INL/MIS-23-71338-Revision-1

Data-Driven Model Predictive Control for Temperature Management of Heat Pipe Microreactor

August 2023

Changing the World's Energy Future

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Idaho National Laboratory

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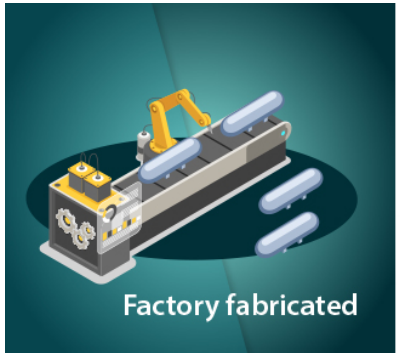
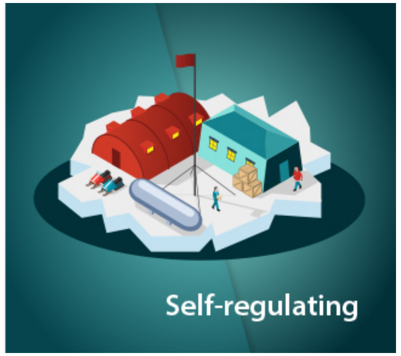
Self-Regulating Microreactor

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



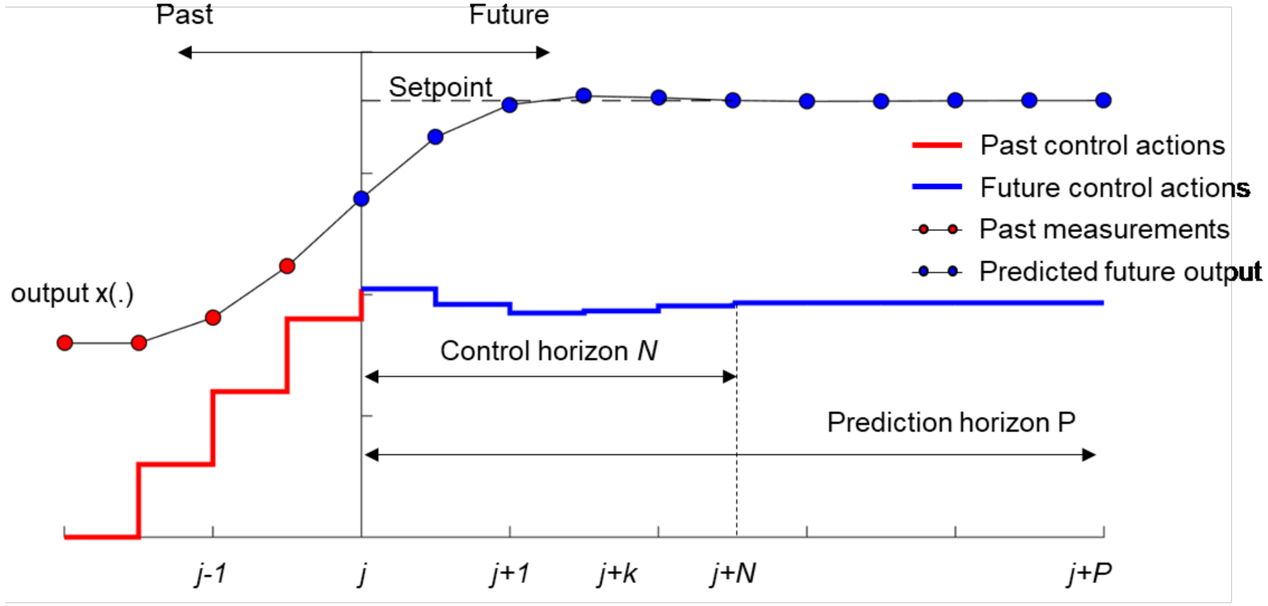


- Self-regulating requires remote and semi-autonomous microreactor operations
  - Reduced number of specialized operators onsite
  - Load following capability

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

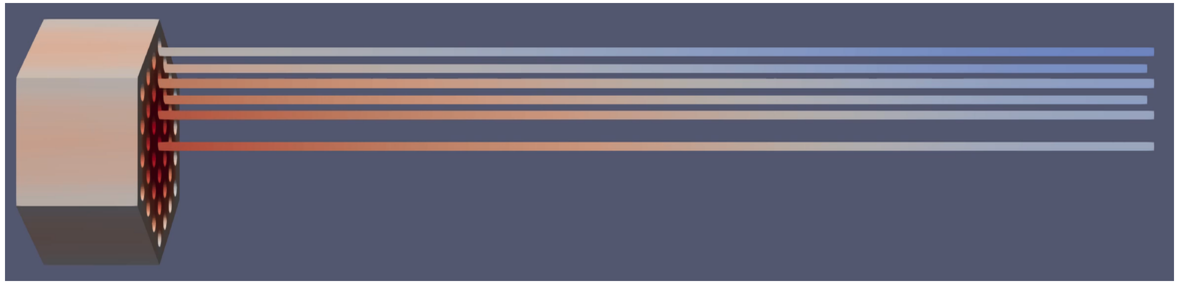
Anticipatory Control

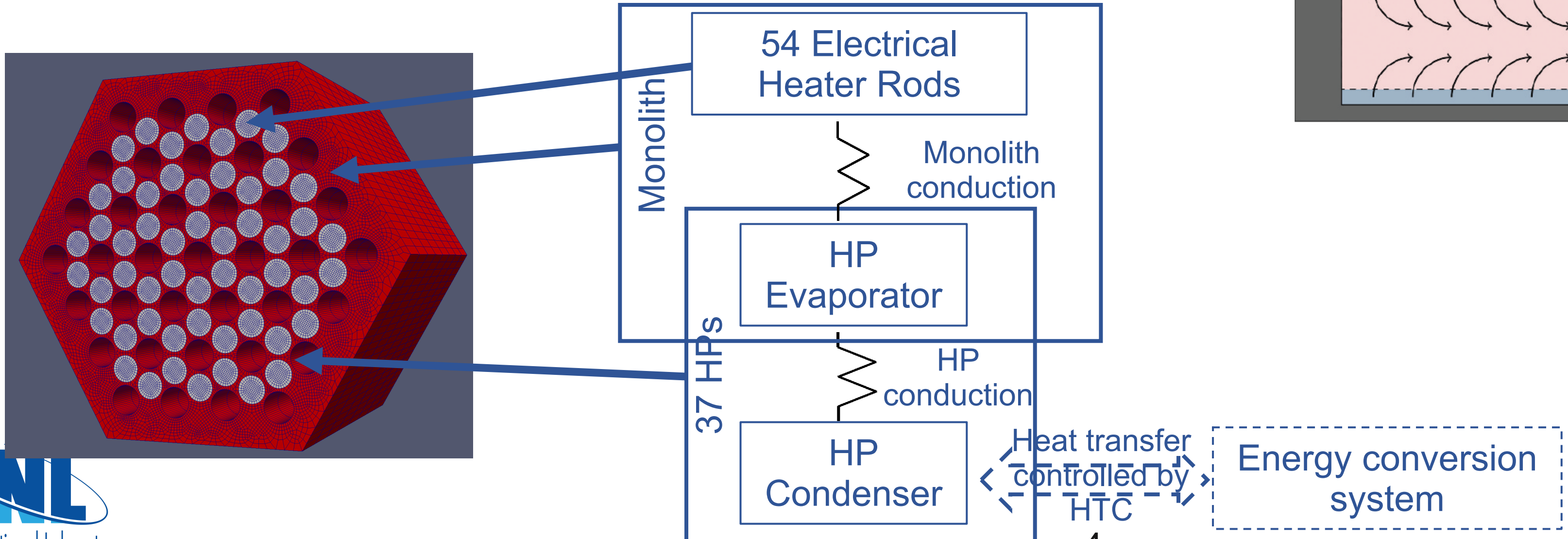
- Anticipatory control strategy for establishing technical basis of self-regulating microreactors
  - Proactively respond to disturbances and find optimal control actions to meet operational goals.
  - Explicitly incorporate and handle constraints by system dynamics, operational and safety requirements.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

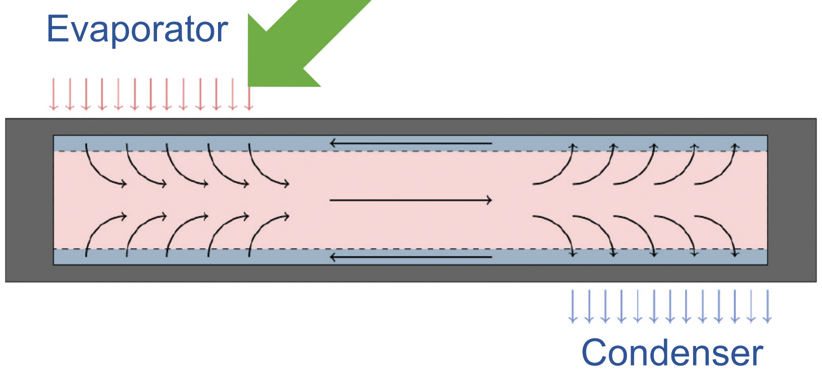


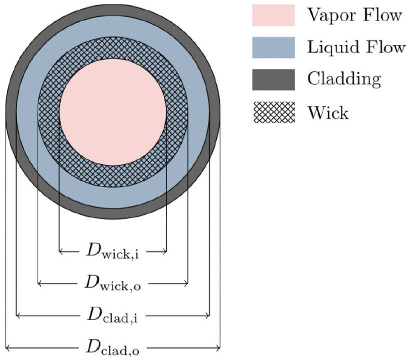
Given the complexity of nuclear energy systems, anticipatory control strategy shows better capabilities in efficiently and safely achieving (semi-) autonomous operations for microreactors

37 Heat Pipe Microreactor Simulator









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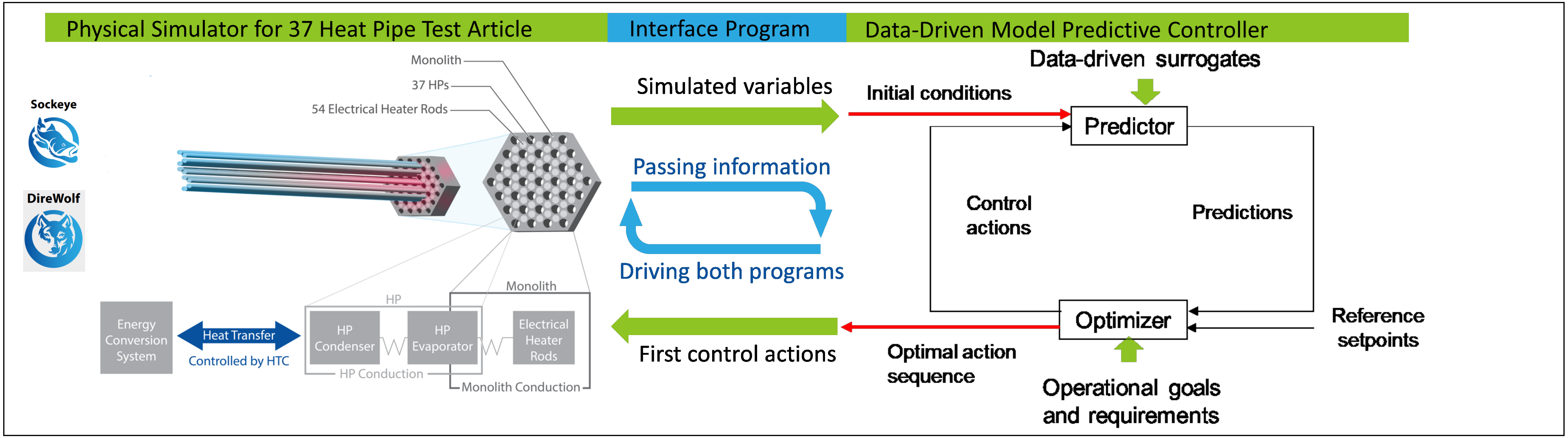
Anticipatory Control with Plant Simulator

Autonomous Control fOr Reactor techNologies (ACORN)



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Anticipatory Control

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

		Optimization
subject to		Process Model
	for all	Constraints on range, magnitudes, and derivatives of control actions and state variables
	for all	
		Initial conditions at every shifted time window

- Process model with data-driven methods

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.

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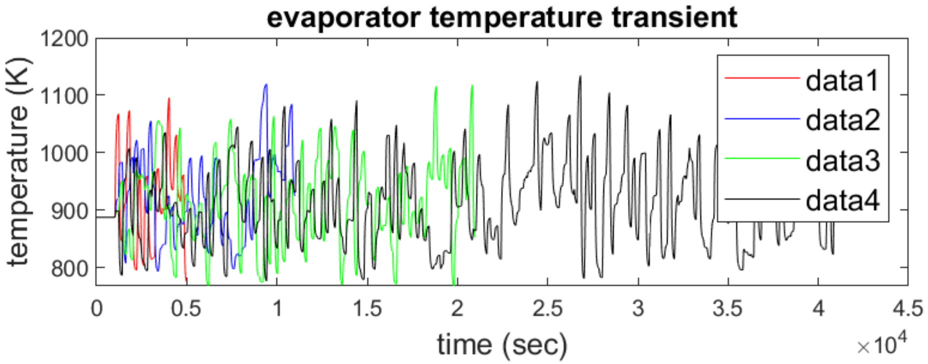
Sparse Identification of Nonlinear Dynamics with Controls (SINDYc) is a data-driven system identification method for nonlinear dynamical system with inputs and forcing using regression methods

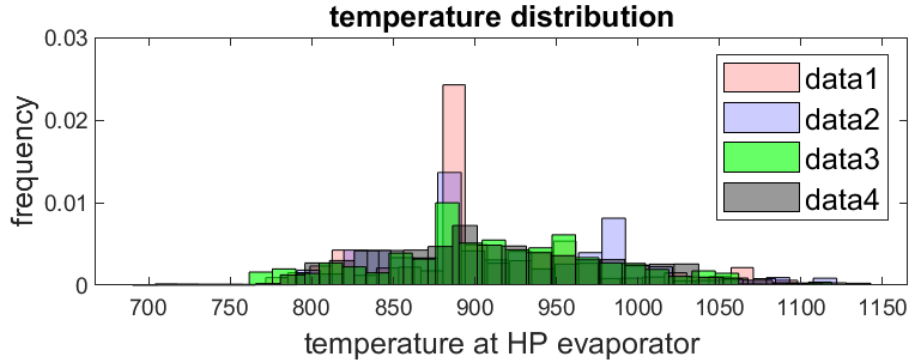
Training Data

- Four transient data for single heat pipe with different number of setpoint changes
  - data1: 20 setpoints, each of which results in 200 sec transient
  - data2: 50 setpoints
  - data3: 100 setpoints
  - data4: 200 setpoints

Setpoints	Sampling range	Sampling distribution
Input heat rates through HP evaporator	[400, 1800]	Uniform
Ramping speed (linear) for input heat rates	[0, 140]	Uniform
heat transfer coefficients at HP condenser	[400, 1200]	Uniform
Ramping speed (linear) for HTC	[0, 80]	Uniform

Transient with different length and number of setpoint changes

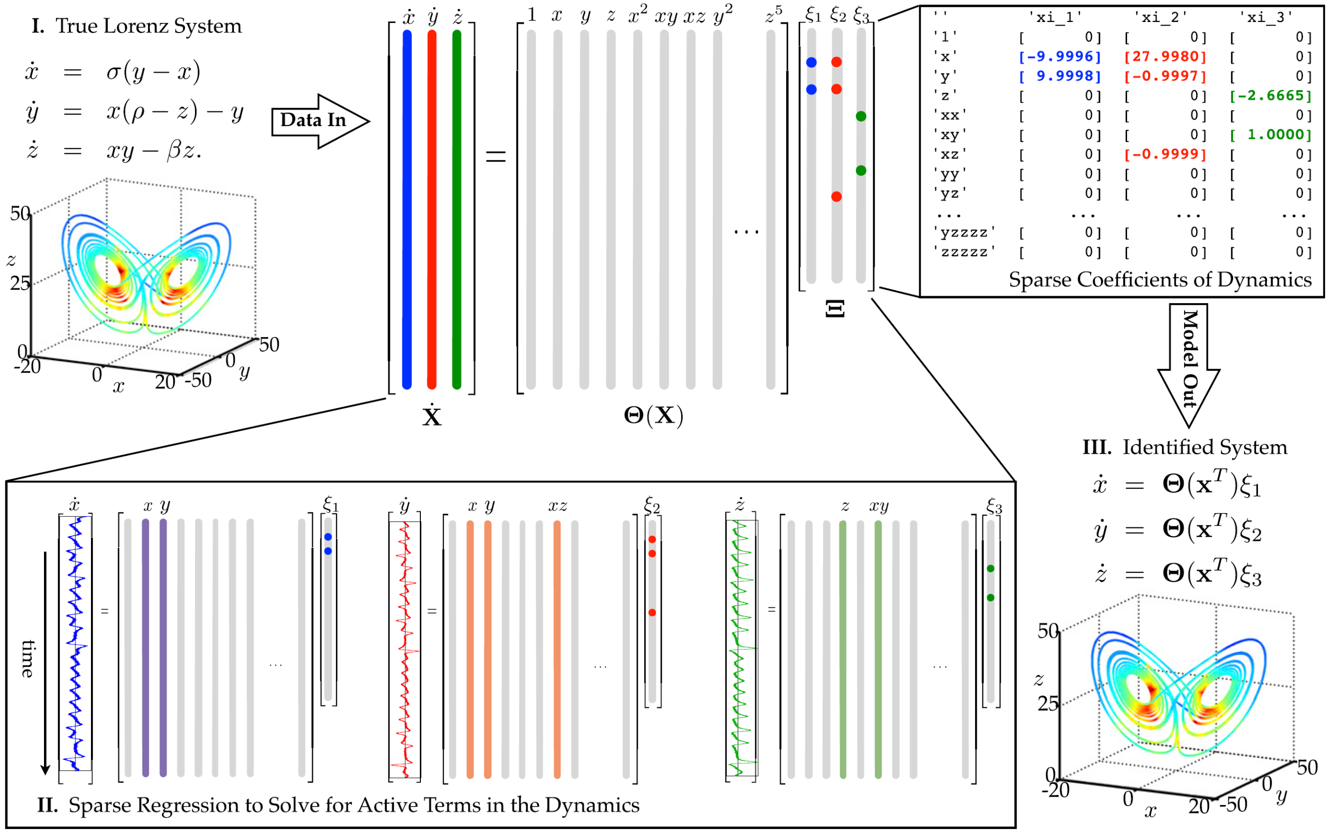




Temperature distributions get smoother as more setpoint changes

SINDYc

- SINDYc data-driven for representing transient data
  - State-space model form
  - Coefficient matrix calibrated by SINDYc
  - DMD + Sparsity-promoting L1 penalty term



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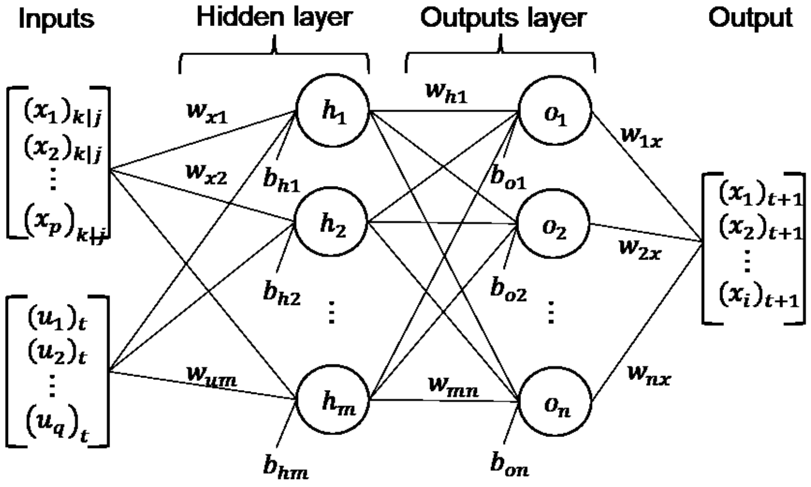
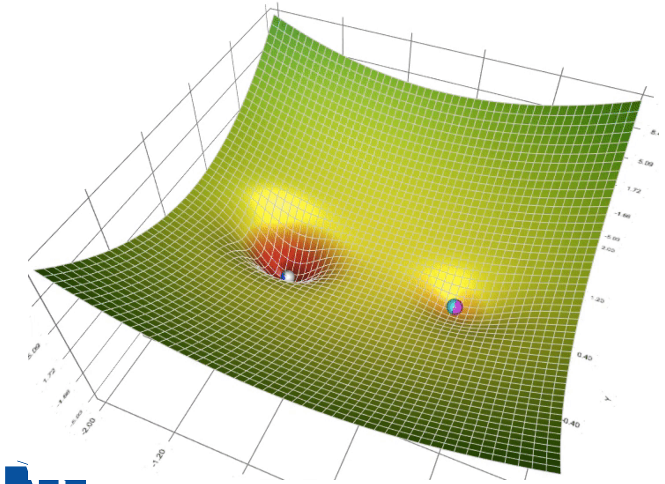
Feedforward Neural Network

- Feedforward neural networks for representing system dynamical behaviors



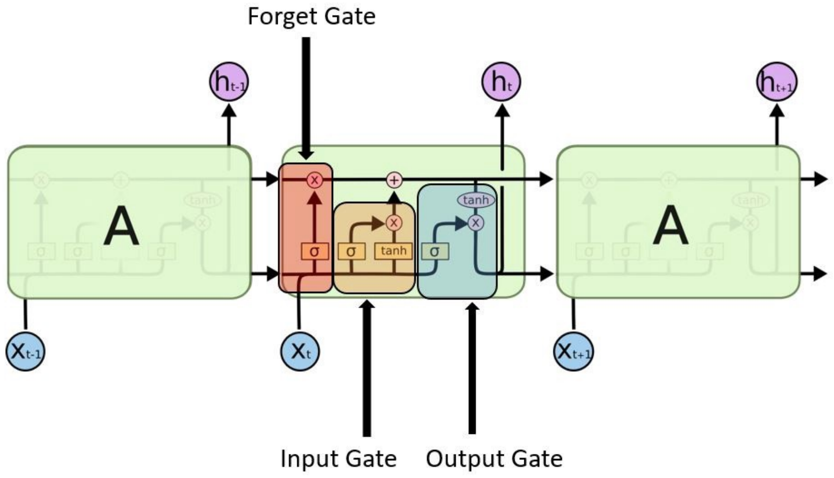


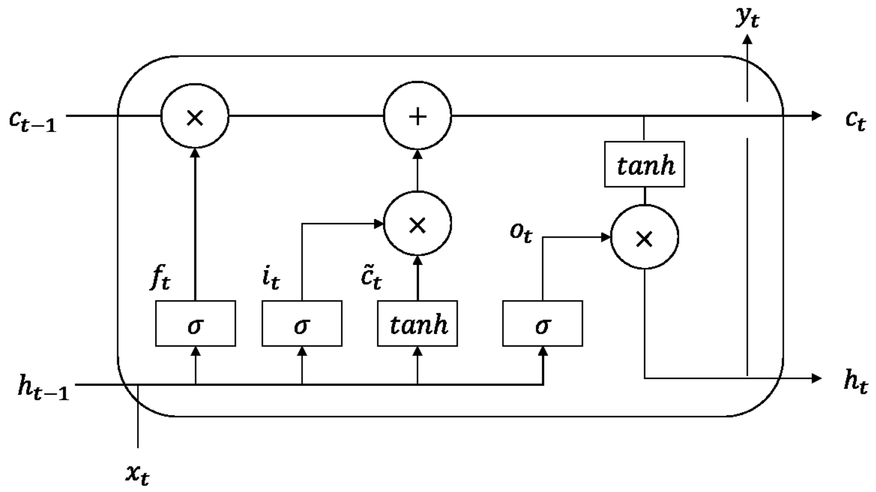
Gradient descent methods on a surface (Adam in blue)

L. Jiang, “a visual explanation of gradient descent methods”, https://towardsdatascience.com/a-visual-explanation-of-gradient-descent-methods-momentum-adagrad-rmsprop-adam-f898b102325c

Long Short-Term Memory

- Recurrent neural networks with Long short-term memory units
  - Input, forget, and output gates to remember information for long period of time
  - Less prone to vanishing/exploding gradient issues





Process Model Validation

- Predictive accuracy measured by agreements between predicted and actual temperatures of a single heat pipe
  - Tested by unseen data points
  - Tested with single-step and recursive predictions

Recursive prediction mode

State variables at

Control actions

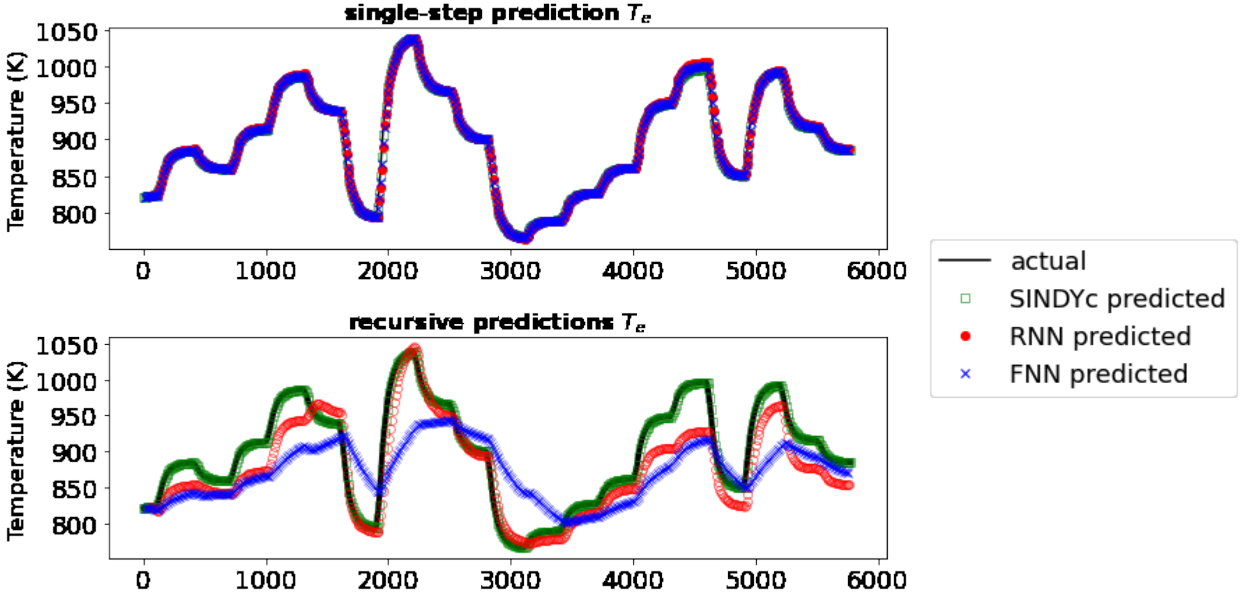
Surrogate Models

State variables at

MOOSE transient data (high-fidelity)

Root Mean Squared Errors

- Perfect agreement in single-step predictions
- SINDYc results in best agreement in recursive predictions

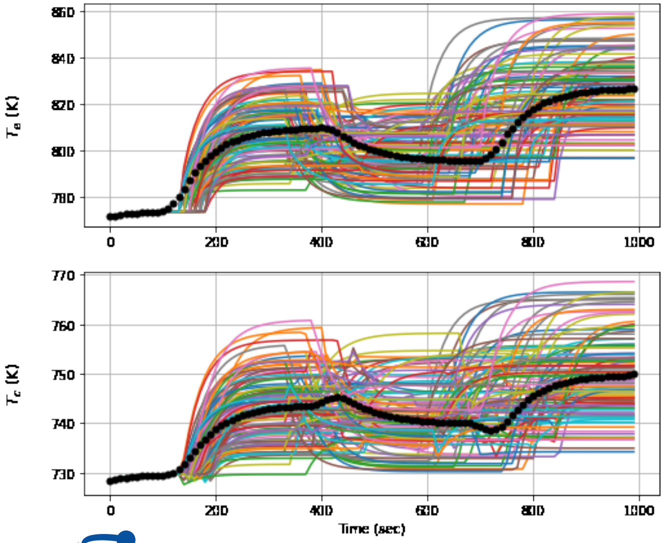


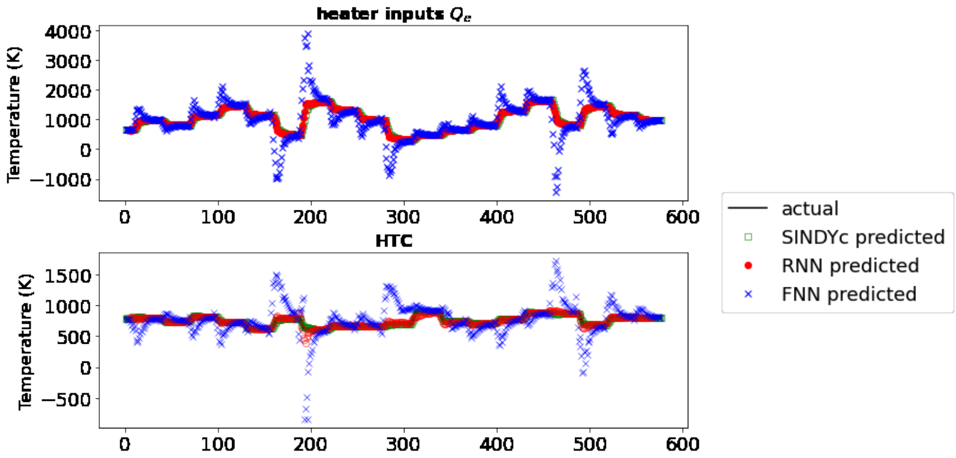
Process Model Validation

- MPC performance on a single heat pipe measured by capability in finding the actual control actions

- Given the same reference trajectory
  - SINDYc is more capable of finding the actual actions
  - Fluctuated actions found by FNN

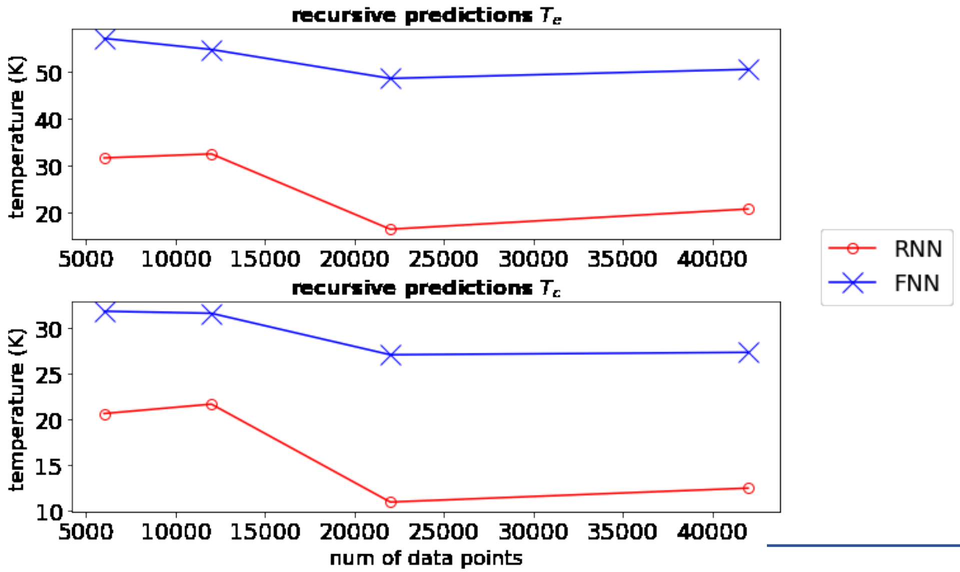
Reference trajectories for system response quantities (SRQs) from transient data → MPC with predictor and optimizer → Find control actions that minimize discrepancies between predicted transient and reference trajectories

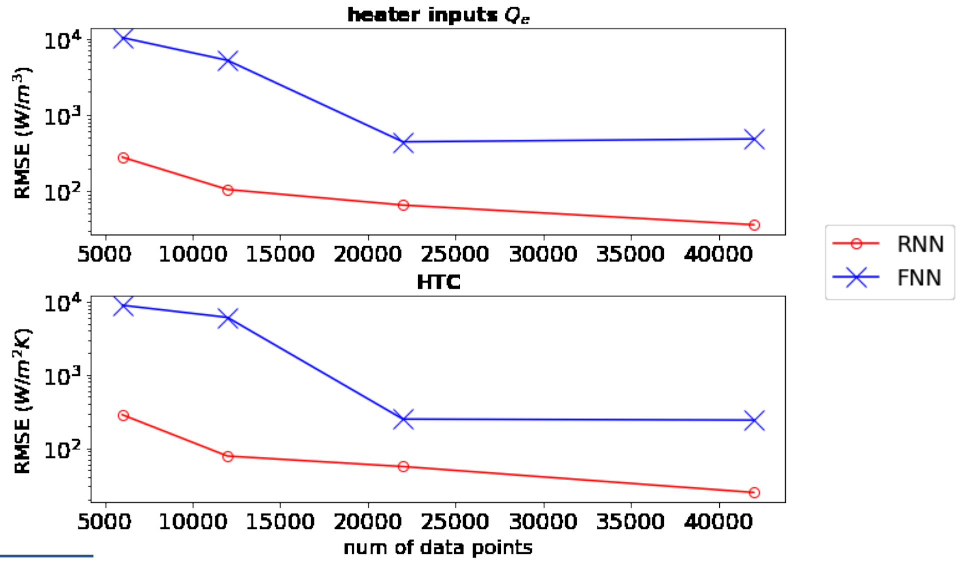




Validation Results

- More data help reduce errors of recursive predictions and MPC performance on a single heat pipe
  - RNN with LSTM shows smaller errors than FNN
  - FNN shows stronger correlations with the amount of data





	Average PCC
RNN recursive	-0.76
RNN optimization	-0.78

PCC= 1 or -1: Linearly correlated
PCC = 0: no linear dependency

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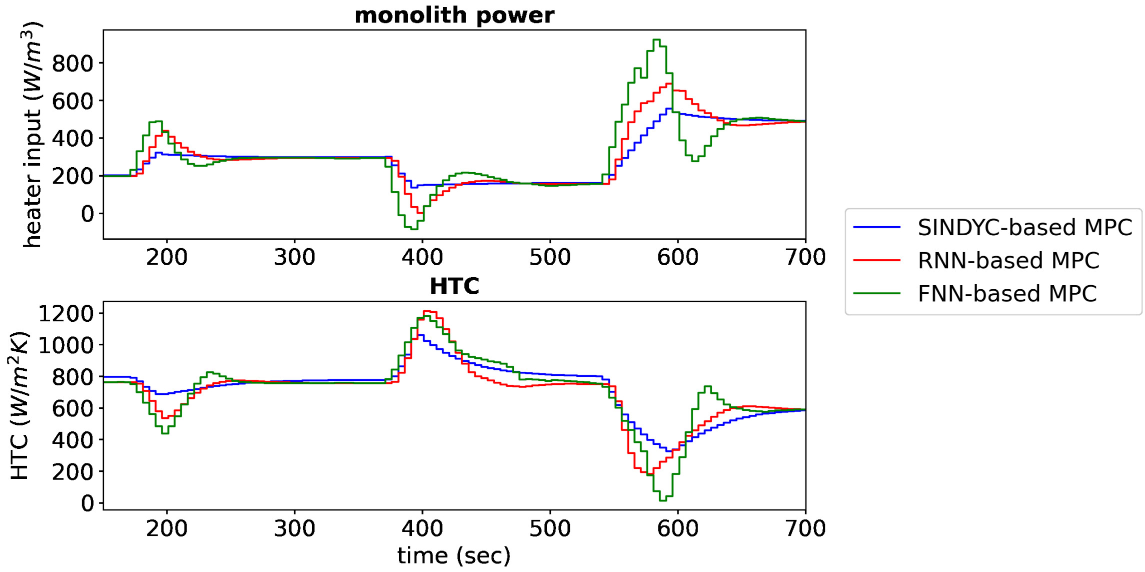
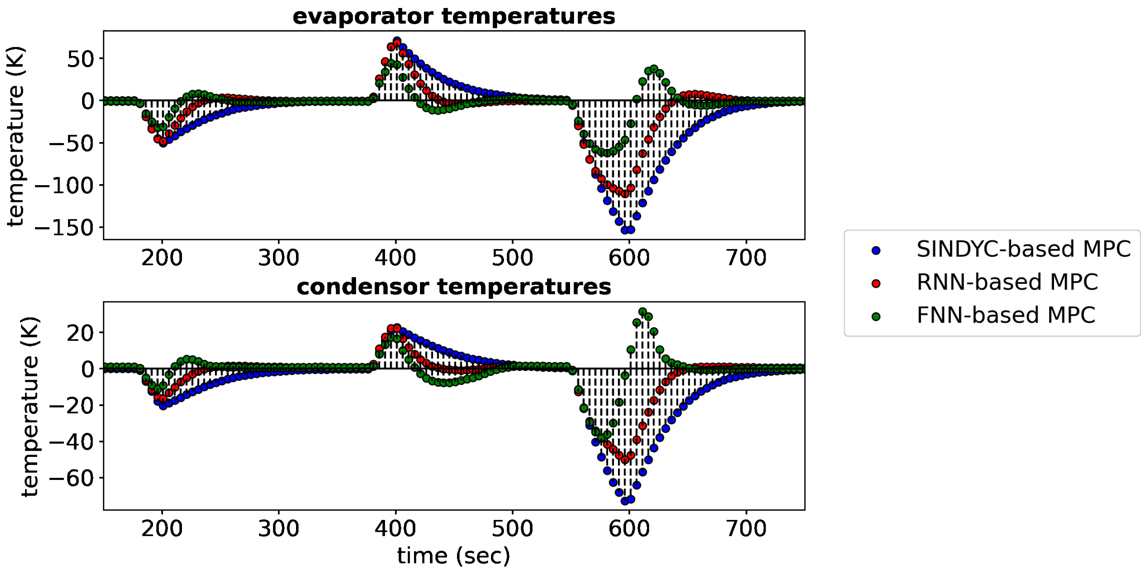
Comparative Results

- All MPCs have the same settings except for different modeling approaches
  - More fluctuated predictions from NN models than SINDYc model
  - NN-based MPCs result in larger changing speeds in control actions than SINDYc.

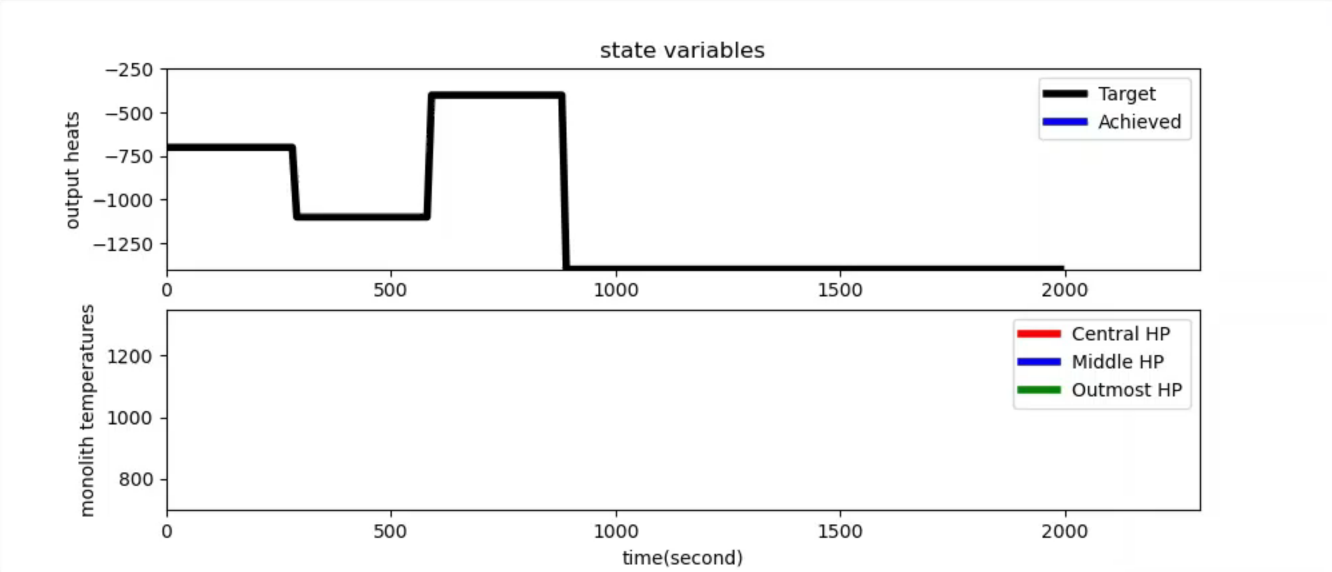


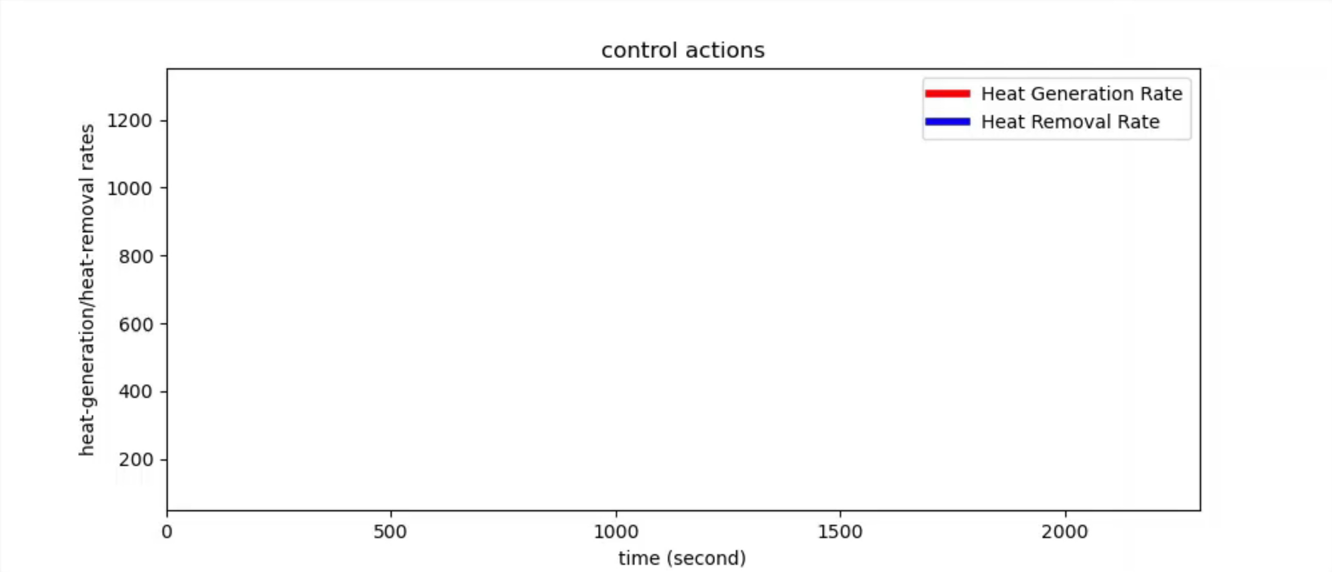


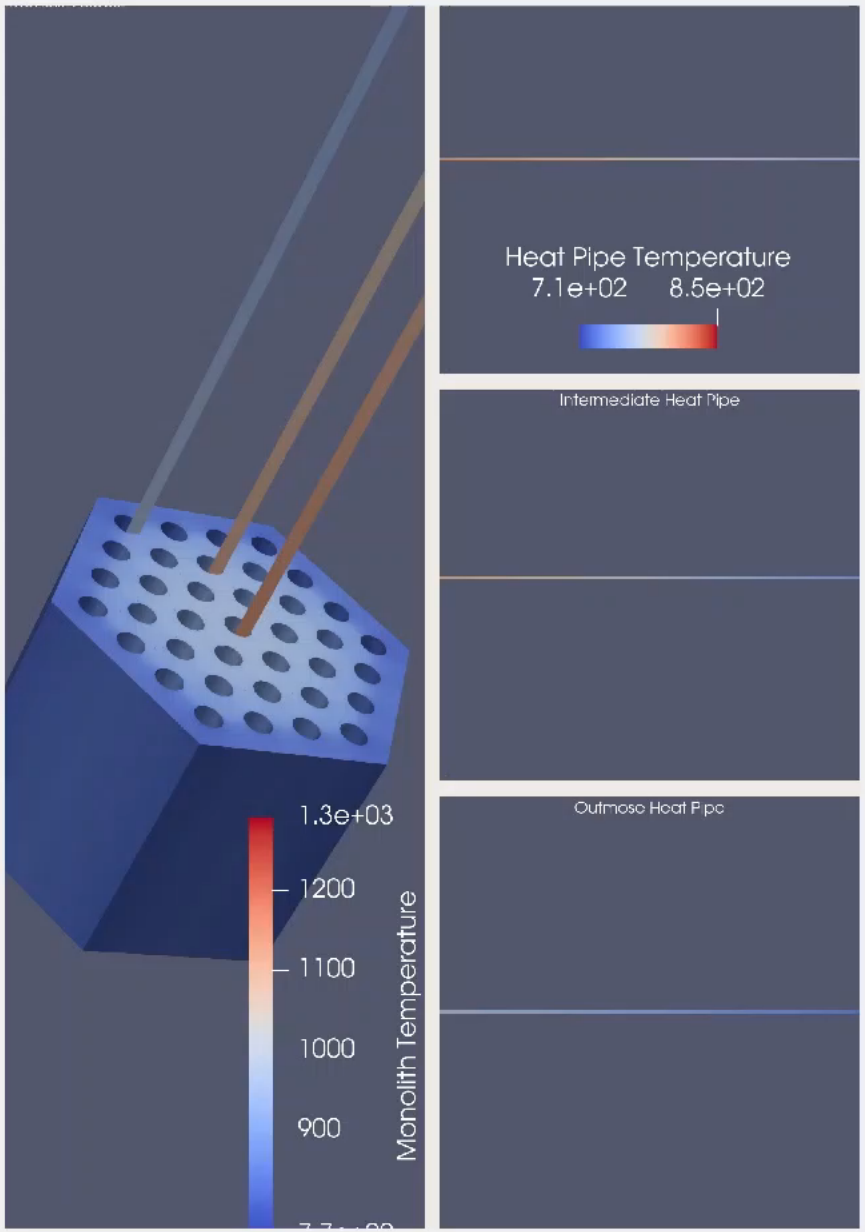
FNN-based MPC	27.54	11.63

Summary Remarks

- Data-driven MPCs with three data-driven algorithms using a SINDYc calibrated linear state-space model, FNN, and RNN with LSTM cells.
  - Perturb inputs to the simulator model of a single HP and 37-HP system.
  - Test adaptability of data-driven models when gaps between the single HP system and 37 HP system.
- Process model validations for data-driven models in making single-step and recursive predictions and in finding actual control actions
- All MPCs have the same settings except for different modeling approaches
  - More fluctuated predictions from NN models than SINDYc model
  - NN-based MPCs result in larger changing speeds in control actions than SINDYc







Normal_Power_Tracking

GO

EXIT

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SINDYc

Algorithm 1: Data-driven predictive control with SINDY

Design Stage

Procedure: Model training using SINDY

Set : heater inputs, HTC <- manipulatable features

Set : evaporator heat flux of selected HPs <- state variables

Set : evaporator and condenser temperatures of selected HPs<- state variables

For all time steps k **do**

For all coefficient matrix **do**

End for

End for

End procedure

Demonstration Stage

Procedure: closed-loop predictive control

While do

For all time steps in prediction horizon **do**

Solve Equation (*)

End do

Solve Equation (*) for optimal control sequence

Apply first action in control sequence

End while

End procedure

Process Model Validation

- Selections of transient data have significant impacts on RNN performance

	Single-Step Predictions		Recursive Predictions		Optimization	
data #1 (baseline)	0.26	0.14	62.13	39.80	139	566
data #2	2.31	1.35	47.77	26.23	104.36	77.73
data #3	16.32	9.81	32.55	21.63	52.43	79.45
data #4	23.95	14.84	31.70	20.60	29.19	39.18

Process Model Validation

- Similar trends are found for FNN

	Single-Step Predictions		Recursive Predictions		Optimization	
data #1 (baseline)	6.6	3.2	51.7	34.2		
data #2	0.3	0.005	48.6	27.0		
data #3	0.2	0.3	54.8	31.6		
data #4	0.2	0.08	57.1	31.8		

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