Physics-Informed Neural Networks for 3D Heat Transfer Prediction in Additive Manufacturing

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OVERVIEW

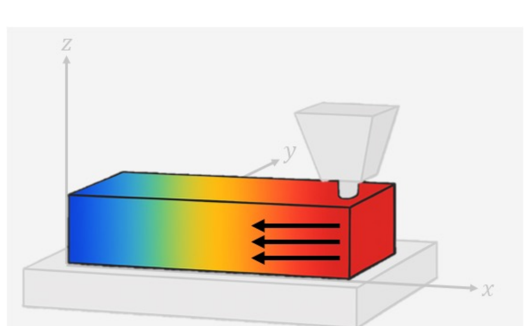
We explore physics-informed neural networks (PINNs) as a mesh-free alternative to finite element methods (FEM) for predicting thermal history during extrusion deposition additive manufacturing (EDAM). By embedding the heat equation directly into a neural network loss function, PINNs can handle evolving 3D geometries and mixed boundary conditions without meshing or time-stepping schemes. Our results suggest PINNs may offer a scalable path toward parametric thermal simulations in additive manufacturing.

J. Kil et al. (2025) "Physics-informed neural networks to accelerate heat transfer predictions in additive manufacturing" *SAMPE Technical Proceedings*

A. J. Thomas et al. (2025) "Causality enforcing parametric heat transfer solvers for evolving geometries in advanced manufacturing" *Comp Methods in Applied Mech & Engineering*

PROBLEM & MOTIVATION

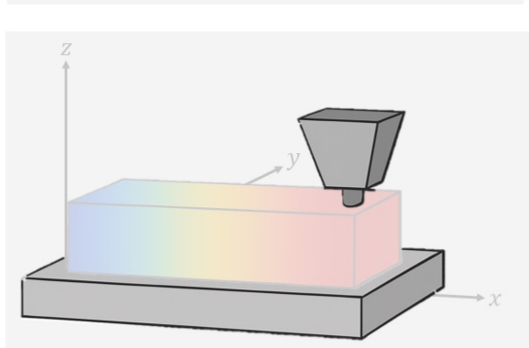
Predicting temperature evolution during EDAM with fiber-reinforced polymers is essential for understanding how thermal history influences material properties and final part performance. The finite element method (FEM) is the established numerical approach, but its computational cost grows substantially with mesh refinement and smaller time increments. We formulate the problem as 3D transient heat conduction on an evolving domain and define three cases of progressively increasing complexity, each representing more realistic manufacturing scenarios.



Governing Equation (PDE):

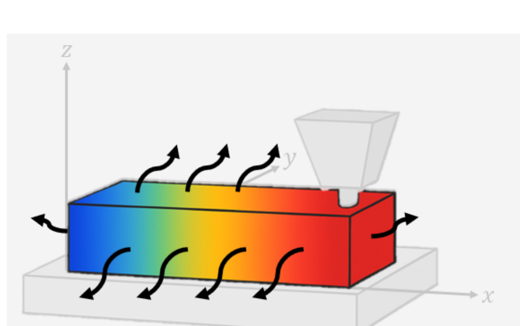
$$\rho C \frac{\partial u}{\partial t} = \nabla \cdot (k(u) \cdot \nabla u)$$

ρ: Material density
C: Specific heat capacity
k: Thermal conductivity



Initial Condition (IC):

$$u(x, y, z, t = 0) = u_\infty$$



Boundary Conditions (BC):

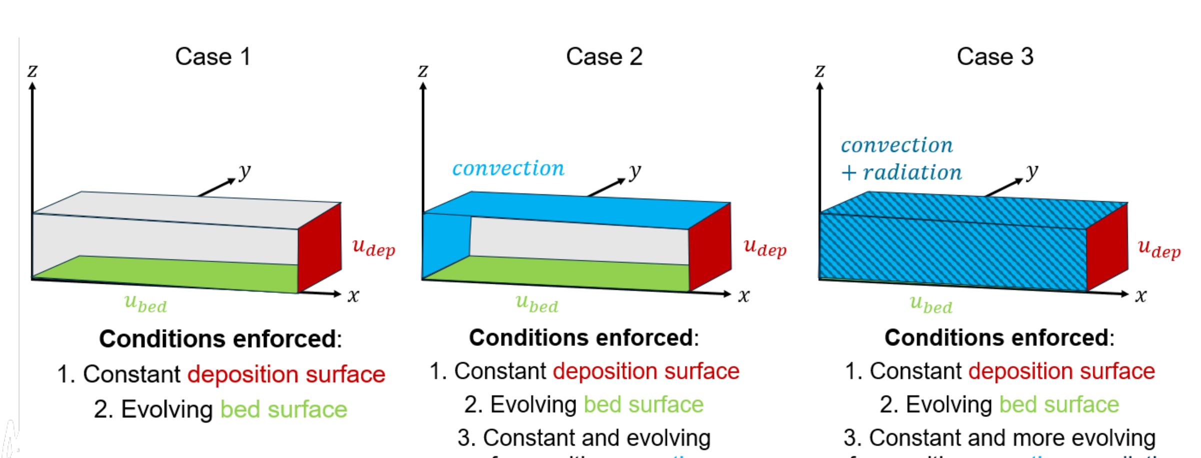
At deposition front: $u(x, y, z, t) = u_{dep}$

At print bed: $u(x, y, z, t) = u_{bed}$

Adiabatic (no heat flux):
$$\frac{\partial u}{\partial n} = 0$$

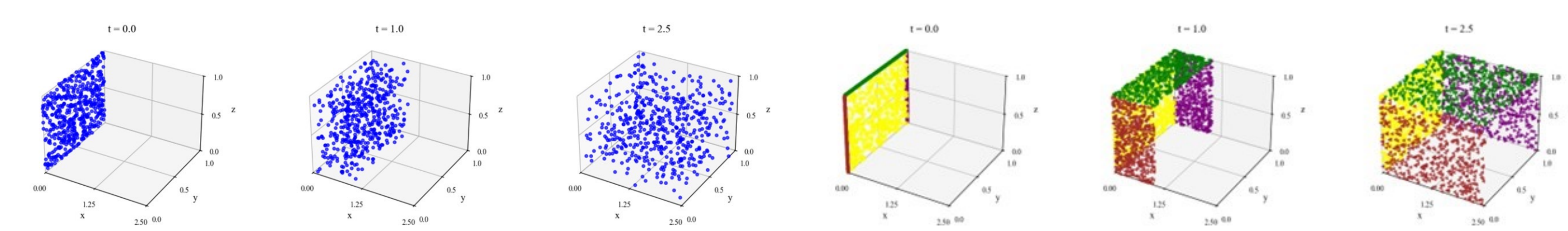
Convection:
$$k\frac{\partial u}{\partial n} = -h(u - u_\infty)$$

Radiation:
$$k\frac{\partial u}{\partial n} = -\varepsilon\sigma(u^4 - u_\infty^4)$$

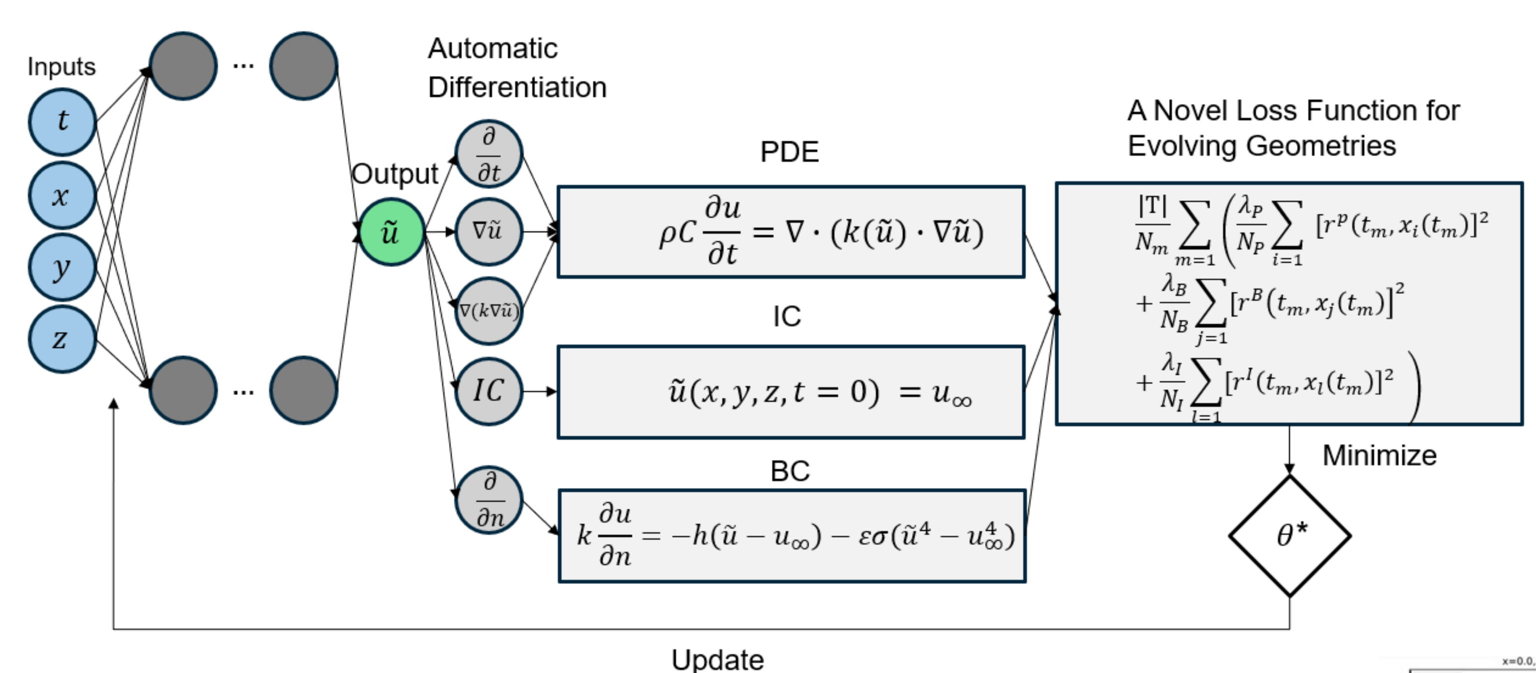


METHODOLOGY

PINNs recast the governing PDE as a stochastic minimization problem, eliminating the need for mesh generation and time-stepping schemes. The total loss function combines squared residuals of the heat equation evaluated at collocation points throughout the domain, along with penalty terms enforcing Dirichlet boundary conditions (deposition front and bed temperatures), Neumann boundary conditions (convection and radiation on exposed surfaces), and initial conditions.



Time points are sampled first, then collocation points are generated within the spatial domain at each sampled time. Because collocation point density naturally decreases as the geometry grows, the estimator variance increases for later times, biasing the optimizer to converge on earlier time steps first and enforcing causality without explicit constraints. All equations are non-dimensionalized to improve training stability. Training took ~27 minutes on NVIDIA RTX 4060 8GB.



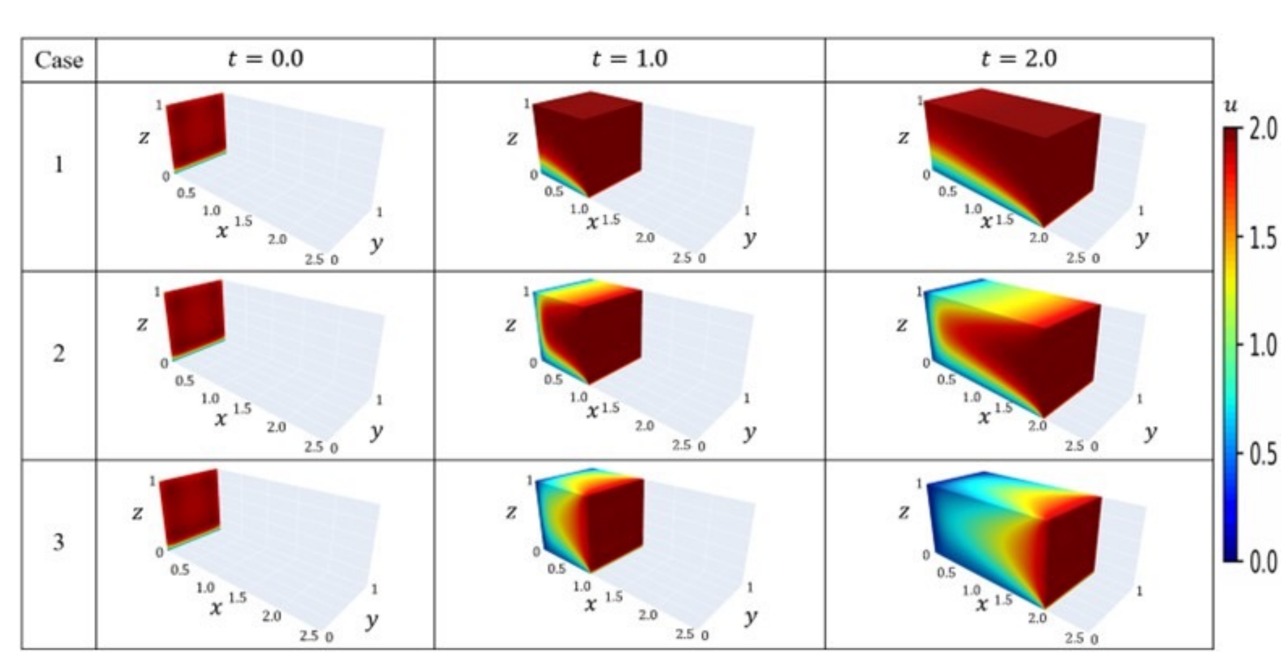
Fully connected FFNN:

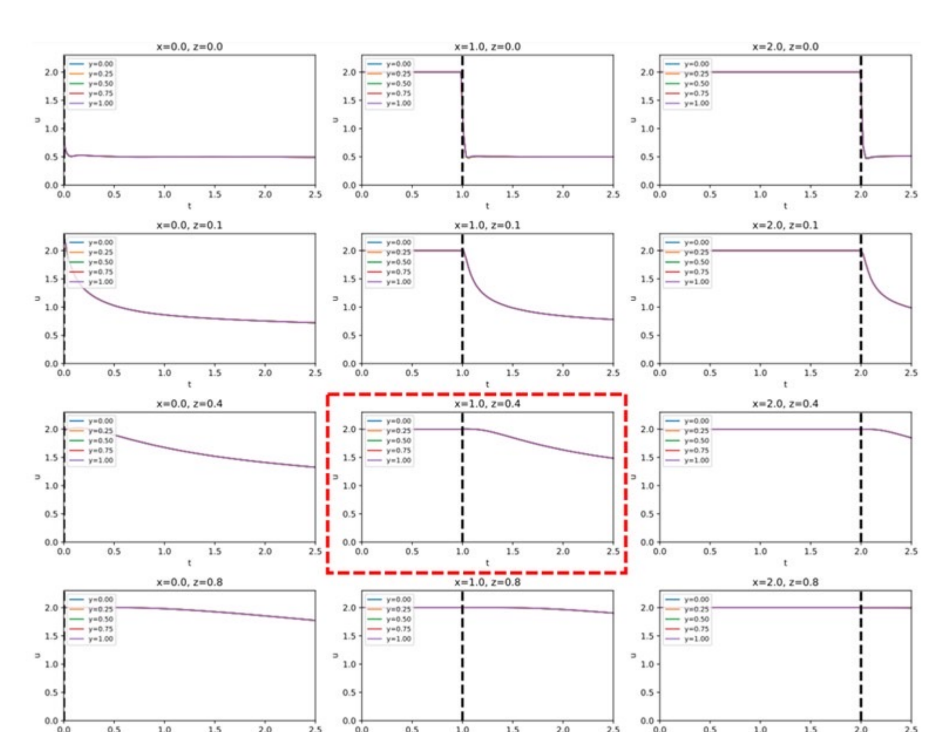
4 inputs (t, x, y, z) →

4 hidden layers × 238 neurons →

1 output (temperature).

Tanh activations, Fourier feature embeddings for high-frequency components, Xavier initialization. Trained with Adam optimizer (lr = 5×10^{-4}) for 200K iterations.



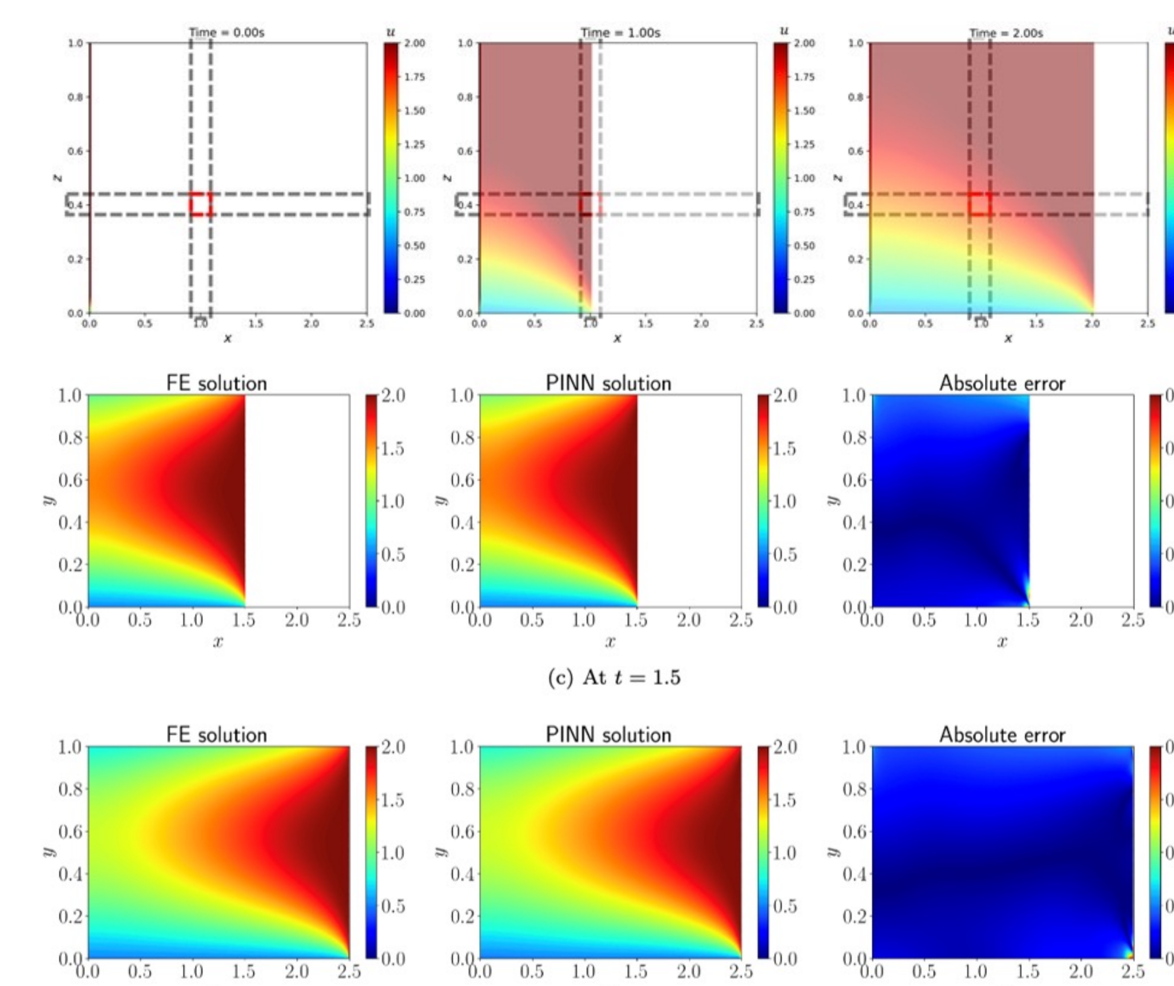


RESULTS & FUTURE WORK

Case 1: Regions near the deposition front cool rapidly under the Dirichlet condition while regions farther away retain heat longer, consistent with expected diffusion behavior.

Case 2: Convective losses on back and top surfaces produce noticeably accelerated cooling compared to insulated lateral surfaces, reflecting the interplay between competing boundary conditions.

Case 3: Radiation on all exposed surfaces introduces temperature gradients across the y-direction, with points near lateral surfaces cooling faster than those at the core.



Across all three cases, the predicted temperature fields are qualitatively consistent with prior 2D formulations verified with FE solution. Loss convergence curves show that boundary condition terms level off well before 200,000 iterations, suggesting adequate training.

We aim to extend this framework to parametric problems where PINNs solve families of scenarios under varying conditions in a single training pass. Immediate further work includes quantitative validation of 3D solution against FEM, multi-layer deposition, alternative sampling strategies, and network architectures.