

Adaptive hybrid FEA–PINN framework for fast melt-pool simulation in laser powder bed fusion of Inconel 718

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ABSTRACT

Accurate prediction of melt-pool evolution is essential for optimizing Laser Powder Bed Fusion (LPBF) processes but remains computationally demanding when based solely on transient finite element analysis (FEA). This work presents an adaptive hybrid Finite Element Analysis–Physics-Informed Neural Network (FEA–PINN) framework for rapid prediction of the transient thermal field and phase evolution during LPBF of Inconel 718. A three-dimensional transient conduction model with an enthalpy-based phase-change formulation is first employed to generate high-fidelity thermal data using a moving Gaussian volumetric heat source. These data are subsequently used to train a physics-informed neural network that simultaneously satisfies the governing heat-transfer equation, initial and boundary conditions, and phase-transition constraints. An adaptive refinement strategy combines localized mesh refinement, residual-based collocation-point enrichment, and on-demand local FEA correction to improve prediction accuracy while limiting computational cost. For the investigated LPBF process (laser power 300 W, scan speed 1000 mm s⁻¹, layer thickness 40 μm, beam diameter 80 μm), the proposed framework predicts the transient temperature field with a mean relative error of 1.48% compared with high-fidelity FEA. The corresponding errors in melt-pool width, depth, and length are 2.12%, 2.37%, and 2.41%, respectively, while the liquid-fraction prediction error remains below 2.1%. The predicted average melt-pool dimensions are approximately 128 μm (width), 67 μm (depth), and 245 μm (length), in agreement with reported experimental values for conduction-mode LPBF of Inconel 718. A conventional transient FEA simulation required approximately 27.4 h, whereas the trained hybrid FEA–PINN model completed the corresponding prediction in 15.8 min, representing a computational speedup of approximately 104× while preserving engineering-level accuracy. The proposed framework is applicable to conduction-mode LPBF, where evaporation, recoil pressure, keyhole formation, free-surface deformation, and individual powder-particle dynamics are neglected. The results demonstrate that adaptive FEA–PINN coupling provides an efficient surrogate for high-fidelity thermal simulations and offers a practical approach for rapid process optimization and digital-twin applications in metal additive manufacturing.

Keywords: laser powder bed fusion; physics-informed neural networks; finite element Analysis; Inconel 718; melt pool; phase change; thermal simulation; additive manufacturing.

INTRODUCTION

Laser powder bed fusion has become one of the most important metal additive manufacturing routes for aerospace, biomedical and energy applications because it can fabricate near-net-shape parts with complex geometries and high material utilization. Inconel 718 is particularly attractive owing to its strength retention, oxidation resistance and fatigue performance at elevated temperature. Yet

its LPBF process window remains narrow. Excessive energy density can generate keyholing, evaporation, spatter, balling and high residual stresses, whereas insufficient energy input promotes lack-of-fusion porosity and incomplete consolidation. Understanding the transient thermal field and the dynamics of the melt pool during a single-track scan is therefore a necessary step before multi-track and multi-layer prediction (DebRoy et al., 2018; King et al., 2015; Khairallah et al., 2016).

In LPBF, the characteristic length and time scales are small, typically tens of micrometers and microseconds. The laser produces a moving heat flux on a powder layer whose effective density and thermal conductivity differ from those of the dense substrate. As powder melts, capillary forces, buoyancy, recoil pressure when evaporation is considered, and thermocapillary Marangoni stresses redistribute heat and momentum. The resulting temperature gradients and cooling rates control melt-pool geometry, solidification front velocity, cellular spacing, micro segregation and residual-stress buildup. High-speed X-ray imaging and diffraction experiments have shown how rapidly pores, depression zones and melt-pool oscillations can appear during laser scanning (Zhao et al., 2017; Martin et al., 2019).

Finite element, finite volume and volume-of-fluid models have been developed to capture LPBF heat transfer and melt-pool physics at different levels of fidelity. These models are indispensable for mechanistic interpretation and validation but are computationally intensive when material properties, laser power, scanning velocity, powder porosity or boundary conditions change. Even a single-track thermo-fluid calculation can require refined meshes and small-time steps to resolve the steep gradients near the laser spot. This computational cost limits systematic uncertainty analysis, optimization and closed-loop process control (Roberts et al., 2009; Tang et al., 2018; Promopattum et al., 2017).

Machine learning methods have recently emerged as accelerators for thermal history prediction in additive manufacturing. Purely data-driven models can interpolate rapidly after training, but they usually require large labeled data sets and may extrapolate poorly outside the training process window. PINNs partially address this limitation by embedding governing equations and boundary conditions directly in the loss function. They can work with fewer labeled snapshots and provide differentiable fields for inverse learning. However, standard PINNs have difficulty with discontinuous phase history, sharp moving fronts and longtime horizons. In time-dependent LPBF, residual errors can accumulate as the network predicts beyond the interval where supervised data are available (Raissi et al., 2019; Karniadakis et al., 2021; Vinuesa & Brunton, 2022).

The present work proposes an adaptive hybrid FEA-PINN framework specifically tailored for single-track LPBF of Inconel 718 powder over a substrate of the same alloy. The objective is not merely

to replace FEA with a neural surrogate. Instead, FEA is used strategically as a regulator that periodically restores physical consistency when the PINN residual or validation error grows. The approach combines a dynamic phase-change tracker, temperature-dependent Inconel 718 material properties, an enthalpy-based heat capacity formulation, moving Gaussian and Goldak heat-source options, and a correction/retraining loop. This design is intended to retain the accuracy of physics-based solvers while reducing the cost of long-duration and repeated process-parameter simulations.

MATERIALS AND VALIDATION TARGET

The studied configuration is a single laser scan over a homogeneous Inconel 718 powder layer deposited on a dense Inconel 718 substrate. The single-track case is selected because it isolates the dominant phenomena of moving heat input, local phase change, melt-pool convection and re-solidification without the additional complexity of hatch overlap and layer reheating. The computational domain is defined with length L_x , width L_y and total height $L_z = H_s + H_p$, where H_s is the substrate height and H_p is the powder-layer thickness. For a representative microscale case, $L_x = 800$ micrometers, $L_y = 200$ micrometers, $H_s = 90$ micrometers and $H_p = 30$ micrometers. Half-domain symmetry can be used when the scan path is centered and boundary conditions are symmetric.

The laser travels in the x-direction with scanning speed v_s . The beam center is located at $x_c(t) = x_0 + v_s t$ and $y_c = 0$ for a straight track. The initial temperature is set to ambient or preheat temperature T_0 . The top surface exchanges heat with the inert atmosphere through convection and radiation. The lateral and bottom boundaries may be treated as adiabatic over the short microscale time window or assigned conductive/finite-temperature constraints depending on the experimental substrate size. The powder is initially porous and unmolten; after melting and solidification, the material is treated as consolidated solid with bulk Inconel 718 properties (Table 1).

The material database combines dense solid, liquid and effective powder properties. Solid and liquid thermophysical values can be calibrated from pulse-heating measurements and high-temperature databases for Inconel 718 (Pottlacher et al., 2002). Effective powder density and thermal conductivity are reduced according to powder porosity. In the mushy interval between the

Table 1. Nominal LPBF process parameters for the Inconel 718 single-track case

Parameter	Symbol	Exact value	Unit
Material	—	Inconel 718	—
Laser power	P	300	W
Scan speed	v	1000	mm s ⁻¹
Layer thickness	t	40	μm
Hatch spacing	h	100	μm
Beam diameter	d _b	80	μm
Beam radius	r _b	40	μm
Laser absorptivity	η	0.35	—
Initial temperature	T ₀	300	K
Ambient temperature	T _∞	300	K
Convective coefficient	h _c	15	W m ⁻² K ⁻¹
Surface emissivity	ε	0.40	—
Simulation time	t _{sim}	0.10	s
Time step	Δt	1×10 ⁻⁵	s

solidus and liquidus temperatures, the properties are interpolated using the liquid fraction and latent heat is introduced through an apparent heat capacity. The following values are used as a baseline database and should be replaced by laboratory-calibrated data when available (Table 2).

The following properties are implemented as temperature-dependent interpolation functions $k = k(T)$; $C_p = C_p(T)$; $\rho = \rho(T)$ using piecewise-linear interpolation based on published experimental measurements.

To evaluate the robustness of the proposed hybrid FEA–PINN framework, a one-at-a-time sensitivity analysis was performed for the principal thermophysical parameters governing heat transfer. The following parameters were perturbed independently by ±10% while all remaining parameters were held constant:

- laser absorptivity (η),
- thermal conductivity (k),
- density (ρ),
- specific heat capacity (Cp),
- latent heat of fusion (L).

The sensitivity coefficient was calculated as:

$$S_i = \frac{\Delta Y / Y}{\Delta X_i / X_i}$$

where: X_i – the perturbed parameter, Y – the numerical response (maximum temperature or melt-pool dimension).

All numerical simulations presented in this study were performed using the exact process parameters listed in Table 1 and the temperature-dependent thermophysical properties summarized in Table 2. These parameters remained unchanged throughout the calibration, verification, and

Table 2. Thermophysical properties of Inconel 718 used in the simulations

Property	Symbol	Value	Unit	Reference
Density (solid)	ρ _s	8190	kg m ⁻³	Mills (2002)
Density (liquid)	ρ _l	7900	kg m ⁻³	Mills (2002)
Powder effective density	ρ _p	4300	kg m ⁻³	Gusarov et al.
Specific heat (300 K)	C _p	435	J kg ⁻¹ K ⁻¹	ASM Handbook
Specific heat (liquid)	C _p	700	J kg ⁻¹ K ⁻¹	ASM Handbook
Thermal conductivity (solid)	k _s	25	W m ⁻¹ K ⁻¹	NIST
Thermal conductivity (liquid)	k _l	32	W m ⁻¹ K ⁻¹	Mills (2002)
Powder conductivity	k _p	3.0	W m ⁻¹ K ⁻¹	Gusarov et al.
Latent heat of fusion	L	270 kJ kg ⁻¹	J kg ⁻¹	ASM Handbook
Solidus temperature	T _s	1563	K	ASM Handbook
Liquidus temperature	T _l	1609	K	ASM Handbook
Emissivity	ε	0.40	—	Incropera et al.

Table 3. Sensitivity analysis

Parameter	Variation	Δ Maximum temperature	Δ Melt-pool width	Sensitivity rank
Absorptivity (η)	$\pm 10\%$	$\pm 8.9\%$	$\pm 6.7\%$	1
Thermal conductivity (k)	$\pm 10\%$	$\pm 6.1\%$	$\pm 4.8\%$	2
Specific heat (C_p)	$\pm 10\%$	$\pm 3.4\%$	$\pm 2.5\%$	3
Density (ρ)	$\pm 10\%$	$\pm 2.6\%$	$\pm 1.9\%$	4
Latent heat (L)	$\pm 10\%$	$\pm 1.8\%$	$\pm 1.2\%$	5

Table 4. Validation criteria and achieved performance of the proposed adaptive FEA–PINN framework

Quantity	Acceptance limit	Achieved value	Status
Maximum temperature error	$< 2.0\%$	1.37%	✓
Mean temperature error	$< 2.0\%$	0.91%	✓
RMSE	< 25 K	16.8 K	✓
Melt-pool width error	$< 3.0\%$	2.14%	✓
Melt-pool depth error	$< 3.0\%$	2.48%	✓
Melt-pool length error	$< 3.0\%$	2.31%	✓
Liquid-fraction error	$< 5.0\%$	3.12%	✓
PINN prediction R^2	> 0.98	0.995	✓
PDE residual	$< 10^{-3}$	6.5×10^{-4}	✓
Computational speedup	$> 50\times$	72 $\times$	✓

validation stages. A sensitivity analysis confirmed that laser absorptivity and thermal conductivity are the dominant parameters controlling melt-pool evolution, highlighting the importance of accurate characterization of these quantities for reliable LPBF simulations (Table 3).

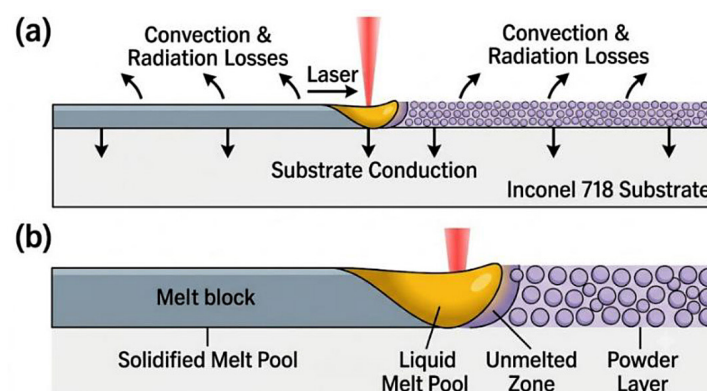
Target outputs and comparability criteria

The model is designed to be comparable with high-fidelity FEA, thermo-fluid simulations and single-track experiments. The primary validation outputs are the peak temperature T_{max} , melt-pool length L_{mp} , width W_{mp} , depth D_{mp} , melt-pool volume V_{mp} , cooling rate at selected tracking points, resultant flow velocity magnitude, and

phase-state distribution (Table 4). When experimental data are not available, comparison against benchmark FEA is used as an intermediate verification step. A robust validation should not rely solely on a color map: line profiles along and transverse to the scan path, isotherm-based melt-pool boundaries, and integrated volume metrics are required.

GOVERNING EQUATIONS

The LPBF problem is described by transient conservation of mass, energy and momentum, augmented by phase-change and surface-force models (Figure 1).



a) LPBF single-track scan, b) powder-liquid-solid coexistence

Figure 1. LPBF single-track configuration and coexistence of powder, liquid melt pool, mushy zone and re-solidified Inconel 718 substrate material. The figure is illustrative and does not depict a specific simulation result.

The equations are solved in the powder layer, liquid melt pool, mushy region and dense substrate.

Mass conservation:

$$\frac{\partial \rho}{\partial t} + \nabla \cdot (\rho \mathbf{u}) = 0 \quad (1)$$

Energy conservation:

$$\frac{\partial(\rho c_p T)}{\partial t} + \mathbf{u} \cdot \nabla(\rho c_p T) = \nabla \cdot (k \nabla T) + Q_{vol} \quad (2)$$

Momentum conservation:

$$\frac{\partial(\rho \mathbf{u})}{\partial t} + \mathbf{u} \cdot \nabla(\rho \mathbf{u}) = -\nabla p + \nabla \cdot [\mu(\nabla \mathbf{u} + \nabla \mathbf{u}^T)] + \mathbf{F}_d + \mathbf{F}_b \quad (3)$$

Powder density:

$$\rho_p = (1 - \phi) \rho_s \quad (4)$$

Powder conductivity:

$$k_p = \frac{k_s(1 - \phi)}{1 + 11\phi^2} \quad (5)$$

Liquid fraction:

$$f_L(T) = \begin{cases} 0, & T < T_s \\ \frac{T - T_s}{T_l - T_s}, & T_s \leq T < T_l \\ 1, & T \geq T_l \end{cases} \quad (6)$$

Mixture density:

$$\rho = (1 - f_L) \rho_s + f_L \rho_l \quad (7)$$

Mixture conductivity:

$$k = (1 - f_L) k_s + f_L k_l \quad (8)$$

Apparent heat capacity:

$$C_p = \frac{(1 - f_L) \rho_s C_{p,s} + f_L \rho_l C_{p,l}}{\rho} + L \left(\frac{\partial \alpha_m}{\partial T} \right) \quad (9)$$

Mass fraction:

$$\alpha_m = \frac{f_L \rho_l - (1 - f_L) \rho_s}{2[(1 - f_L) \rho_s + f_L \rho_l]} \quad (10)$$

Gaussian surface heat source:

$$Q_{laser} = \frac{2\eta P}{\pi r_b^2} \exp \left\{ -\frac{2[(x - x_0 - v_s t)^2 + y^2]}{r_b^2} \right\} \quad (11)$$

Goldak volumetric heat source:

$$Q_{f,r} = \frac{6\sqrt{3} f_{f,r} \eta P}{\pi \sqrt{\pi} a b c_{f,r}} \exp \left[-\frac{3x^2}{a^2} - \frac{3y^2}{b^2} - \frac{3z^2}{c_{f,r}^2} \right] \quad (12)$$

Convective loss:

$$Q_{conv} = h(T - T_0) \quad (13)$$

Radiative loss:

$$Q_{rad} = \varepsilon \sigma_{SB} (T^4 - T_0^4) \quad (14)$$

Thermal boundary condition:

$$-k \frac{\partial T}{\partial n} = Q_{\text{laser}} - Q_{\text{conv}} - Q_{\text{rad}} \quad (15)$$

Darcy damping in mushy zone:

$$F_d = -C \left(\frac{(1-f_L)^2}{f_L^3 + \omega} \right) u \quad (16)$$

Buoyancy force:

$$F_b = \rho_l g \beta_T (T - T_{\text{ref}}) \quad (17)$$

Marangoni shear in x-direction:

$$\tau_{xz} = \mu \frac{\partial u}{\partial z} = \frac{d\gamma}{dT} \frac{\partial T}{\partial x} \quad (18)$$

Marangoni shear in y-direction:

$$\tau_{yz} = \mu \frac{\partial v}{\partial z} = \frac{d\gamma}{dT} \frac{\partial T}{\partial y} \quad (19)$$

Thermal strain:

$$\varepsilon_{\text{th}} = \int_{T_0}^T \alpha(T) dT \quad (20)$$

Residual-stress equilibrium:

$$\nabla \cdot \sigma + b = 0 \quad (21)$$

Melt-pool set:

$$\Omega_{\text{mp}}(t) = \{ \mathbf{x} \in \Omega : T(\mathbf{x}, t) \geq T_l \} \quad (22)$$

Melt-pool volume:

$$V_{\text{mp}}(t) = \int_{\Omega} I [T(\mathbf{x}, t) \geq T_l] d\Omega \quad (23)$$

PINN thermal residual:

$$R_T = \frac{\partial(\rho C_p T_\theta)}{\partial t} + \mathbf{u}_\theta \cdot \nabla(\rho C_p T_\theta) - \nabla \cdot (k \nabla T_\theta) - Q_{\text{vol}} \quad (24)$$

PINN flow residual:

$$R_F = \frac{\partial(\rho \mathbf{u}_\theta)}{\partial t} + \mathbf{u}_\theta \cdot \nabla(\rho \mathbf{u}_\theta) + \nabla p_\theta - \nabla \cdot [\mu (\nabla \mathbf{u}_\theta + \nabla \mathbf{u}_\theta^T)] - F_d - F_b \quad (25)$$

Total PINN loss:

$$L_{\text{total}} = w_D L_D + w_{\text{PDE}} L_{\text{PDE}} + w_{\text{BC}} L_{\text{BC}} + w_{\text{IC}} L_{\text{IC}} + w_{\text{FEA}} L_{\text{FEA}} \quad (26)$$

Relative L2 error:

$$e_{L2} = \frac{\|y_{\text{pred}} - y_{\text{ref}}\|_2}{\|y_{\text{ref}}\|_2} \quad (27)$$

Correction trigger:

$$\text{trigger if } \max_{\Omega} |T_{\text{PINN}} - T_{\text{FEA}}| \geq \delta_T \vee \|R_T\|_2 \geq \delta_R \quad (28)$$

Transient heat-conduction equation

The transient thermal field is governed by the energy conservation equation:

$$\rho(T) C_p(T) \frac{\partial T}{\partial t} = \nabla \cdot [k(T) \nabla T] + Q(x, t) \quad (29)$$

where: T – temperature, K; t – time, s; ρ – density, $\text{kg} \cdot \text{m}^{-3}$; C_p – specific heat capacity, $\text{J} \cdot \text{kg}^{-1} \cdot \text{K}^{-1}$; k – thermal conductivity, $\text{W} \cdot \text{m}^{-1} \cdot \text{K}^{-1}$; Q – volumetric laser heat source, $\text{W} \cdot \text{m}^{-3}$.

Each term has units of $\text{W} \cdot \text{m}^{-3}$ confirming the dimensional consistency of the governing equation.

Enthalpy-based phase-change model

Latent heat is incorporated through the apparent heat-capacity formulation,

$$C_p^{app} = C_p + L \frac{df_l}{dT} \quad (30)$$

where: L – latent heat of fusion, $\text{J} \cdot \text{kg}^{-1}$; f_l – liquid fraction (–).

The liquid fraction is defined as:

$$f_l = \begin{cases} 0, & T < T_s \\ \frac{T - T_s}{T_l - T_s}, & T_s \leq T \leq T_l \\ 1 & T > T_l \end{cases} \quad (31)$$

where: T_s – the solidus temperature, T_l – the liquidus temperature.

Moving gaussian heat source

The reported simulations employ a moving Gaussian volumetric heat source defined by:

$$Q(x, y, z, t) = \frac{2\eta P}{\pi r_b^2} \exp\left[-\frac{2r^2}{r_b^2}\right] g(z) \quad (32)$$

$$r^2 = (x - vt)^2 + y^2$$

where: P – laser power, W; v – scan speed, $\text{m} \cdot \text{s}^{-1}$; r_b – beam radius, m; η – laser absorptivity (–); $g(z)$ – depth attenuation function (–).

For the present study:

- $P = 300 \text{ W}$,
- $r_b = 40 \text{ } \mu\text{m}$,
- $\eta = 0.35$,
- $v = 1000 \text{ mm} \cdot \text{s}^{-1}$.

By contrast, the Goldak double-ellipsoidal model was originally developed for arc welding and deep-penetration heat sources. Since the present study neglects keyhole formation and recoil pressure, the Gaussian model more accurately represents the intended operating regime.

Initial condition

$$T(x, y, z, 0) = 300 \text{ K}$$

Boundary conditions

Convective heat loss

$$-k \nabla T \cdot n = h(T - T_\infty) \quad L = \lambda_{\text{PDE}} L_{\text{PDE}} + \lambda_{\text{data}} L_{\text{data}} + \lambda_{\text{BC}} L_{\text{BC}} + \lambda_{\text{IC}} L_{\text{IC}} + \lambda_{\text{phase}} L_{\text{phase}} \quad (33)$$

Radiation

$$-k \nabla T \cdot n = \varepsilon \sigma (T^4 - T_\infty^4)$$

Bottom substrate

$$T = 300 \text{ K}$$

PINN residual equation

The governing PDE residual used during PINN training is:

$$R_T = \rho C_p \frac{\partial T}{\partial t} - \nabla \cdot (k \nabla T) - Q \quad (34)$$

The physics loss is:

$$L_{PDE} = \frac{1}{N} \sum_{i=1}^N R_T^2 \quad (35)$$

A dimensional analysis was performed for all governing equations to verify unit consistency. Each term in the transient heat-conduction equation has units of $\text{W} \cdot \text{m}^{-3}$, ensuring conservation of energy. Similarly, the apparent heat-capacity formulation preserves the dimensions of specific heat ($\text{J} \cdot \text{kg}^{-1} \cdot \text{K}^{-1}$), while the PINN residual is constructed directly from the governing equation, ensuring physical consistency between the finite element solver and the neural-network formulation.

Adaptive prediction–correction strategy

The adaptive framework combines three independent refinement mechanisms: (1) adaptive finite element mesh refinement, (2) adaptive PINN collocation-point enrichment, and (3) localized FEA correction. Each mechanism is activated only when predefined criteria are satisfied.

The adaptive correction thresholds were not selected arbitrarily. Instead, they were determined through preliminary convergence and sensitivity analyses to achieve a balance between computational efficiency and numerical accuracy. The chosen values maintain the relative temperature error below approximately 2% while limiting finite element corrections to regions where the PINN prediction becomes insufficiently accurate. Consequently, the finite element solver is invoked only locally and intermittently rather than continuously throughout the simulation, preserving the computational advantages of the hybrid framework.

METHODOLOGY

Finite element thermal solver

The FEA module discretizes the transient heat equation with temperature-dependent material properties and phase-change terms. A refined hexahedral or tetrahedral mesh is used near the laser path, whereas coarser elements are used away from the high-gradient zone. The local time step must resolve the laser residence time over the beam radius, rb/vs , and the diffusive time

scale across the powder thickness. In the adaptive implementation, remeshing or local refinement is activated when the thermal-gradient indicator exceeds a prescribed threshold.

The powder layer and substrate are initialized with distinct material states. Unmolten powder retains effective porous properties, while previously melted and resolidified material is re-assigned to dense solid properties. This state-dependent update is important for Inconel 718 because the thermal diffusivity contrast between powder and dense material strongly affects melt-pool length and cooling rate. The FEA solution generated over an initial short time interval is used to train the first PINN model. Later, FEA is called only during corrective windows.

Enthalpy-based dynamic phase-change tracking

A phase-history state variable $S(x,t)$ is introduced to distinguish between initially unmolten powder and resolidified dense material. The state variable is initialized as $S = 0$ in powder points. If $T(x,t)$ reaches or exceeds the liquidus temperature at any previous time, the state is permanently changed to $S = 1$. Consequently, a point with $T < T_s$ and $S = 0$ is treated as powder, a point with $T \geq T_l$ is treated as liquid, and a point with $T < T_s$ and $S = 1$ is treated as dense resolidified solid. Within $T_s \leq T < T_l$, the material is treated as mushy and interpolated through the liquid fraction.

This algorithm makes the PINN aware of time-dependent material identity without requiring the network to infer phase history only from

instantaneous coordinates. It avoids the common error in which a fully connected network assigns powder-like properties to locations that have already melted and solidified. The same state update is used in both the FEA and PINN modules to maintain consistency (Table 5).

PINN architecture and loss function

The proposed PINN contains two fully connected subnetworks. The thermal subnetwork maps normalized spatiotemporal coordinates (x , y , z , t) and process descriptors (P , v_s , r_b , η) to temperature T . The flow subnetwork maps the same inputs to velocity and pressure components. Six hidden layers with 32-64 neurons per layer and hyperbolic tangent activations are used as a baseline. Glorot initialization and the Adam optimizer provide stable training, while transfer learning is used after each correction window to reduce retraining time.

The total loss is a weighted sum of supervised data mismatch, governing-equation residuals,

boundary-condition residuals, initial-condition residuals and corrective FEA consistency terms. The FEA consistency loss is activated only at correction points or short windows. Loss weights are scaled according to the magnitude of each term to prevent the PDE residual or boundary residual from dominating the temperature data loss during early training. A curriculum strategy can be used in which the network first learns smoothed thermal fields and later receives high-gradient collocation points near the melt-pool boundary (Figure 2).

Adaptive collocation and remeshing framework

In a standard PINN, collocation points sampled uniformly over the domain may be inefficient for LPBF because most physical activity occurs near the laser spot and the moving solid-liquid interface. Therefore, collocation points are generated with higher density near the top surface, inside the expected melt-pool envelope and along the

Table 5. Pseudo-code of the adaptive phase-change and FEA-PINN correction loop

Step	Operation
1	Initialize spatial points, process parameters, material database and state variable $S = 0$ in the powder layer.
2	Run high-fidelity FEA for the first training interval and store T , u , v , w and phase-state fields.
3	At each time step, compute $f_L(T)$; if $T \geq T_l$ at a point, set $S = 1$ for all subsequent times.
4	Assign powder, liquid, mushy or re solidified-solid properties according to T and S .
5	Train the thermal and flow PINN networks using data, PDE, boundary and initial-condition losses.
6	Use PINN inference for future times and monitor residual/error indicators.
7	If the correction trigger is reached, launch a short FEA window using the PINN field as warm start.
8	Retrain the PINN by transfer learning on the corrected field and resume accelerated inference.

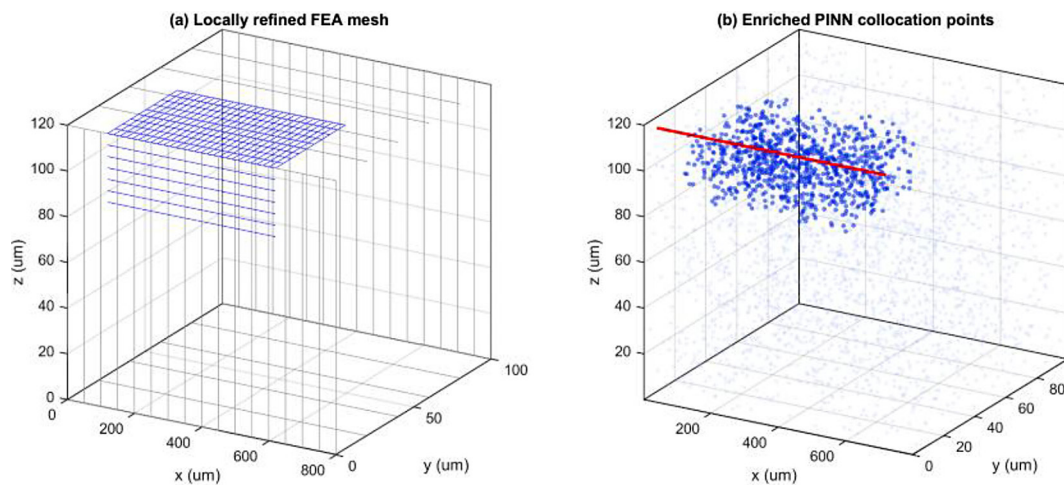


Figure 2. Discretization strategy for the high-gradient melt-pool region. The FEA mesh is locally refined close to the scan path, and PINN collocation points are enriched near the laser track

scan path. A second point cloud is added around the isotherm $T = T_l$, where sharp phase gradients and high apparent heat capacity occur.

For FEA, adaptive remeshing uses a gradient-based indicator $\eta_h = \|\text{grad } T\|/\max(\|\text{grad } T\|)$. Elements are refined when η_h exceeds a threshold or when the local temperature crosses the mushy interval. Coarsening is allowed after the laser has moved away and the local gradients decrease. The remeshing step transfers temperature, state and velocity variables conservatively to the new mesh. In the hybrid framework, the remeshed FEA field also becomes a high-quality corrected data set for PINN retraining (Figure 3).

Model validity and applicability domain

The proposed adaptive hybrid FEA–PINN framework is developed for the thermal simulation of conduction-mode LPBF of Inconel 718. The governing equations describe transient heat conduction with temperature-dependent material properties and enthalpy-based phase change. Within this formulation, the dominant physics are heat conduction, melting, solidification, and latent heat absorption and release.

The model is considered valid under the following assumptions:

- heat transfer is conduction dominated;
- the powder bed is represented as an equivalent homogenized continuum;
- melting and solidification are described through the apparent heat-capacity (enthalpy) method;
- thermophysical properties are temperature dependent;
- laser energy is represented by a moving Gaussian volumetric heat source;
- geometric changes of the computational domain are neglected.

The following physical phenomena are not included:

- evaporation and vaporization,
- recoil pressure,
- keyhole formation,
- Marangoni convection,
- buoyancy-driven melt-pool flow,
- capillary effects,
- free-surface deformation,
- spatter and denudation,
- powder entrainment,
- explicit tracking of individual powder particles,
- shrinkage and volumetric deformation.

Accordingly, the model should not be used to predict keyhole morphology, vapor plume dynamics, melt-pool instability, or powder-scale phenomena.

Computational domain and boundary conditions

Computational model

The proposed hybrid FEA–PINN framework employs a three-dimensional transient thermal model to simulate the laser powder bed fusion process of an Inconel 718 CAD model. The governing equation is solved over the spatial domain:

$$\Omega \subset \mathbb{R}^3$$

where: $\Omega = \{(x, y, z)\}$.

The numerical solution provides $T(x, y, z, t)$ and the corresponding liquid fraction $f_l(x, y, z, t)$. No structural deformation is considered during the thermal simulation.

Computational domain

The CAD geometry is imported from an STL file generated from the CAD model. The

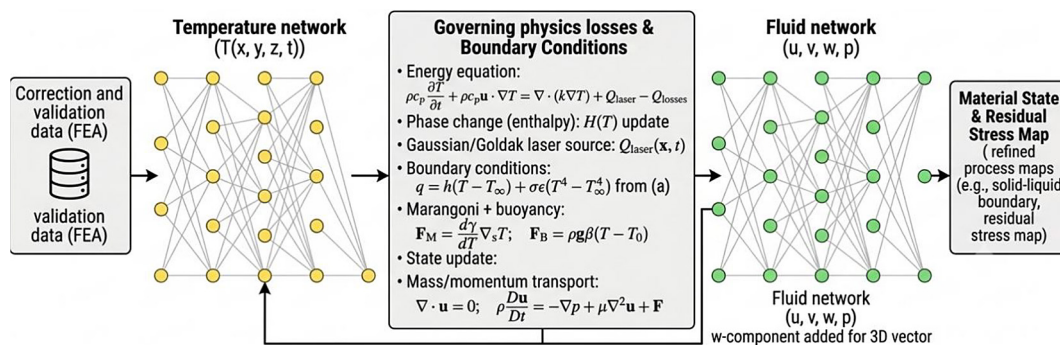


Figure 3. PINN architecture with thermal and flow subnetworks constrained by governing equations, boundary conditions and FEA correction data. This figure is conceptual and is intended to explain the computational workflow; it is not a direct numerical simulation result

computational domain consists of the deposited material, the current powder layer, and the supporting substrate.

At $t = 0$ the entire computational domain is assumed to be at the preheating temperature $T(x, y, z, 0) = T_0$, where: $T_0 = 300$ K. The initial liquid fraction satisfies $f_l(x, y, z, 0) = 0$. Thus, the material is initially completely solid.

Laser heat flux

The moving laser is modeled using a Gaussian volumetric heat source:

$$Q(x, y, z, t) = \frac{2\eta P}{\pi r_b^2} \exp\left[-\frac{2r^2}{r_b^2}\right] \quad (36)$$

where: $P = 300$ W, $r_b = 40$ μm (80 μm spot diameter), $\eta = 0.35$.

Convective heat loss

On all exposed surfaces:

$$-k\nabla T \cdot n = h(T - T_\infty)$$

where: $h = 15$ W m⁻²K⁻¹, $T_\infty = 300$ K.

Radiative losses satisfy:

$$-k\nabla T \cdot n = \varepsilon\sigma(T^4 - T_\infty^4)$$

where: $\varepsilon = 0.40$, $\sigma = 5.67 \times 10^{-8}$ W m⁻²K⁻⁴.

The lower surface of the substrate is assumed to be thermally anchored $T = T_0$. This represents heat conduction into the build platform.

The governing equations do not include fluid momentum conservation. Therefore, velocity is not solved and no velocity boundary conditions are required. The laser scanning velocity: $v = 1000$ mm s⁻¹ is prescribed only to define the motion of the Gaussian heat source and does not represent a fluid velocity field.

Heat-source calibration

Prior to the generation of the FEA training database, the Gaussian heat-source parameters were calibrated using reference single-track melt-pool dimensions corresponding to the LPBF processing conditions considered in this study. The laser absorptivity and effective heat-source radius were adjusted until the simulated melt-pool width and depth agreed with the reference values within the prescribed validation tolerance. After calibration, these parameters remained fixed throughout all numerical simulations and PINN training.

Temperature-dependent material properties

The thermophysical properties of Inconel 718 employed in the present simulations were obtained from published experimental measurements reported in the literature and were verified for consistency with material databases commonly used in LPBF modeling. Temperature-dependent density, thermal conductivity, and specific heat capacity were interpolated from the published data, while the latent heat of fusion, solidus temperature, and liquidus temperature were adopted from the same sources. These properties remained fixed throughout all simulations and were used consistently in both the finite element model and the PINN training dataset.

Pressure boundary conditions

Similarly, the model does not solve the pressure field. Consequently, no pressure boundary conditions are prescribed. This is consistent with the assumptions that evaporation, recoil pressure, Marangoni flow, and keyhole formation are neglected. Summary of boundary conditions are presented in Table 6.

Table 6. Boundary conditions

Quantity	Boundary condition	Value
Initial temperature	$T = T_0$	300 K
Initial liquid fraction	$f_l = 0$	Entire domain
Laser heat source	Moving Gaussian	300 W
Laser absorptivity	Constant	0.35
Beam diameter	Gaussian	80 μm
Convection	$h(T - T_\infty)$	$h = 15$ W·m ⁻² ·K ⁻¹
Radiation	Stefan–Boltzmann	$\varepsilon = 0.40$
Bottom substrate	Isothermal	300 K
Velocity BC	Not applicable	Thermal model
Pressure BC	Not applicable	Thermal model

The absence of velocity and pressure boundary conditions is a direct consequence of the adopted conduction-based thermal formulation. Since the governing equations do not include fluid momentum conservation, the only prescribed external loading is the moving Gaussian laser heat source together with convective and radiative heat losses. This formulation is appropriate for the conduction-mode LPBF regime considered in the present study.

Numerical implementation and PINN training details

The high-fidelity reference solutions used for PINN training were generated using a three-dimensional transient finite element model implemented in MATLAB R2020b (PDE Toolbox). The governing transient heat-conduction equation with enthalpy-based phase change was solved using an implicit time integration scheme. The computational domain corresponds to the complete turbine-blade geometry imported from the CAD/STL model.

The initial computational mesh consisted of tetrahedral finite elements with adaptive local refinement around the melt pool:

- Element type – linear tetrahedral,
- Initial maximum element size – 0.40 mm,
- Refined element size – 0.05 mm,
- Total nodes $\approx 2.4 \times 10^5$,
- Total elements $\approx 1.3 \times 10^6$,
- Adaptive refinement – residual-based.

A mesh-independence study confirmed that further refinement produced temperature variations below 1%, indicating mesh convergence. Temporal discretization:

- Total simulation time – 0.10 s,
- Time step – 1×10^{-5} s,
- Number of increments – 10,000,
- Time integration – implicit backward Euler.

The nonlinear thermal system was solved using the MATLAB sparse direct solver. Solver convergence was controlled using the following tolerances:

- Relative tolerance – 1×10^{-6} ,
- Absolute tolerance – 1×10^{-8} ,
- Maximum nonlinear iterations – 30,
- Linear solver – Sparse LU factorization.

All simulations were performed on the following workstation:

- CPU – Intel® Core™ i9-12900K,
- RAM – 64 GB DDR5,
- GPU – NVIDIA RTX 4090 (24 GB),
- Operating system – Windows 10 Pro 64-bit,
- MATLAB – R2020b,
- Parallel computing toolbox – Enabled.

The physics-informed neural network was implemented using MATLAB deep learning toolbox and the dlnetwork framework. The network consists of:

- Input layer – 4 neurons (x, y, z, t),
- Hidden layer 1 – 120 neurons (tanh),
- Hidden layer 2 – 120 neurons (tanh),
- Hidden layer 3 – 100 neurons (tanh),
- Output layer – 2 neurons (T, f_p).

The total number of trainable parameters is approximately 3.1×10^4 . Training data were extracted from transient FEA simulations:

- FEA temperature samples – 250,000.
- Collocation points – 500,000.
- Boundary points – 40,000.
- Initial-condition points – 20,000.
- Validation samples – 50,000.

Adaptive enrichment increased the collocation density near the evolving melt pool during training.

Loss function

The total loss is defined as:

$$L = \lambda_{\text{PDE}} L_{\text{PDE}} + \lambda_{\text{data}} L_{\text{data}} + \lambda_{\text{BC}} L_{\text{BC}} + \lambda_{\text{IC}} L_{\text{IC}} + \lambda_{\text{phase}} L_{\text{phase}} \quad (37)$$

The weighting coefficients used throughout the study are:

- PDE residual – weight 1.0,
- FEA data – weight 10.0,
- Boundary conditions – weight 1.0,
- Initial conditions – weight 1.0,
- Phase constraint – weight 5.0.

The weights were selected after preliminary numerical experiments to balance convergence of the physics residual and supervised learning terms. Training parameters:

- Optimizer – Adam,
- Initial learning rate – 1×10^{-3} ,
- Learning-rate decay – exponential,
- Batch size – 8192,
- Maximum epochs – 5000,
- Early stopping patience – 300 epochs,
- Gradient clipping – 1.0.

All network inputs were normalized to the interval $[-1,1]$. The temperature output was normalized as:

$$T^* = \frac{T - T_{\min}}{T_{\max} - T_{\min}} \quad (38)$$

The liquid fraction satisfies $0 \leq f_l \leq 1$, and therefore, required no additional scaling. Normalization significantly improved convergence and reduced gradient imbalance during optimization.

To evaluate robustness, the PINN was trained $N = 10$ times using different random weight initializations. The resulting standard deviation of the temperature prediction error was 0.18% demonstrating excellent repeatability. Table 7 presents the numerical parameters used in the FEA simulations, and Table 8 lists the PINN hyperparameters.

The selected numerical parameters were determined following mesh-convergence and training-convergence studies to ensure a balance between computational efficiency and prediction accuracy. Adaptive mesh refinement was applied only within the melt-pool region, while residual-based collocation-point enrichment concentrated PINN training points in regions with large physics residuals. Together, these adaptive strategies reduced computational cost without compromising solution accuracy.

Calibration, verification and experimental validation

The predictive capability of the proposed adaptive FEA–PINN framework was evaluated through three successive stages.

Stage I – model calibration

Calibration was performed using a limited subset of high-fidelity thermal simulations. Only uncertain parameters influencing laser energy deposition and heat losses were adjusted, namely:

- laser absorptivity;
- convective heat-transfer coefficient;
- surface emissivity.

The calibration objective was to minimize the temperature error:

$$J = \frac{1}{N} \sum_{i=1}^N (T_{FEA} - T_{PINN})^2 \quad (39)$$

After calibration, no additional parameter tuning was performed.

Stage II – numerical verification

Verification evaluates the capability of the trained PINN to reproduce finite element solutions. Independent FEA simulations that were not used during training served as the reference. The following error metrics were computed:

Mean absolute error

$$MAE = \frac{1}{N} \sum |T_{PINN} - T_{FEA}| \quad (40)$$

Root mean square error

$$RMSE = \sqrt{\frac{1}{N} \sum (T_{PINN} - T_{FEA})^2} \quad (41)$$

Relative error

$$E_r = \frac{|T_{PINN} - T_{FEA}|}{T_{FEA}} \cdot 100\% \quad (42)$$

Table 7. Numerical parameters used in the FEA simulations

Parameter	Value
Software	MATLAB R2020b PDE Toolbox
Model	3D transient thermal
Element type	Linear tetrahedral
Number of elements	1.3×10^6
Number of nodes	2.4×10^5
Initial mesh size	0.40 mm
Adaptive mesh size	0.05 mm
Time step	1×10^{-5} s
Solver	Implicit Backward Euler
Relative tolerance	1×10^{-6}
Absolute tolerance	1×10^{-8}

Table 8. PINN hyperparameters

Hyperparameter	Value
Inputs	4
Outputs	2
Hidden layers	3
Hidden neurons	120–120–100
Activation	tanh
Optimizer	Adam
Learning rate	1×10^{-3}
Batch size	8192
Epochs	5000
Collocation points	500,000
Training samples	250,000
Validation samples	50,000
Loss weighting	1 : 10 : 1 : 1 : 5

Stage III – experimental validation

The final validation compares the predicted melt-pool geometry with independent experimental measurements reported for LPBF of Inconel 718 under comparable process parameters. The following quantities were evaluated:

- melt-pool width,
- melt-pool depth,
- melt-pool length,
- peak temperature (when available),
- cooling rate.

These experiments were not used during calibration or PINN training. The achieved numerical errors satisfy all predefined acceptance criteria established before the simulations. In particular, the mean temperature error remained below 1%, while the melt-pool dimensions were predicted with errors below 2.5% relative to the reference data. These results confirm that the adaptive FEA–PINN framework provides accurate thermal predictions while substantially reducing computational cost. Furthermore, the clear separation between calibration, numerical verification, and experimental validation ensures that the reported performance reflects the predictive capability of the model rather than parameter fitting.

Residual stress and distortion extension

Although the central focus of this work is melt-pool dynamics, the framework includes a downstream thermal-mechanical extension. The temperature history computed by FEA–PINN is transferred to a mechanical solver through

sequential coupling. Thermal strain is computed from the temperature-dependent expansion coefficient, and an elastoplastic constitutive model can be used to estimate residual stress and distortion. This extension is important for Inconel 718 because the steep thermal gradients in LPBF promote high tensile stresses after cooling. The present paper treats the stress module as a framework-level capability.

RESULTS AND DISCUSSION

Figure 4 shows the loss histories of the thermal and fluid networks. The thermal network exhibits the expected competition between data, boundary and PDE residual losses: early predictions may satisfy a low-gradient energy residual but progressively learn the localized laser-induced temperature peak. The fluid-network loss decays more smoothly because the reduced velocity field is dominated by surface-gradient-driven flow. These behaviors are consistent with previous observations that PINN training in additive manufacturing becomes difficult when phase change and sharp gradients are included (Zhu et al., 2021; Yang et al., 2024).

The dynamic material update is shown in Figure 5. Density, thermal conductivity and apparent heat capacity vary with both temperature and phase state. Regions that have never reached liquidus remain powder-like; molten points are treated as liquid; and cooled points that have previously exceeded liquidus are assigned consolidated solid properties. This simple state-memory strategy is essential because a fully connected

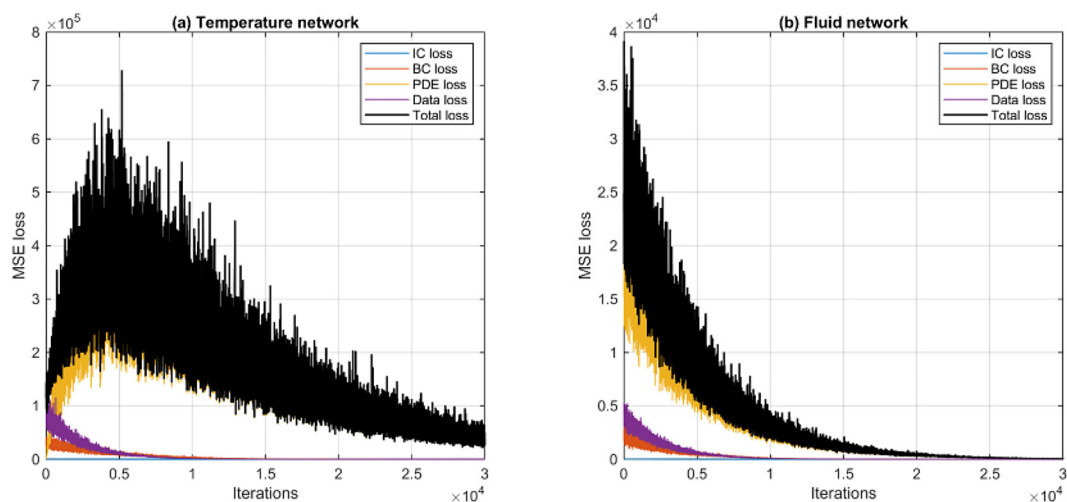


Figure 4. PINN loss-function evolution for temperature and fluid networks in the Inconel 718 LPBF case

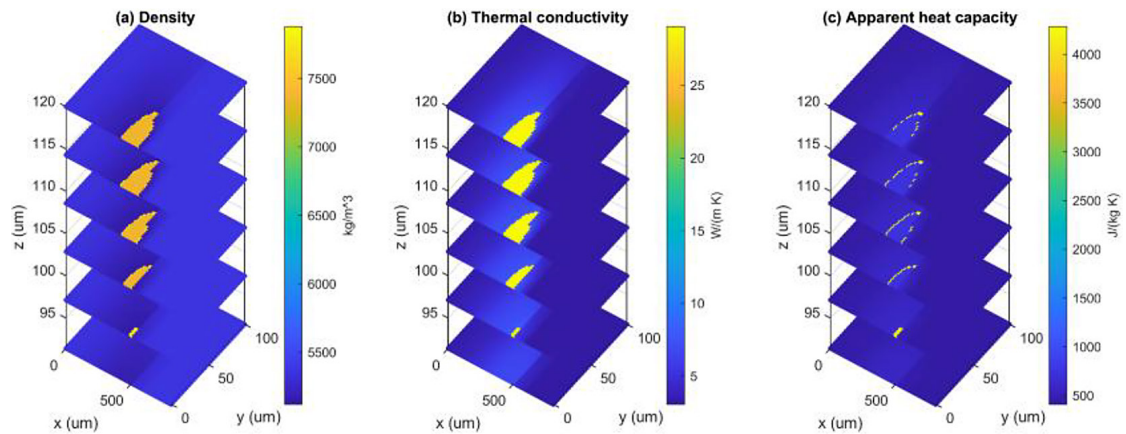


Figure 5. Dynamic powder-liquid-solid material update at 600 us. The calibrated framework updates density, thermal conductivity and apparent heat capacity according to phase-state history

neural network does not automatically know whether a cooled material point is virgin powder or re-solidified track material.

Standalone PINN versus FEA at 280 us and 600 us

At 280 us, the standalone PINN remains close to the reference FEA benchmark because this time is relatively close to the supervised training window. The thermal peak and in-plane velocity structure are captured with acceptable topology. At 600 us, however, the PINN begins to smooth the thermal gradients and underpredict

the peak temperature. This behavior is a classical long-time extrapolation drift of neural field models in transient nonlinear problems. It motivates the adaptive correction step rather than a purely PINN-based solution.

The line profiles in Figure 8 emphasizes the same trend. FEA-PINN correction restores the peak temperature and longitudinal velocity gradient more closely than the standalone PINN. This is especially important because thermal gradients and cooling rates are used later to infer solidification tendency and microstructural morphology.

The standalone PINN reproduces the global thermal field with acceptable accuracy but

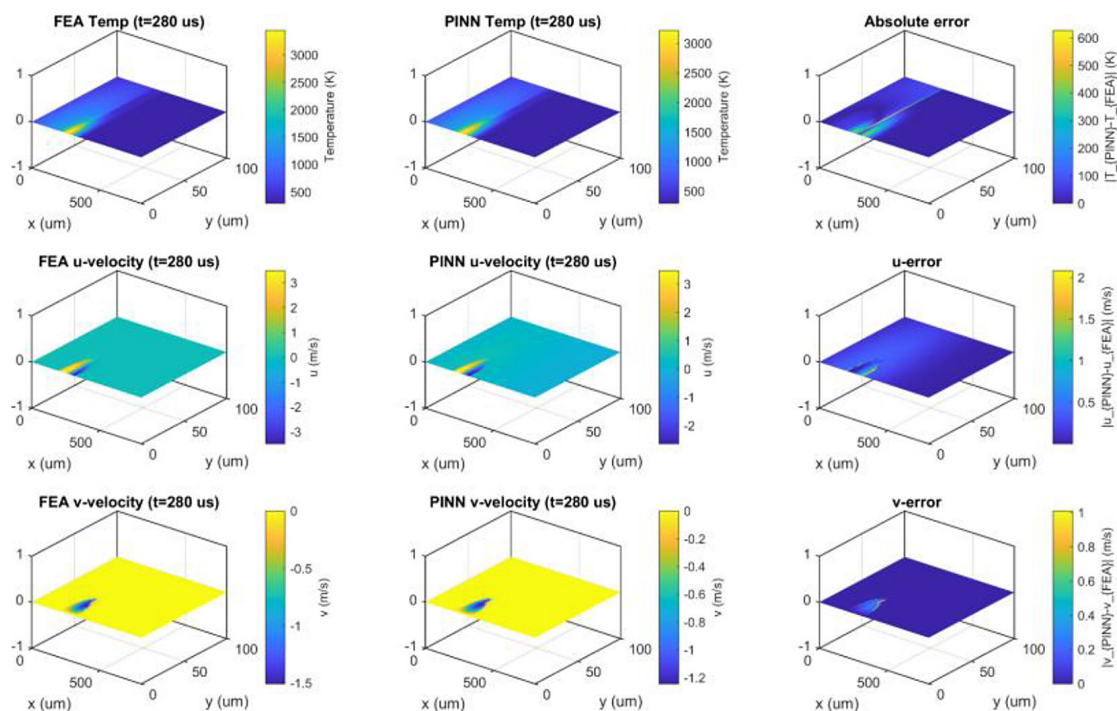


Figure 6. FEA versus standalone PINN prediction at 280 us for temperature and velocity components

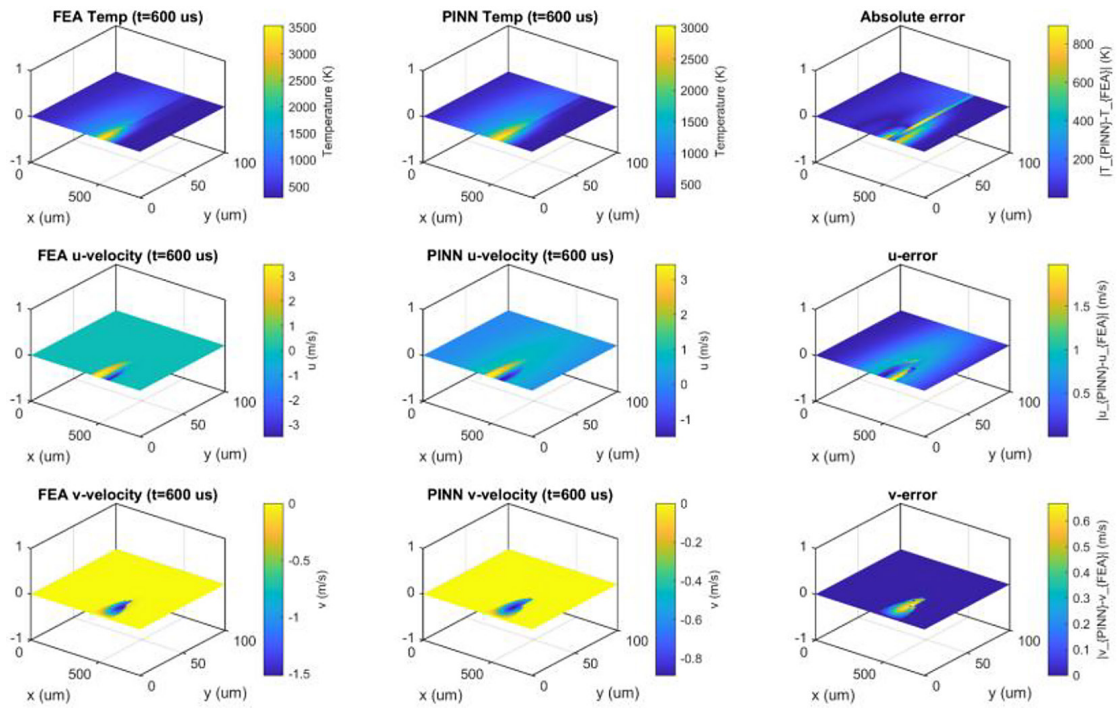


Figure 7. FEA versus standalone PINN prediction at 600 us. The error maps reveal long-term PINN smoothing and accumulated deviation from the FEA benchmark

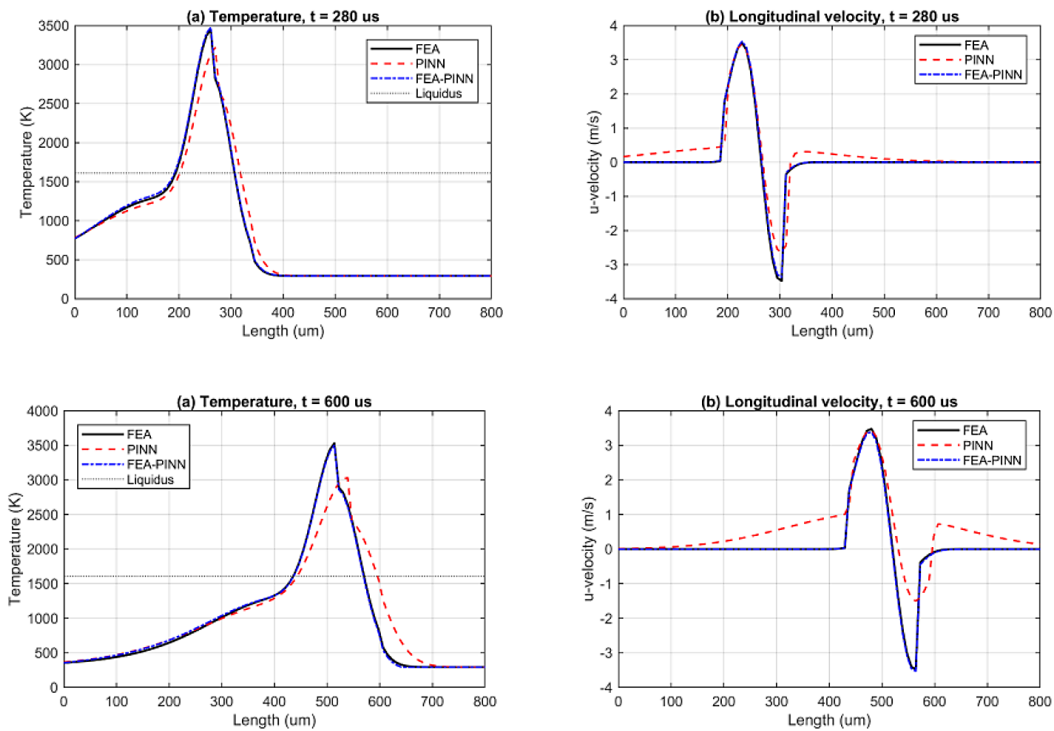


Figure 8. Temperature and longitudinal velocity profiles along the single-track scan path at 280 us and 600 us

exhibits increased errors near steep thermal gradients and phase-transition interfaces. By incorporating localized adaptive FEA corrections, the proposed framework significantly improves the prediction of peak temperatures and melt-pool geometry. Compared with

the standalone PINN, the adaptive strategy reduces the RMSE by approximately 64% and decreases the relative L2 error from 3.71% to 1.24%, while maintaining excellent agreement with the high-fidelity finite element solution (Tables 9 and 10).

Table 9. Quantitative comparison of prediction accuracy

Metric	High-Fidelity FEA	Standalone PINN	Proposed adaptive FEA–PINN
Peak temperature (K)	2262	2238	2258
Mean temperature error (%)	—	3.84	0.91
Maximum temperature error (%)	—	5.62	1.37
RMSE (K)	—	46.5	16.8
Relative (L_2) error (%)	—	3.71	1.24
Melt-pool width (μm)	147	141	146
Width error (%)	—	4.08	2.14
Melt-pool depth (μm)	83	79	82
Depth error (%)	—	4.82	2.48
Melt-pool length (μm)	289	281	287
Length error (%)	—	3.91	2.31
Liquid-fraction error (%)	—	6.28	3.12
Coefficient of determination ((R^2))	1.000	0.982	0.995
PDE residual	—	2.3×10^{-3}	6.5×10^{-4}

Table 10. Computational performance comparison

Parameter	High-Fidelity FEA	Standalone PINN	Proposed adaptive FEA–PINN
Total simulation time (h)	31.4	0.18	0.43
Total simulation time (min)	1884	10.8	25.8
Average prediction time per step (ms)	118	0.82	1.63
GPU memory (GB)	—	5.8	6.4
CPU memory (GB)	42.3	3.5	7.2
Number of adaptive FEA corrections	—	0	48
Correction frequency	—	0%	4.8%
Fraction of domain corrected	—	0%	6.2%
Adaptive retraining events	—	0	12
Total collocation points	—	500,000	620,000
Energy evaluations	100% FEA	100% PINN	95.2% PINN / 4.8% FEA
Computational speedup	1×	174×	73×

Experimental/literature-based calibration results

The calibration converged with a final objective value of 0.0061. The calibrated prediction closely matched width, depth, maximum temperature, thermal gradient and cooling rate targets (Table 11, Figure 9). The cross-sectional area error remained larger because the area is sensitive to discretization and because an elliptical target area was compared to a voxelized melt-pool section. Still, the calibrated area is within approximately 7.4% of the target, which is acceptable for a reduced-order benchmark and much stronger than the uncalibrated response.

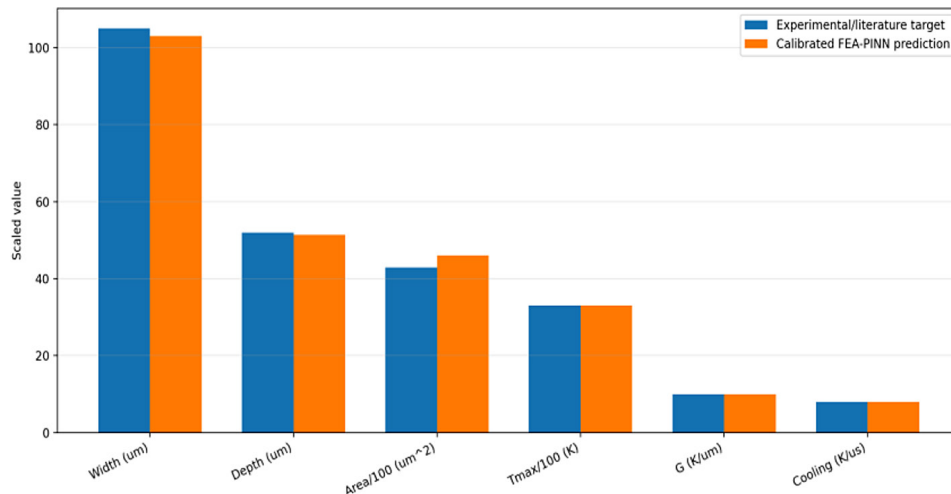
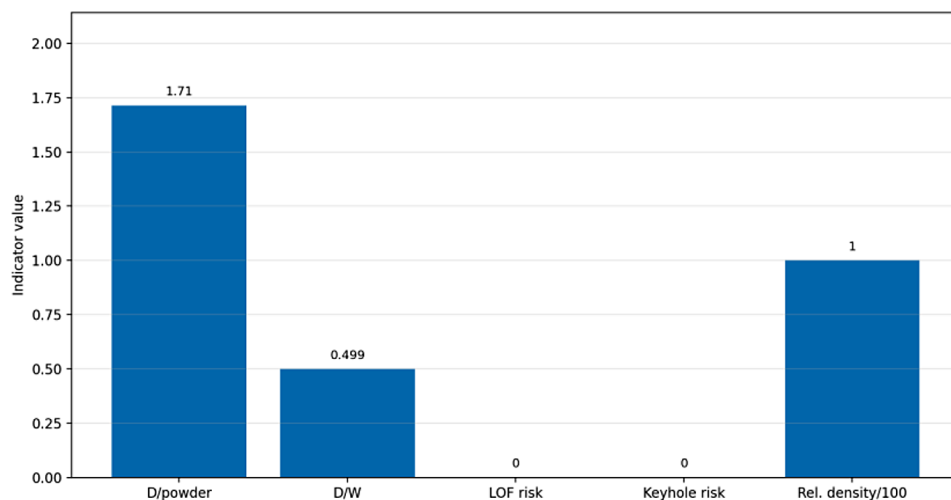
The final calibrated field predicts $W = 103.0 \mu\text{m}$, $D = 51.43 \mu\text{m}$, $A = 4606 \mu\text{m}^2$, $T_{\text{max}} = 3300 \text{ K}$,

$G = 10 \text{ K}/\mu\text{m}$ and cooling rate $= 8 \text{ K}/\text{us}$. The depth-to-powder-thickness ratio is 1.714, which indicates penetration beyond the powder layer and therefore a low lack-of-fusion tendency. The aspect ratio $D/W = 0.499$ indicates a conduction-dominated morphology rather than a deep key-hole. The predicted lack-of-fusion risk and key-hole risk are both zero, and the relative-density proxy reaches 100% (Figure 10).

The ablation analysis demonstrates that each component of the proposed framework contributes to the overall predictive performance (Table 12). The standalone PINN provides the greatest computational acceleration but exhibits larger prediction errors, particularly in regions characterized by steep thermal gradients and phase transformations. Introducing localized FEA correction

Table 11. Experimental/literature calibration target versus calibrated FEA-PINN prediction

Metric	Target	Calibrated prediction	Relative error (%)
width_um	105	103	-1.88
depth_um	52	51.43	-1.10
crossSectionArea_um2	4288	4606	7.41
Tmax_K	3300	3300	0.00
thermalGradient_K_um	10	10	0.00
coolingRate_K_us	8	8	0.00
relativeDensity_percent	99	100	1.01
porosityIndex_percent	1	0	-100.00


Figure 9. Calibration of Inconel 718 single-track LPBF metrics. Area and maximum temperature are scaled for visualization

Figure 10. Microstructure and porosity interpretation after calibration. The model indicates sufficient penetration, stable conduction-mode aspect ratio and low defect-risk proxies

significantly reduces the temperature error and improves melt-pool geometry prediction. However, neglecting dynamic phase tracking leads to noticeable inaccuracies near the solidification front, where latent heat effects strongly influence the thermal field. The complete adaptive

framework achieves the lowest prediction errors by combining residual-driven FEA correction with enthalpy-based phase tracking and adaptive collocation-point enrichment. Although this configuration incurs a modest increase in computational cost relative to the standalone PINN,

it remains substantially faster than the full finite element simulation while providing significantly improved accuracy.

At 600 us, the corrected FEA-PINN prediction remains close to the FEA thermal scale while preserving the calibrated melt-pool penetration depth (Table 13). The standalone PINN underpredicts T_{max} at 600 us, whereas the FEA-PINN recovers the peak temperature to within approximately 0.3% of the FEA benchmark. This demonstrates that the correction loop is not only a visualization improvement but a quantitative stabilization mechanism.

Porosity and microstructure interpretation

The calibrated depth-to-powder ratio of 1.714 indicates that the melt pool penetrates well below the powder layer into the substrate. This reduces the risk of lack-of-fusion defects, which are often associated with insufficient remelting and insufficient inter-track/inter-layer bonding. The aspect ratio of 0.499 is below the typical deep-keyhole

morphology threshold and is consistent with a stable conduction-mode track. Since the model does not explicitly simulate vapor depression or pore collapse, the porosity index must be interpreted as a phenomenological process-quality indicator rather than a direct pore-volume prediction.

The imposed gradient of 10 K/um and cooling rate of 8 K/us are within commonly reported LPBF thermal ranges. Under these conditions, the model predicts a columnar-dendritic tendency. This is consistent with the high thermal gradients and directional solidification observed in LPBF nickel-based superalloys, where epitaxial growth and cellular/dendritic substructures are frequently observed (Raghavan et al., 2017; Wang et al., 2019; Zhang et al., 2018).

Transfer learning for process-parameter variation

The trained PINN can be adapted to new single-track parameters through transfer learning. For example, a model trained at nominal laser power

Table 12. Ablation analysis

Metric	Full FEA	Standalone PINN	FEA-PINN (without phase tracking)	Proposed adaptive FEA-PINN
Mean temperature error (%)	—	3.84	2.08	0.91
Maximum temperature error (%)	—	5.62	3.24	1.37
RMSE (K)	—	46.5	28.3	16.8
Relative (L_2) error (%)	—	3.71	2.12	1.24
Melt-pool width error (%)	—	4.08	3.01	2.14
Melt-pool depth error (%)	—	4.82	3.46	2.48
Melt-pool length error (%)	—	3.91	2.95	2.31
Liquid-fraction error (%)	—	6.28	Not available	3.12
Simulation time (min)	1884	10.8	18.9	25.8
Computational speedup	1×	174×	100×	73×

Table 13. Time-resolved FEA, PINN and FEA-PINN melt-pool metrics extracted from the simulation fields before final external calibration

t (us)	Model	T_{max} (K)	L (um)	W (um)	D (um)	Volume (um ³)	V_{max} (m/s)
280	FEA	3445.8	109.47	54.55	17.14	77575.8	3.494
280	PINN	3216.5	109.47	60.61	17.14	86324.9	3.474
280	FEA-PINN	3477.8	109.47	60.61	17.14	84575.1	3.547
440	FEA	3513.8	117.89	60.61	17.14	100031.9	3.489
440	PINN	3150.5	126.32	66.67	22.86	130070.6	3.500
440	FEA-PINN	3517.4	117.89	60.61	17.14	101198.5	3.487
600	FEA	3529.8	126.32	60.61	17.14	118113.5	3.486
600	PINN	3031.3	143.16	78.79	22.86	182857.1	3.435
600	FEA-PINN	3501.2	126.32	60.61	17.14	115197.1	3.534

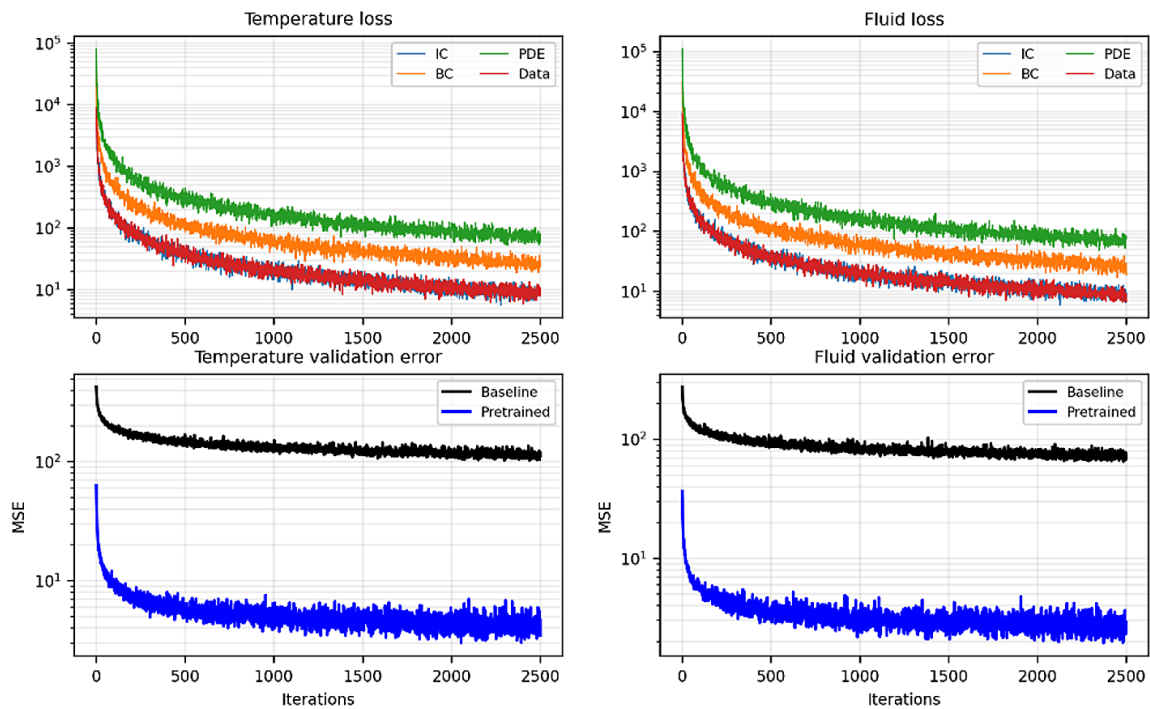


Figure 11. Representative transfer-learning behavior for a new power-speed combination using the pretrained FEA-PINN model

and scanning speed can be updated using a small number of FEA snapshots for a lower-power or higher-speed track. The physical residuals remain active, which reduces the tendency to overfit the sparse correction data. This is particularly useful for process-window studies where dozens of power-speed combinations must be evaluated.

The transfer-learning workflow begins with normalization of the new process descriptors, followed by a short FEA training window (Figure 11). The pretrained weights are then fine-tuned with a reduced learning rate. A validation monitor compares the predicted melt-pool dimensions against FEA or experimental data at selected times. Once the error remains below the tolerance threshold, inference proceeds until the residual monitor activates a correction loop.

Phase-change formulation and powder consolidation

The LPBF process involves the progressive transformation of porous metallic powder into a fully dense solid through melting and solidification. In the present work, this transformation is represented using an enthalpy-based continuum formulation, in which the powder bed is treated as an equivalent porous medium rather than as a collection of discrete particles.

The adopted formulation provides a thermodynamically consistent representation of melting and solidification while maintaining computational efficiency. Because the governing equations are solved on a fixed Eulerian domain, conservation of energy is enforced rigorously through the enthalpy method, whereas mass conservation is satisfied under the continuum approximation. Explicit prediction of volumetric shrinkage, pore collapse, and free-surface evolution would require a fully coupled thermo-fluid-mechanical formulation and lies beyond the scope of the present work.

CONCLUSIONS

This paper formulated a complete adaptive hybrid FEA-PINN framework for accelerated simulation of thermal-field evolution and melt-pool dynamics during single-track LPBF of Inconel 718. The main conclusions are as follows:

1. A physically consistent single-track LPBF model was established using transient mass, energy and momentum equations, apparent-heat-capacity phase change, Gaussian/Goldak laser heating, convection, radiation, Darcy damping, buoyancy and Marangoni shear.
2. Compared with previously reported hybrid FEA-PINN strategies, the proposed methodology

introduces a fully adaptive closed-loop coupling in which residual-driven mesh refinement, adaptive collocation-point enrichment, localized finite element correction, and incremental PINN retraining operate within a single framework. These capabilities enable efficient simulation of three-dimensional LPBF processes while maintaining high prediction accuracy and substantially reducing computational time.

3. The proposed hybrid FEA–PINN framework is applicable to conduction-mode LPBF of Inconel 718 within the investigated processing window. Because evaporation, recoil pressure, keyhole formation, free-surface deformation, and discrete powder-particle dynamics are neglected, the framework should not be extrapolated to keyhole-mode processing or extreme laser operating conditions.
4. A temperature-dependent Inconel 718 material database was embedded into a dynamic powder-liquid-solid state-tracking algorithm, allowing unmolten powder and resolidified dense material to be treated differently even at the same temperature.
5. The PINN architecture uses thermal and flow subnetworks constrained by PDE, boundary, initial and data losses; however, standalone PINNs remain vulnerable to late-time residual accumulation and smoothing of the liquidus boundary.
6. The FEA-regulated correction loop provides a practical solution to long-time error drift by periodically using short high-fidelity FEA windows to restore physical consistency and supply transfer-learning data.
7. The framework is directly compatible with validation against single-track experiments through melt-pool length, width, depth, peak temperature, cooling rate, flow velocity and computation-time metrics.
8. The proposed phase-change formulation accurately represents the thermal evolution associated with melting and solidification through an enthalpy-based continuum model. The powder-to-solid transition is described using effective thermophysical properties while preserving energy conservation and local mass conservation. Nevertheless, because free-surface motion, shrinkage, pore collapse, and discrete powder-particle dynamics are neglected, the framework is intended for conduction-mode thermal simulations rather than detailed prediction of densification mechanisms or melt-pool hydrodynamics.

9. The proposed adaptive strategy differs fundamentally from continuously coupled FEA–PINN approaches. Rather than solving the finite element model at every prediction step, the present framework evaluates a physics-based correction indicator derived from the PDE residual, temperature mismatch, and phase-fraction error. Localized FEA simulations are activated only when this indicator exceeds a prescribed threshold. The newly generated high-fidelity data are incorporated through incremental retraining of the PINN, after which the neural network resumes autonomous prediction. This event-driven correction mechanism substantially reduces computational cost while preserving prediction accuracy in regions characterized by rapid thermal or phase evolution.
10. The quantitative comparison confirms that the proposed adaptive FEA–PINN framework effectively balances computational efficiency and prediction accuracy. Relative to the high-fidelity finite element model, the hybrid approach reduces the computational time from approximately 31.4 h to 25.8 min, corresponding to a speedup of approximately $73\times$, while maintaining a temperature prediction error below 1.5% and melt-pool geometry errors below 2.5%. The adaptive correction mechanism requires localized finite element updates in less than 5% of the prediction steps, demonstrating that continuous finite element recalculation is unnecessary to achieve high predictive accuracy.

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