Hybrid Physics-Informed Neural Networks for Thermal Process Identification & Control

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NUMERICAL DERIVATIVES
Physics enforced without time-input autodiff, sidestepping gradient saturation.

SPARSE DATA & EXTRAPOLATION
Physically consistent predictions well beyond the training window.

PINN-DRIVEN MPC
Surrogate embedded in receding-horizon controller for rod-tip temperature.

01 Motivation

Modeling thermal dynamics
First-principles thermal models are accurate but can be computationally demanding.

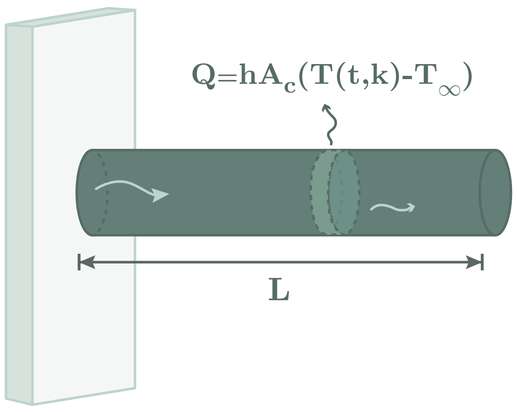
Pure data-driven models
Black-box neural networks often extrapolate poorly outside training data.

Physics-based models
Classical PINNs may suffer from training issues when time is directly used as an input.

Control
Control applications require fast, robust, physically consistent surrogate models.

? Can a compact PINN trained with numerical derivative enforcement serve as a reliable surrogate model for MPC of a thermal process?

02 Heating Rod



A 1D heating rod with heater duty as the manipulated input and rod-tip temperature as the controlled output.
The system captures transient heat conduction with boundary heat losses.

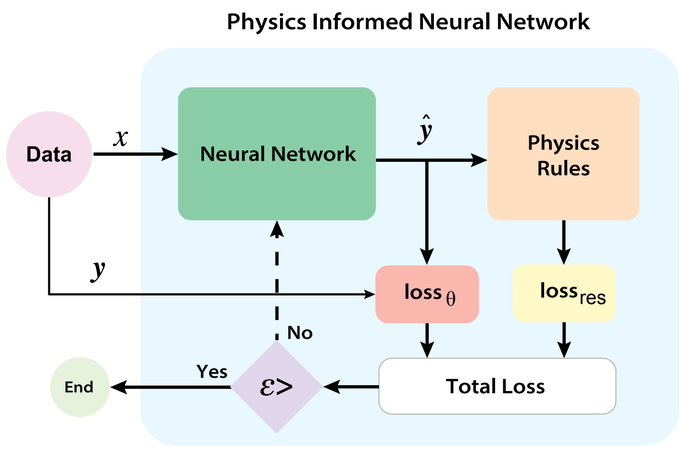
03 Data & Model Setup

Compact, control-oriented architecture
Inputs are the location on the rod, past temperature records and heater duty.
The output is the next-step temperature.

TABLE 1. PINN Model Structure

#	LAYER	UNITS	ACTIVATION
1	Dense	3	—
2	Dense	10	tanh
3	Dense	10	tanh
4	Dense	1	linear

04 Hybrid PINN Framework



A neural network approximates the input-output dynamics while first-principles equations guide learning. The network maps heater duty u and location x to the next-step temperature:

$$\hat{y}(t) = f_\theta(\, u(t), \mathbf{x}(t)\,)$$

Physical knowledge enters through a composite loss balancing data fidelity against the discretized heat-transfer residual, weighted by λ:

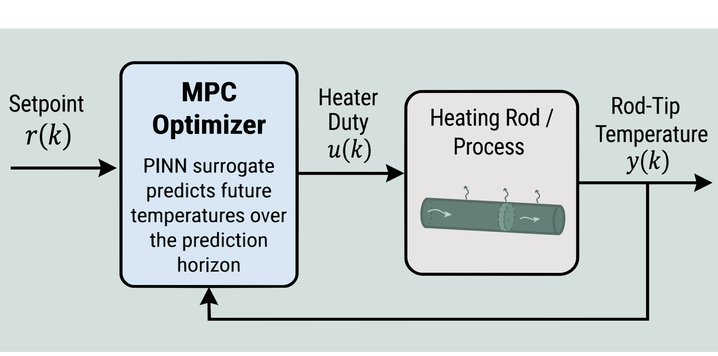
$$L = L_\theta + \lambda\, L_{res}$$

? **Why Numerical Derivatives?**

$\frac{d}{dt}$

- Avoids gradients saturation
- Improves robustness in continuous thermal processes
- Eliminates the need to use time as an input to the neural network model

05 PINN-MPC Controller Design



MPC minimizes tracking error and penelizes aggresive changes in heater duty.

- Recesing-horizen optimization
- Input and move constraints enforced
- Only the first control action is applied at each step

06 Prediction & Extrapolation

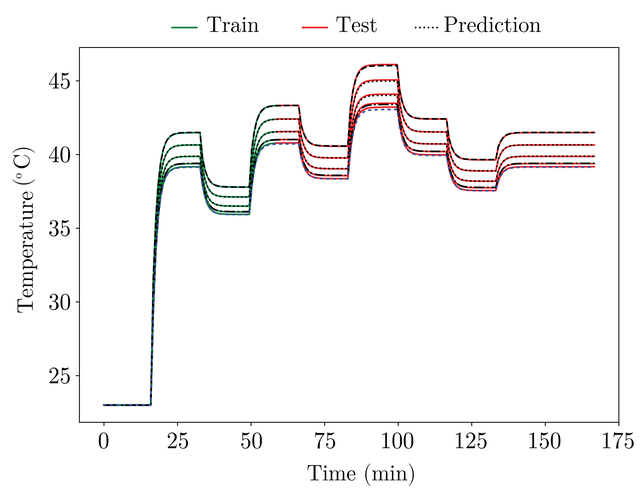


Figure 1. Identification Result

The trained PINN accurately predicts the temperature both within and far beyond the training window while maintaining physical consistency. Since the spatial coordinate (x) is an input to the network, a single surrogate model can estimate the temperature at any point along the rod. In this way, the PINN serves as a physics-informed reduced-order model of the complete thermal field.

07 Closed-Loop Control

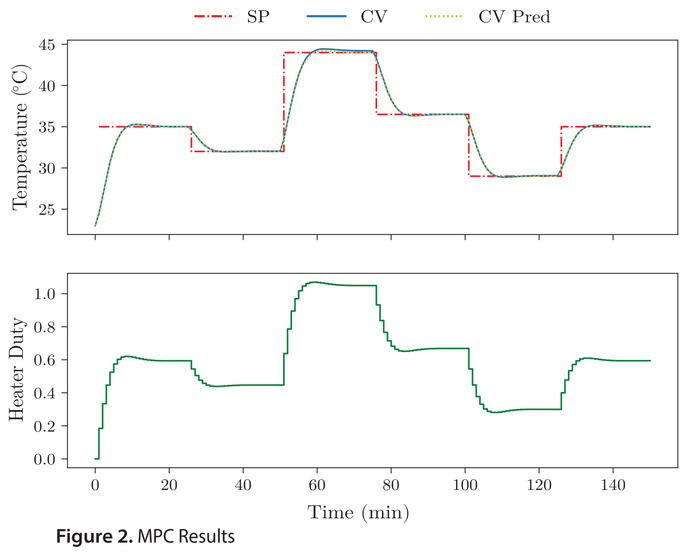


Figure 2. MPC Results

The controlled variable follows the setpoint across steps with low overshoot. the move-suppression term damps oscillation.
Heater duty stays within actuator limits.

08 Conclusion

This work presents a hybrid physics-informed neural network for thermal process identification and control. The model combines data and heat-transfer physics, demonstrates reliable prediction and extrapolation, and enables efficient closed-loop temperature regulation when embedded in MPC.

- Extend to high-dimensional thermal systems
- Intergrate physics-informed dimensionality reduction / Model Order Reduction (MOR)
- Explore uncertainty quantification and advanced neural architecture