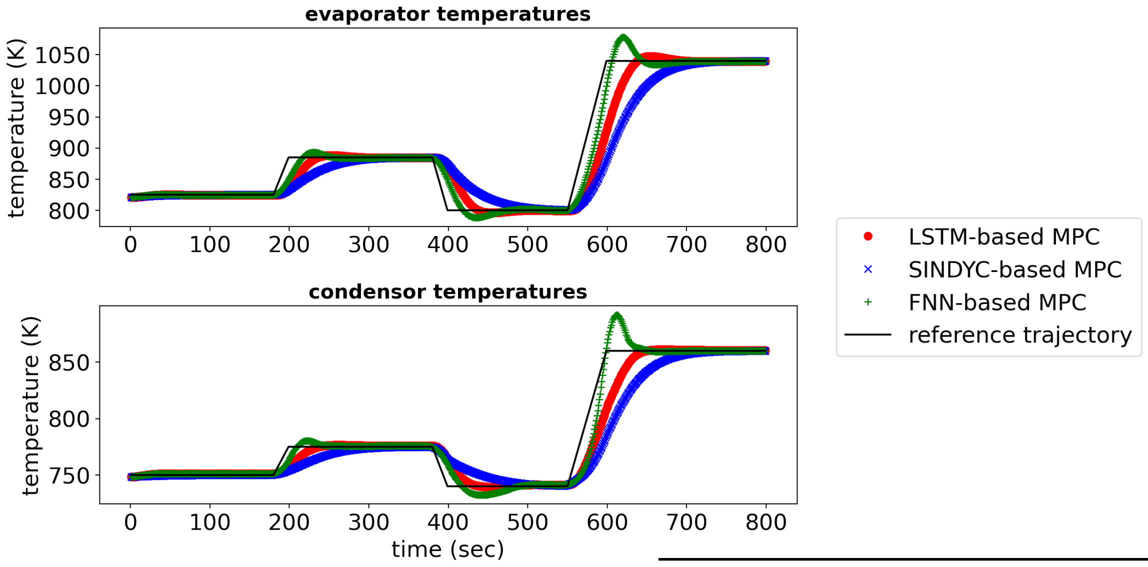
Recurrent neural network (RNN)

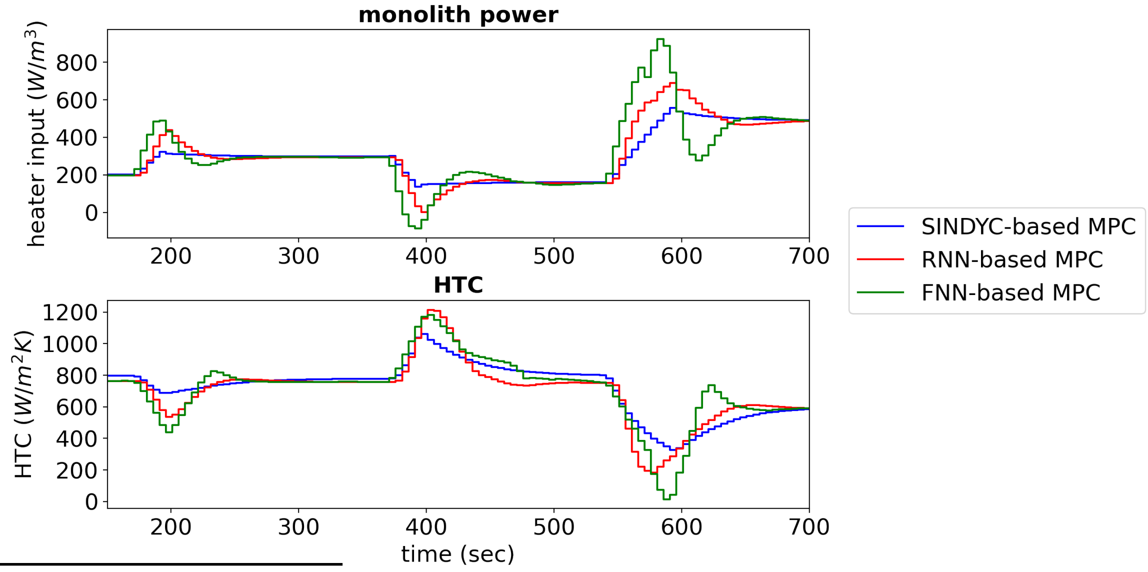
Compared to physics-based models, data-driven surrogates are computationally efficient, accurate, and adaptive.

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

- Model predictive controllers (MPCs) with different modeling approaches result in similar performance in tracking the reference setpoints
  - 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

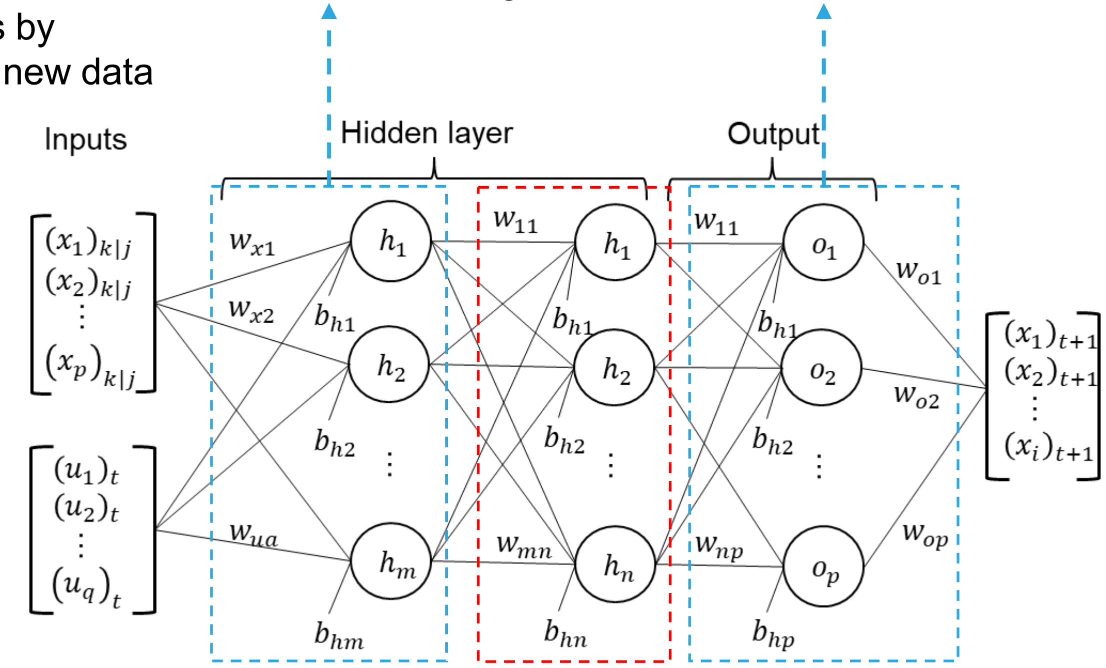
$$x_{k+1|j} = f\left(x_{k|j}, u_{k|j}, w_j\right) \pm \cancel{\delta}$$

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.

"Untrainable": Fixed for remembering training information

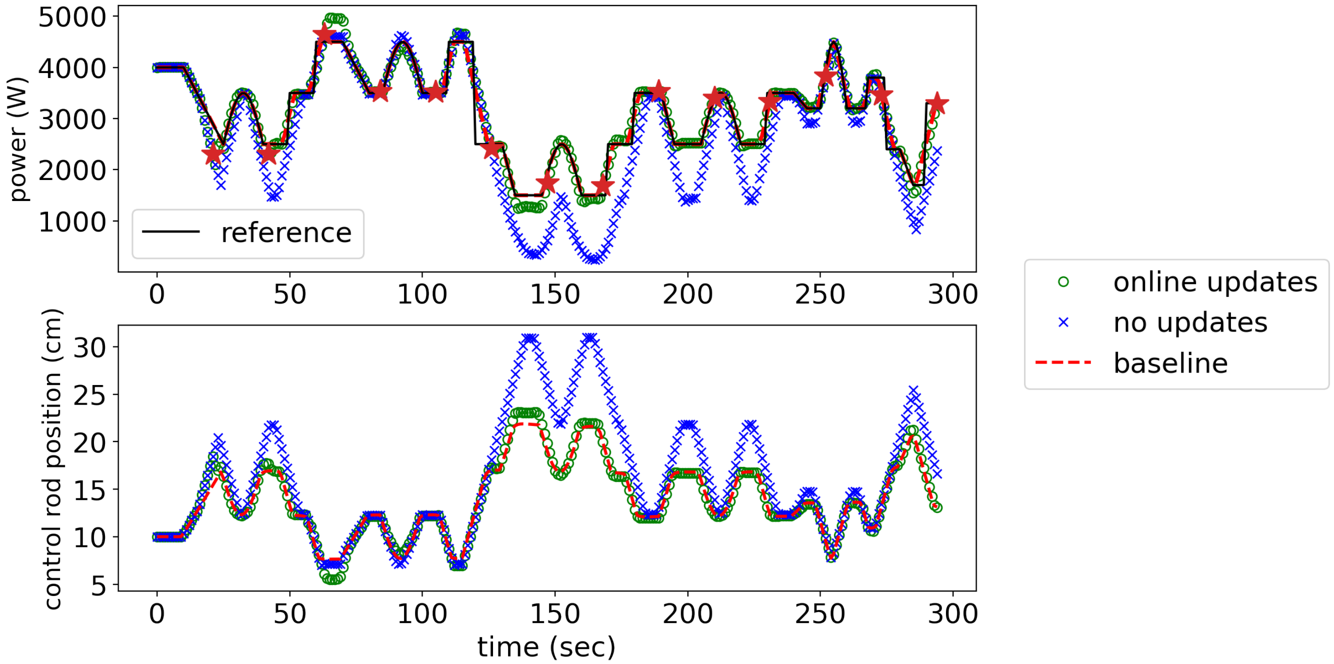


"**Trainable**": Updated based on new data

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.

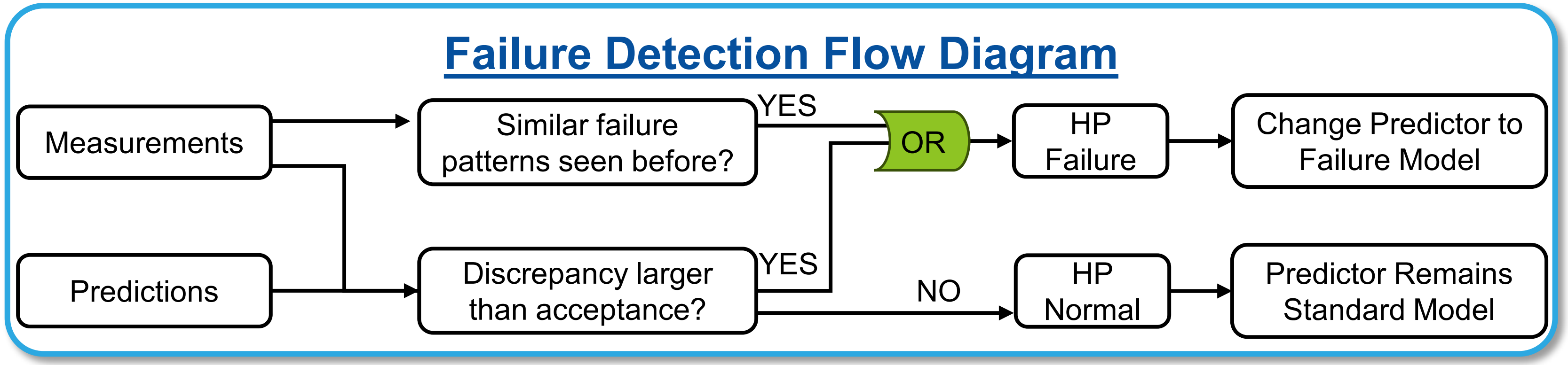


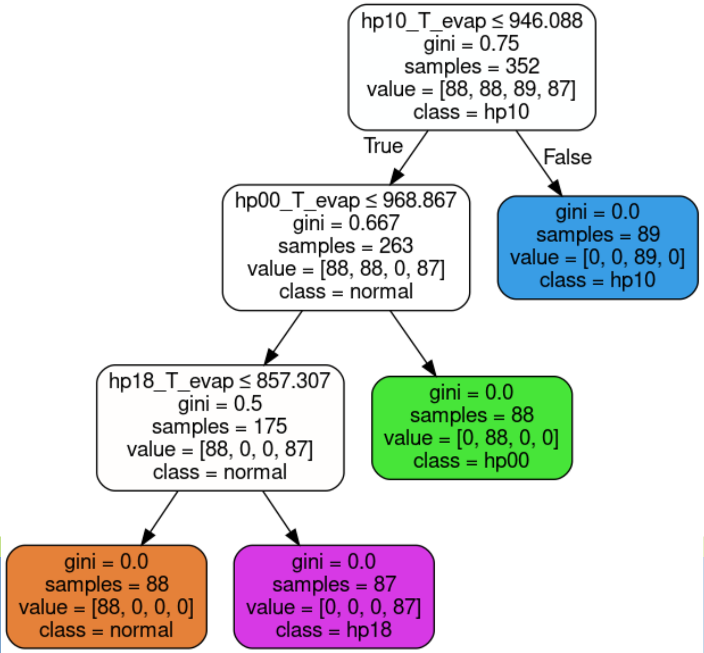
	Surrogate models	RMSE (W)
Prediction errors	FNN without update	510
	+ FNN with online updates	223.5
	+ Optimized online updating strategy	130.5
	Target (ground-truth) model	0.0
Discrepancy between target and achieved power rates	FNN without update	649.9
	+ FNN with online updates	214.7
	+ Optimized online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

Adaptive Control Beyond Normal Operations

- In the event of a system anomaly, such as a heat pipe failure, the control system needs to be capable of controlling the reactor in the degraded state.
- A detection module was built into the model predictive controller (MPC) to detect HP failure and—should a failure be detected—to adapt the predictor model accordingly thus creating and adaptive-MPC (A-MPC).
- Should a failure be detected, the surrogate predictor models are replaced with pre-trained models that match the failure case.



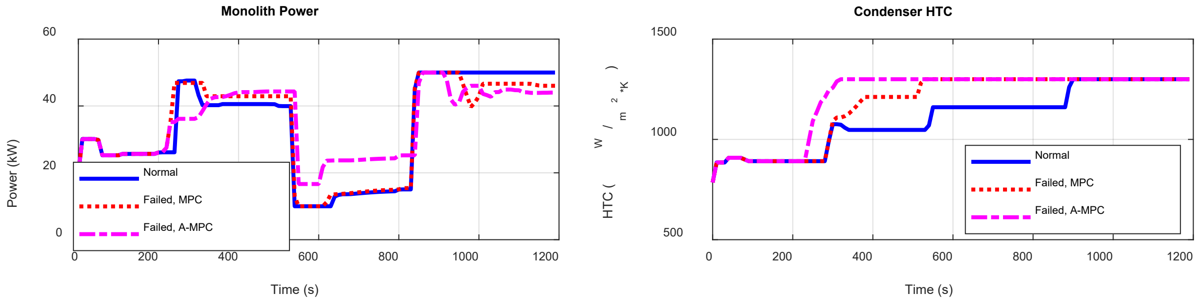


$$Discrepancy_{Evap} = abs\left(\frac{T_{Meas} - T_{Pred}}{T_{Meas}}\right)$$

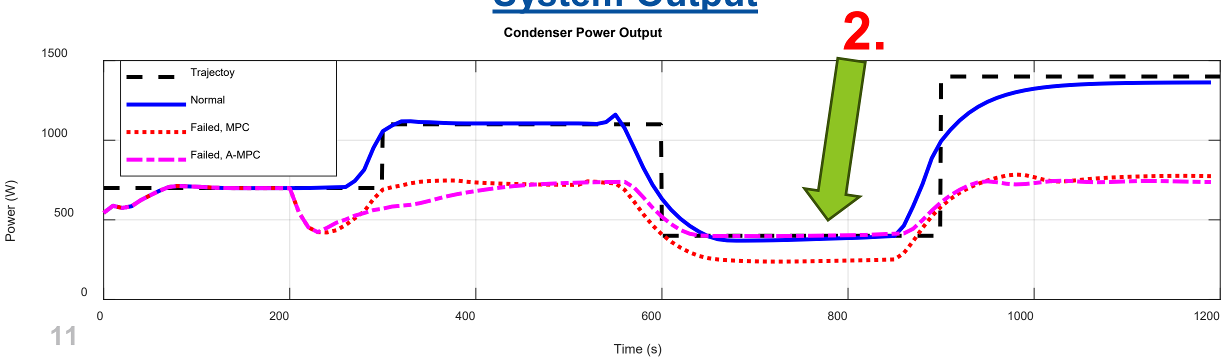
Case Study #3

1. A-MPC controller proactively alters its commands to avoid a predicted breach of upper constraints.
2. The A-MPC controller makes an accurate prediction and follows the reference trajectory.
3. A-MPC maintains steady state temperatures within constraints.

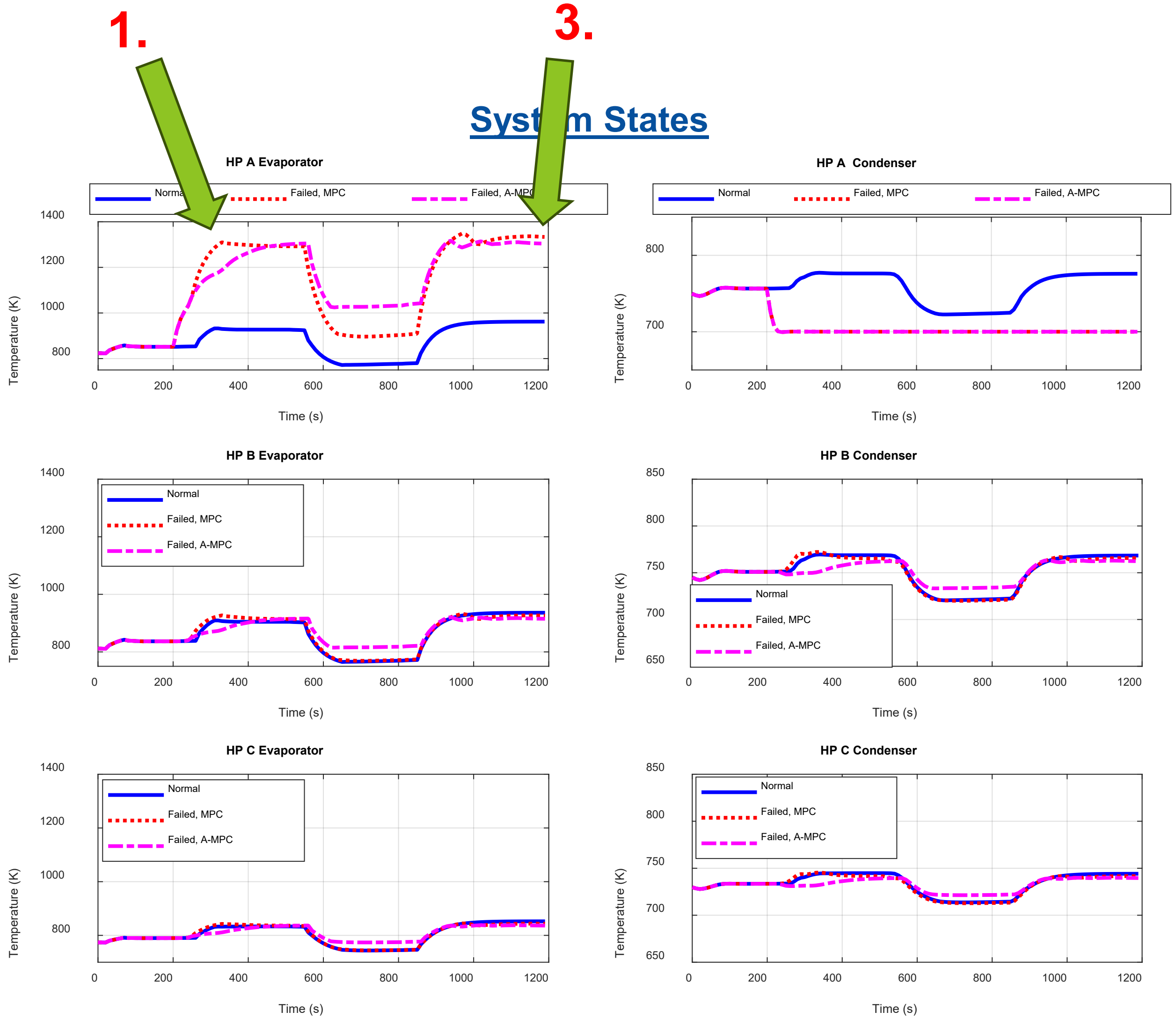
System Inputs



System Output



System States



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Conclusions

- This work demonstrates anticipatory control strategy in controlling a HP-cooled microreactor
  - Data-driven predictors, using SINDYc, feedforward, and recurrent neural networks, are generated and evaluated under normal power tracking conditions.
  - All models provide similar accuracy, while neural networks-based control systems show better tracking capabilities.
- Adaptive control strategy is demonstrated with online updating and with pre-trained models for anticipatory controls beyond normal operations.
  - The tracking and constraints handling capabilities are improved.
  - The prediction accuracy is improved.
  - A user interface prototype for human-in-the-loop tests
- Future works include expanding to multiple heat pipe failures, adapting the control strategy to gas-cooled microreactor, and quantifying the uncertainty.

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