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Review of physics-informed machine learning in laser metal additive manufacturing: a process-lifecycle perspective on prediction, monitoring, and post-process evaluation

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ABSTRACT

Laser powder bed fusion (L-PBF) and laser directed energy deposition (L-DED) are widely applied across industries owing to their high geometric freedom and manufacturing precision. However, porosity and residual stress can arise from complex interactions among process parameters, degrading the mechanical performance and reliability of manufactured parts. This makes accurate prediction, monitoring, and quality assessment essential. Conventional analytical methods rely on simplified assumptions that limit their ability to capture complex, coupled physical phenomena, while data-driven approaches remain data-dependent and lack interpretability. Physics-informed machine learning (PIML), which integrates physical laws with data-driven learning, has recently attracted considerable interest as a means of overcoming these challenges. This review investigates PIML utilisation strategies across the process lifecycle of L-PBF and L-DED. First, the relationships between process parameters and the formation mechanisms of porosity and residual stress are analysed. PIML approaches applied in the pre-, in-, and post-process stages are then comparatively reviewed. Finally, current challenges and future research directions are discussed in terms of prediction accuracy, computational efficiency, generalisation capability, and industrial applicability. This provides an integrated perspective on PIML's application in next-generation intelligent laser metal additive manufacturing (LAM).

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Laser powder bed fusion; laser directed energy deposition; physics-informed machine learning; defect prediction; In situ monitoring

1. Introduction

Metal powder-based laser additive manufacturing (LAM) has been widely adopted in the aerospace, defense, and energy industries owing to its ability to yield high-performance components with complex geometries and high design flexibility [1–5]. Among various LAM technologies, laser powder bed fusion (L-PBF) and laser directed energy deposition (L-DED) are the two most widely used [6]. In particular, L-PBF selectively irradiates thin layers of metallic powder using a high-power laser, enabling localised melting and solidification in a layer-by-layer manner [7,8]. This process is distinguished by its ability to produce intricate and highly detailed geometries with superior dimensional accuracy [9,10]. In contrast, L-DED simultaneously delivers metallic powder and laser energy to generate a melt pool for material deposition, thereby offering a flexible processing route and high deposition rates [11]. These characteristics make L-DED particularly suitable for fabricating large-scale structures, as well as repairing and

remanufacturing existing components [12,13]. Owing to differences in material delivery mechanisms and processing principles, L-PBF and L-DED exhibit distinct characteristics in terms of geometric complexity, process flexibility, material utilisation efficiency, and manufacturing cost. Therefore, they are employed according to specific application requirements. Despite these advantages, both processes are susceptible to various defects resulting from complex multi-physics interactions during fabrication.

During the L-PBF and L-DED processes, multiple coupled physical phenomena, including heat transfer, melt-pool fluid dynamics, phase transformation, and thermo-mechanical behaviour, occur simultaneously as a result of laser-powder interactions [14–17]. These phenomena are influenced by process parameters such as laser power, scanning speed, and powder feed rate [18–21]; inadequate process control can result in various defects. Representative defects include porosity [22,23], residual stress-induced cracking [24,25], and microstructural inhomogeneity [26]. Porosity is primarily

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associated with keyhole collapse, lack of fusion (LOF), and gas entrapment mechanisms, all of which depend on the thermal behaviour and complex fluid-flow characteristics of the melt pool [27–31]. In contrast, residual stresses originate from thermal gradients and phase transformations occurring during the fabrication process [32–35]. These defects can significantly deteriorate the mechanical performance, structural integrity, and service life of additively manufactured components [36–38]. Therefore, a comprehensive understanding of the underlying multi-physics phenomena, together with the precise control of process parameters, is essential to ensuring part quality and process reliability. This has increased the demand for in situ monitoring and defect prediction technologies for real-time process assessment and control.

Various analytical and data-driven approaches have been proposed to achieve precise defect prediction and process control in L-PBF and L-DED. Traditionally, thermal, mechanical, and fluid-flow phenomena during the fabrication process have been analysed using numerical methods such as finite element method (FEM) [39–41] and computational fluid dynamics (CFD) [42–44]. Although these approaches provide insights into the underlying process physics, their predictive capabilities are often limited by simplified assumptions when modelling highly complex multi-physics interactions [45,46]. Furthermore, their computational cost makes real-time implementation of process monitoring and control challenging [47]. To address these limitations, scholars have increasingly adopted machine learning (ML)-based data-driven approaches [48]. By learning complex relationships from large volumes of experimental and process data, ML models can rapidly predict defects and manufacturing outcomes [49,50]. However, their performance depends on the availability and quality of training data [51,52], and their black-box

nature often limits their physical interpretability and generalizability beyond the training domain [53]. To bridge the gap between physics-based and data-driven methodologies, physics-informed machine learning (PIML) has emerged as a promising framework that combines physical knowledge and data-driven learning [54]. Therefore, it offers improved prediction performance while maintaining physical consistency and interpretability. Consequently, PIML has become an attractive approach to intelligent process monitoring, defect prediction, and adaptive process control in L-PBF and L-DED [55,56].

Previous reviews have mainly focused on ML-based in situ process monitoring [57] or process optimisation strategies [58], with limited discussion of practical strategies for implementing PIML. Notably, Shenghan Guo et al. [59] reviewed the state of the art in metal LAM process modelling and control, examining the potential applications of PIML through case studies. Meysam Faegh et al. [60] introduced PIML approaches for Process-Structure-Property (P-S-P) modelling in LAM and classified related studies based on how physical knowledge is incorporated into machine learning models. Additional PIML-based review studies on LAM processes are summarised in Table 1. However, these existing reviews focus primarily on the classification of PIML methodologies and their application cases, without addressing how PIML is utilised at each stage of the process or what is required at each stage. In other words, while these reviews provide detailed methodological classifications, they fall short of examining the characteristics, performance requirements, and practical applicability of these methodologies across the different phases of the overall process lifecycle. Furthermore, PIML utilisation strategies should be tailored to the distinct process mechanisms of L-PBF and L-DED at each stage of the process lifecycle.

Table 1. Comparative summary of PIML review studies in L-PBF and L-DED.

Year, Ref	LAM Process	Contribution	Research Gap	Control method
2023, [61]	L-PBF / L-DED	Classifies ML-based LAM research by data type, modelling strategy, and physics integration from a process–structure–property perspective	Does not address detailed PIML subcategories or process-specific implementation	ML
2025, [62]	L-PBF / L-DED	Classifies PIML frameworks methodologically and presents PINN (physics-informed neural network)-based prediction, optimisation, and defect control	Treats L-PBF and L-DED together, without distinguishing how their mechanistic differences affect PIML design	PIML
2025, [63]	L-PBF / L-DED	Compares microstructure formation via experimental, physics-based, and data-driven approaches; proposes multiscale PIML directions	Limited to microstructure; does not link to quality defects (porosity, residual stress) or the process lifecycle	Numerical modelling / ML / PIML
2026, [64]	L-PBF / L-DED	Classifies PIML applications across manufacturing by governing physical phenomena; presents process-specific challenges	Broad in scope but lacks depth on L-PBF/L-DED defect mechanisms or stage-wise performance requirements	PINN
This review	L-PBF / L-DED	Identifies porosity/residual stress formation mechanisms at the process-parameter level; compares how L-PBF/L-DED differences shape PIML design; re-evaluates accuracy, cost, generalizability, and validation across process stages	Addresses gaps in prior PIML reviews: process-specific breakdown, L-PBF/L-DED distinction, defect–lifecycle integration, and in-depth single-process analysis are all missing.	PIML

To address this gap, this review aims to discuss how PIML techniques can be applied throughout the entire process lifecycle of L-PBF and L-DED, along with the key characteristics of PIML that should be considered at each stage. First, the process parameters and physical mechanisms underlying the formation of porosity and residual stress, which are the major defects occurring during the process, are identified, and based on this, the key physical knowledge relevant to these defects is analysed. The necessity of adopting PIML is then derived by reviewing the advantages and limitations of simulation-based and pure machine learning techniques conventionally used in LAM. Next, PIML methodologies are classified into three types based on how physical knowledge is integrated: Physics-based Feature Engineering, Physics-based Simulation-assisted Machine Learning, and Physics-constrained Learning. Subsequently, studies applying PIML at each stage of the L-PBF and L-DED process lifecycles are reviewed. Differences in PIML utilisation strategies arising from the distinct mechanisms of the two processes, together with the practical applicability and research limitations at each stage, are then discussed in detail. Finally, the limitations of PIML revealed through this discussion are summarised, and future research directions are proposed based on the identified research gaps. Ultimately, this paper aims to present an integrated understanding of defect formation mechanisms in the L-PBF and L-DED processes together with the corresponding PIML

research trends, thereby highlighting the potential for this approach to be extended toward intelligent quality control across the entire process lifecycle. An overview of this paper is presented in [Figure 1](#).

The remainder of this paper is organised as follows. Section 2 discusses the formation mechanisms of key defects in L-PBF and L-DED, focusing on porosity and residual stress. Section 3 compares the characteristics, advantages, and limitations of analysis-based, data-driven, and PIML-based models. Section 4 reviews PIML-based defect control strategies across the entire process lifecycle, including prediction, real-time monitoring, and quality evaluation. Section 5 discusses the main limitations and challenges of PIML-based approaches. Section 6 presents the future directions and prospects of PIML-enabled technologies in LAM, including L-PBF and L-DED processes. Finally, Section 7 summarises the key findings of this review and presents concluding remarks.

2. Defect formation mechanisms

2.1. Porosity

Porosity is one of the most representative internal defects in both L-PBF and L-DED. It induces localised stress concentration, promotes crack initiation and propagation, and consequently degrades the mechanical properties, including fatigue life [65–69] and

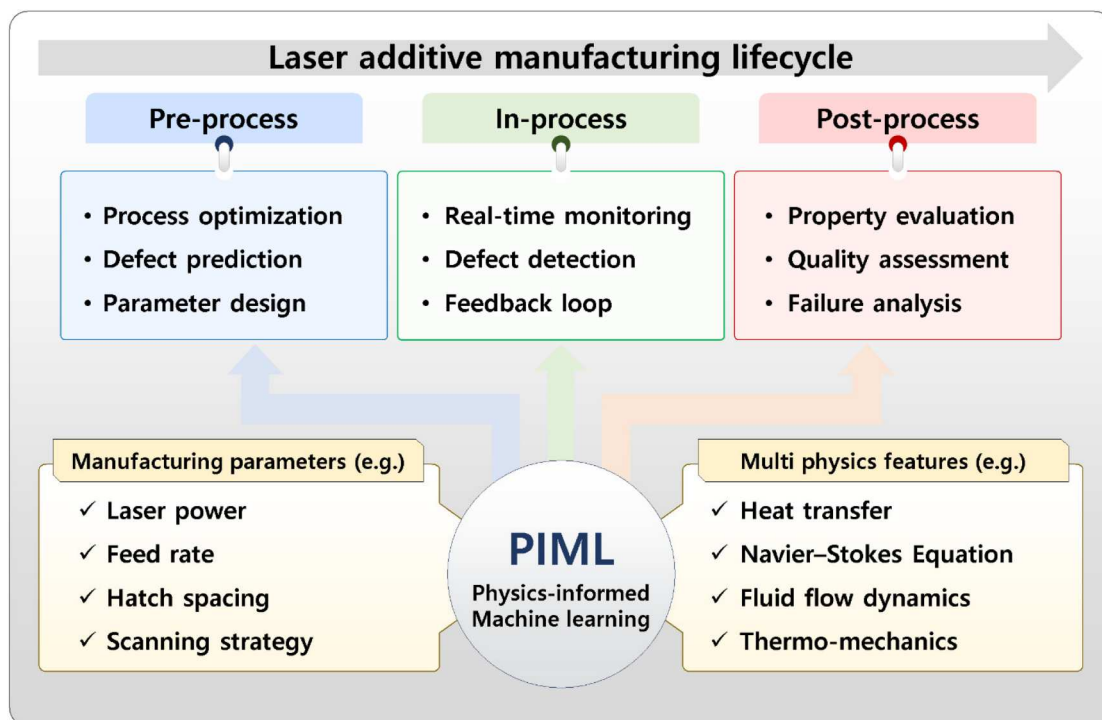


Figure 1. Schematic overview of this review.

strength [70,71]. Therefore, understanding and effectively controlling pore-formation mechanisms are essential to ensure component reliability. In this section, the pore-formation mechanisms observed in L-PBF and L-DED, as well as the effects of the major process parameters, are analysed.

2.1.1. L-PBF

The pores generated in L-PBF can be classified into keyhole-induced pores, gas pores originating from feed-stock materials and the surrounding environment, and LOF pores. In particular, keyhole-induced porosity is closely associated with metal vaporisation and keyhole instability under process conditions involving high energy input or low scanning speeds [72–75]. Huang et al. [76] categorised keyhole stability into three regimes based on a refined enthalpy factor ($\Delta H / h_m \cdot L_{th}$), which incorporates the melting enthalpy and thermal diffusivity of the material, as illustrated in Figure 2(a). When $\Delta H / h_m \cdot L_{th} < \sim 10$, the keyhole remains in a quasi-stable state with a wide and shallow morphology, resulting in negligible pore formation. In contrast, when $\Delta H / h_m \cdot L_{th} = 10 \sim 20$, the keyhole becomes unstable, and pores are primarily generated by localised collapse at the rear wall. Furthermore, when $\Delta H / h_m \cdot L_{th} > \sim 20$, the keyhole develops into a narrow and deep high-aspect-ratio structure. In this regime, capillary instability near the bottom region induces localised keyhole collapse, trapping metal vapour inside the melt pool and ultimately leaving pores. These results demonstrate that the stability and collapse behaviour of the keyhole depend on the laser energy input conditions, thereby determining the occurrence and location of pore formation. In addition, Bayat et al. [77] reported that increasing laser power intensifies the temperature gradient within the melt pool, resulting in surface-tension

variations and altering the dynamic force equilibrium inside the molten region. Consequently, when the force balance within the melt pool is locally disrupted, keyhole-wall instability increases, resulting in the collapse and subsequent entrapment of metal vapour, which ultimately forms pores, as shown in Figure 2(b). Through numerical simulations, they further verified that a strong vortical flow inside the melt pool can either trap pores at the solidification front or transport them toward the free surface. Accordingly, the keyhole-induced pore formation mechanism in L-PBF is influenced by the energy input and scanning speed, and can be summarised in four stages: (1) keyhole formation, (2) keyhole growth and destabilisation, (3) keyhole collapse and pore generation, and (4) pore migration and entrapment.

(1) Keyhole formation: A Gaussian laser heat source heats the metal powder locally and forms a melt pool. Under high-energy input conditions, metal vaporisation generates recoil pressure within the melt pool, which drives the molten metal downward beneath the free surface and initiates keyhole formation [78–80].

(2) Keyhole growth and destabilisation: The initially formed keyhole evolves into a deep and narrow structure owing to the continuous metal vaporisation and recoil pressure. During this process, interactions between thermal accumulation and melt-pool flow can induce an asymmetric keyhole morphology and instability [81,82].

(3) Keyhole collapse and pore generation: Keyhole stability is governed by complex interactions among recoil pressure, surface tension, and Marangoni flow within the melt pool. However, when the balance among these forces is locally disrupted, unstable behaviours such as necking or protrusion may occur along the keyhole wall, eventually causing the keyhole to

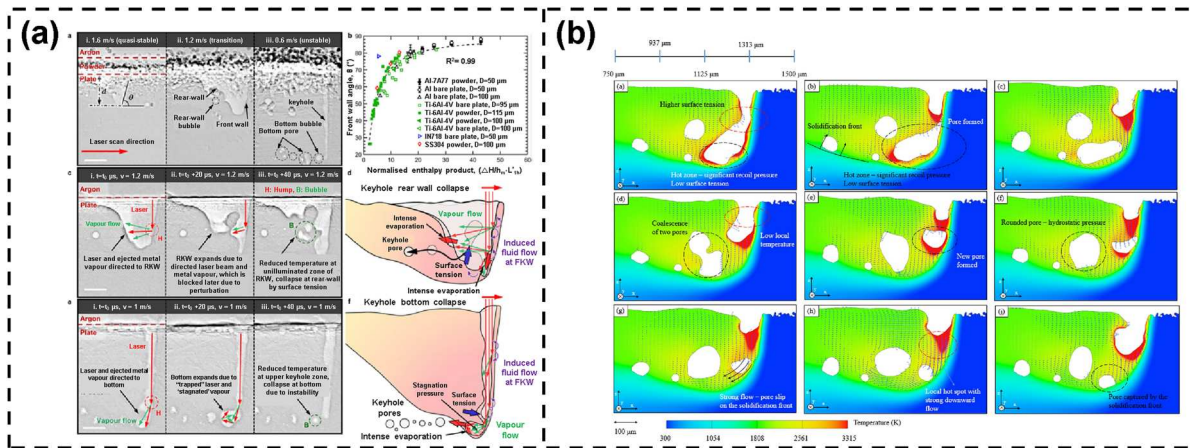


Figure 2. Mechanism of keyhole collapse-induced porosity formation in L-PBF: (a) Keyhole instability evolution and associated pore formation mechanisms [76]. (b) Thermo-fluid dynamics during keyhole pore formation [77].

collapse. As the keyhole partially closes, metal vapour and gas are trapped in the molten region, resulting in pore formation within the melt pool [79,81].

(4) Pore migration and entrapment: The generated pores migrate and deform under complex flow behaviours within the melt pool. Marangoni flow drives the surface flow from the front to the rear of the melt pool, accompanied by internal recirculating vortices that influence pore migration and entrapment. Some pores may dissolve during remelting, whereas those trapped at the solidification interface remain as final pore defects [77].

In L-PBF, both gas and LOF porosities are major defect types. LOF pores are primarily generated when sufficient melting is not achieved because of process conditions such as low laser power, high scanning speed [83], and excessive hatch spacing [84]. The formation of this defect is affected by heat accumulation and surface morphology [85]. Compared with gas pores, these defects typically exhibit larger pore sizes and irregular morphologies [75]. Yang et al. [86] classified LOF porosity into three categories according to the formation location and process conditions. First, single-track LOF occurs within an individual melt track due to a nonuniform energy input or localised insufficient melting. Second, multi-layer LOF is generated when adequate bonding with the previous layer is not achieved because of increased layer thickness or insufficient remelting, resulting in the accumulation of interlayer voids. Third, multi-track LOF forms when adjacent tracks overlap insufficiently owing to excessive hatch spacing, resulting in continuous voids between neighbouring tracks. In addition to these LOF categories, several studies have further classified fusion-related defects based on their formation characteristics. Rezaei-far et al. [87] analysed the lack of penetration (LOP) independently of LOF and defined it as a defect that forms when the melt pool does not sufficiently penetrate the previously solidified layer or neighbouring tracks. LOP results from inadequate melt-pool penetration and insufficient inter-track bonding, with rapid solidification and high melt-pool viscosity contributing to pore formation. Moreover, the formation of LOP and keyhole porosity was observed to depend on the combination of laser power and scanning speed. These findings indicate the importance of process parameters, as well as the associated melt-pool size and temperature, in determining defect formation behaviour.

In summary, the process parameters in L-PBF, such as laser power, scanning speed, and hatch spacing, affect the melt-pool size, morphology, and thermal behaviour. Variations in these melt-pool characteristics are closely linked to the formation of defects, including LOF and

keyhole porosity. Figure 3 illustrates the relationships between the process parameters and porosity formation in L-PBF. Accordingly, a comprehensive understanding of melt-pool behaviour is essential to elucidating defect-formation mechanisms and establishing effective strategies for process-parameter optimisation and defect mitigation.

2.1.2. L-DED

The L-DED process is characterised by defect structures such as LOF, gas entrapment originating from residual gas trapped within powder particles or shielding gas, and keyhole instability [89,90]. However, since L-DED operates in the molten state rather than under evaporation-dominated conditions, porosity in this process arises predominantly from LOF and gas entrapment rather than from keyhole formation [91,92]. LOF is a discontinuity defect that arises from insufficient melting between adjacent deposition beads or at the substrate–deposit interface, resulting in incomplete metallurgical bonding. For example, Luiz Eduardo dos Santos Paes et al. [93] investigated the effectiveness of remelting strategies in reducing LOF defects in iron AHC 100.29 (99.88% purity) and Inconel 625 deposits. In the absence of a remelting process, LOF defects were predominantly observed, resulting in relatively high porosity levels of 5.3–7.1%. Furthermore, in the iron specimens, LOF defects were found both between adjacent beads and at the substrate–deposit interface, whereas in Inconel 625, they were observed only at the substrate–deposit interface (Figure 4). These findings indicate that although the manifestation of LOF varies with material properties, its underlying cause is consistently attributable to insufficient melting. The resulting pores act as stress concentration sites, accelerating crack initiation and premature failure.

LOF is generally attributed to insufficient energy input arising from an inappropriate combination of laser power and scanning speed. However, it should not be regarded as an isolated defect governed solely by the applied energy density. Such defects are also closely associated with complex multi-physical interactions within the melt pool dynamics [94–96]. Accordingly, recent studies have focused not only on optimising energy input but also on directly monitoring and controlling melt pool conditions to effectively suppress porosity defects. For instance, I. Jeon et al. [97] employed an infrared camera and a line scanner to measure melt pool depth (MPD) in real time and maintained a constant MPD through a proportional–integral–derivative (PID) control system. Compared with conventional control strategies based on energy density or melt pool width, MPD-based control achieved

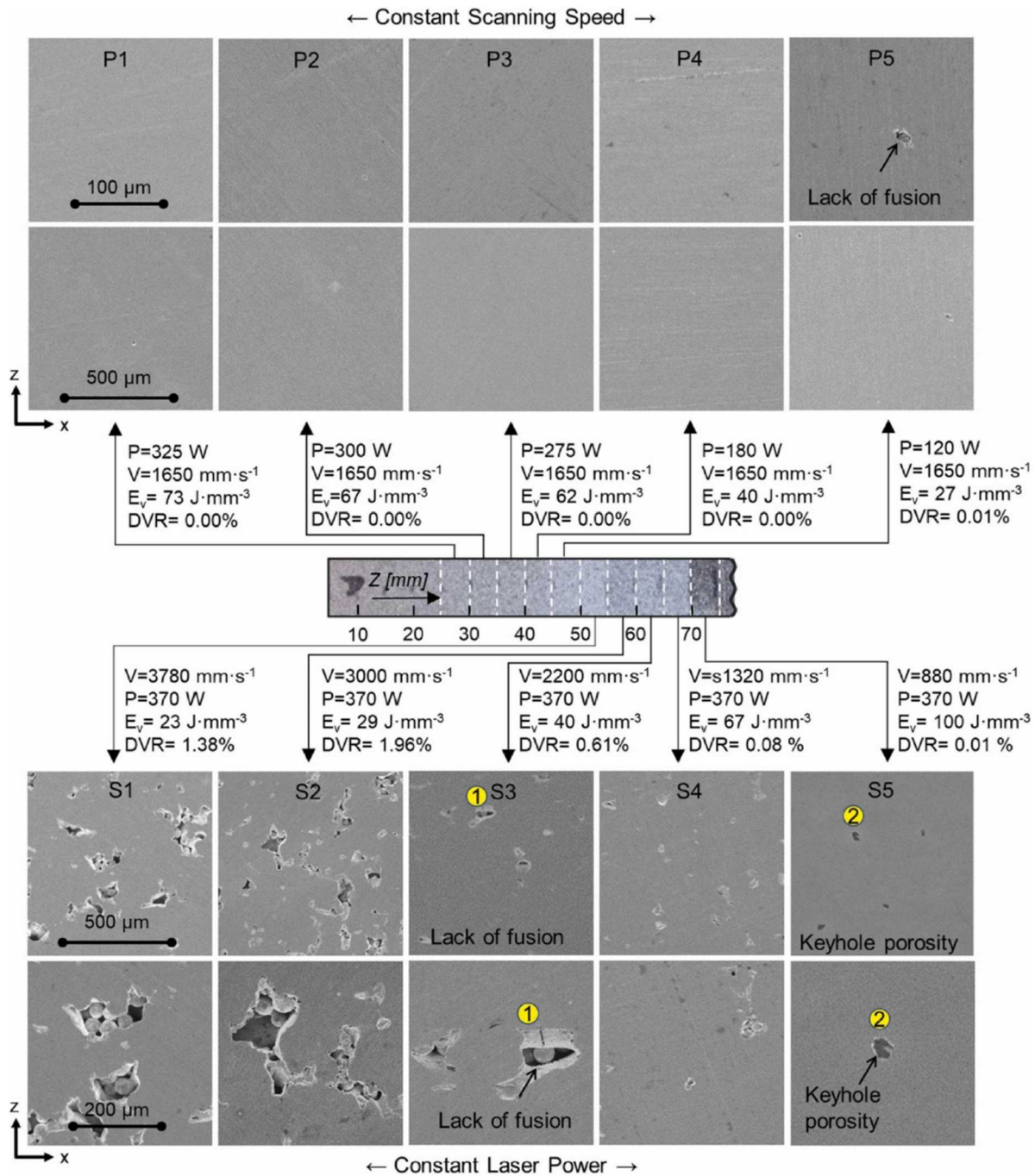


Figure 3. Relationship between process parameters and porosity-formation mechanisms in L-PBF. Insufficient energy input from a low laser power or excessively high scanning speed leads to LOF porosity, whereas excessive energy input associated with low scanning speed promotes keyhole pore formation [88].

the lowest porosity level, at 0.0082%. In addition, LOF defects and gas entrapment arising from unstable scanning conditions were simultaneously reduced. These results demonstrate that melt pool conditions play a critical role not only in LOF formation but also in pore evolution, underscoring that precise control of melt pool behaviour is essential for minimising porosity in the L-DED process.

Unlike LOF, gas porosity primarily originates from residual gas trapped within powder particles or from shielding gas. Once formed, however, the migration, growth, and eventual entrapment of gas pores are largely governed by melt pool flow behaviour. In L-DED, the mechanisms underlying pore evolution have been extensively investigated through studies of melt pool fluid flow. For example, Zhang et al. [98] analysed

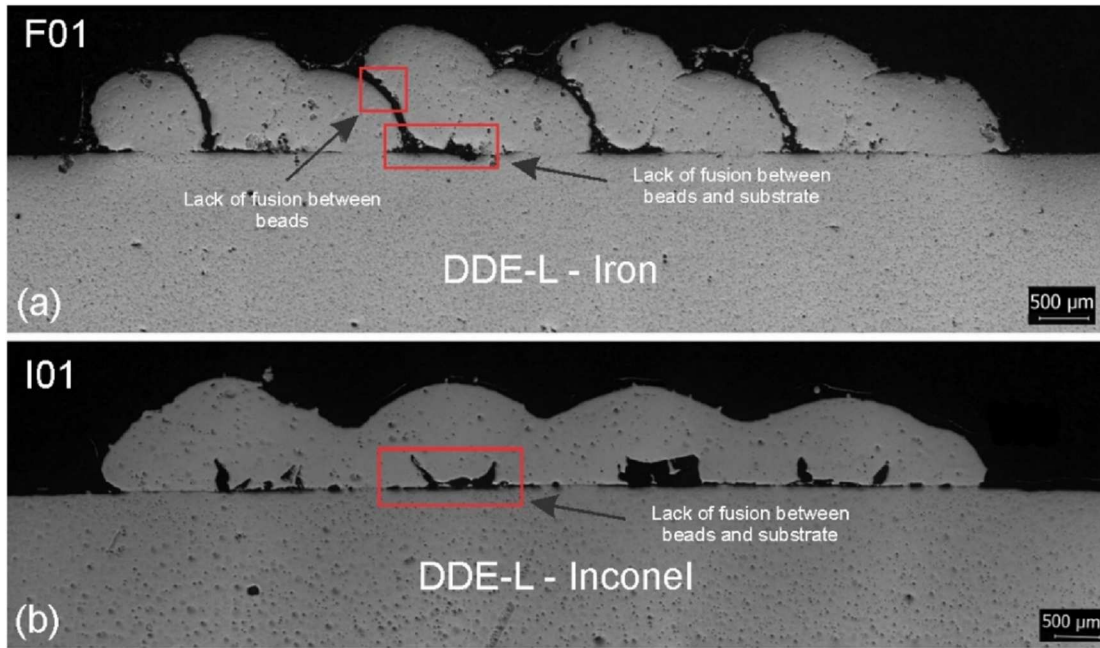


Figure 4. Iron and Inconel samples after L-DED deposition at a laser power of 450 W, scanning speed of 600 mm/min, and powder feed rate of 10 g/min, showing porosity analysis [93].

the generation, migration, and growth of pores originating from gas-atomized RR1000 nickel-based superalloy powder and shielding gas during the L-DED process, proposing a five-stage mechanism of pore formation and evolution, as shown in Figure 5(a). In the first stage, argon bubbles trapped within gas-atomized powder particles during atomisation are released into

the melt pool as the particles melt, generating initial gas pores. These small pores subsequently circulate along Marangoni flow within the melt pool, gradually growing through repeated collision and coalescence. During interactions with the solidification interface, smaller pores tend to be trapped within the solidified region, whereas larger pores are pushed ahead of the

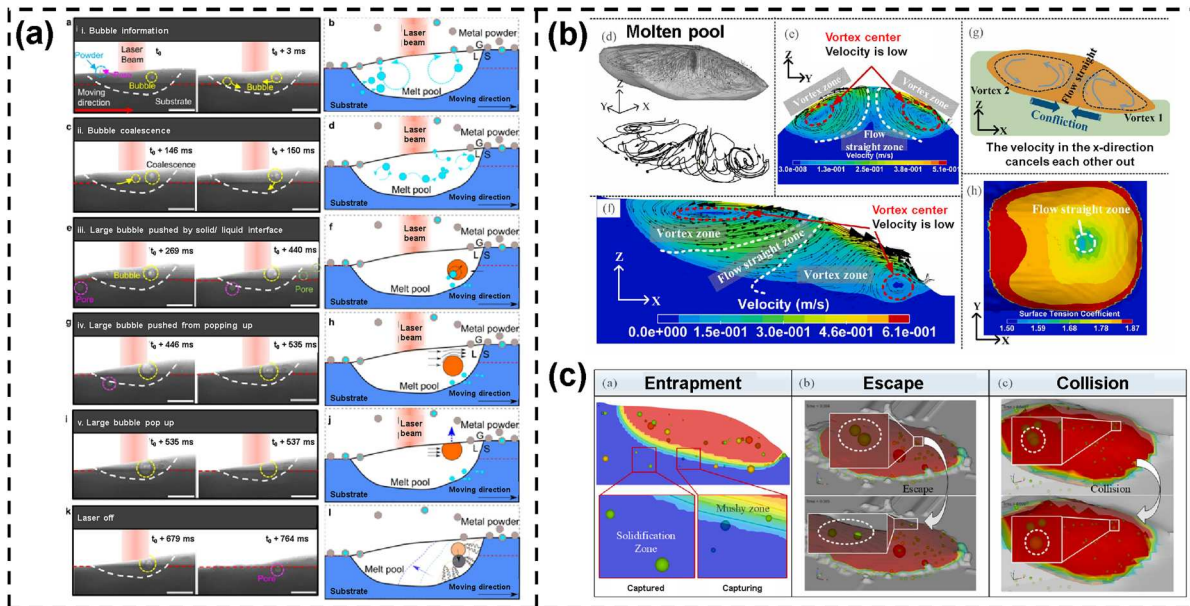


Figure 5. Pore formation, transport, and evolution mechanisms in the L-DED process. (a) Five-stage pore formation and evolution mechanism [98], (b) pore transport behaviour in straight and vortical flow regions, and (c) flow-driven pore entrapment, escape, and collision [99].

solidification front. When the pore size exceeds a critical threshold, buoyancy becomes dominant, causing the pores to rise toward the melt-pool surface and eventually escape from the molten region.

In addition, Chen et al. [99] investigated the behaviour of small pores in L-DED by distinguishing the melt-pool flow into straight-flow and vortical regions. Pores located in the straight-flow region are transported out of the melt pool along the flow direction. In contrast, pores trapped within vortical regions follow spiral trajectories induced by the circulating flow and remain inside the melt pool, as shown in Figure 5(b). In particular, the vortical flow at the front and rear regions of the melt-pool transports pores toward the solidification interface, promoting pore entrapment within the solidified material. In some scenarios, the small pores in the rear region merge with larger ones and continue to grow. Consequently, the pores exhibit distinct behaviours in terms of entrapment, escape, and collision, depending on the melt-pool flow, as shown in Figure 5(c). Therefore, the complex melt-pool flow behaviour in L-DED is closely related to process conditions, such as the laser energy density, powder feed rate, and powder material properties, and directly influences pore generation, migration, and entrapment behaviour [100].

Previous studies have primarily focused on the effects of laser power and scanning speed on porosity formation mechanisms in L-DED. Recent studies, however, have revealed that melt pool behaviour is also influenced by process factors such as laser scanning strategy and bead overlap conditions, in addition to energy input. For example, Alessia Teresa Silvestri et al. [101] investigated the effects of laser power, scanning speed, overlap ratio, and scanning strategy in the L-DED process of H13 tool steel. At low overlap ratios, LOF defects predominantly formed due to insufficient melting between adjacent beads. Conversely, excessive overlap led to repeated remelting of the same region, increasing shielding gas entrapment, and consequently promoting the formation of gas pores and larger pores. In addition, different scanning strategies, such as zig and zigzag patterns, altered heat accumulation and cooling behaviour, resulting in differences in melt pool stability and defect formation. These findings indicate that laser scanning path and bead overlap conditions are also critical process variables, as they alter the thermal history and internal fluid flow of the melt pool.

In summary, porosity formation and evolution in the L-DED process cannot be explained by a single process variable. Energy input factors such as laser power, scanning speed, energy density, and powder feed rate, together with laser scanning strategy, bead overlap

conditions, powder characteristics, and shielding gas conditions, collectively determine the thermodynamic and fluid-dynamic characteristics of the melt pool. These characteristics, in turn, directly affect pore nucleation, growth, migration, entrapment, and LOF defect formation. This demonstrates that although L-PBF and L-DED differ in their underlying pore formation mechanisms and governing factors, they share a common feature in that the thermal and fluid-dynamic behaviour of the melt pool, as determined by process conditions, ultimately governs porosity formation. Accordingly, accurate prediction and monitoring of melt pool behaviour are essential for effectively mitigating porosity defects.

2.2. Residual stress

L-PBF and L-DED processes induce residual stress within the fabricated part due to repeated localised high-energy heat input and rapid cooling. Since residual stress is a major cause of critical defects in the final product, such as cracking [102,103], distortion [104,105], and degradation of fatigue properties [106], it is essential to analyse and understand its formation mechanisms in depth.

It is widely accepted that residual stress generation in both processes is primarily attributed to three distinct mechanisms (Figure 6). The first is the Temperature Gradient Mechanism (TGM). At the instant of laser irradiation, the locally and rapidly heated region attempts to thermally expand but is constrained by the relatively cold surrounding material, causing it to undergo compressive plastic deformation. The second is the cool down mechanism. After the laser has passed, the molten region shrinks upon solidification, and this shrinkage is constrained by the already solidified underlying material, remaining as tensile residual stress. The two mechanisms are temporally distinguished in that they operate during the heating stage and the cooling stage, respectively. The third is the volumetric change associated with solid state phase transformation during cooling [109,110]. This mechanism has a metallurgical origin distinct from the preceding two mechanisms. The contribution of solid-state phase transformation varies considerably depending on the alloy system. It is negligible in materials that maintain a stable single phase throughout the cooling range, such as austenitic stainless steels or nickel-based alloys, whereas in steels undergoing martensitic transformation, its contribution can be large enough to even reverse the sign of the stress.

However, these three mechanisms do not account for the entirety of residual stress, as additional contributors

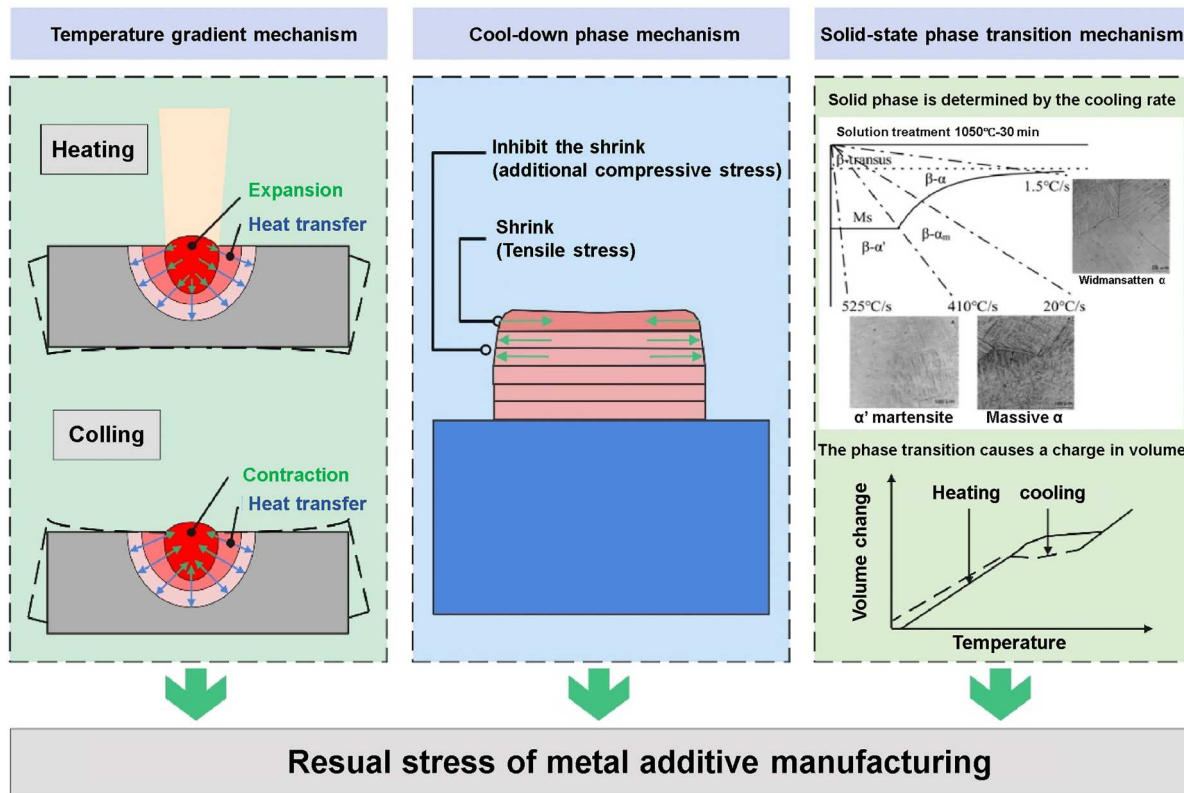


Figure 6. Mechanisms of residual stress formation in LAM [106].

such as convection within the melt pool and localised stress relaxation induced by porosity also play a role. These origins are not fully captured by temperature field or melt pool geometry alone, so accurate temperature prediction does not necessarily translate into accurate residual stress prediction.

The residual stress within a part is classified into three types according to characteristic length scale [106–108]. Type I (macroscale) stress arises from deformation incompatibility across the overall geometry of a component and has been regarded as the most important type in LAM because it is directly associated with critical defects such as cracking, delamination, and reduced fatigue strength [109]. Type II (mesoscale) stress arises from microstructural heterogeneities, such as differences in crystallographic orientation, elastic modulus, and coefficient of thermal expansion between grains. When phase transformation proceeds non-uniformly between grains, local stresses can develop and persist due to differences in transformation strain. Type III (microscale) stress refers to localised deformation caused by lattice defects such as dislocations, vacancies, and precipitates. Among these three types, Type I stress is generally regarded as the most critical in LAM because of its direct association with macroscopic deformation and failure, while Type II stress is also important due to

its close relationship with deformation induced by phase transformation and microstructural heterogeneity. L-PBF and L-DED share the common feature that residual stresses develop as a result of their thermal and mechanical behaviour and microstructural evolution. However, the two processes differ in terms of the interaction between the heat source and material, melt-pool size, heat input and cooling behaviour, and repeated thermal history, and these process-level differences influence the mechanisms of residual stress formation as well as their final magnitude and distribution. Therefore, the following sections examine the major mechanisms of residual stress formation in L-PBF and L-DED according to their respective process characteristics and discuss the differences between the two processes.

2.2.1. L-PBF

L-PBF fabricates a part layer by layer by selectively irradiating a thin metal powder layer with a laser, thereby repeating localised melting and solidification (Figure 7(a)). L-PBF applies a thin layer, 20–60 μm in thickness, of fine spherical powder on the order of 10–60 μm [110,111]. This powder is melted with a very small beam spot on the order of 40–100 μm . A relatively low power on the order of 0.1–1.0 kW is irradiated at a

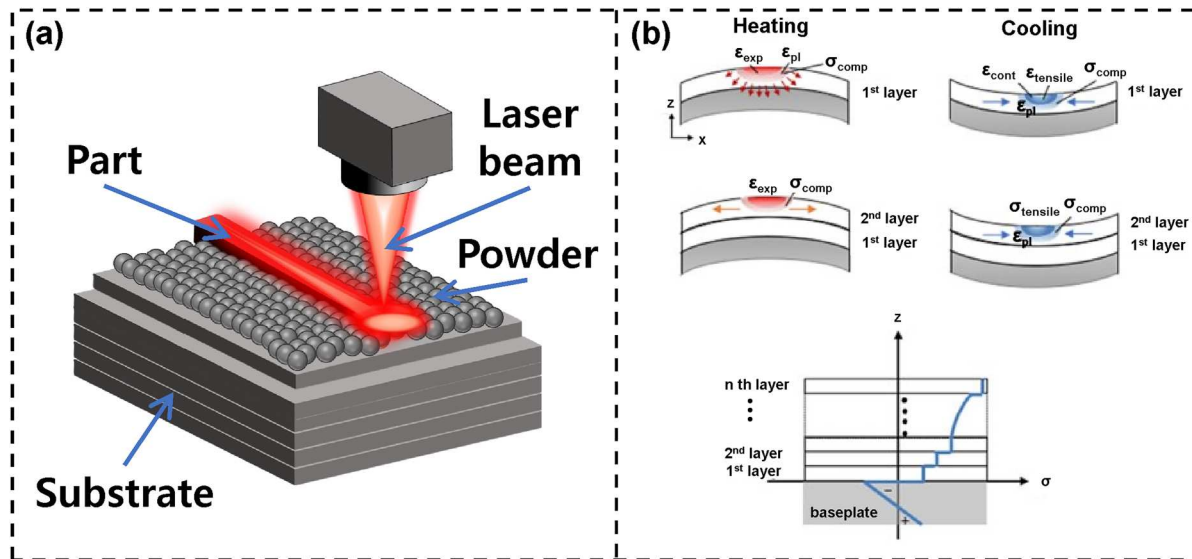


Figure 7. Schematic diagram of (a) L-PBF, (b) Residual stress evolution during heating and cooling [116].

very high scan speed reaching 200–1500 mm/s [112]. Because this process configuration means the laser interacts with only a small, selected amount of powder for a short duration, it produces a rapid cooling rate reported in the literature to be on the order of 10^4 – 10^6 K/s [113,114]. However, this cooling rate can vary depending on the mode in which the melt pool forms. In the keyhole-mode melt pool formed under high energy density conditions, the keyhole zone dissipates heat mainly through the substrate, resulting in a cooling rate of approximately 10^7 K/s. The upper part of the melt pool, in contrast, loses heat only through the powder layer and the surrounding atmosphere, resulting in a cooling rate of only about 10^4 K/s [115]. Due to this process characteristic, during laser irradiation the molten region attempts to expand rapidly thermally, but this expansion is constrained by the cooler underlying deposited material and the adjacent solidified region. As a result, compressive stress develops in the heated region, while tensile stress develops in the surrounding and underlying regions (Figure 7(b)). Conversely, after the laser has passed, the molten region solidifies and shrinks, but this shrinkage is likewise constrained by the solidified layer beneath it, leaving tensile residual stress in the upper region and compressive stress in the lower region. This repeated cycle of constrained expansion and contraction, together with the accompanying accumulation of plastic deformation, is the key mechanism underlying the formation of thermo-mechanically-induced residual stress in L-PBF.

The magnitude and distribution of the residual stress arising from this thermomechanical effect are sensitive to process parameters such as layer thickness, laser

power, scan strategy, and scan speed [117–123]. Among these, scan pattern is a key factor determining the directionality and spatial distribution of residual stress, because the laser repeatedly follows a prescribed path within the thin powder layer. Serrano-Munoz et al. [120] compared, for an IN718 alloy, a Y-scan strategy that maintains the scan vector along the Y-axis with a Rot-scan strategy that rotates the scan vector by 67° between successive layers. In the in-plane direction, the Y-scan specimen exhibited residual stress along the Y-axis more than 200 MPa higher than that of the Rot-scan specimen. The Rot-scan specimen, in contrast, instead showed higher stress in the Z direction. In addition, learning-based toolpath optimisation has also been attempted. Huang et al. [124] applied a DQN-based graph toolpath planner to L-PBF 316L, reducing the maximum thermal distortion on a Femur model by 24.9% and 24.3% compared with zigzag and chessboard toolpaths, respectively. This demonstrated that toolpath design itself can serve as an active means of reducing residual stress and distortion.

Meanwhile, the rapid cooling arising from the process characteristics described above also directly affects the phase transformation behaviour that can influence residual stress formation, one example being alloy systems undergoing martensitic transformation [125,126]. This phase transformation may not proceed uniformly throughout the part. In a study fabricating AISI 420 martensitic stainless steel by L-PBF, the short high-temperature dwell time caused by the rapid cooling rate resulted in retained austenite of approximately 21% in the upper layers and up to 57% in the interior layers. This was confirmed through direct

measurement that the extent of phase transformation varies considerably by location even within the same part [127]. This location-dependent variation arises because the cooling rate differs depending on the layer position. Unlike the upper layers, the interior layers are repeatedly reheated with the deposition of each subsequent layer, which alters the local cooling rate itself, so that even when stress relief due to phase transformation occurs, its effect may remain confined to that local region. A study on L-PBF of high-speed steel explains that the combination of the martensite start temperature and repeated thermal cycling in this manner is the primary cause of residual stress, and that the complex thermal boundary conditions unique to L-PBF and the interaction between multiple layers further reinforce this constraint formation [128].

This phase transformation is likewise sensitive to process parameters, particularly laser power. An et al. [129] showed that laser power plays a key role not only in the macroscopic thermal field but also in the microstructural stress-relief mechanism arising from phase transformation. The final stress in martensitic transformation depends on the martensite start temperature (M_s) and the constraint conditions of the surrounding matrix. In the L-PBF process of a 17-4PH alloy, it was shown that when martensitic transformation occurs at low temperatures of approximately 118.4°C and 169.5°C due to the rapid cooling rate, the accompanying volumetric expansion can offset the tensile residual stress arising from thermal contraction. Therefore, residual stress in L-PBF should be understood as a

compound outcome in which the two origins, thermo-mechanical deformation, and phase transformation, respond simultaneously to a single process parameter.

2.2.2. L-DED

L-DED involves depositing material through a process in which metal powder ejected through a nozzle is fed directly into the melt pool formed by the laser, where it melts and solidifies (Figure 8(a)). Residual stress in L-DED likewise originates from two sources: thermomechanical deformation caused by localised laser heat input [34,130,131], and volumetric change accompanying solidification and phase transformation [132–135]. When a new layer is deposited, the high temperature gradient near the melt pool first constrains thermal expansion by the surrounding material, forming compressive stress, which is subsequently replaced by tensile stress as the melt pool material shrinks during cooling, so the underlying principle is the same as in L-PBF. Directly beneath the heat source, compressive stress develops at the centre of the temperature peak, with tensile stress on either side; however, moving toward the trailing region where the heat source has passed and cooling has progressed, this compressive stress region disappears, and tensile stress becomes predominant overall (Figure 8(b)).

However, in L-DED, this tensile stress does not simply remain confined to the underlying layer. As the shrinkage of the newly deposited layer is constrained by the previously deposited layers and remains as tensile stress, compressive stress simultaneously accumulates

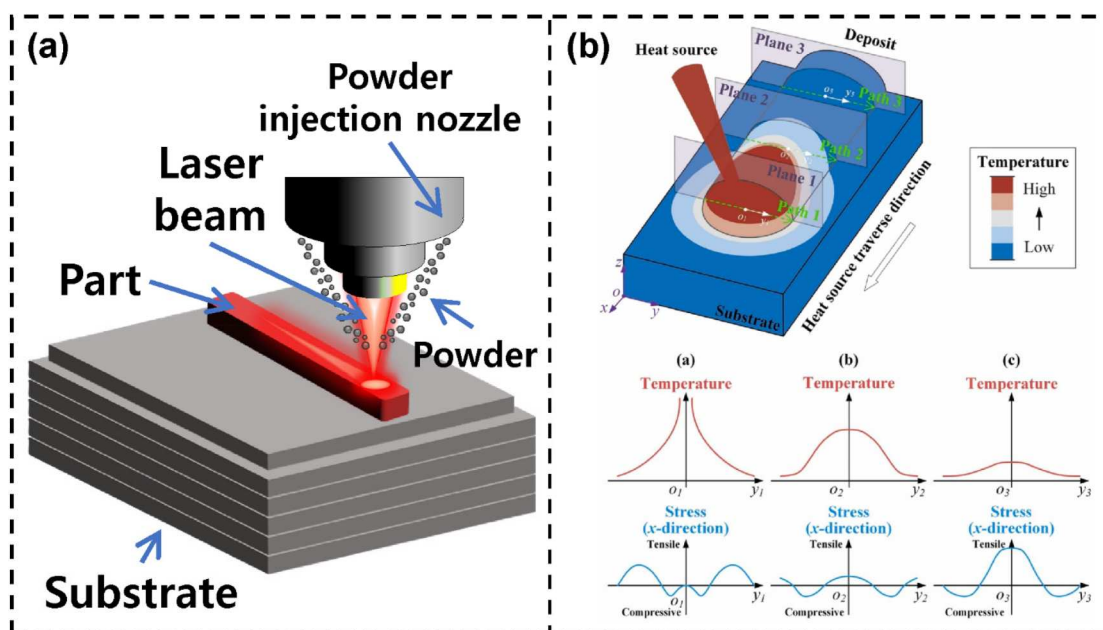


Figure 8. Schematic diagram of (a) L-DED, (b) Temperature and stress distribution of L-DED [136].

as the previously deposited layers are repeatedly remelted and re-solidified by subsequent passes in order to maintain equilibrium [137]. As deposition proceeds and the build height increases, both the thickness of the underlying layers constraining the newly deposited layer and the extent remelted by subsequent passes also increase. As a result, the equilibrium point formed between the tensile stress of the new layer and the compressive stress of the existing layers is not fixed. Instead, it continues to shift depending on the material composition and the extent of deposition progress [138]. It has also been reported that a heat transfer model calculating the superposition of these layer-wise thermal effects and the cyclic accumulation of thermal stress improves the accuracy of temperature, residual stress, and distortion prediction [25].

These differences in mechanism originate from the process parameters themselves adopted in L-DED. The powder used is relatively coarse, on the order of 45–150 μm , and the beam spot size (300–800 μm) and layer thickness (150–400 μm) are also large. As a result, the combination of a large melt pool relative to the deposited volume with high heat input produces a relatively wide heat-affected zone [139,140]. A distinctive characteristic also appears in the combination of laser power and scan speed, with a high power of 0.5–4 kW irradiated at a slow speed of 3–15 mm/s [112]. L-PBF uses a much faster scan speed (200–1500 mm/s), and the parameter differences between the two processes can be summarised as in Figure 9 [141].

These process characteristics of L-DED lead to distinctive heat transfer behaviour. Since the melt pool is in direct contact with the substrate or the previously deposited bead, the conduction path is relatively favourable, but the cooling rate is reported to be only on the order of 10^2 – 10^6 K/s [142]. Because of the large, deep melt pool and slow scan speed, heat is transferred

deeply into the already deposited underlying layers, and the thermal influence of previous layers through remelting and re-solidification also extends over a wide range. Because of this, even an already-formed stress state tends to continue being redistributed or relaxed through the repeated thermal history accompanying subsequent layer deposition. In fact, cases have been reported in which compressive residual stress induced by interlayer peening was completely lost simply through the deposition of subsequent layers, which contrasts with L-PBF, where the effect of reheating is confined to only the topmost few layers and the stress state of the underlying layers remains relatively fixed [143].

Research has generally focused on analysing residual stress caused by process parameters that can directly affect heat input, such as laser power and scan speed. However, the laser scan pattern has also been identified as a process parameter that governs residual stress and distortion. Saboori et al. [144] used hole-drilling measurements to demonstrate that, in L-DED of 316L, the interlayer scan rotation angle (67° vs. 90°) alters the cooling rate and microstructure, which in turn can produce clearly different magnitudes and distributions of residual stress depending on the surface direction of the part. In a study on path-dependent residual stress by Wang et al. [145], it was confirmed that, in high-power L-DED, the island size and the laser jump strategy between islands alter the pattern of layer-wise heat accumulation, thereby significantly affecting residual stress and distortion. That is, not only the rotation angle of the scan vector but also higher-level toolpath design such as island partitioning and jump strategy is meaningfully involved in residual stress formation in L-DED. Interpass dwell time has also been identified as a variable involved in residual stress and multilayer equilibrium, but the direction of its effect varies depending on

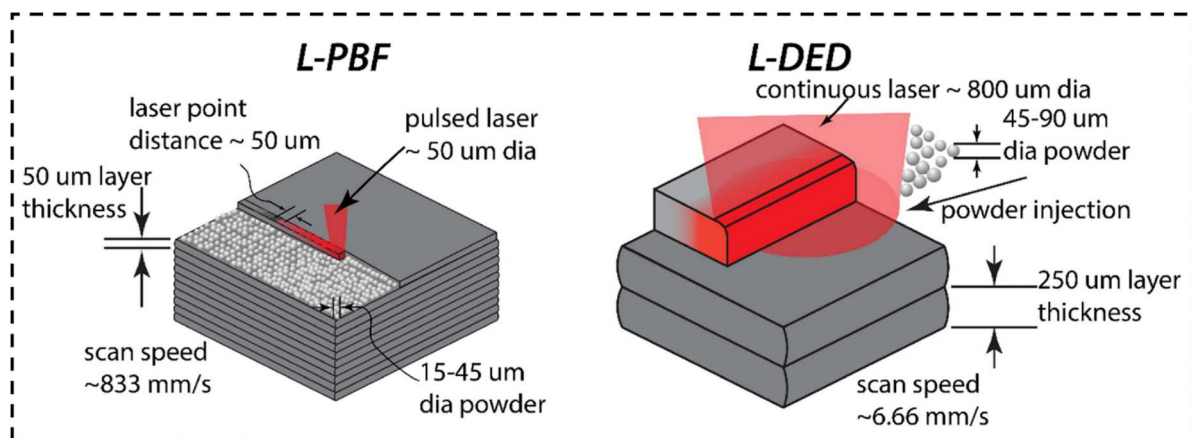


Figure 9. Schematic diagram of the differences in process parameters between L-PBF and L-DED [141].

the alloy system. Denlinger et al. [146] adjusted the inter-pass dwell time in L-DED deposition of Ti-6Al-4V and Inconel 625, and found that, for Ti-6Al-4V, reducing the dwell time decreased residual stress and accumulated distortion by approximately 55%, whereas for Inconel 625, increasing the dwell time instead decreased distortion and residual stress by approximately 23%.

Unlike residual stress arising from thermomechanical deformation, in alloy systems undergoing phase transformation, phase-transformation-induced stress additionally comes into play. In a study depositing 316L (austenitic, fcc) and 17-4PH (martensitic, bcc) by L-DED with varying composition ratios, it was found that as the proportion of the bcc (17-4PH) phase increased, the compressive residual stress within that phase increased, reaching approximately -150 MPa at maximum for the composition of 60 wt% 17-4PH, and that as the 316L content decreased, the stress in the fcc phase also tended to shift toward the compressive side [147]. Chen et al. [148] clad a Ni-Cr-based low transformation temperature (LTT) martensitic alloy with $M_s \approx 150^\circ\text{C}$ onto an S41500 substrate by L-DED and confirmed that compressive residual stress (average -150 MPa, maximum -300 MPa) formed in the clad layer while tensile stress (maximum ~ 400 MPa) formed on the substrate side. This directly demonstrates, in L-DED, that

phase transformation is an independent variable governing the residual stress state separately from cooling shrinkage. Because the effect of phase-transformation-induced stress acts together with these other factors, residual stress is a complex physical phenomenon that is difficult to predict accurately using a single governing equation or a simple heat transfer model alone. Table 2 summarises the key process parameters influencing porosity and residual stress across L-PBF and L-DED studies. As shown, these defects degrade the mechanical performance and reliability of the final part, making accurate prediction and monitoring essential.

3. Modelling of metal LAM

As discussed in Section 2, the defects generated during LAM processes, such as porosity and residual stress, directly affect the mechanical performance and reliability of the final components. Therefore, technologies that can predict and control these defects during processing are important. This section reviews and compares analysis-based approaches, data-driven approaches, and PIML methods for defect prediction and control with a focus on the L-PBF and L-DED processes. Additionally, the characteristics and applicability of each approach are discussed.

Table 2. Summary of studies on defect types and key influencing factors in L-PBF and L-DED.

Ref	LAM Process	Material type	Defect type	Important factors
[149]	L-PBF	Ti-6Al-4V	Porosity	Laser power, scan speed, absorptance
[150]	L-PBF	Ti-6Al-4V	Porosity	Laser power, scan speed, ambient pressure
[151]	L-PBF	SS316L	Porosity	Laser power, scan speed, sulfur/oxygen content
[92]	L-DED	AlMgScZr alloy	Porosity	Powder morphology, powder oxidation, process conditions
[152]	L-PBF	Inconel 718	Residual stress	Laser power, scan speed, hatch spacing, layer thickness, scan pattern
[153]	L-PBF	Inconel 718	Residual stress	Lattice geometry, strut thickness, thermal concentration
[154]	L-PBF	Inconel 718	Residual stress	Laser mode, build direction, hatch spacing, layer thickness, point distance
[155]	L-DED	SS316L	Residual stress	Laser mode, pulse condition, cooling rate
[156]	L-DED	SS316L / IN718	Residual stress	Laser power, scan speed, thermal expansion mismatch
[157]	L-DED	SS316 / IN718	Residual stress	Composition ratio, composition gradient, remelting
[158]	L-DED	AISI M4 / 4C / 8C / AISI 1045	Residual stress	Laser power, powder feed rate, scan velocity, powder gas flow, shielding gas flow

3.1. Analysis-based method

In L-PBF and L-DED processes, analysis-based approaches are used to model and predict physical phenomena such as heat transfer, fluid flow, and phase transformation. These approaches can generally be classified into theoretical analyses based on simplified assumptions and numerical methods, including FEM [156,159] and finite volume methods [160–162]. In particular, numerical-analysis-based approaches have been employed to investigate process mechanisms because they can incorporate complex multi-physics phenomena, including thermo-mechanical coupling, Marangoni flow, solidification, and remelting behaviour [163–166].

For example, Li et al. [167] predicted the deformation and residual stress generated during selective laser melting (SLM) through a multi-scale thermo-mechanical coupled analysis. Their study incorporated multi-physics phenomena such as heat transfer, temperature distribution, and the thermal expansion/shrinkage behaviour of materials. Using a multi-scale approach, they further investigated the effects of microscale thermal behaviour on the macroscopic deformation and residual stress in a twin-cantilever structure.

In addition, Qu et al. [168] performed computational thermo-fluid simulations to investigate the keyhole-pore mitigation mechanism induced by nanoparticle addition in L-PBF. They calculated the multiple reflection and absorption behaviour of the laser energy inside the keyhole based on the Fresnel equations. The keyhole dynamics within the melt pool were analysed by considering the recoil pressure, thermocapillary force, gravity, and buoyancy. Related studies utilising analysis-based approaches to control porosity and residual stress defects are summarised in Table 3.

However, most analysis-based models assume material homogeneity and isotropy, which limit their ability to accurately capture microstructural characteristics and process heterogeneity. In addition, the computational cost increases when complex geometries and coupled multi-physics phenomena are considered simultaneously. Furthermore, these approaches have limitations in responding to changing process conditions in real time. Therefore, although analysis-based approaches provide physical interpretability, their practical application in real-time process monitoring and control remains limited.

3.2. Data-driven methods

Data-driven approaches learn and predict the relationships between process parameters and defects using

data collected through experiments and process monitoring. With recent advances in ML and artificial intelligence, these approaches have been studied for both L-PBF and L-DED. In particular, technologies for real-time defect detection and process control using data acquired from various monitoring systems, such as high-speed cameras [169–171], X-ray imaging [172,173], and optical systems [174,175], have been developed.

For example, Chen et al. [176] proposed a convolutional neural network (CNN)-based model for real-time defect monitoring during L-DED using acoustic signals collected from microphone sensors as input data. In their study, Mel-frequency cepstral coefficient features were extracted from acoustic data to classify normal conditions, cracks, and keyhole porosity, thereby demonstrating the feasibility of in situ defect detection during processing.

Feng et al. [177] utilised in situ optical tomography images and ML-based analysis techniques to predict defects generated during L-PBF. They integrated layer-wise images, process parameters, and X-ray computed tomography data (XCT) to develop an ML model for predicting the local porosity in each layer. Studies on data-driven defect prediction and monitoring of porosity and residual stress in L-PBF and L-DED are summarised in Table 4.

Unlike conventional analysis-based approaches, these methods do not require complex physical assumptions

Table 3. Summary of simulation-based studies for defect analysis in L-PBF and L-DED processes.

Ref	LAM method	Material type	Defect type	Simulation type	Theoretical models and numerical methods	Comment
[148]	L-DED	LTT alloy	Residual stress	FEM	Heat source calibration with coupled thermal, metallurgical, and mechanical models	Proposes compressive residual-stress mitigation via martensitic transformation
[184]	L-DED	Inconel 718	Melt pool / porosity	FEM	Heat transfer and controller-based power regulation	Proposes laser power control for melt-pool depth variation along scan paths
[185]	L-DED	316L-Si stainless steel	Residual stress	FEM	Heat source model, heat transfer, solidification, and mechanical deformation	Investigates residual stress accumulation and buckling behaviour
[186]	L-PBF	Ti6Al4V	Melt pool / porosity	CFD	Navier–Stokes equations, VOF method, surface tension, Marangoni effect, recoil pressure, and heat loss	Evaluates melt-pool stability and keyhole evolution under different beam profiles
[187]	L-PBF	Copper / bronze / SS316L	Melt pool / porosity	CFD	Heat transfer, cap-shape analysis, balling criterion, and Rosenthal analytical solution	Investigates balling behaviour and mitigation via laser spot control under different scanning speeds
[188]	L-DED	AISI M4 powder	Residual stress	FEM	Enthalpy-based thermal model considering solid fraction and temperature-dependent material properties	Investigates thermal interaction and stress accumulation between the substrate and deposited region
[189]	L-DED	SS316L	Melt pool	CFD	Solid–liquid phase change, VOF method, Gaussian heat source, Marangoni effect, and particle dynamics	Investigates melt-pool stability according to energy input, scanning speed, and powder feed rate
[190]	L-PBF	Inconel 718	Melt pool / porosity	CFD + DEM	Melting, solidification, evaporation, radiation and heat transfer, multiphase flow, recoil pressure, and Marangoni effect	Analyzes porosity caused by LOF defects in multi-track/multi-layer structures and scanning strategy control
[191]	L-DED	Nb-based refractory C103	Melt pool / porosity	CFD	Mass, momentum and energy conservation, VOF method, laser–substrate interaction, powder–melt-pool interaction, and solid-phase transformation	Evaluates melt-pool stability and defect formation trends under varying process parameters using process maps
[192]	L-PBF	Ti6Al4V	Melt pool / porosity	CFD	VOF method, recoil pressure, microstructural model, and beam profile modelling	Optimizes laser beam profiles using spatter, melt pool, and porosity analysis

Table 4. Summary of ML-based studies for defect analysis in L-PBF and L-DED processes.

Ref	LAM method	Material type	ML algorithm	Defect type	Dataset type (input)	Comment
[193]	L-PBF	HAYNES®282® powder	RF	Porosity	In situ SWIR thermography data	Local porosity prediction based on in situ thermal imaging data using ML
[194]	L-PBF	Ti-6Al-4V	CNN-RNN	Porosity	X-ray images, Optical/thermal signals	Melt pool images and process signals were combined to analyse defect-related changes
[195]	L-PBF	Multiple alloys	RF	Porosity	Melt-pool defect data	A defect classification framework for L-PBF melt pools was proposed under limited data conditions
[196]	L-PBF	Ti-6Al-4V	RF / ResNet-LSTM	Porosity	Coaxial melt-pool images, process features	Keyhole pore detection was performed by combining coaxial melt-pool imaging with XCT-based labels
[197]	L-DED	AISI SS316L	CNN	Porosity	Acoustic / thermal / sensor data	Surface porosity prediction in hybrid DED was performed through multimodal sensor fusion
[198]	L-DED	Inconel 718	ViT	Porosity	Thermal images	Global thermal image features were extracted and utilised for melt-pool defect detection
[199]	L-DED	CoCrNi medium-entropy alloy / SS316L substrate	ResCIFNN / VGG16 / K-means / ResNet18 / FPCA	Porosity	In situ monitoring sensor data	Defects and mechanical properties in L-DED were predicted together using a proposed monitoring framework
[200]	L-PBF	SS316L	DRL / DQN	Residual stress	Toolpath state / temperature field	DRL-based toolpath generation was employed to achieve a more uniform thermal distribution in L-PBF
[201]	L-PBF	Ni-based superalloy/ 316 stainless steel	MLP / GB / RF	Residual stress	Residual stress map / temperature parameters	Residual stress and distortion in L-PBF were rapidly predicted by combining FEM and ML
[202]	L-PBF	Model material	MVE-BiConvLSTM	Residual stress	3D voxel geometry / base layer	A BiConvLSTM-based surrogate model was used to estimate both residual stress and predictive uncertainty in L-PBF
[203]	L-PBF	18Ni300 maraging steel	NSGA-II/ StyleGAN2-ADA deep learning model	Residual stress	Laser power, scan speed, annealing temperature	A GAN-based approach was used to predict the full-field residual stress distribution under various process conditions
[204]	L-PBF	IN625	Multi-response neural network (3-N-3) architecture	Residual stress	Laser power, scanning speed, layer thickness	Effects of laser power, scanning speed, and layer thickness on the morphology and geometry of single-track IN625 deposits were predicted.
[205]	L-PBF	SS316L	CNN	Residual stress	Layer images of the powder bed	A CNN-based automatic defect detection model was proposed for multi-label classification across seven categories, including defect-free samples
[180]	L-DED	Inconel 718	CNN	Residual stress	Thermal histories	A data-driven approach was shown to enable the extraction of meaningful mechanical features, including critical temperature ranges and critical frequencies

and can respond flexibly to process variability. In addition, their relatively high computational speed enables real-time process control. However, data-driven approaches require large amounts of input data, and their prediction performance can deteriorate when biased datasets are used. Furthermore, their black-box characteristics limit physical interpretability and generalisation capability regarding process mechanisms.

3.3. PIML

Recently, PIML approaches have emerged in LAM. They constitute a hybrid framework that incorporates physical knowledge into data-driven learning to improve prediction accuracy and reliability. Generally, PIML approaches can be categorised into three types. Below, we discuss the methodology and representative research cases for each of the following three types. We also examine the

advantages and disadvantages of each type to clarify their distinguishing characteristics. Detailed learning procedures and data preparation methods are presented in Table 5.

(1) Physics-based Feature Engineering

This approach utilises physically meaningful information as input features for machine learning models and can be broadly divided into two categories. The first constructs a theoretical model based on physical equations and directly uses the resulting physical quantities as inputs to the machine learning model. The second constructs statistical or probabilistic models from data obtained through experimental processes and integrates them into the machine learning framework. Thus, the two methods are distinguished by whether physical quantities are derived directly from

Table 5. Characteristics of the three PIML types.

PIML Method	Physical Knowledge Embedding	Network Architecture	Training Procedure	Optimization Strategy	Data Preparation Method	Features
Physics-based Feature Engineering	Physical quantities are used as input features of the model	Architecture-agnostic (applicable to regression/tree-based models as well as deep learning)	Features are first derived from physical equations or experimental statistics, followed by standard supervised learning	Minimisation of standard loss functions (e.g. MSE)	Physical quantities computed from physics-based theoretical models, or features derived from the statistical distribution of experimental data	- Fast computation and relatively simple implementation. - However, physical knowledge is reflected only at the input-feature stage and is not directly involved in the model's own training process.
Physics-based Simulation-assisted ML	Physics-based simulations generate the training data itself	Standard architectures suited to the data modality (image, time-series, tabular, etc.)	Simulation data and measured data are aligned/fused, followed by supervised learning	Minimisation of standard loss functions (e.g. MSE)	CFD/FEM simulations are used to supplement insufficient measured data; verification of the correlation between experiments and simulations is required	- Can compensate for the limited diversity of experimental data and the ambiguity of defect representation through simulation, improving both prediction accuracy and interpretability. - However, results are dependent on the accuracy of the simulation itself, and verifying consistency between experiments and simulations requires additional cost and effort.
Physics-constrained Learning	Physical laws are directly incorporated into the loss function	A differentiable network mapping spatiotemporal inputs to the corresponding physical quantities	Data loss and physical residual loss are minimised simultaneously; training is possible even without labels	Optimisation of a composite loss function including physical residuals (violations of PDEs, initial conditions, and boundary conditions)	Can be trained without labels, though a small amount of measured/simulation data is often combined to improve accuracy	- Achieves high accuracy and physical interpretability even with limited data. - However, initial training cost is high, and application is challenging for complex phenomena whose governing equations are difficult to formulate explicitly.

governing equations or are indirectly reflected through the statistical distribution of experimental data.

Physics equation-based methods aim to establish quantitative correlations between process variables and defect formation in LAM. As discussed in Section 2, predicting, and detecting melt pool geometry in L-PBF and L-DED enables the classification and control of quality indicators such as balling, porosity, and mechanical properties. This approach generally consists of three components: experimental processes, mechanistic models, and machine learning. Process variables such as laser power and scanning speed are input into a mechanistic model to derive physically meaningful variables, which are then used as inputs for machine learning. For example, Y. Du et al. [178] developed a model to predict balling defects in the L-PBF process. They constructed a three-dimensional transient heat transfer and fluid flow model incorporating conservation of mass, energy, and momentum along with governing equations for the free surface. From this model, they calculated the temperature field, velocity field, melt pool geometry (depth, width, and length), peak temperature, cooling rate, and flow velocity. From these results, six mechanistic variables were derived, namely energy density, Richardson number, aspect ratio, surface tension force, solidification time, and Marangoni number, forming a dataset of 166 samples. These variables were input into a genetic algorithm to predict the Balling Susceptibility Index, achieving a prediction accuracy of approximately 90%. This demonstrates that physics equation-based machine learning can replace repetitive experiments and costly simulations while achieving high accuracy in capturing the quantitative relationship between process variables and defect formation.

Statistical methods construct statistical or probabilistic models based on features obtained from experimental processes to predict and detect the characteristics and defects of LAM [179,180]. For instance, Li et al. [181] proposed a model that performs probabilistic calibration of heat source model parameters in the L-PBF process to statistically predict defects such as melt pool geometry, LOF porosity, and surface roughness. To construct a physics-based probabilistic model, experimental data were first collected by measuring melt pool width and depth at 100–200 points under various laser power and scanning speed conditions, from which probability distributions were constructed. These data were converted into probability density functions (PDFs) using kernel density estimation (KDE). In parallel, a physics-based CFD model incorporating heat transfer, fluid flow, the free surface, and the Marangoni effect was developed. Because phenomena such as keyhole

formation and laser absorptivity are difficult to reproduce accurately using CFD alone, three parameters, namely absorptivity (η), heat source depth (d), and beam radius (r_b), were treated as probabilistic variables and calibrated to compensate for this limitation. Notably, rather than fitting deterministic single values for the heat source parameters, a stochastic calibration approach was applied to calibrate the probability distributions of the parameters themselves. Specifically, Monte Carlo sampling was used to draw numerous samples from the parameter distributions, which were then input into a tensor decomposition (TD) surrogate model to propagate the results into output distributions (melt pool width and depth). These outputs were converted into PDFs using KDE, and the parameter distributions were iteratively updated to minimise the Kullback–Leibler divergence (KLD) between the predicted and experimental PDFs. Using this calibrated model, a dataset of 50,000 samples was generated from 25 single-track conditions, with 2,000 samples per condition, and used to train a deep autoregressive network (DARN) to predict melt pool geometry, surface roughness, and LOF. This approach achieved high prediction accuracy, with an inference time of 0.4 ms and an error rate of 6.7%.

In this way, statistical methods integrate prior knowledge into machine learning based on the causal relationships and statistical probabilities among process variables, in-process sensor signals, part quality, and geometry obtained from preceding experimental processes. Both approaches described above, physics equation-based and statistical, share the common advantage of fast computation, which accounts for their widespread use in the PIML field.

(2) Physics-based Simulation-assisted Machine Learning

This approach utilises physics-based models or numerical simulation results to design machine learning architectures or generate training datasets. Relying solely on experimental processes in LAM to obtain the data required for machine learning training presents fundamental limitations, as experimental data often lack feature diversity and provide ambiguous observations of defect morphology. To address these limitations, simulations that embed physical knowledge, such as the finite volume method or CFD, are used to generate data. This data is then integrated into machine learning after validating its correlation with experimental results. In other words, CFD simulations are gaining attention as a means of generating features across diverse process conditions that are difficult to obtain from a single experiment alone, thereby

compensating for the lack of data diversity and the ambiguity of defect representation. This integration of physics-based simulation and machine learning is being actively studied, as it can improve not only the accuracy of defect prediction but also the interpretability of the model.

For example, Vidita Gawade et al. [182] developed a hybrid model that captures melt pool information by combining experimental and simulation data. Thermal images of the melt pool were first acquired using a pyrometer during the laser metal deposition (LMD) process of Ti-6Al-4V. In parallel, a finite element analysis model was used to calculate the thermal history of the melt pool from the input parameters and material properties. After matching the experimental and simulation data at corresponding melt pool locations and time points, melt pool shape features were extracted from the experimental data using functional principal component analysis (FPCA), while shape and thermal characteristic features were extracted from the simulation data. In addition, the maximum temperature difference between the experimental and simulation results was defined as a residual feature to reflect the informational discrepancy between the two data sources in the model. These combined features were used to train a supervised gradient boosting model to predict the occurrence of porosity, achieving an accuracy of 99% and a recall of 86.67%. This study presents an approach that combines experimental and simulation data to compensate for the limitations of each. Experimental data capture the actual melt pool behaviour observed during the process, while simulation data provide physics-based information that is difficult to obtain directly from experiments, enabling more reliable porosity prediction.

(3) Physics-constrained Learning

The two approaches discussed above utilise physical knowledge in the form of input features or training data, without directly integrating physical knowledge into the machine learning modelling process itself. In contrast, the third approach directly incorporates physical knowledge into the training and evaluation of machine learning models in the form of a loss function. Specifically, physical residuals derived from governing equations are included in the loss function, so that the model is trained to minimise not only prediction error but also the degree of violation of physical laws. In the field of LAM, PINN-based models represent a widely adopted implementation of this approach. For example, Liao et al. [183] proposed a hybrid PINN framework for predicting the three-dimensional temperature field and identifying unknown parameters in LAM

processes. This framework takes spatiotemporal coordinates as input and predicts the temperature at the corresponding point, optimising the model through a loss function that combines physical laws and data. The physics-based loss function was designed to include residuals derived from the governing equation of heat conduction, the initial conditions (ICs), and the boundary conditions (BCs). A data-based loss term for actual experimental measurements or simulation data was then added to this to enforce physical consistency. In this study, the framework was validated using FEM simulations and actual L-DED experimental data while varying process parameters such as laser power and scanning speed. According to the results, FEM took approximately 4 hours for a single bare-plate scanning simulation, whereas the initial training of the PINN took approximately 2.5 hours, so the computational-time advantage was not pronounced at the initial training stage. However, when transfer learning using a pre-trained model was applied, the model converged more than 5 times faster than a randomly initialised model even when process conditions changed, demonstrating a dramatic improvement in computational efficiency. In addition, despite using only sparse, partially observed data obtained from an infrared (IR) camera, the framework succeeded in identifying unknown parameters such as laser absorptivity, specific heat, and thermal conductivity with an error of less than 5%. In an actual 40-layer thin-wall fabrication experiment as well, the RMSE between the predicted and measured values was on the order of 47.28 K, demonstrating high accuracy. These results suggest that although the PINN model requires considerable time for initial training, it can rapidly adapt to various process conditions governed by the same physical laws. Furthermore, it can achieve high predictive performance based on physical interpretability even under limited data conditions.

PIML approaches can be classified into various forms depending on how training data are prepared and how physical laws are integrated into the machine learning algorithm. Common to all these approaches is their ability to reduce data dependency and capture complex physical phenomena while enhancing physical interpretability. The value of applying PIML is particularly pronounced in LAM processes such as L-PBF and L-DED, where heat transfer, melt pool flow, phase transformation, and solidification behaviour are strongly coupled. However, L-PBF and L-DED differ not only in process variables such as laser power, scanning speed, and cooling rate but also in the powder delivery mechanism itself. As a result, the strategies for applying PIML to each process must also differ accordingly. It is therefore important to select an appropriate PIML

approach based on the characteristics of each process and its intended purpose, with metrics such as prediction accuracy, computation time, cost, and generalisation performance serving as criteria for evaluating PIML performance. In the following section, based on these PIML approaches, the applicability of PIML across the entire process lifecycle of L-PBF and L-DED for minimising defects such as porosity and residual stress is examined, along with the gaps identified in existing research.

4. PIML strategies across the process lifecycle of L-PBF and L-DED

This section discusses PIML approaches and their limitations for practical implementation across the entire process lifecycle of L-PBF and L-DED. The process lifecycle can be divided into three stages: (1) pre-process defect prediction, (2) in-process detection and classification of defects, and (3) post-process evaluation of the strength and quality of fabricated specimens. Each stage imposes different performance requirements on PIML. In the pre-process prediction stage, optimal process variables must be designed in advance for conditions that have not yet been obtained. This requires not only accuracy but also generalisation performance across diverse process types and materials. In contrast, the in-process real-time monitoring stage prioritises fast computation time above all else. It also requires robustness to in-process sensor signals and high accuracy in anomaly detection. Finally, in the post-process quality evaluation stage, accuracy is critical, as it serves as the criterion for determining the pass or fail status of the final product and is thus directly linked to safety and reliability. From this perspective, this section discusses the practical industrial applicability of PIML-based approaches to defects occurring across the entire process lifecycle of L-PBF and L-DED, and explores optimal strategies for applying PIML to each process.

4.1. Pre-process: defect prediction and parameter optimisation

4.1.1. Melt-pool morphology and porosity prediction

In L-PBF and L-DED processes, process variables such as laser power, scanning speed, hatch spacing, and laser absorptivity affect the thermal and fluid behaviour of the melt pool. As discussed in Section 2, these variables are closely related to porosity and LOF defects. Accordingly, extensive research has focused on predicting melt pool information to analyse its correlation with porosity. Furthermore, because L-PBF and L-DED differ in

their governing process variables and underlying physics, these differences must be accounted for in melt pool and porosity prediction.

Mao et al. [206] proposed a spatiotemporal graph-based framework for L-PBF processing of 304L stainless steel, representing melt pool images as time-series graph nodes. They applied a Physics-based Feature Engineering methodology to improve prediction accuracy by capturing spatiotemporal correlations across monitoring data at different time points. Input data were first obtained through experiments and a physics-based heat transfer model, which were then used to predict melt pool geometry. In this framework, laser power was varied between 225 and 400 W while a high-speed camera captured melt pool images. Field of view transformation and optical flow techniques were used to track position and motion, extracting trajectories and evolution patterns. The cumulative thermal contribution of previous scan paths was then incorporated into the graph edge weights using a physics-based heat transfer model and the superposition principle (Figure 10(a)). A dataset of 112,334 training graphs and 74,884 test graphs was constructed, and a hybrid GCN-LSTM architecture was trained to simultaneously learn spatial and temporal features (Figure 10(b)). The resulting model achieved a MAPE of 11.92% for melt pool area and 8.25% for perimeter, outperforming conventional multi-SVR and multi-XGBoost models. It also achieved fast inference, with a total computation time of 6.45 s. However, from the perspective of generalisation required for pre-process prediction, this approach reflects physical knowledge only during the data preprocessing stage, specifically in computing graph weights. As a result, any error arising from the actual experimental process propagates directly into the model without being constrained by physical laws. In addition, because this approach requires a large volume of experimental data, applying it to new materials or process environments would again demand considerable time and cost.

To address these limitations, Sharma et al. [207] proposed a Physics-constrained Learning model that directly incorporates physical laws into the loss function rather than the data itself. They analysed the effect of inert gas flow, including argon, nitrogen, and helium, on the laser-melt pool interaction zone in the L-PBF process. The governing equations for melt pool dynamics under gas shear force were established based on conservation of mass, momentum, and energy. The loss function was composed of three terms: a data-fitting term, a governing-equation residual term, and a boundary-condition term. Using temperature fields obtained from COMSOL simulations and

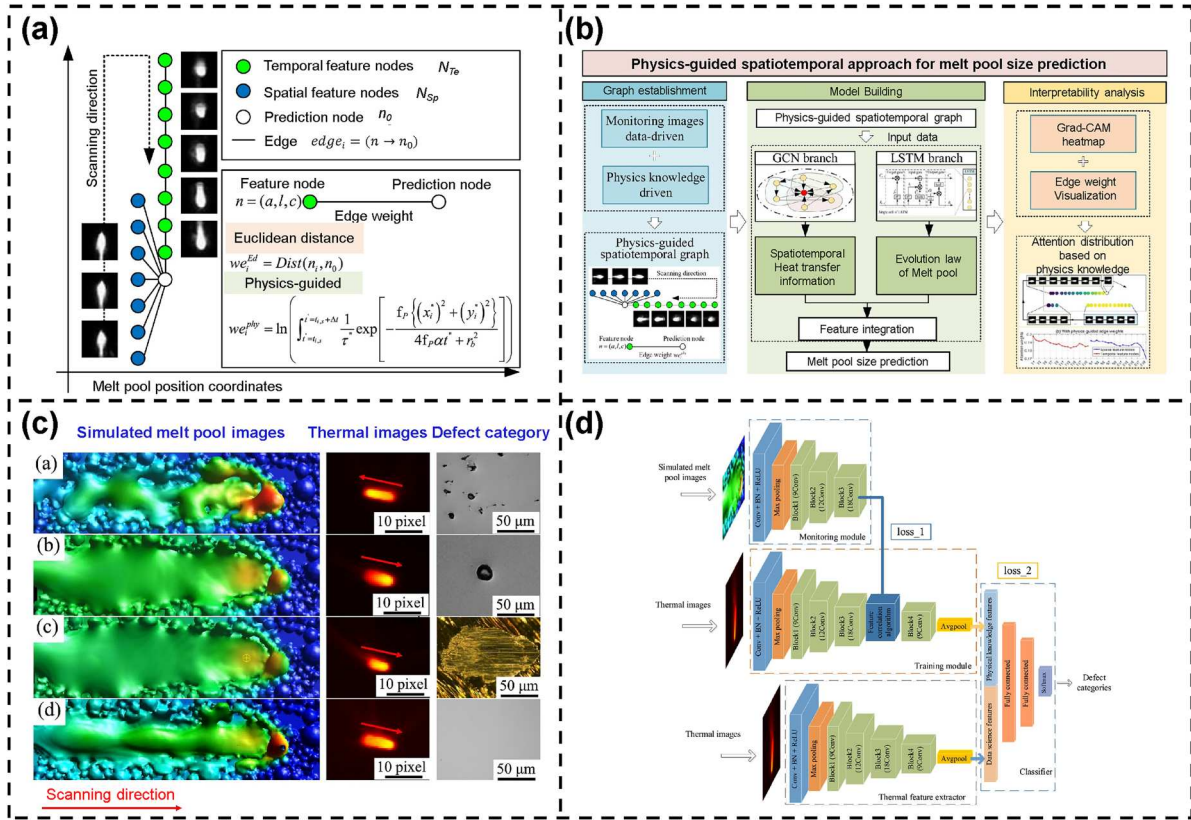


Figure 10. Physics-informed spatiotemporal graph learning framework for predicting melt-pool dynamics. (a) Physics-informed spatiotemporal graph construction; (b) GCN-LSTM framework for predicting melt-pool dynamics [206], (c) Simulated images and thermal images for four defect classes (Class I: lack of fusion, Class II: keyhole induced porous defect, Class III: recoater interference, Class IV: no defect). (d) Schematic diagram of the PSN model [208].

spatiotemporal coordinates as inputs, a total of 10,000 data points were used to predict melt pool temperature, velocity, and pressure. These predictions showed strong agreement with CFD simulation results. Notably, the Reynolds number and Peclet number were treated as trainable parameters rather than fixed values, enabling inverse estimation. Forward training converged in approximately 16 minutes over 6,000 iterations, while inverse estimation required approximately 5 hours. The resulting errors were 5.38% for the Reynolds number and 0.62% for the Peclet number. Compared with Mao et al., this study substantially reduced dependence on experimental data using PINNs. However, generalisation to new conditions remains limited. Generating the large volume of input data required CFD simulations, incurring additional cost and time. Moreover, the 5-hour inverse estimation process must be repeated whenever conditions change to re-estimate unknown physical constants. Both studies predicted melt pool temperature and velocity fields closely related to porosity. However, neither established the correlation between process variables, such as scanning speed and laser power, and the resulting defects.

To bridge this research gap, Yang et al. [208] directly analysed the correlations among L-PBF process variables, melt pool geometry, temperature, and porosity defects for stainless steel powder. Applying a Physics-based Simulation-assisted Machine Learning methodology, they proposed a physical supervision network (PSN) model to predict melt pool behaviour for different defect types. Laser power, scanning speed, beam diameter, substrate size, and sample size were set as process variables, and thermal images were captured using an infrared camera. In parallel, a CFD model was constructed by combining the discrete element method and the finite volume method, incorporating surface tension, the Marangoni effect, recoil pressure, gravity, and drag through a heat source model and the VOF technique. Simulation results distinguished LOF, keyhole porosity, recoater interference, and steady-state conditions according to different combinations of process variables, revealing their correlations with melt pool size and temperature. These results were validated against experimental data, showing strong consistency (Figure 10(c)). A total of 2,000 experimental thermal images and 2,000 simulated

melt pool images were used to construct a hybrid neural network (HNN) model. A PSN model was then proposed by adding two additional loss terms, an error term between CFD and experimental features and an error term between predicted values and labels (Figure 10(d)). The results showed prediction accuracies of 93.75% for a standard ResNet50 model, 97.25% for the HNN model, and 96% for the PSN model. In terms of computation time, the PSN model converged approximately 3 times faster than ResNet50 and 2 times faster than HNN. These results illustrate a practical trade-off among the three key factors required for PIML: accuracy, generalisation, and computation time. This comparison suggests that no single approach simultaneously satisfies all three requirements. The choice of PIML strategy should instead be guided by the specific demands of the target process.

In contrast, L-DED differs substantially from L-PBF in terms of process mechanism. Regarding porosity and melt pool behaviour, L-PBF is characterised by a smaller melt pool size and faster cooling rate compared with L-DED. In addition, because L-DED delivers powder directly, the interaction among the laser, powder, and substrate differs from that in L-PBF. This introduces powder capture efficiency as a new variable and requires the additional consideration of powder feed rate as a process variable.

For example, Cao et al. [209] proposed a Physics-based Simulation-assisted Machine Learning approach that integrates physics-based analysis with process variables to predict defects in the L-DED process of 12CrNi2 alloy. The research workflow is presented in Figure 11(a). A precise thermal-fluid flow simulation was performed using a three-dimensional finite element model. In

addition to conservation of mass, momentum, and energy, changes in melt pool height were captured using an Arbitrary Lagrangian–Eulerian method, while mass and heat loss due to evaporation within the melt pool were neglected. Using laser power, nozzle travel speed, and powder mass flow rate as process variables, a physics-informed dataset comprising 99 combinations was constructed. Random forest, KNN, support vector machine, and neural network models were trained on this dataset, achieving over 95% accuracy in predicting LOF and keyhole defects as well as in parameter optimisation. In terms of computation time, the standard FEM-based thermal-fluid analysis required approximately 21 hours, whereas inference using the trained ML models took only about 5 minutes. This demonstrates a substantial improvement in computational efficiency.

Ye et al. [210] developed a dimensionless group integrated-artificial neural network (DI-ANN) model to identify the relative importance of factors influencing single-track depth in L-DED. The model was also used to relate these factors to porosity from keyhole and LOF defects. Using a Physics-based Simulation-assisted Machine Learning approach, the model's input features were composed of three categories: process variables, experimentally obtained process signals, and dimensionless groups derived from multiphysics simulations. Experimental data were obtained by fabricating straight single-track SS316L specimens using a continuous-wave laser with a top-hat profile. Separately, a three-dimensional multiphysics CFD model was constructed by coupling a transient energy conservation equation, including a volumetric heat input term accounting for powder heating during laser passage, with melt pool fluid dynamics. Dimensionless physical features,

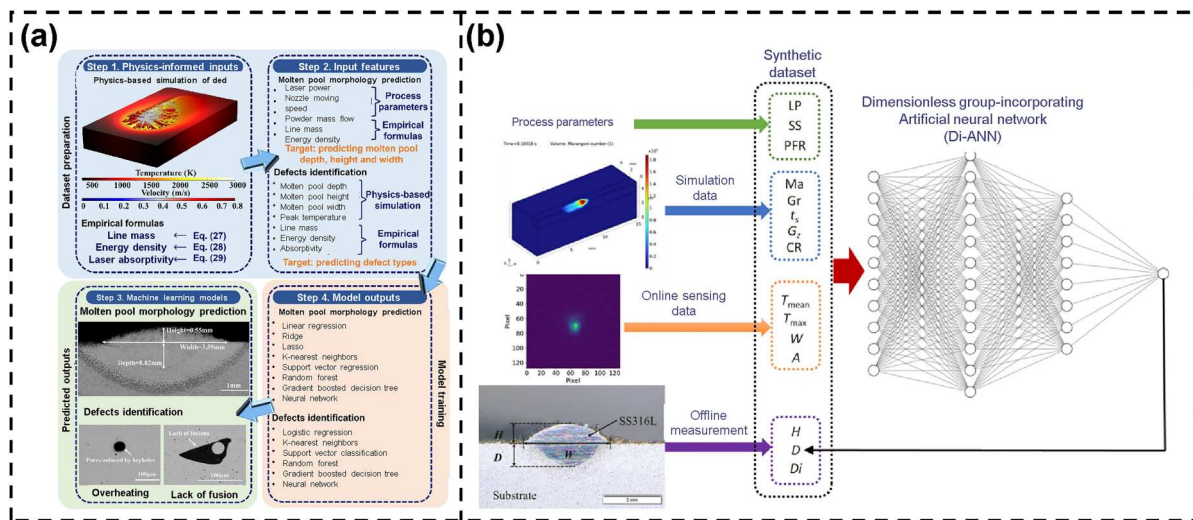


Figure 11. (a) Framework for training different ML models based on the physics-informed model inputs for the molten pool morphology prediction and defects identification tasks [209]. (b) Schematic of a workflow developed here for the DI-ANN model [210].

including the Marangoni number, Grashof number, solidification time, vertical temperature gradient, and cooling rate, were extracted from 60 single-track simulations. As shown in the workflow in Figure 11(b), the influence of each feature was first analysed using the Spearman correlation coefficient. The DI-ANN model was then trained and evaluated using process variables such as laser power, scanning speed, and powder flow rate, experimentally derived signals such as melt pool width, area, and peak temperature, and the dimensionless physical quantities as combined inputs. The model achieved a MAPE of 6.1% and an MXAPE of 11.7% in predicting single-track depth, representing improvements of approximately 30% and 70%, respectively, over values reported in existing literature. This study is notable for representing melt pool conditions in a physically interpretable form using dimensionless numbers. However, its generalisation performance has not been fully validated. Although dimensionless numbers theoretically have the potential to represent the same physical regime across different materials and scales, this study's validation was limited to single-track conditions. As a result, it does not capture the multi-track and multi-layer behaviour, specifically bead overlap and interlayer heat accumulation, that is essential in actual L-DED processes.

These two studies indicate that L-DED presents greater constraints than L-PBF for applying PIML. Because bead height increases in real time as powder is deposited, the prediction target itself constitutes a three-dimensional free-surface problem. This makes 3D multiphysics models practically indispensable for generating physics-based simulation training data. As shown in the study by Cao et al., 3D moving-boundary simulations incur substantial computational cost, requiring approximately 21 hours per case. As a result, studies on L-DED have commonly been constrained to relatively small datasets, ranging from 60 to 99 samples, compared with those available for L-PBF.

4.1.2. Predicting and mitigating residual stress

As reviewed in Section 2.2, residual stress has two physically distinct origins. These are thermomechanical deformation (TGM and cool-down shrinkage) and volumetric change due to solid-state phase transformation. However, most physics-based studies have been limited to thermomechanical deformation. They have focused on temperature field prediction under the premise that achieving a uniform thermal distribution is important for minimising residual stress and distortion. In addition, while research on phase transformation itself and on microstructure formation is actively conducted, there are not many cases that have linked

such mechanisms to defects such as residual stress formation. The reason lies in the fact that direct observation of residual stress is difficult, whereas the temperature field and microstructural state, which are its precursor variables, are relatively accessible. Based on the above, this section addresses the current state of development of research and its limitations.

A case that clearly illustrates this temperature-field-centered trend is the L-PBF study by Hosseini et al. [211,212]. Rather than directly addressing residual stress or phase transformation, they focus on how quickly and accurately the temperature field itself, as the precursor variable, can be predicted. Hosseini et al. [211] trained a PINN without label data by directly imposing the residual of the heat transfer PDE and boundary condition mismatches on the loss function, thereby embedding the physical laws themselves into the learning process (Figure 12(a)). Process and material variables themselves were taken as inputs to derive a parametric solution. As a result, unlike FEM, which requires recalculation for each scenario, this approach achieved an accuracy of MAE below 5% compared to FEM, but its validation scope was limited to a single-track (1.5 mm) temperature field. Extension to multi-track and multi-layer cases was carried out in a follow-up study. The Pulse approach of Scheel and Hosseini [212], instead of purely learning the governing equations, uses a small number of low-cost FEM results as label data to train the neural network in a supervised manner. By jointly imposing a structure that expresses the moving heat source as a superposition of pulse responses together with a symmetry-condition loss term, this approach reconciled simulation-data-based learning with physical constraints. As a result, it successfully generalised to an 8 mm long track and a 33-layer cuboid geometry not included in training, and achieved an evaluation speed more than five orders of magnitude faster than FEM. However, the error is large in boundary and corner regions without a separate corrector function, and even this was validated only for a simple cuboid geometry, showing the limitation that accuracy degrades when temperature-dependent properties are introduced.

Whereas the two studies above focused on temperature field prediction itself, the L-PBF study by Qin et al. [200] goes beyond predicting the temperature field, using it as a learning signal for scan path (toolpath) optimisation to achieve reductions in residual stress and distortion as well (Figure 12(b)). However, this study also does not directly measure or predict residual stress. Instead, it adopts temperature uniformity itself as the optimisation objective, under the premise that distributing the temperature field uniformly to minimise the

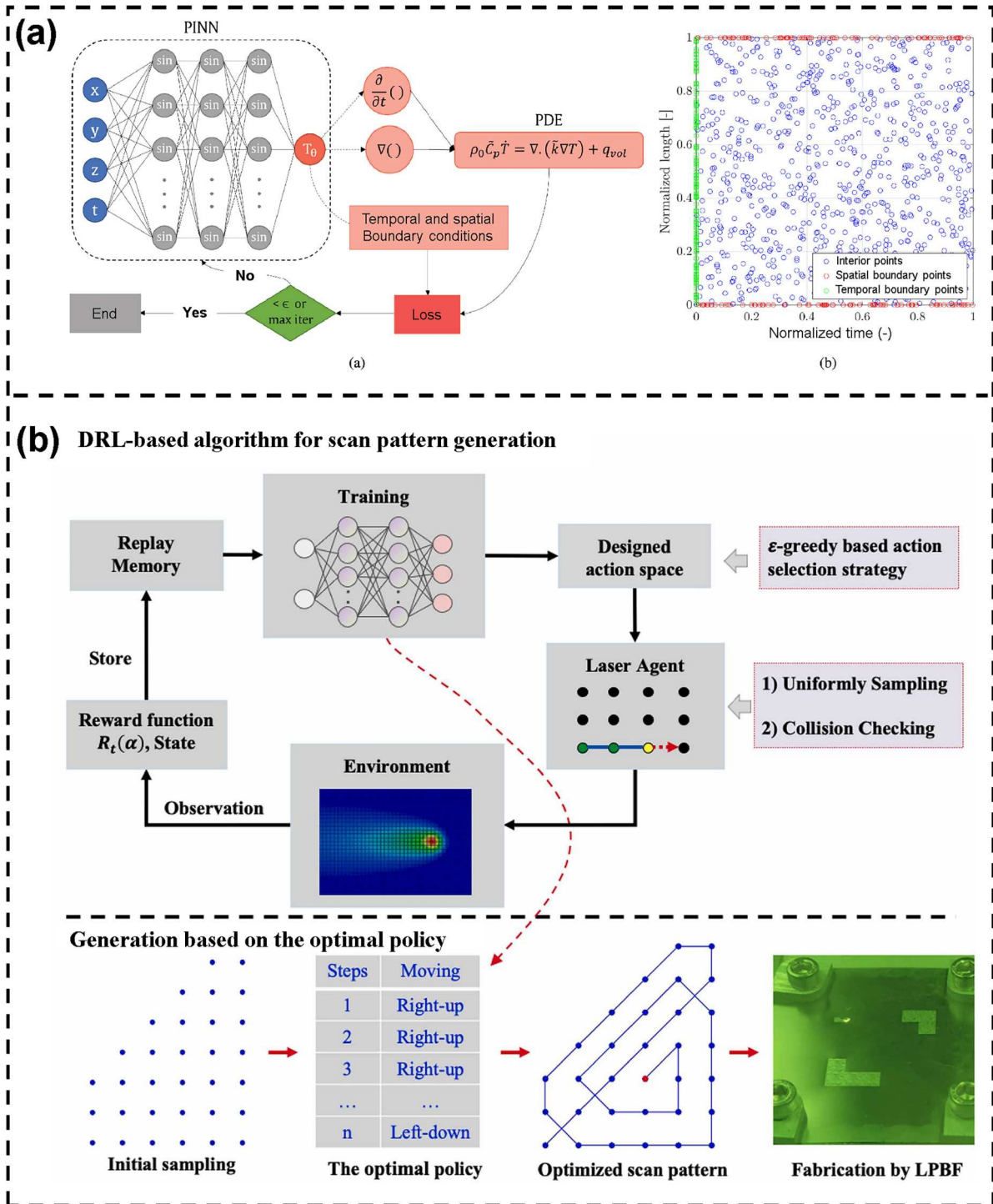


Figure 12. (a) Schematic of a PINN framework for heat equations, where the loss includes boundary condition mismatches and PDE residuals at collocation points in the time–space domain [211], (b) Overall pipeline of a Deep Reinforcement Learning (DRL)-based algorithm for toolpath optimisation [200].

thermal gradient will jointly minimise residual stress and distortion. Using DQN-based reinforcement learning, the laser beam is treated as a moving agent that learns the traversal order of uniformly sampled points itself, while process constraints such as boundary and corner constraints and void-moving rules are explicitly encoded.

Initially, the reward was computed by calculating the melt pool depth at every step using RUSLS numerical analysis, but this took hundreds of hours for 1000 episodes of training. The authors therefore first established the correlation between turning angle and melt pool depth, observing a sharp increase in depth below

90 degrees. They then adopted a Physics-based Feature Engineering strategy that replaced the costly temperature-field calculation with turning angle. This physically meaningful, low-dimensional indicator was used as the input to the reward function. As a result, the training time was reduced to approximately one hour. In polygonal-shape simulations, this approach achieved a 13% reduction in average depth compared to zigzag and eliminated sensitive regions compared to ATG. In actual experiments, it achieved maximum distortion reductions of 47%, 29%, and 17% compared to zigzag, chessboard, and ATG, respectively. However, this study addresses only intra-layer heat accumulation, and extension to interlayer heat accumulation, free-form boundaries, and curved paths remains a task for future work.

Collectively, these three studies address only thermo-mechanical deformation, under the premise that achieving temperature uniformity directly leads to minimisation of residual stress. Volumetric change due to solid-state phase transformation is excluded from the governing equations. This premise itself is repeated without ever being directly validated against measured residual stress. When applied to materials in which phase transformation occurs significantly, the physical validity of these models is not guaranteed.

Attempts to incorporate the phase transformation mentioned above into PIML together with the temperature field are found in the following studies. Yang [213]'s Micro-Mechanism Informed Neural Network adopted a Physics-constrained Learning strategy. This approach directly fused six metallurgical mechanisms into the learning process in the form of loss functions. These mechanisms included the Koistinen-Marburger martensitic transformation kernel, Hall-Petch strengthening, Ashby-Orowan particle bypass, and the JMAK precipitation kernel. As a result, this approach was applied to the L-PBF process of SiC-reinforced SKD61 tool steel, for which no training data existed at all. It showed that embedding physics substantially improved out-of-distribution extrapolation performance compared to soft constraints. However, the prediction target was limited to hardness, and extension to residual stress was deferred as future work requiring a separate physical baseline to be established. As a result, the potential of embedding physics has not actually been carried through to the residual stress problem.

To overcome this limitation, Xu et al. [214] jointly considered the temperature field and phase transformation and quantitatively presented their association with residual stress. Targeting an L-PBF TA15 (Ti-6.5Al-2Zr-1Mo-1 V) alloy, they augmented the training data with FEM simulations. These simulations considered eight process variables, including laser power, scan speed,

and interlayer rotation angle. Using a dataset composed of 70% simulation data and 30% measured data, they trained tree-based machine learning models (GBDT, LGBM, XGBoost). They also proposed a framework that combines multi-objective optimisation (NSGA-III) with active learning to search for optimal process conditions that simultaneously reduce porosity, residual stress, and distortion (Figure 13). As a result, they reduced the measured (XRD) residual stress from 728 to 384 MPa, and for an aircraft backplate, reduced the maximum residual stress by 43.1% and distortion by 62.8% (RS prediction $R^2 = 0.845$). The cause of this improvement is explained by two pathways. One is based on the FEM thermal gradient analysis, in which the optimal parameters lowered the maximum temperature gradient by approximately 30% ($4.98 \times 10^6 \rightarrow 3.51 \times 10^6$ °C/m), thereby reducing thermal stress. The other is based on microstructural analysis. In the specimens with optimal parameters, finer α' -martensitic laths (0.619 ± 0.012 vs. 0.704 ± 0.009 μm) and lower kernel average misorientation (KAM) (0.210 ± 0.004 vs. 0.450 ± 0.006) were observed. This indicates a phase-transformation pathway in which local plastic deformation and stress inhomogeneity were reduced. That is, this study presented two physical causes, the temperature field and phase-transformation microstructure, together with the measured reduction in residual stress. However, the two pathways are not actually coupled. Residual stress itself is predicted directly from process parameters by a black-box ML model, without passing through microstructure or thermal gradient. The connection with thermal gradient and KAM is therefore a post-hoc explanation based on the correlation between observed values, rather than a governing equation. Validation is also limited to a single TA15 alloy and a specific backplate geometry.

The discussion so far has all concerned L-PBF. In contrast, even for the same problem of residual stress, the picture changes when the process changes. The pattern of defects that appears differs depending on the process characteristics, which means that the physics-based modelling strategies for addressing residual stress, and their limitations, must likewise be reconstructed in a different form depending on the process. From this perspective, L-DED, which has process characteristics distinct from L-PBF, is examined next.

In L-DED as well, studies focusing solely on temperature field prediction appear first. Li et al. [215] trained a PINN for a single track of L-DED 42CrMo alloy steel without label data. The loss function imposed only the residual of the heat transfer PDE and mismatches in the initial and boundary conditions (Figure 14(a)).

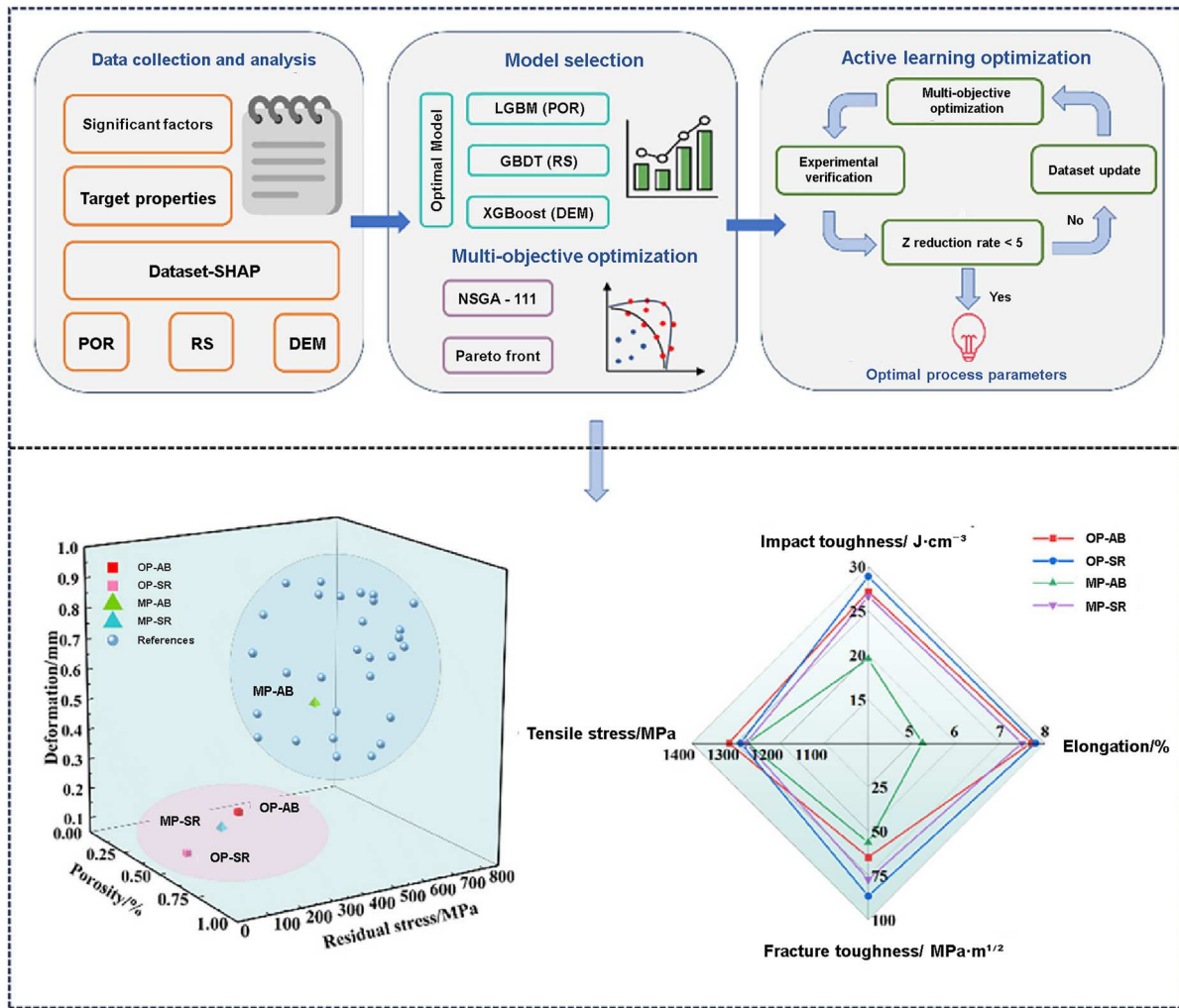


Figure 13. Schematic diagram of an integrated ML-based multi-objective optimisation framework [214].

They excluded the latent heat of phase transformation on the grounds that its effect on the temperature distribution is negligible. This approach achieved an accuracy of approximately 2% maximum error in the melt pool compared to FEM (temperature deviation of 55 K), with an average relative error of 0.64-0.95%. When process parameters changed, recalibration through transfer learning converged in 180 s, far shorter than the 650 s for base training, approximately one-third of the FEM computation time (600 s). However, this had the limitation that validation was confined to a single track, and the XPINN of Peng and Panesar [216] sought to overcome this limitation. They extended the existing PINN into a spatiotemporal domain decomposition structure (Figure 14(b)). This broadened the prediction scope to conditions unique to L-DED, namely dwell time, voids, and scan interruptions. In L-DED, heat remains deep in the underlying layers, so even a single interpass dwell time can substantially alter the thermal history. As a result, they reduced the

RMSE and maximum absolute error by approximately 50% compared to the existing PINN, but validation was still confined to 2D benchmark simulations, and no comparison was made against actual 3D multilayer deposition experimental data.

Building on the study above, Kushwaha et al. [217] directly predicted the residual stress field itself by accounting for plastic deformation. Targeting L-DED deposition of Inconel 625 in a topology-optimized 2D geometry, they first calculated the temperature field. Using this temperature field as input, they then performed a sequential thermo-structural coupled analysis, in which an elastic-perfectly plastic structural analysis was carried out. They then used a total of 4,574 FEM data points as training data to build a residual stress prediction model based on Physics-based Simulation-assisted Machine Learning. The ResUNet-based DeepONet takes printing speed and an arbitrary topology-optimized geometry as input. It simultaneously outputs the temperature field and the von Mises residual

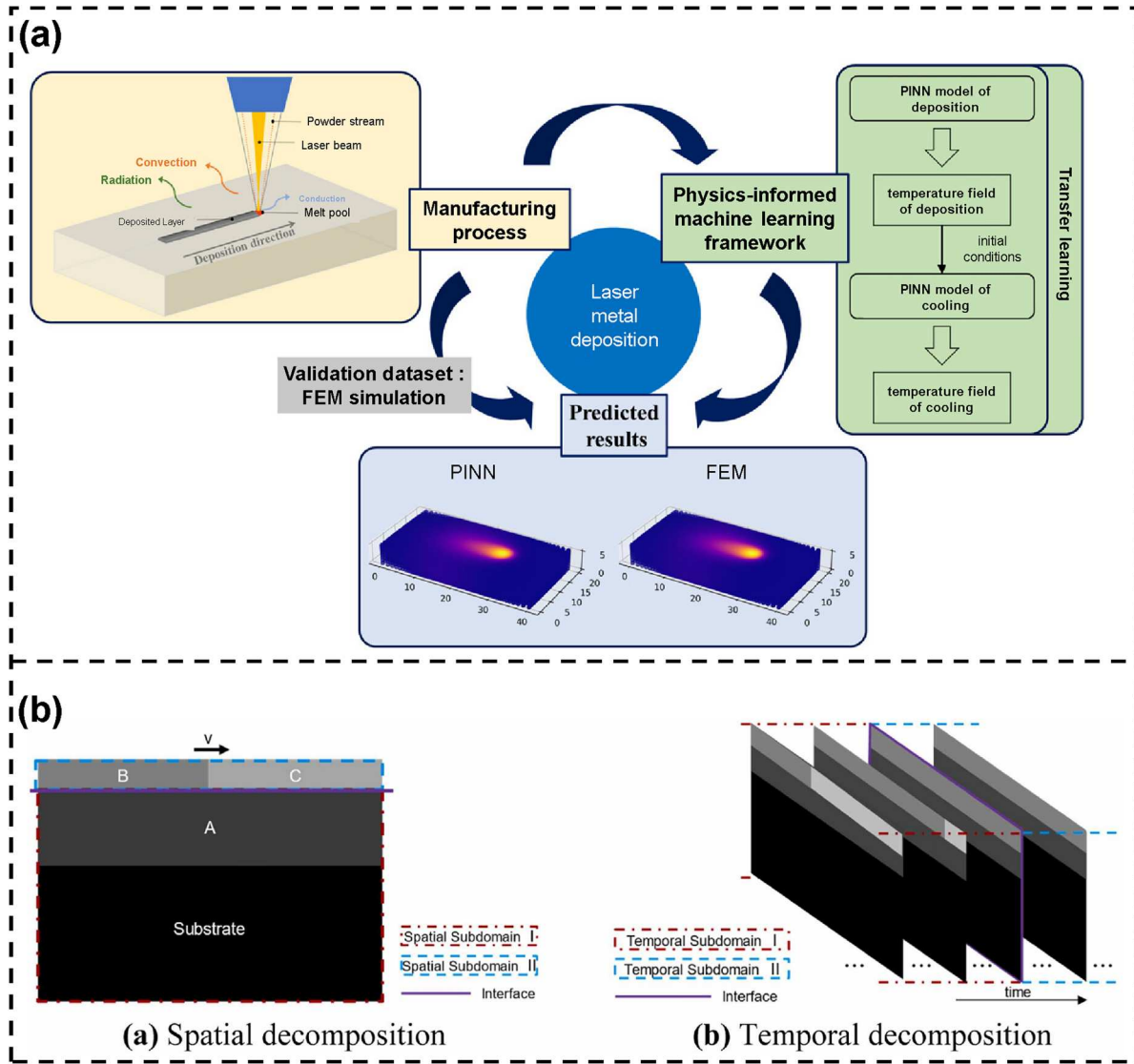


Figure 14. (a) Schematic diagram of a physics-informed neural network framework to predict a 3D temperature field [215], (b) Illustration of spatial and temporal decomposition, Zone A indicates the layers being printed, Zone B indicates the deposited portion of the active layer, and Zone C indicates the portion to be deposited (i.e. to be changed from void to solid) [216].

stress field as full node-wise fields. This model achieved an accuracy of temperature MRL2E 3.14% and CoP 0.998, and stress MRL2E 5.53% and CoP 0.994. The inference speed was 0.0146 s per case, approximately 43,000 times faster than FEM (631 s). For 915 geometries not included in training, it even captured the trend in which the maximum residual stress generally increases as printing speed increases. This demonstrates its function as a rapid exploration tool at the design stage. However, it is limited to materials without phase transformation, remaining confined to a purely TGM pathway. Validation is also confined to internal consistency with FEM, and the geometry is limited to 2D topology-optimized designs, restricting extension to 3D parts.

Although there has been no attempt like the examples above to extend phase transformation modeling to PIML, there has been an attempt to extend a grain growth model, which shares the same phase-field framework, to PIML. Zhang et al. [218] built a multiscale physical model that couples finite element thermal analysis with a phase-field grain growth model for the L-DED Ti-6Al-4V process. They proposed a framework that trains a JADE-Kriging two-level surrogate model on the data generated from this model to predict the temperature field and grain morphology (Figure 15). A total of 200 simulation samples were used with 180 for training and 20 for validation. The thermal surrogate model achieved a temperature field prediction accuracy with a correlation coefficient of approximately 0.98. The

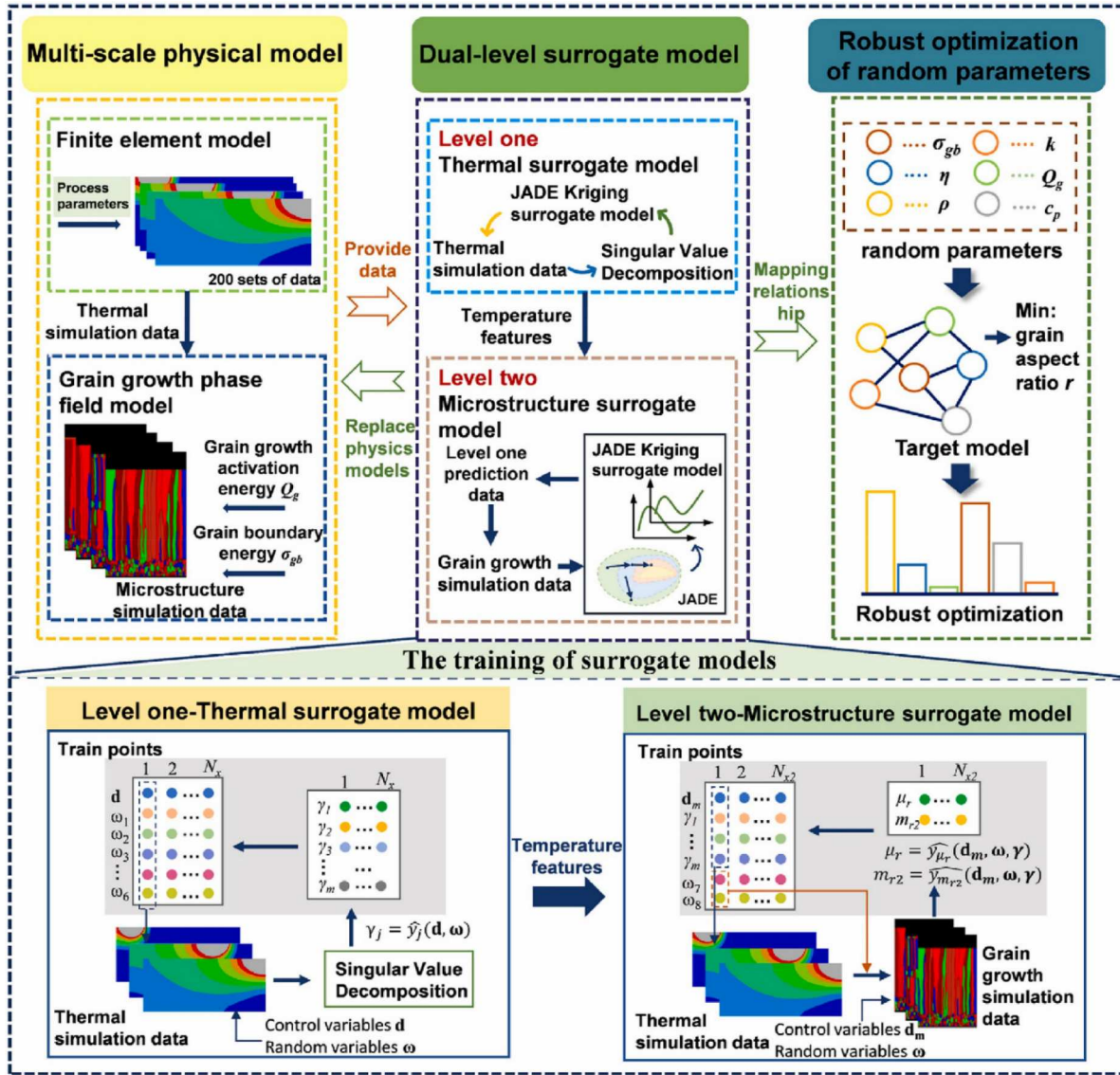


Figure 15. Framework of multiphysics-enhanced data-driven model [218].

microstructure surrogate model reproduced the grain aspect ratio closely matching experimental measurements under four experimental conditions (600–700 W, 8–12 mm/s). However, validation of the physical model itself is limited. It covers only pyrometer temperature under a single condition, with an average relative error of 10.4%, and β -grain pole figures under two conditions. Extension to solid-state phase transformation during cooling is not carried out. Extension to the residual stress field is also not carried out.

Taken together, research in the L-DED field has also attempted to extend from temperature field prediction to residual stress. However, existing studies either do not explicitly address phase transformation or focus on materials in which phase transformation does not occur, such as Inconel 625 or pure nickel. This limitation is particularly important because materials for which

residual stress management is critical in L-DED, such as tool steels and high-strength steels, often undergo phase transformation. Ultimately, for both L-PBF and L-DED, a framework that integrally addresses the temperature field, phase transformation, and residual stress for materials undergoing phase transformation remains a gap.

4.2. In-process: real-time monitoring and detection of defects

In L-PBF and L-DED, various in situ monitoring techniques have been investigated, including defect detection and process control during fabrication. Recently, PIML-based approaches that integrate sensor data with physical information have attracted interest for improving defect detection and classification performance.

4.2.1. In situ monitoring of porosity and melt pool geometry

Process-monitoring techniques for pore detection are primarily based on melt-pool imaging. For this purpose, various sensor data are acquired using coaxial and off-axis cameras [219], infrared thermal cameras [220,221] and photodiodes [222] to analyse defect behaviour. In particular, recent advances in deep-learning-based image analysis have facilitated real-time defect detection based on melt-pool morphology and thermal behaviour [223–226]. However, L-PBF and L-DED involve high scanning speeds and complex thermofluidic behaviour of the melt pool, requiring high computational efficiency for rapid defect analysis within limited time scales [227–229]. Accordingly, recent studies have focused on lightweight PIML-based monitoring frameworks that integrate physics-based information, such as heat transfer and melt-pool behaviour, into ML models. These approaches aim to reduce the computational cost while improving real-time applicability.

Mao et al. [230] proposed a physics-based multi-source data fusion framework based on Physics-based Feature Engineering for low-cost real-time monitoring in L-PBF. In their study, a multi-sensor platform consisting of a near-infrared (NIR) sensor, a photodiode, a visible-light camera, and a high-speed camera was used to acquire thermal radiation information, light intensity variation, surface images, and melt pool images, respectively. The collected data were reconstructed into melt pool feature sequences, with 32 images per region of interest (ROI), resulting in a dataset of 28,160 samples in total (Figure 16(a)).

Additional melt pool sequences were then generated through analytical heat transfer simulation and incorporated as weighting information into a physics-guided deep feature fusion model (PG-DFFM) (Figure 16(b)). A 3D-CNN-based variational autoencoder combined with an attention module was used to extract spatiotemporal melt pool features and reduce dimensionality. This overall framework is summarised in Figure 16(c). The melt pool generation model, based on the fusion of three low-cost sensors (photodiode, NIR, and visible light), achieved an RMSE of 31.17, an MAPE of 9.13%, and an R^2 of 0.936. This represents an improvement over the best single-sensor input, the photodiode alone, which achieved an RMSE of 38.17. The reconstruction performance of the upstream 3D-CVAE module itself was even higher, with an RMSE of 23.62, an MAPE of 6.11%, and an R^2 of 0.964. This corresponds to an error approximately 51% lower than that of a conventional 2D CNN-based autoencoder (RMSE of 48.22). Using the resulting melt pool information, porosity was classified into five levels with an accuracy of approximately 90.36%. This represents an improvement over the accuracy achieved without using generated data (88.27%), demonstrating the feasibility of low-cost porosity monitoring based on physics-informed thermal behaviour. However, this study does not report computation time, which is one of the most critical PIML performance metrics for in-process real-time monitoring. Given that the model combines a 3D CNN, transformer-based attention, and a VAE into a relatively heavy architecture, further validation is essential before applying it directly to real-time monitoring.

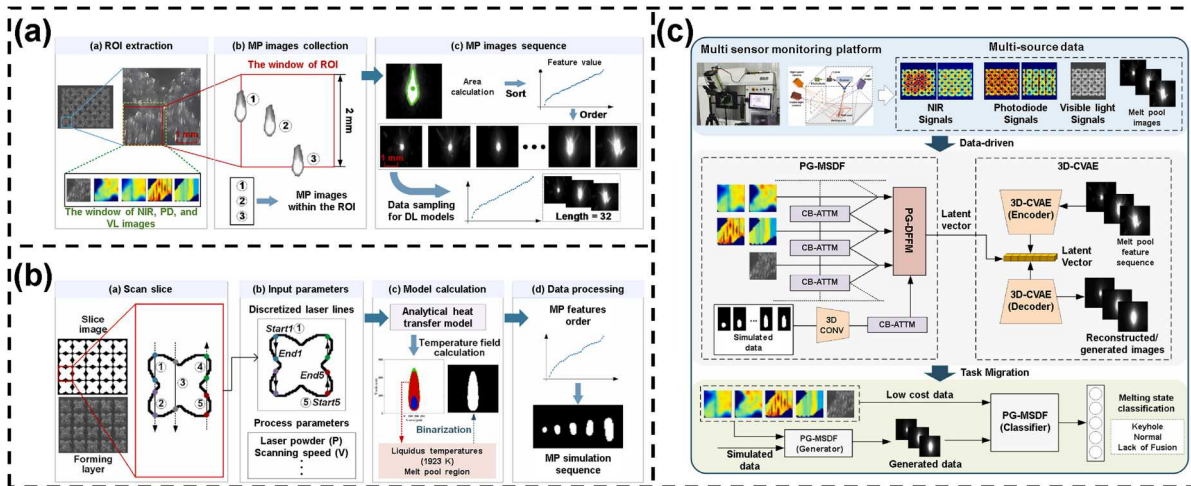


Figure 16. Physics-informed multi-source data fusion framework for porosity monitoring in L-PBF: (a) Reconstruction of melt-pool feature sequences from multi-sensor data acquired using NIR sensors, photodiodes, and visible-light cameras. (b) Integration of analytically simulated thermal information into the PG-DFFM. (c) Overall framework combining multi-source sensing data, physics-based thermal modelling, and deep learning for real-time porosity monitoring [230].

Zhang et al. [231] proposed a physics-informed multi-task framework based on infrared thermal video for real-time defect detection in L-PBF, using Ti-6Al-4V. This study used top-view infrared image sequences as input data. A Physics-based Simulation-assisted ML methodology was applied. Melt pool depth obtained from simulation was incorporated as an auxiliary regression task during training, thereby embedding physics-based information into the model (Figure 17(a)). In other words, side-view information from the simulation was used only during training, while the goal was to predict

defects using only top-view thermal images during actual operation. The dataset was generated from a validated powder-scale multiphysics simulation for a single scan track measuring 4,000 by 500 μm . It consisted of 2,069 samples, classified into four melting states, keyholing, desirable, balling, and LOF, according to combinations of laser power and scanning speed. This framework used a video vision transformer (ViViT) based architecture to learn the spatiotemporal characteristics of the melt pool, improving defect detection performance without requiring additional side-view

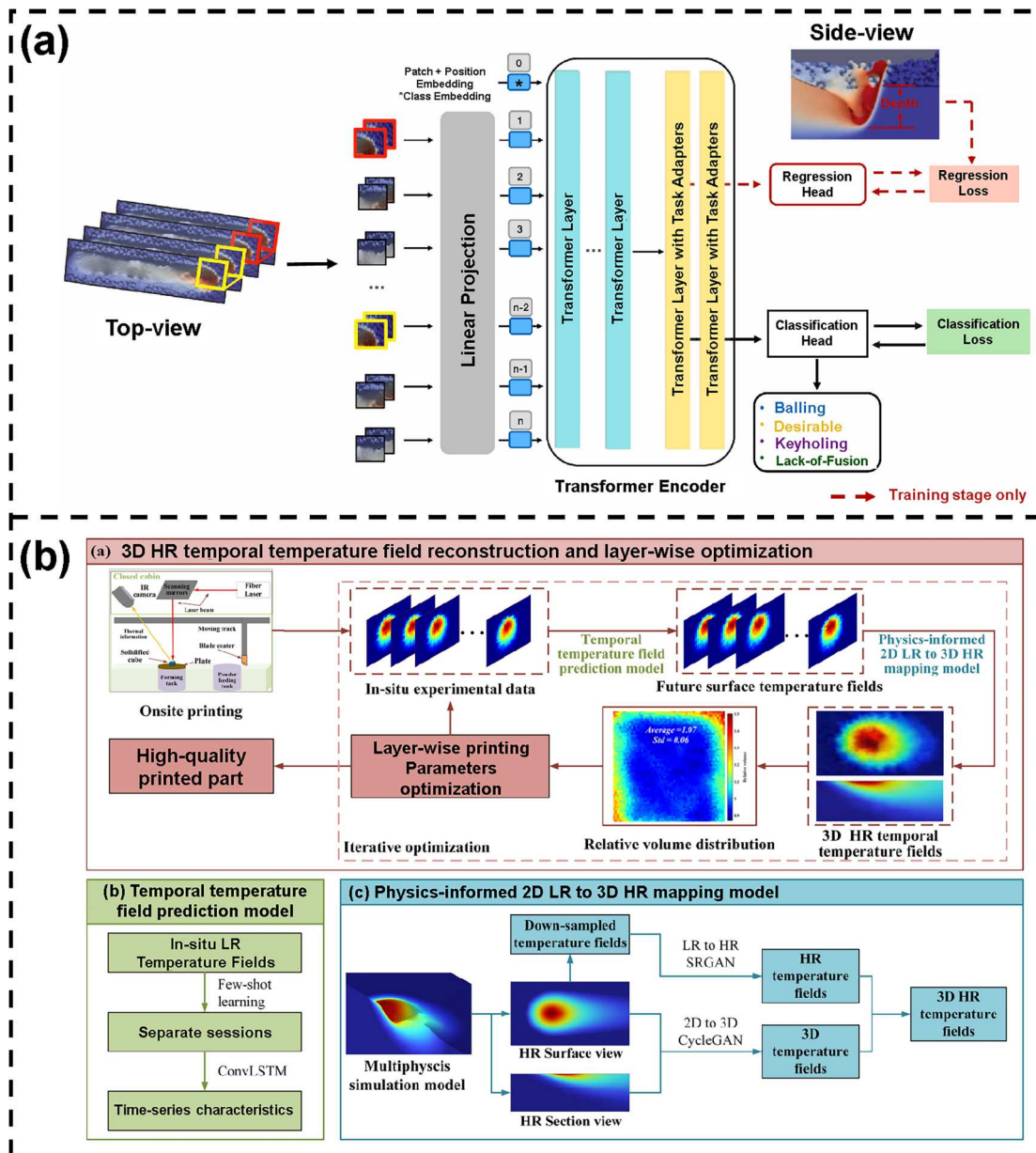


Figure 17. Physics-informed learning frameworks for defect detection and quality assessment in L-PBF: (a) ViViT-based multi-task framework integrating simulated melt-pool depth information for real-time defect detection using infrared thermal videos [231]. (b) Overall framework for reconstructing the 3D high resolution temporal temperature field and optimising layer wise process parameters [232].

data. Lightweight dual adapters for classification and regression were placed in the final two transformer layers. Shared representations were maintained in the earlier layers, while task-specific features were refined only in the later layers. This model achieved a classification accuracy of 97.72% and an F1-score of 96.78% across four defect classes. This represents a clear improvement over the baseline model using only top-view data without the auxiliary task (93.46%). In a control experiment where random values replaced the auxiliary labels, this performance improvement was not observed. This confirmed that the improvement stemmed from the physically meaningful information of melt pool depth, rather than from the auxiliary task structure itself. Inference time was 1.48 ms per sample. Although this fell short of the upper-bound model using both top-view and side-view data (10.4 ms inference time, 98.84% accuracy), the top-view-only model achieved comparable performance while demonstrating fast, millisecond-level inference. In other words, rather than directly embedding simulation-based physical knowledge into the model itself, this study used it only as an auxiliary role during training. This reduced computation time while improving accuracy. However, both studies above were limited to developing classification models for defects and did not extend to optimising process variables to improve actual part quality.

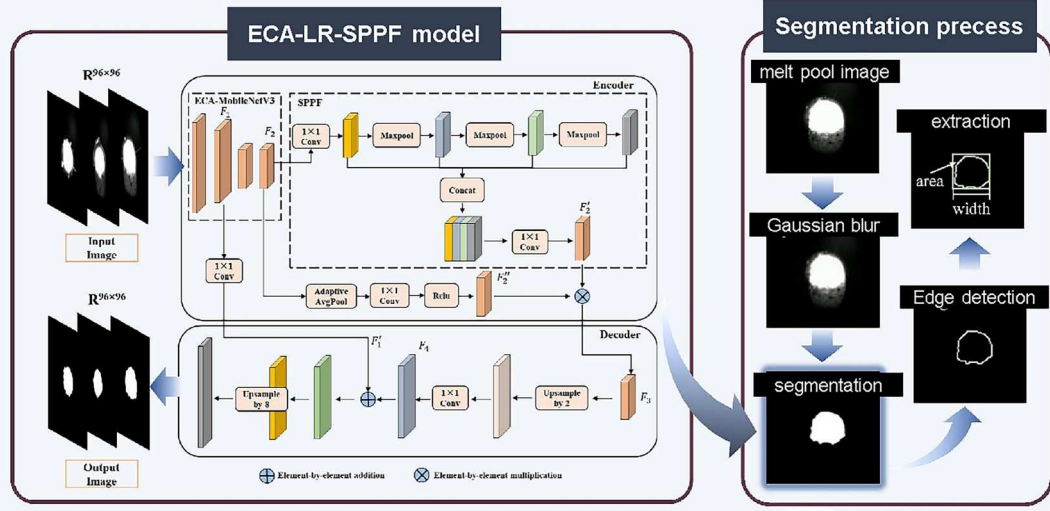
Addressing this gap, Wang and Lu [232] proposed a model that evaluates melt pool stability by integrating in-situ monitoring data with high-precision simulation results to reconstruct the three-dimensional temperature distribution of the melt pool. This corresponds to a Physics-based Simulation-assisted ML methodology. High-resolution temperature fields generated from multiphysics finite element simulations were used as training data to train generative adversarial networks (GAN)-based mapping model. The L-PBF process was conducted on 316L stainless steel, and a FLIR A500 infrared thermal camera was used to construct a temperature monitoring dataset across combinations of laser power and scanning speed. The overall framework consists of three stages (Figure 17(b)). First, a ConvLSTM network combining CNN and LSTM predicts the future low-resolution surface temperature field of the melt pool. To reduce computational burden, few-shot learning (FSL) divides the data into 30 frame units, with intervening intervals interpolated through prediction. Second, since low-resolution results alone cannot reveal the internal temperature distribution, high-resolution temperature fields are generated through FEM simulation incorporating phase change, surface tension, the Marangoni effect, and recoil pressure. Using these high-resolution and low-resolution pairs as training data, an

SRGAN is trained to reconstruct the measured low-resolution surface temperature field into high resolution. A CycleGAN then learns the mapping between simulated surface and cross-sectional temperature fields, allowing the unmeasurable 3D internal temperature field to be inferred from surface information alone. Third, the relative melt pool volume is calculated from the reconstructed 3D temperature field to evaluate stability. If it deviates by more than 5% from the reference, the laser power for the next layer is adjusted, enabling layer-by-layer quality control. Temperature fields were sampled at 0.033 s intervals, corresponding to the frame rate of the thermal camera, and divided into uniform subsets of 30 consecutive images. Using 30 time steps to predict the temperature distribution at the 31st time step achieved high accuracy, with an MRE below 2.5%. For high-resolution reconstruction, SRGAN achieved the lowest LPIPS (0.03) among existing super-resolution techniques, including SRResNet, sub-pixel, bicubic, and EDSR. Training these GAN models required approximately 4 hours. Generalisation validation on Ti-6Al-4V also showed high agreement, with an MRE of 1.89% and an SSIM of 0.97. Finally, applying layer-wise optimisation improved the average relative melt pool volume from 1.06 (unstable) to 0.99 (stable). SEM observations confirmed a reduction in internal porosity in the adjusted samples. This study is significant in that it adjusted process variables and verified the resulting quality improvement. However, the authors note that this optimisation is limited to the layer level and cannot respond in real time to rapid fluctuations occurring within a layer. Ultimately, although this study performed defect optimisation, it does not constitute a closed-loop form of active control during the actual process. From this perspective, given the rapid progression of the actual L-PBF process, this suggests that challenges remain in advancing toward precise real-time monitoring and optimisation techniques.

L-PBF offers high process stability and a relatively enclosed powder bed environment, making real-time monitoring easier to implement. In contrast, L-DED exhibits greater process variability and has an open architecture, which presents inherent limitations [233]. Currently, research on PIML-based real-time monitoring of porosity and melt pool geometry in L-DED remains limited.

Nevertheless, attempts have been made to apply PIML-based monitoring to the L-DED process. Notably, Niu et al. [234] proposed an image-physics dual-driven framework that combines melt pool imaging with a physical model to predict cross-sectional geometry using only a small number of samples (Figure 18). This framework used coaxial and off-axis CMOS industrial

Part I: Image segmentation



Part II: Prediction by physics-guided neural network

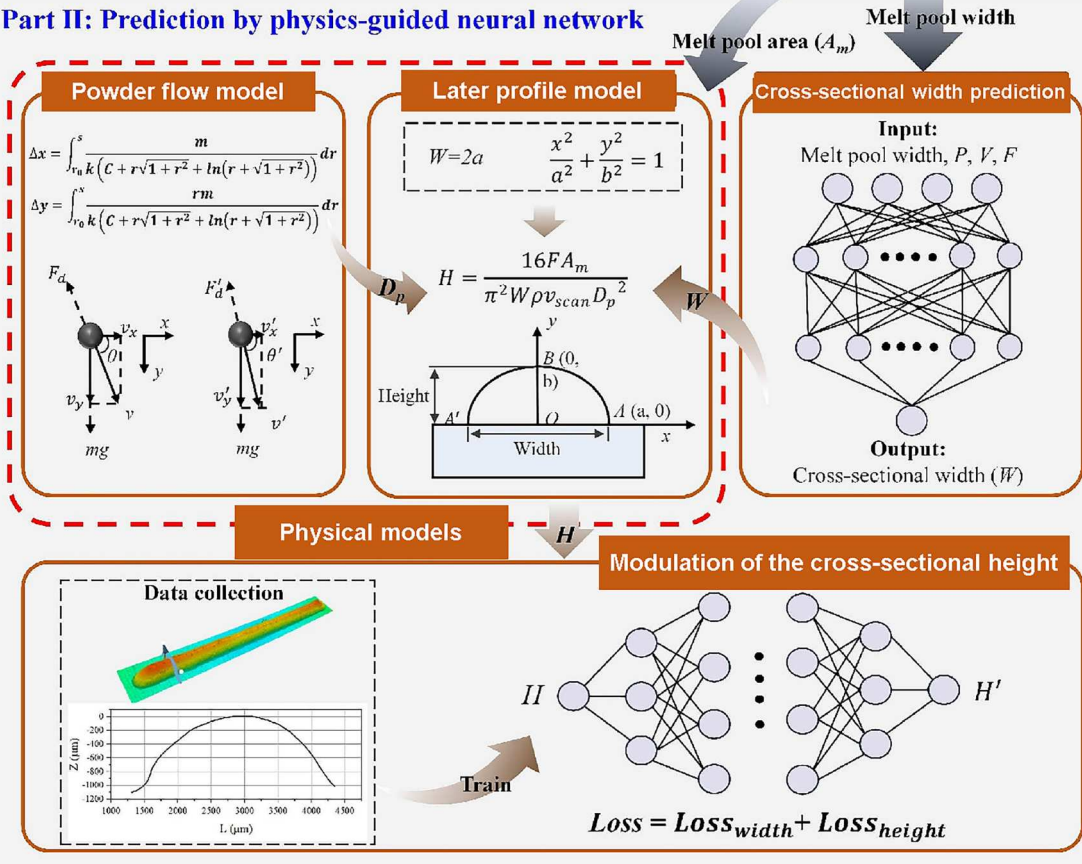


Figure 18. Schematic diagram of the framework structure [234].

cameras to observe the melt pool and powder flow in real time. Experiments were conducted on 27 single-pass specimens by depositing IN718 powder onto a 42CrMo substrate under various combinations of laser power, scanning speed, and powder feed rate. Among these, 1,000 melt pool images were augmented through rotation, flipping, scaling, and brightness adjustment to construct a segmentation training

dataset of 3,000 images. Cross-sectional geometry was measured at five points per specimen using a five-axis 3D optical profilometer, yielding a total of 135 cross-sectional data points. Of these, 120 were used for 5-fold cross-validation training and 15 for testing. The framework consists of two stages. First, a lightweight segmentation model (ECA-LR-SPPF), combining efficient channel attention (ECA) and spatial pyramid pooling-fast (SPPF)

modules, extracts the width and area of the melt pool from the images. These values, together with the process variables, are then input into a first multilayer perceptron (MLP) to predict the cross-sectional width. Next, a physics layer computes a preliminary estimate of cross-sectional height. This layer is composed of a powder flow model based on Newton's equations of motion, accounting for air resistance and gravity, along with an elliptical-curve-based layer profile model. It uses the predicted width, melt pool area, and powder jet diameter to perform this computation. This estimate is then refined by a second MLP to produce the final predicted height. In other words, the physical model is embedded directly as a computational layer within the forward pass of the neural network, rather than as a loss function term or an input feature. The segmentation model achieved an mIoU of 0.9377 and a processing speed of 22.48 ms per image, improving both accuracy and speed over existing models such as UNet3+ (64.91 ms) and PSPNet (207.78 ms). Compared with an MLP without the physics layer, the MSE for cross-sectional height was reduced by 82–95% when trained on 60 samples. Even under the extreme condition of only 15 training samples, the model achieved an MSE of 0.0875, outperforming the physics-free model trained on 120 samples. These results demonstrate that the strategy for integrating physical knowledge can vary depending on process characteristics, in order to meet the fast computation requirements of in-process real-time monitoring. However, because this framework was validated only on single-track specimens, heat accumulation effects were not accounted for, and its applicability to actual multilayer processes remains unverified. In addition, no direct correlation with porosity or porosity detection was established.

Overall, research on L-DED remains less developed than on L-PBF, and studies on L-PBF itself are still relatively limited as well. By nature, real-time monitoring requires not only detecting and classifying porosity defects but also actively responding to them. Both processes should therefore be further developed toward closed-loop feedback strategies in future research.

4.2.2. In situ monitoring of residual stress via thermal and shape surrogates

This section examines PIML studies that have attempted in situ monitoring and indirect estimation of residual stress using thermal and shape-related surrogate variables in L-PBF and L-DED.

As one study addressing this requirement for real-time capability in the L-PBF process, Alfattani and Hotami [235] proposed a framework operating at three scales: micro (melt pool fluid dynamics), meso

(pore damage), and macro (thermo-mechanics and residual stress). At each scale, the framework embeds the governing equation residual as a loss function in PINN/Fourier Neural Operator (FNO) surrogates. The outputs from these three scales are then fused with thermal, optical, and acoustic emission sensor signals using a CNN-LSTM (Figure 19). The defect classification accuracy was $98.72 \pm 0.22\%$. The surrogate relative errors were 1.42% for micro, 1.87% for meso, and 1.63% for macro, with 2.14% for the coupled model. The entire pipeline was processed within 11.3 ms using an edge-fog-cloud three-tier architecture, achieving millisecond-level real-time capability. Training used 5,000 simulation data points per scale (15,000 in total) and 1,500 measured label data points. However, validation was conducted only by comparing the macro-scale temperature and shape-related outputs against actual pyrometry. No experimental validation was performed for the residual stress value itself or for the physical quantities at the micro and meso scales. The proposed process control scenario was also only a simulation-based example, with no validation on actual equipment.

In contrast, Li et al. [236] focused on directly validating the residual stress value itself against measured data. They pre-built a database of the temperature-residual stress relationship under various process conditions using finite element analysis. During actual deposition, temperature signals were acquired by an infrared camera. Residual stress at a given moment was then estimated in real time through weight-based matching of these signals against the database. Rather than training a separate neural network end to end, this approach is closer to a procedure that uses the simulation database as a reference frame, to which measured signals are matched. This approach has the characteristic that it can be applied with relatively little measured data. When compared against actual residual stress measured by the contour method for two L-PBF Ti-6Al-4V parts, the results showed agreement with a closeness measure of 0.436, an RMSE of 0.024–0.106, and a correlation coefficient of 0.96–0.88. This can be regarded as a case in which residual stress itself was directly validated against measured data. Although processing speed is a critical factor for defect detection, this study does not quantitatively report computation time. As a result, there is insufficient basis to judge real-time applicability, and the data scale is limited. In addition, this study deals with Ti-6Al-4V, which is capable of phase transformation. However, metallurgical behaviour such as the volumetric change or latent heat release accompanying phase transformation is not reflected in the modelling, which remains a limitation to be addressed in future research.

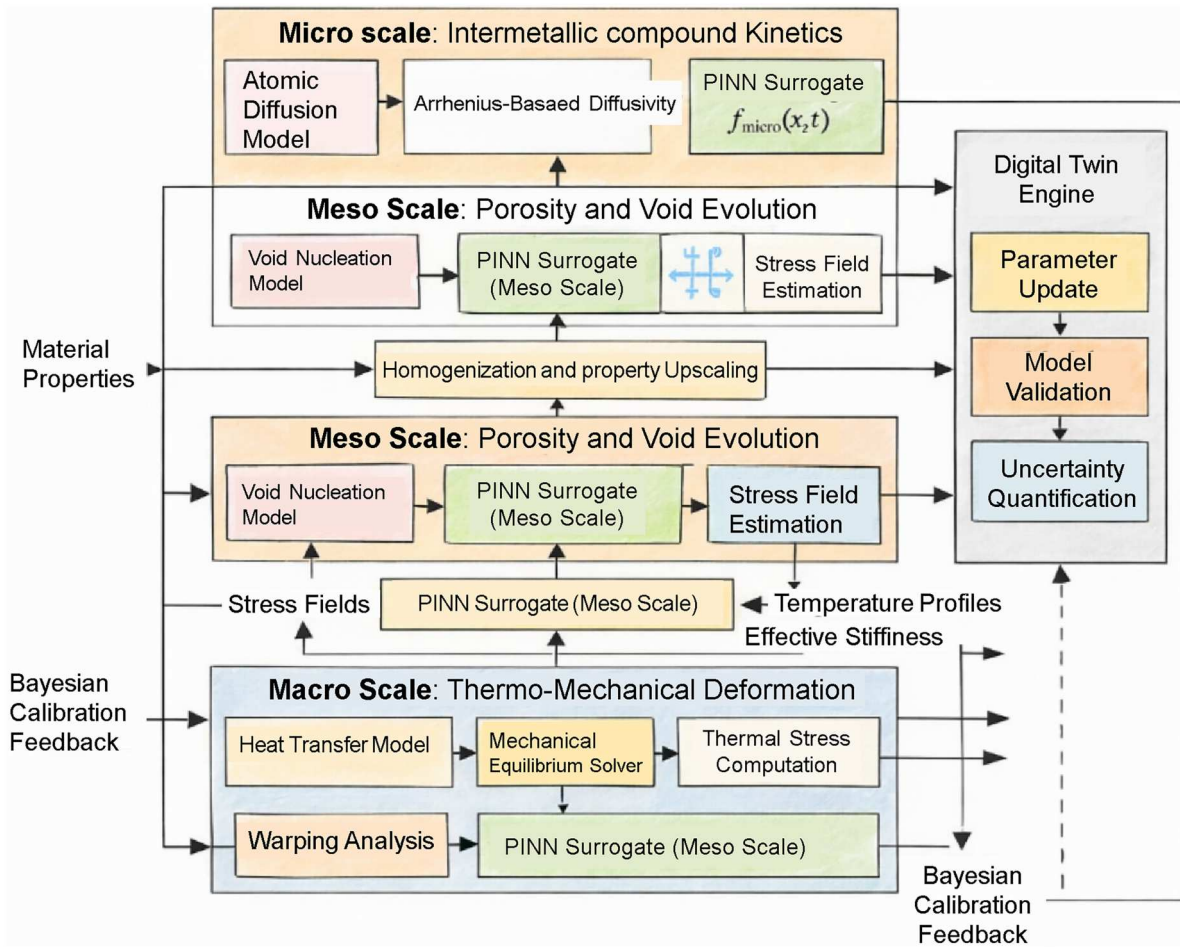


Figure 19. Framework of a multiphysics-enhanced data-driven model [235].

Taken together, these L-PBF-related studies show a tendency to apply PIML using thermal, optical, and acoustic emission signals obtainable from the upper surface. This tendency reflects the process characteristics of the enclosed chamber and powder bed. Overall, these studies fail to satisfy all three key elements, namely securing real-time capability, incorporating physics, and validating against measured data. Each study tends to be skewed toward only partial achievements. As a result, it is difficult to say that balanced progress has been made in terms of the applicability or reliability of the models. A substantial gap remains between physical interpretability and practical usability in actual processes. A similar trend is also observed in the L-DED process. However, unlike L-PBF, L-DED proceeds with the geometry accumulating layer by layer, which allows layer-wise shape shrinkage to be observed. As a result, a different approach from that of L-PBF is also being attempted for estimating residual stress.

As one example of an attempt to indirectly capture the effect of residual stress through shape information, a study in a hybrid manufacturing process can be

cited. He et al. [237] focused on the fact that, in a process alternating between L-DED and machining, stress redistribution caused by machining induces shape distortion [238]. Based on this, they proposed a system that inserts 5-axis contact on-machine inspection (OMI) between AM-subtractive manufacturing (SM) alternating sequences and reconstructs the full deformation field from sparse measurement points using a PINN (Figure 20). Instead of the thermo-mechanical governing equations of the material, this PINN included a geometric regularisation term enforcing local rigidity in the loss function, enabling physically plausible reconstruction even from sparse data. In addition, with a lightweight structure of 397,318 parameters, it achieved training in under 1 s and an inference time of 0.7104 ms per point, demonstrating that real-time processing is possible. It was validated through actual SS316L hybrid manufacturing experiments on four types of geometries: a conical shell, two cylinders of different thicknesses, and a free-form curved pipe. When compared against both wire-cut cross-section and 3D optical scan measurements, it showed agreement with an average

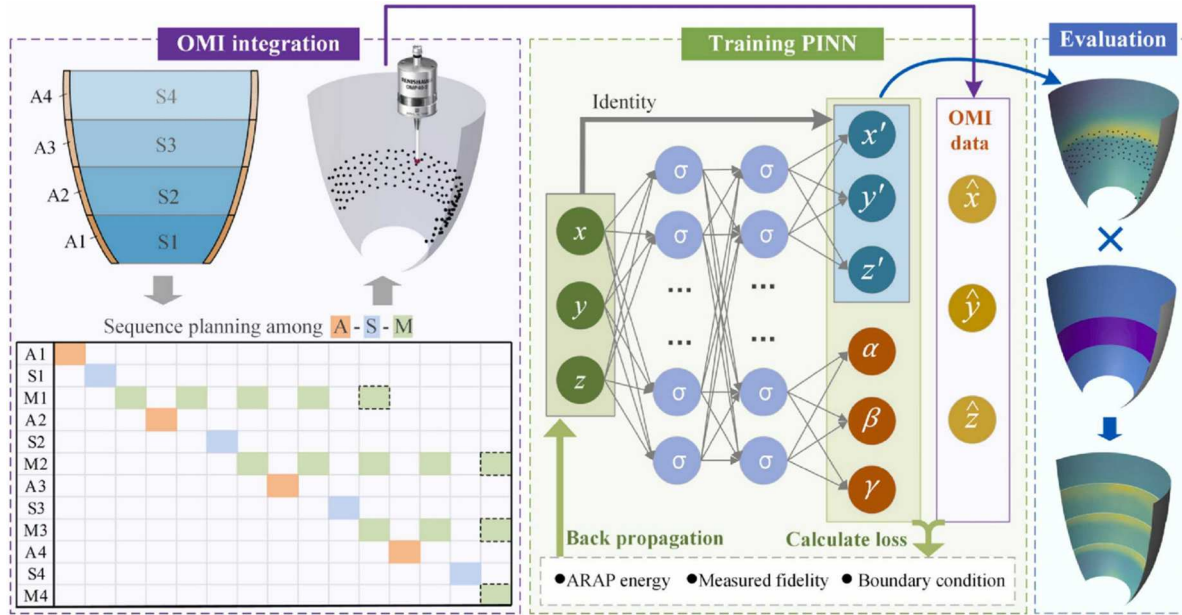


Figure 20. The pipeline of the HM deformation reconstruction system, including OMI planning and experiment, PINN training and evaluation of the deformation field [237].

error of 0.05 mm. It also produced reconstruction results that were more physically plausible, with less local oscillation, than the existing Kriging interpolation method. The authors present a future direction of extending this reconstruction technique to a neural network linking process parameters and deformation data. This would make it possible to predict deformation from part geometry and process conditions, and further to reach inverse-design-based process compensation. Therefore, this high-precision real-time capture technology for the geometric consequences induced by residual stress can be regarded as a potential foundation for future work. It could be extended to future detection and control research targeting residual stress itself.

Unlike this shape-based approach, there are also studies that attempt to predict the temperature field in real time for use in early warning or monitoring. Yang et al. [239] predicted the melt pool temperature field of the L-DED process using a lightweight neural network (8,705 parameters) that embeds the residual of the coupled heat conduction-convection equation in the loss function. This model achieved 98% accuracy (MAE 8.24 K). In addition, based on a processing speed of 4,964 frames per second, they issued early warnings approximately two layers before actual defect occurrence. This achieved a performance of Precision 1.00 and Recall 0.92/0.75. Duan et al. [240] predicted the melt pool temperature distribution using a spatiotemporal neural network. This network combined a Fourier module corresponding to the thermal diffusion Green's function with a local discrete vector quantisation

module. The model was directly validated with measured infrared data, achieving an accuracy of RMSE 0.023 for single-track and RMSE 0.028 for multi-track, along with a processing speed 2–3.5 times faster than the actual thermal history. However, both studies only mention, as background motivation, that a steep thermal gradient induces residual stress. They do not predict or measure residual stress itself, and validation was conducted only under a single material and a single experimental condition, so generalizability has not been confirmed either.

Overall, these L-PBF and L-DED studies show a tendency in both processes to approach residual stress indirectly through surrogate variables such as temperature or shape deformation, rather than directly predicting and validating residual stress itself in real time. In L-PBF, studies combining multi-scale surrogates with multiple sensor signals (thermal, optical, acoustic emission) predominantly focus on either processing speed or validation accuracy. In contrast, in L-DED, studies appear that either utilise layer-wise shape shrinkage as a surrogate indicator of residual stress or focus on early warning through temperature field prediction.

4.3. Post-process: reliability assessment

Minute pores, residual stress, microstructural inhomogeneity, and the like may remain incompletely removed within the final fabricated part. Therefore, in the post-process stage, it is important to evaluate the effect of remaining defects on final quality and structural

reliability. This evaluation utilises data obtained after fabrication, such as non-destructive inspection, surface and cross-sectional images, heat treatment history, and mechanical test data. However, because this stage targets a completed part, unlike the pre-process and in-process stages, the situation differs. The PIML approaches of the two processes themselves converge similarly, in that they combine defect statistics and thermal history with physical constraints. PIML research at this stage is broadly divided into two branches. One is research that directly predicts final product quality indicators and mechanical properties from remaining defects and process history, and the other is research that predicts fatigue crack initiation and failure behaviour induced by defects.

4.3.1. Predicting part quality and mechanical properties

Since prediction at the post-process stage targets a part that has already been completed, there is no room to reverse or modify the process once this point has passed. Accordingly, the accuracy of the prediction is treated as a priority above any other criterion, which is tied to the fact that mispredictions remain entirely in the form of scrap costs or quality risk. However, the basis on which this accuracy rests varies considerably from study to study.

For instance, a large sample size does not necessarily mean that a model possesses robustness. Bevans et al. [241] dealt with an L-PBF-fabricated IN718 part. They combined the end-of-cooling temperature and cooling time obtained from meshless thermal analysis with sensor signals such as melt pool intensity and interlayer time. Using a hierarchical kNN, they jointly predicted a defect indicator (porosity presence), microstructural indicators (melt pool depth and grain size), and a mechanical property indicator (microhardness) (Figure 21(a)). This physics-sensor combined configuration showed higher accuracy across all items compared to a single source (porosity F1 99.3%, melt pool depth $R^2 = 99.6\%$, grain size/hardness $R^2 = 93.7\%/91.1\%$), and the thermal analysis used here is itself 10–20 times faster than FEM. However, this is only a repeated evaluation within a narrow sample of 18 out of 22 parts, and robustness under conditions outside the training range was not confirmed. In contrast, Yang et al. [242] predicted high-cycle fatigue life using a PINN in which a neural network directly generates the Basquin coefficients and eight monotonicity inequalities are imposed as physical constraints in the loss function (Figure 21(b)). Trained on 856 data points from 21 papers spanning both L-PBF and L-DED, they obtained high accuracy (R^2 97.0%/95.7%) with as few as 922 parameters. Although

the sample size is far larger than that of Bevans et al., these 856 points are not measured values but rather values stitched together by imputing missing entries across different papers and processes using XGBoost, and there is no repeated or extrapolation validation beyond a single split. Ultimately, since the two studies reach the same conclusion by opposite means, the level of confidence can differ even when the reported accuracy figures appear similar on the surface.

The basis supporting accuracy also differs from study to study. Some studies verify whether predictive performance is maintained under conditions outside the training range, while others evaluate how efficiently a similar level of accuracy can be achieved. Zhu et al. [243] fabricated a mixture of 316L and AlCrFeNi by L-DED. They built a strengthening-theory-based physical model for only 13 compositions and proposed a Physics-based Feature Engineering framework, in which a GPR learns the residual between the physical model's predictions and the measured values (Figure 22(a)). The physical model's predictive performance for yield strength, tensile strength, and elongation initially showed an R^2 of 0.355–0.904 with an error level of 18%. Through residual correction, this was improved to an R^2 of 0.978–0.992 with an error of 1.79–7.18%. In addition, they performed repeated validation with varying training sample sizes (6–10), as well as extrapolation validation on compositions outside the training range. The results showed that the error of the purely data-driven model reached 633%, whereas the physics-coupled model showed a relatively low error of 74.7%. This shows that coupling with physics may, beyond simply improving predictive accuracy, mitigate the degradation of performance under conditions outside the training range. However, the entire dataset consists of only 13 compositions. Given this small sample size, it is difficult to distinguish whether this difference solely reflects the effect of the physical information, or whether the limitation of GPR's extrapolation performance with a small amount of data is also acting together.

In contrast, Cooper et al. [244] also targeted L-DED. They proposed a Physics-based Feature Engineering framework that predicts the tensile strength and yield strength of IN718, using 40 thermal history features linked to physical quantities such as local grain size and density (Figure 22(b)). For 135 specimens, this framework maintained predictive performance equal to or better than an existing CNN benchmark. At the same time, it reduced the forward-pass computational load to 379 FLOPs, about 1/4,700,000 of the benchmark, and shortened the total prediction time from 5.8 s to 1.2 μ s. That is, in this study, the primary benefit of coupling with physics appears in computational efficiency rather

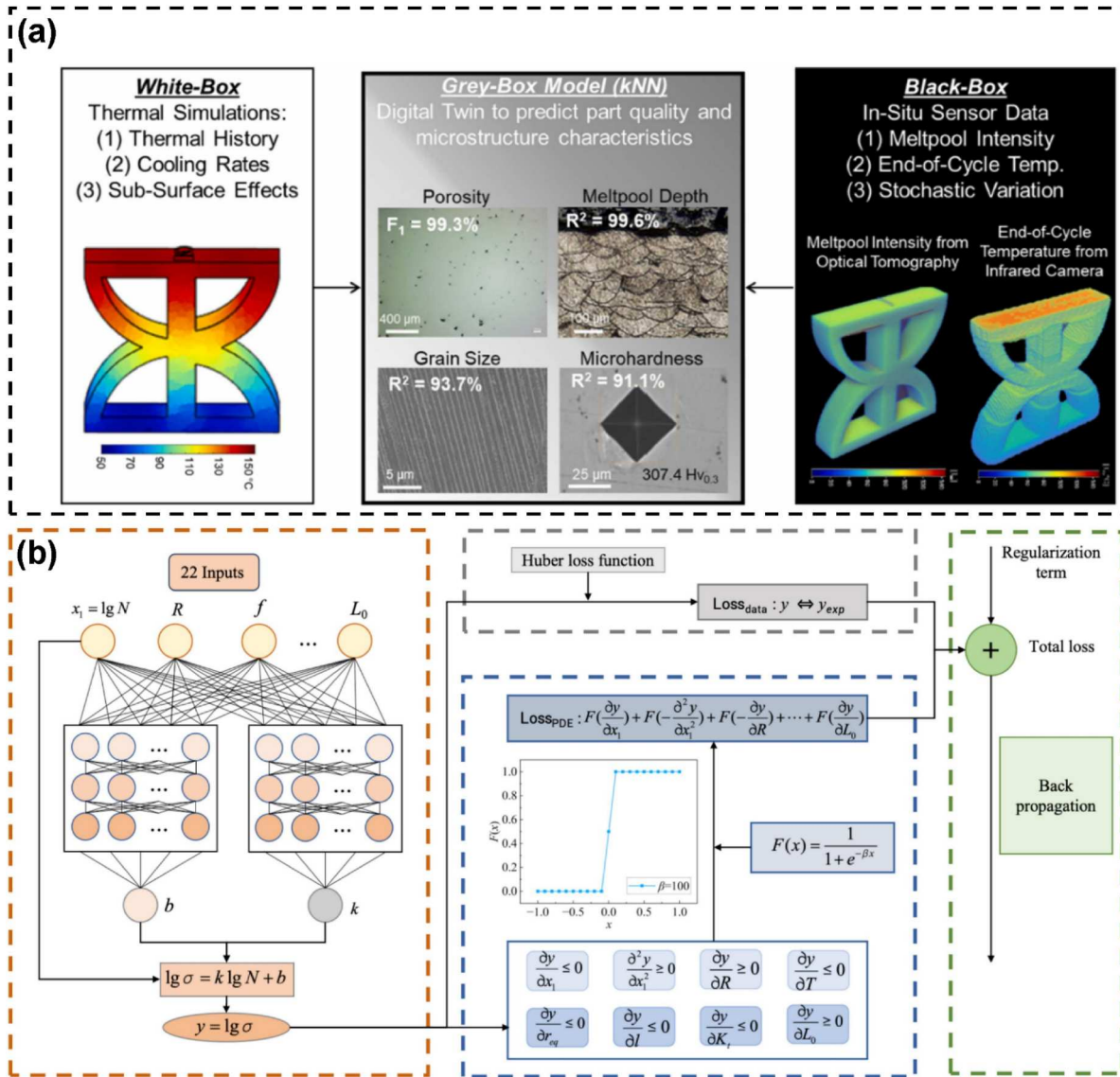


Figure 21. (a) Physics-based model predictions of the part-scale thermal history [241], (b) A PIML model combining the Basquin equation with a neural network to predict the high-cycle fatigue behaviour of L-PBF [242].

than extrapolation robustness. However, since all specimens were in the as-built state without heat treatment, this does not reflect the effect of post-processing history, which is important in this section. In addition, temperature variance, presented as the most influential feature, is also open to interpretation as a surrogate indicator distinguishing the deposition method, rather than as a variable whose direct physical causal relationship has been verified.

In summary, the value of PIML in quality and property prediction cannot be judged from a single performance metric such as R^2 or error rate alone. Even when sample size or accuracy figures appear similar, the underlying validation approaches differ substantially, and the benefits brought by coupling with physics also manifest in different forms, namely extrapolation robustness and

computational efficiency. Ultimately, what the studies covered in this section show is that the practical value of PIML can only be judged by considering, together, robustness under limited data, the interpretability of physical variables, and computational efficiency, rather than accuracy alone.

4.3.2. Predicting defect-induced fatigue and failure

Prediction of fatigue cracking and failure caused by defects is different in nature from the quality and property prediction discussed earlier. This is because the task is not to judge the state of a completed part at a specific instant. Rather, it is to assess how long an already-identified defect will endure under repeated loading, and at what point it will progress into a crack leading to failure. Therefore, how the information on defects is

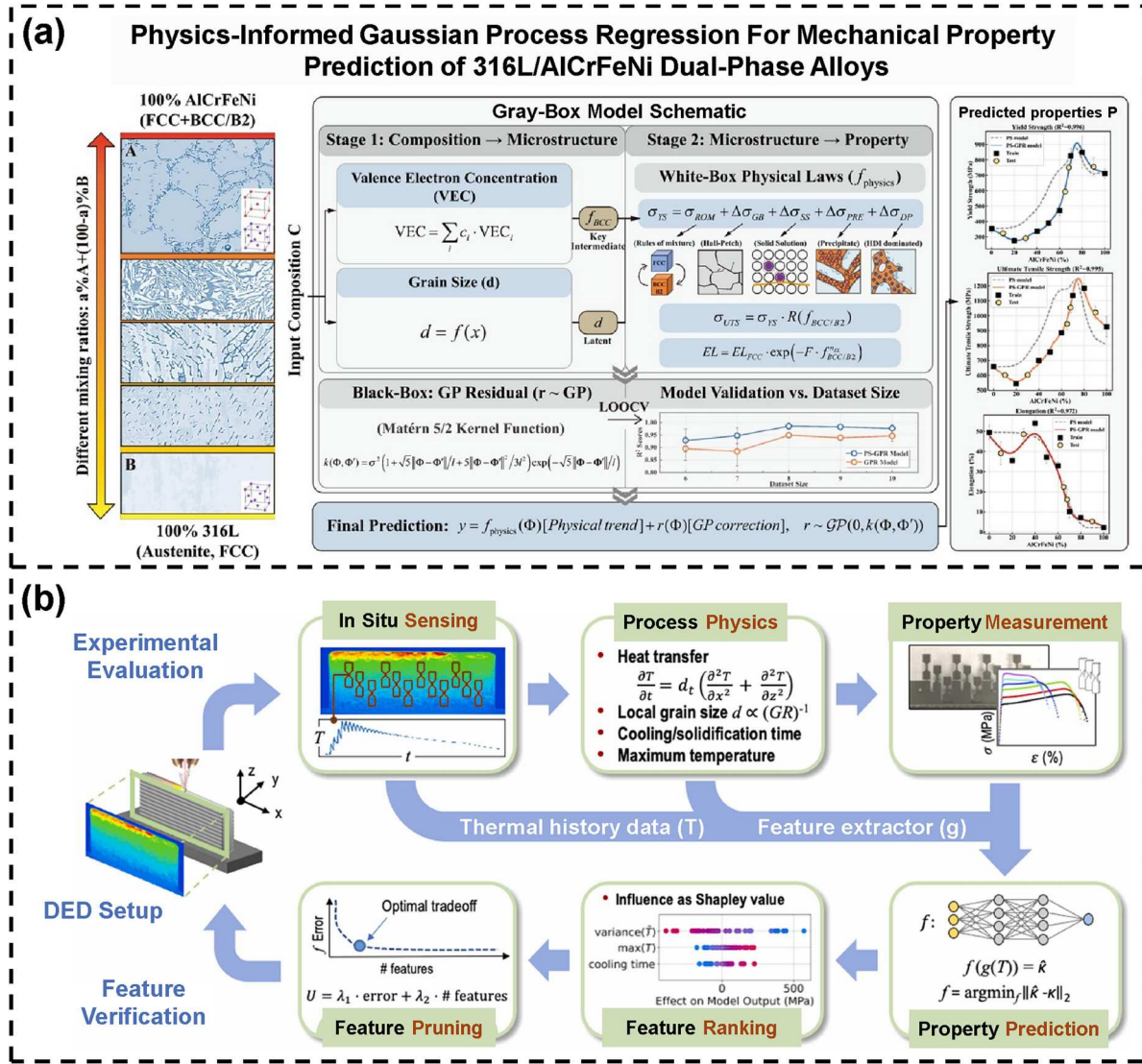


Figure 22. (a) Framework of mechanical property prediction based on a physics-informed GPR residual correction model [243], (b) An overview of interpretable machine learning for tensile strength prediction in L-DED using SHAP [244].

linked to physics-based fracture mechanics and damage models becomes the key issue.

Hills and Becker [245] proposed a defect-based PINN that directly incorporates defect characteristics into the fatigue strength prediction of L-PBF Ti-6Al-4V. Large or near-surface defects act as initiation sites for cracking and significantly reduce fatigue strength, and this study ensured that such defect-controlled behaviour was predicted in a physically valid direction through the Kitagawa-Takahashi relation and threshold stress intensity factor (ΔK_{th}) constraints. However, since only 143 measured defect data points were available, a three-stage pipeline was used in which the model was first pretrained on 4,800 NASGRO-based synthetic data points generated from XCT defect statistics, and then fine-tuned with physical constraints. The coefficient of determination improved from 0.70 (baseline neural

network) to 0.77 (pretrained) to 0.82 (PINN), and the mean absolute error improved from 40.5 MPa to 29.9 MPa. However, a substantial portion of this improvement already occurred at the synthetic-data pretraining stage rather than from the physical constraints, and since the synthetic data itself is the output of another physical model, NASGRO, it is not clear whether what the neural network learns is new physical information or the existing assumptions of NASGRO.

Unlike the study above, which predicted fatigue strength from defects, Ince [246] instead took the growth rate of an already existing crack as the prediction target. For three L-PBF alloys, Ti-6Al-4V, IN625, and 17-4PH, Ince imposed monotonicity between ΔK and R (or K_{max}) as a constraint. A key strength of this study is the validation approach it adopted. Under random cross-validation, in which data from the same curve

could be mixed between training and validation, the physics-constrained model reduced the error by 10–20% (Ti-6Al-4V RMSE 0.219–0.179). However, under a validation scheme separated by specimen, so that data from the same specimen were not mixed, the absolute accuracy of all three models dropped substantially. This means not that the effect of the physical constraint disappeared, but that the random split had made the performance of all models appear optimistic. Furthermore, under this stricter validation, the benefit of the physical constraint differed by alloy. For Ti-6Al-4V and 17-4PH, the benefit was clear. However, for IN625, the difference between the physics-constrained model and the baseline neural network effectively disappeared. The traditional Walker model even achieved a higher coefficient of determination than both. This shows that the physical constraint is meaningful only when it pertains to the variable that governs the data.

Bartošák et al. [247] addressed multiaxial low-cycle fatigue of L-PBF 316L. They proposed a hybrid PINN framework (Figure 23(a)), in which the SWT damage parameter of the critical plane approach is multiplied by a correction factor reflecting the damaging effect of defects. This factor is computed from the size (Murakami parameter), sphericity, and distance to the surface of the top 10 defects identified by XCT. The neural network that computes the correction factor uses a CONV plus FC architecture. Physical limiting conditions were enforced on this architecture through weight-sign constraints. Specifically, the factor approaches 0 as the defect size converges to 0 or the surface distance goes to infinity, and it increases monotonically as the defect size increases. The existing SWT model, which does not incorporate defect information, achieved only a coefficient of determination of 0.586. In contrast, this framework improved to 0.905, with most of the validation data falling within a factor of 2 error range relative to the predicted values. Fracture surface analysis also confirmed lack-of-fusion defects as the primary cause of crack initiation, consistent with the actual failure mechanism. However, these results were obtained from a small sample of 20 specimens, so generalizability requires further validation. Moreover, the criterion of selecting only the top 10 defects as input itself presupposes a prior judgment about which defects are important.

Meanwhile, Wang et al. [248] considered residual stress, which varies with post-processing history, as an extension of defect information. They targeted L-PBF AlSi10Mg and predicted fatigue life by combining a continuous damage mechanics (CDM) model with machine learning (Figure 23(b)). They considered six post-processing conditions, ranging from the as-built state to

combinations of shot peening and heat treatment. Accordingly, variables such as surface compressive residual stress and its depth were included among the input features. The CDM-only model showed such low performance that almost no predicted values fell within a factor of 1.5 error range. However, when the CDM predictions were used as ML input features, the coefficient of determination improved from 0.832 with the original features to 0.913 after sensitivity-based feature selection, and further to 0.927 after adding the CDM predictions. RF showed the same trend, improving from 0.833 to 0.858–0.874. However, a substantial portion of the performance improvement had already occurred at the feature selection stage, and the additional improvement from adding the CDM predictions was relatively limited. In addition, the total dataset consisted of only 89 points, with 72 for training and 17 for validation. This is not sufficient relative to the 12 input features, limiting the extent to which the generalisation performance of this physics-data coupling can be judged.

The four studies reviewed in this section all targeted the L-PBF process, and within the scope of this review, it was difficult to identify studies addressing defect-induced fatigue failure in L-DED based on PIML. In addition, in the prediction of defect-induced fatigue failure, approaches utilising the morphological characteristics of defects and fracture-mechanical behaviour as physical information predominated. However, the way physical information was incorporated and its effect differed from study to study, and coupling with physics itself did not guarantee an improvement in predictive performance. Ultimately, the effectiveness of PIML appears to depend less on the amount or complexity of physical information. It depends more on how appropriately that physical information is connected to the variables that govern the fatigue behaviour.

4.4. Summary and comparative discussion

4.4.1. PIML considerations for different process characteristics of L-PBF and L-DED

The preceding sections show that L-PBF and L-DED differ in process conditions and in data-acquisition and measurement environments, and accordingly the considerations relevant to applying PIML also differ. The principal axes distinguishing the application of PIML between the two processes can be summarised as (I) differences in governing physics and physical constraints, (II) differences in scale and computational cost, and (III) differences in data-acquisition and measurement environments. In what follows, these three axes are examined in turn.

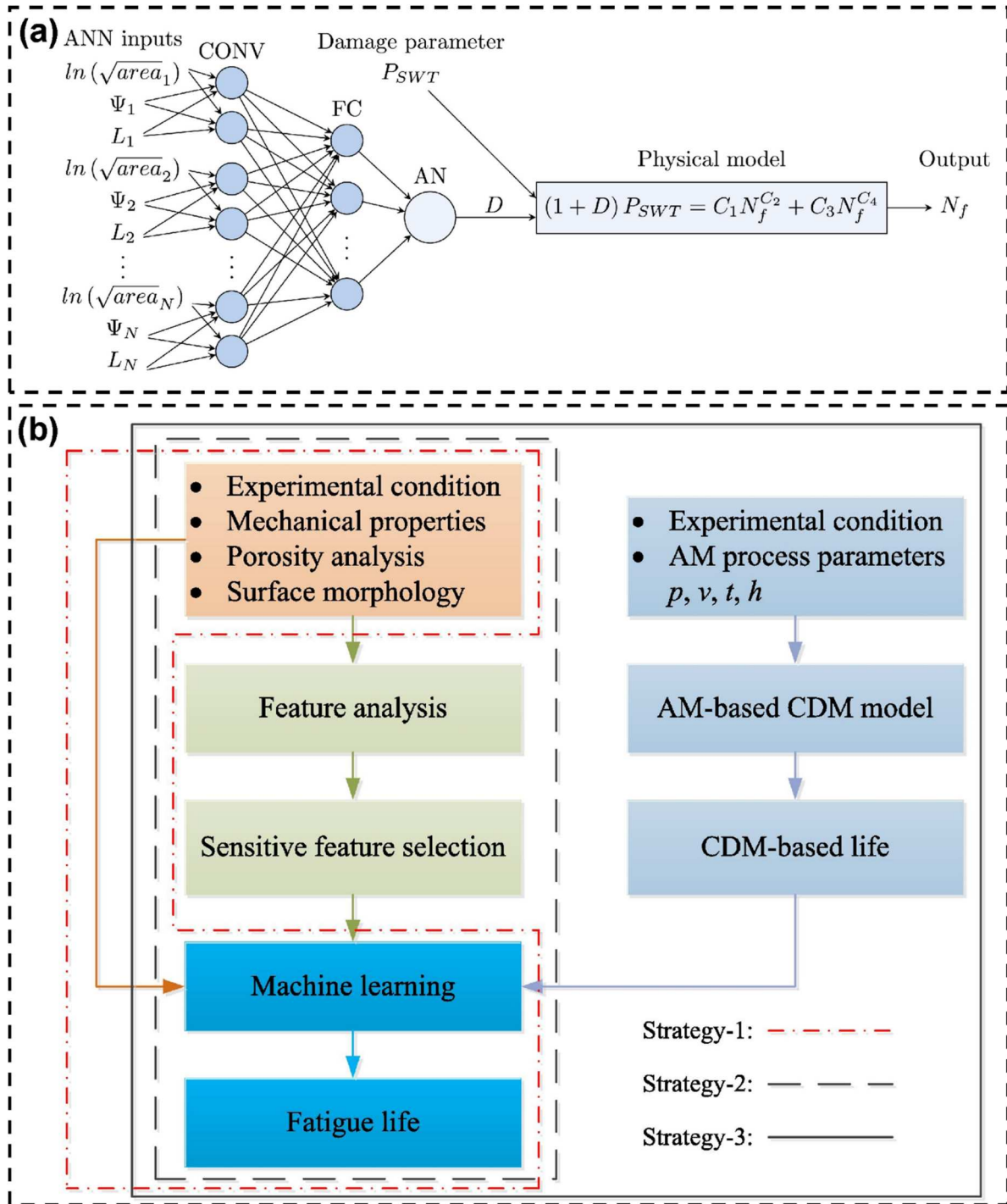


Figure 23. (a) Diagram of the proposed physics-informed neural network based damage model (with two neurons in CONV and a single neuron in FC after optimisation) [247], (b) Strategy diagram of ML-based fatigue life prediction model [248].

1 Differences in Governing Physics and Physical Constraints

L-PBF involves a small beam rapidly scanning over a static powder bed, so stress induced by rapid cooling (10^4 - 10^6 K/s) is dominant. Accordingly, the physical constraints of PIML consist of a multiphysics residual

combining surface tension, Marangoni convection, and phase transformation kinetics. Since the effect of reheating is confined to the topmost few layers, the range of thermal history memory can be designed to be relatively short. L-DED, in contrast, is a real-time powder feeding method through a nozzle. Accordingly, the powder-laser interaction and feed rate are fundamentally

different from those of L-PBF. Factors such as in-flight powder preheating, laser attenuation, and powder capture efficiency must be considered, while the moving boundary condition associated with the increasing deposition height must also be updated. In addition, since the powder size, beam size, and laser power are all large, a large, deep melt pool and repeated remelting are dominant. Because this remelting affects the already-formed stress state, PIML requires a structure that retains long-term memory of the multilayer thermal history together with the melt pool flow field and powder feeding conditions.

II. Differences in Scale and Computational Cost

Even when using the same laser power and scan speed variables, the melt pool of L-PBF is much smaller than that of L-DED. This difference in melt pool scale leads to a corresponding difference in the part sizes each process can handle. It also results in distinct forms of simulation being coupled with PIML for each process. Since L-DED is an inherently 3D free-surface problem, in which powder is fed from a nozzle and a bead is progressively built up on the melt pool, 3D multiphysics analysis is practically unavoidable for securing training data. L-PBF, in contrast, has a structure in which a laser scans a static powder layer, so the three-dimensional deformation of the geometry itself is relatively small. As a result, many studies simplify the problem to 2D in order to reduce the computational domain and time. Due to this difference, the computational cost of L-DED increases sharply as the melt pool grows larger and the thermal-fluid interaction becomes more complex. It therefore takes far more time and cost to secure training data of the same scale as L-PBF. In this respect, a PIML approach that can reduce dependence on these two data sources is relatively advantageous for L-DED, rather than relying entirely on costly 3D simulation or the accumulation of large-scale experiments.

III. Differences in Data-Acquisition and Measurement Environments

L-PBF is conducted in an enclosed chamber under an inert atmosphere. This enables the active use of upper surface signals, such as thermal imaging cameras, optical top-view imaging, high-speed cameras, and acoustic emission. However, because the powder layer obscures the underlying geometry and the state of previous layers, direct observation of the free surface inside the chamber or of interlayer shape changes is limited. L-DED, in contrast, is conducted in an open process

environment. This allows a variety of real-time signals to be acquired, including infrared cameras, coaxial melt pool imaging, line scanners for real-time measurement of melt pool depth and width, 3D optical scanning, and contact-based on-machine inspection (OMI), with the advantage that layer-wise shape accumulation can be directly observed. However, the complex thermal gradients and solidification rates in the open environment raise the likelihood of defect occurrence. Since variations in process parameters, material response, and environmental conditions have a decisive effect on defect distribution, the technical difficulty of simultaneously controlling these factors is very high [249]. Accordingly, while the application of machine learning is rapidly expanding, PIML based real-time monitoring and closed-loop control research remains a substantial gap. In practice, the industrial application of L-DED is constrained by limited process repeatability and inconsistent feedback, making sophisticated monitoring strategies essential [250]. In summary, L-PBF has the relative advantage of data acquisition based on standardised upper surface observation, while L-DED has the relative advantage of diversity in real-time signals. However, both processes share a commonality. Rather than directly measuring residual stress and internal defects, which are difficult to observe in real time, research is being actively conducted to indirectly predict them using surrogate variables such as the temperature field or microstructure.

4.4.2. PIML utilisation across the process lifecycle

The three approaches of PIML each have distinct characteristics depending on the methodology, but are widely utilised in both the L-PBF and L-DED processes. In this section, studies applying PIML across the process lifecycle are summarised in Tables 6–8, and using these tables together with the studies introduced earlier as the basis, the utilisation of PIML across the process lifecycle is compared and the corresponding strategy is presented.

In the pre-process stage, differences appear in how the two processes utilise the various approaches. Physics-based Feature Engineering appears to be primarily utilised in L-PBF. This is because, as a small beam rapidly scans over a static powder layer, stress induced by rapid cooling (10^4 – 10^6 K/s) is dominant, making it relatively easy to secure predictive performance using physical-quantity-based features alone. L-DED, in contrast, is a real-time powder feeding method through a nozzle, and accordingly, factors such as in-flight powder preheating, laser attenuation, and powder capture efficiency must additionally be considered, while the moving boundary condition

Table 6. Summary of studies on PIML for defect prediction in the pre-process stages of L-PBF and L-DED.

PIML method	LAM process	Prediction	Dataset	Model	Model Performance / comment	Year, Ref
Physics-based Feature Engineering	L-PBF	Porosity	605 specimens measured via XCT	Six regression algorithms trained on three input configurations (Setting, PIM, Combined)	• Best error ~13% (svrG/svrRBF); PIM comparable to Setting. Validated on a single machine only, so generalizability is unverified.	2021, [251]
	L-PBF	Melt pool	16 single-track experiments + 87 OpenFOAM mechanistic-model sets (103 total)	MLP (multilayer perceptron) deep learning	• Accuracy up–96.6% vs. 68.3% with experiments alone. High dependency on mechanistic-model accuracy, whose errors may propagate or amplify.	2023, [252]
	L-PBF	Melt-pool	NIST AMMT images (118,928)	FFNN + NBEM (neighbouring-bead effect modelling)	• Error improved from 19.41% to 12.12% with NBEM. Poor generalisation beyond NIST-specific equipment.	2023, [253]
Physics-based Simulation-assisted Machine Learning	L-PBF	Keyhole size	62 high-fidelity thermal-fluid simulations	NNPR classification + GPR (Gaussian Process Regression) for dimension/contour prediction	• Classification 95–100%; dimensional MAE 3.9–49 μm . High accuracy but 25 h simulation time per case.	2024, [254]
	L-PBF	Melt pool size	CFD + single-track experiments + literature (417 total)	Six classifiers (RF, DT, SVC, Gaussian Process, Gradient Boosting, XGBoost) + SHAP interpretation	• Macro-F1 0.79 across materials, but drops to 50% when a material (SS316L) is excluded from training. Generalisation to new alloys is unreliable.	2026, [255]
	L-DED	Spatial temperature history	GPU-accelerated FEM (80 laser profiles)	Bayesian LSTM + Attention	• $R^2 = 0.75$ with 95% CI via MC dropout. Lower accuracy; autoregressive errors accumulate sharply after the first peak.	2024, [256]
	L-DED	Substrate temperature	LHS-based FEM (200 groups) + experiments	LPIN (layer embedding energy conservation law)	• Error reduced from 27.9% to 9.7% ($R^2 = 0.96$). Extreme data simplification (20 points) and high FEM cost.	2026, [257]
Physics-constrained Learning	L-PBF	Thermal History	In-situ IR images (1,000 samples)	APIDL (deep-unfolding-based architecture)	• MAPE 2.8%, 55.7% lower than a purely data-driven baseline. Limited to single track/layer, ignores 3D accumulation and gas-phase physics.	2022, [258]
	L-PBF	Melt pool fluid flow	COMSOL simulation, 13,500 points/step over 13 steps	PINN	• Re error 1.07%, Pe error 1.56%; forward 48 min, inverse 20 h. Hemispherical shape assumption limits flexibility across conditions.	2024, [259]
	L-DED	Melt pool size and temperature	FEM calibrated with experiments, region-wise sampling	DLR-PINN + transfer learning	• Temperature MAPE 0.53%; size MAPE 2.5–7.0%. Validated only on one alloy and single track, limiting generalisation.	2025, [260]
	L-DED	Melt pool fluid flow	CMOS images (4,000, 8 classes) + IR point temperature + robot coordinates	CNN (ResNet-18, defect-state classification) + modified PINN + motion analysis	• CNN 97.8%; PINN peak-temperature error 5.8–7.3%. Four functions were validated only at the individual level, and their system-level interactions were not verified.	2026, [261]
	L-DED	Temperature field	Simulation pre-training + IR fine-tuning	PINN (ResNet/Attention + transfer learning)	• Error <1.3%, RMSE 6.365 K. 2D to 3D reconstruction, but substantial training time (1.5 h + 0.9 h).	2025, [262]

associated with the increasing deposition height must also be updated. This suggests that it may be relatively difficult to ensure accuracy using only simple physical features of melt pool scale and thermal history.

Physics-based Simulation-assisted Machine Learning is relatively more prominently utilised in L-DED, which is interpreted as being because the wide heat-affected zone of L-DED makes it difficult to cover diverse

Table 7. Summary of studies on PIML for defect monitoring in the in-process stages of L-PBF and L-DED.

PIML method	LAM process	Monitoring	Input dataset (Applied sensor)	MODEL	Model Performance / comment	Year, Ref
Physics-based Simulation-assisted Machine Learning	L-PBF	Thermal history	Part geometry (CAD) + LWIR camera (for validation)	Graph-based thermal model + MPC (feedforward)	<7 min/iter; error <5%, grain deviation –60%, geometric error –43%. No real-time disturbance response; limited multi-variable optimisation.	2025, [263]
Physics-constrained Learning	L-PBF	Porosity	High-speed camera, acoustic sensor, multi-spectral sensor (10-parameter set)	O-PINN (ontology + CNN)	Melt pool error ~3–5%, porosity error 0–10%. Compute time unreported; limited real-time applicability.	2026, [264]
	L-PBF	Real-time porosity and cracking likelihood	Acoustic emission (100–1000 kHz) + coaxial pyrometer (ratio/intensity signals)	VAE + physics-based loss (density eq.)	~2 ms/loop, >90% accuracy. Signal attenuation at upper layers; poor generalisation to new materials.	2026, [265]

Table 8. Summary of studies on PIML for post-process defect assessment in L-PBF and L-DED.

PIML method	LAM process	Purpose	Input dataset	MODEL	Accuracy / comment	Year, Ref
Physics-based Feature Engineering	L-PBF	Fatigue life	2 experimental batches + literature data (validation)	Symbolic regression (domain-knowledge guided)	$R^2 = 0.80$; highly interpretable via explicit equations. Based on 2D fracture data only, missing 3D defect distribution/interaction.	2024, [266]
Physics-constrained Learning	L-PBF	Fatigue life	164 fatigue test datasets	PIPNN (physics-informed probabilistic NN)	Tighter S-N curves and 95% CI vs. conventional PNN. Reflects physical variance trend, but imputation may introduce bias.	2024, [267]
	L-PBF	Fatigue life	36 experimental sets (defect size/area, location, shape, max stress)	PINN	$R^2 = 0.823$, all within 2-factor band. Small dataset ($n = 36$) limits robustness; validated mainly on surface defects.	2024, [268]
	L-PBF	Fatigue life	164 experimental sets + LAM-CDM model outputs	IPINN (multi-physics integrated NN)	27.51% accuracy gain over pure ANN. Simplified energy-density metric misses complex thermal history; overfitting risk on local samples.	2024, [269]
	L-PBF	Energy absorption	108 SHPB (Hopkinson bar) impact tests	PINN	$R^2 = 0.988$; better generalisation than pure data-driven NN. Constraint limited to elastic regime, missing plasticity/strain-rate effects.	2025, [270]

process conditions using measured data alone, thereby requiring greater reliance on simulation-based training data. Physics-constrained Learning is utilised to a similar extent in both processes, showing a tendency to be adopted as a method for reducing data dependence regardless of process type.

In the in-process stage, the requirement for real-time capability acts as a key variable. Physics-based Feature Engineering shows an approach in both processes that attempts real-time processing by simplifying physical features, but a single feature alone may be insufficient to capture complex real-time defect and stress behaviour. Physics-based Simulation-assisted Machine Learning, by contrast, is prominently utilised in L-PBF. This is interpreted as reflecting the fact that surface signals obtainable in the enclosed chamber environment, such as thermal imaging, optical imaging, and acoustic emission, alone are insufficient to directly estimate the

internal physical state. As a result, it is relatively advantageous to secure real-time capability by matching a pre-built simulation-based database with measured signals. In addition, thanks to L-PBF's relatively narrow process parameter range and small melt pool scale, the simulation cost of building such a database is also relatively low. This approach was not identified in L-DED. This is presumably because the computational cost of 3D free-surface simulation itself is high, and the complexity is further increased by multiphysics coupling. As a result, even if a database is built in advance, the computational-time benefit expected from the real-time matching process is relatively small. Physics-constrained Learning is utilised in both processes, but it is relatively more prominent in L-DED. This appears to be because directly embedding the physical residual in the loss function works effectively even with little data, thereby reducing the cost incurred by simulation.

In the post-process stage, prediction of final properties and defects is important, so accuracy and physical validity take priority. Physics-constrained Learning was widely used in L-PBF, but this approach was not identified in L-DED. Fracture mechanics theory itself is equally applicable regardless of the process. L-PBF, whose process is relatively stable and whose microstructure is relatively uniform, has accumulated a substantial amount of data related to crack growth rate and fatigue life. L-DED, in contrast, has a large heat input and a complex thermal history, leading to large variability in microstructure and residual stress. This appears to have made it difficult to directly reflect, in the loss function, the uncertainty in input values such as material constants or defect characteristics needed to apply physical laws. Following this trend, L-DED appears to have progressed toward development based on Physics-based Feature Engineering. Crack problems affecting fatigue and tensile strength are dominated by experiment-based approaches, due to process uncertainty. As a result, extension toward Physics-based Simulation-assisted Machine Learning remains limited for now.

In summary, rather than any single approach being superior, it is necessary to selectively adopt the PIML type suited to the target prediction accuracy, available computational resources, and data-acquisition conditions. L-PBF and L-DED differ in process parameter scale and thermal history characteristics. As a result, even for the same PIML approach, the data preparation strategy and computational cost required when applied to the two processes may differ.

5. Limitations and challenges of PIML in LAM

Section 4 reviewed the applications of PIML-based approaches in L-PBF and L-DED, including pre-process defect prediction, in situ process monitoring, and post-process quality evaluation. This section discusses the current limitations of PIML approaches and future research directions across the LAM process lifecycle.

5.1. Data-driven dependency and physical constraint sensitivity in PIML

PIML has been widely adopted as a hybrid approach that combines physics-based modelling with data-driven learning to overcome the limitations of conventional black-box models. However, L-PBF and L-DED involve coupled phenomena such as heat transfer, melt-pool flow, solidification, and phase transformation. Therefore, the current PIML approaches cannot fully represent all process behaviours. In addition, model performance depends on the quality of the input data and the

formulation of physics-based constraints. Inaccurately defined governing equations, boundary conditions, and physical constraint terms can result in increased prediction errors or physically inconsistent results. Furthermore, data bias and inaccuracies in physical modelling may affect the convergence stability and prediction accuracy.

Notably, examining how the studies reviewed in this paper make use of their datasets reveals several unresolved issues. First, dataset sizes vary by several orders of magnitude across studies, ranging from a few dozen simulations to tens of thousands of segmented images or graphs. In many cases, the number of independently fabricated specimens is not clearly distinguished from the number of samples derived through sliding-window or ROI-based segmentation. As a result, a dataset nominally comprising tens of thousands of samples may in fact originate from only a handful of physical builds, raising concerns about the statistical independence of the train-test split. Second, no standardised benchmark dataset currently exists for defect prediction in L-PBF or L-DED. Unlike more mature ML fields, each study constructs its own dataset using different equipment, materials, and process conditions, making it difficult to directly compare reported accuracy, generalisation, and computation time across studies. Third, validation methods for labelling protocols differ across studies. Some derive ground-truth labels at the specimen level through destructive or non-destructive testing after fabrication. Others assign labels at the process-condition level based on CFD-based defect classification. Still others rely entirely on simulation-generated labels without any experimental correspondence. Taken together, these different approaches suggest that dataset quality and reporting rigour, rather than model architecture alone, remain a fundamental bottleneck for reliable and comparable PIML research in metal LAM.

Nevertheless, PIML approaches are increasingly being explored as promising alternatives that can complement the limitations of both data-driven and physics-based models in L-PBF and L-DED. Recently, the scope of PIML applications has expanded, and integration into process systems has increased to enhance reliability and predictive accuracy. Therefore, the development of high-quality datasets and improved formulations of physics-based constraints is expected to enhance PIML performance.

5.2. Computational efficiency and real-time applicability of PIML in in-situ monitoring

In L-PBF and L-DED, defect prediction using melt-pool behaviour and temperature-field information requires

both high accuracy and physical consistency. PIML has been widely adopted as an effective approach for capturing complex multi-physics interactions. However, real-time monitoring in LAM requires rapid defect detection and response under strict time constraints; thus, computational efficiency and inference speed are critical factors. From this perspective, two limitations can be identified.

First, even when a PIML model reports a relatively fast computation time, this does not necessarily mean it meets the actual time scale required by L-PBF or L-DED processes. Yeung [271], focusing on in-line correction in L-PBF, noted that given a typical laser scanning speed of 1000 mm/s and a beam spot size of approximately 100 μm , correction must occur within a response time of roughly 100 μs for the adjustment to take effect before the laser exits the current scan line. However, none of the PIML studies discussed in Section 4.2 meet this criterion. In other words, the fast computation times reported in existing studies generally reflect relative improvement over prior models, rather than confirmation that an absolute time requirement for actual in-process adjustment has been satisfied. Whether this requirement is met needs to be examined separately for each study.

In response to this limitation, neural operator approaches such as DeepONet and FNO [272] have been explored as a means of reducing computation time in PIML-based real-time monitoring. In particular, DeepONet offers the advantage of inferring the full-field solution for new parameter combinations at a speed far exceeding standard numerical methods, while maintaining acceptable accuracy [217]. Building on this direction, Tian et al. [273] proposed a physics-informed DeepONet for real-time distortion prediction in the WAAM process. Temperature and distortion history were input into the trunk and branch networks respectively, and a ConvLSTM was incorporated to learn spatiotemporal long-range dependencies, enabling future distortion field prediction while suppressing error accumulation. The heat conduction equation was embedded as a physical constraint in the loss function to reduce data dependency and improve generalisation performance. This model achieved the best accuracy across all stages compared with CNN, ST-ConvLSTM, and a baseline DeepONet. Although its training time was the longest at 104 minutes, its inference time was the shortest at 150 ms, demonstrating the potential of neural operator based PIML for real-time long-term distortion prediction. However, since this study targeted the wire-based WAAM process, which differs in process mechanism from powder-based L-PBF and L-DED, its direct

applicability remains limited. Nonetheless, it suggests the broader potential of applying neural operator based PIML across LAM processes.

Second, there is no shared, agreed-upon definition of what constitutes real-time monitoring. Even among the studies reviewed in Section 4.2, sensors with time resolutions differing by several orders of magnitude, such as near-infrared imaging, photodiode signals, and high-speed cameras, are all described under the same label of real-time, despite operating at fundamentally different time scales. For example, Zhang et al. [231] achieved an inference time of 1.48 ms per sample, demonstrating a response fast enough to operate within a single scan track. In contrast, Wang et al.'s study predicted the temperature field at 0.033 s intervals, matching the camera's frame rate, yet the actual laser power adjustment was only applied after each layer was completed. In other words, the same term real-time refers in one case to millisecond-level immediate response, and in another to a response occurring on the scale of tens of seconds to minutes, after an entire layer is finished. Because how quickly a detected defect can be reflected into the process is determined precisely by this time scale, the real-time applicability claimed by each study needs to be evaluated on its own terms.

5.3. Scalability challenges of PIML in practical LAM environments

L-PBF and L-DED are widely applied in industries such as aerospace, energy, and defense, which require the fabrication and repair of large, high-value components. However, most existing PIML-based approaches focus on limited ROIs and encounter challenges when evaluating full-scale components. Accurate defect control and evaluation using PIML in L-PBF and L-DED require simultaneous consideration of multi-physics phenomena; thus, as the spatial domain expands, computational complexity and memory requirements increase substantially. Moreover, because thermal histories and process conditions evolve spatiotemporally during layer-by-layer fabrication, repeated evaluations of large-scale components further increase the computational cost and processing time.

To address these limitations, recent studies have employed dimensionality-reduction methods to improve the computational efficiency of large-scale LAM defect analyses. Therefore, the development of multi-scale computational frameworks that can bridge local melt-pool behaviour and component-scale responses is expected to become an important research direction. This approach can enable more effective PIML-

based defect control and quality evaluation for industrial L-PBF and L-DED processes.

5.4. Physics-data balancing challenges in PIML

In PIML approaches, model performance depends on the appropriate integration of physical constraints and data-driven learning. Although physical models provide essential prior knowledge that ensures physical consistency and interpretability, they are often limited in capturing the highly nonlinear and nonstationary nature of LAM processes. Conversely, experimental and in situ sensing data can capture complex process behaviours but are affected by noise, limited resolution, and distribution shifts under varying operating conditions. Relying solely on either physics-based formulations or data-driven learning can lead to incomplete or unstable representations of the defect formation mechanisms.

Therefore, in PIML approaches, physics-based constraints and data-driven learning should be properly balanced. In PINN-based frameworks, the balance between data loss and physics-based loss terms directly impacts convergence stability and predictive performance. Future PIML research should focus on developing adaptive weighting strategies that dynamically balance physics- and data-driven information based on process conditions and data reliability.

5.5. Generalisation challenges in practical LAM environments

PIML-based models have been used to improve physical consistency and reliability compared with conventional data-driven approaches. However, in practical L-PBF and L-DED processes, complex multi-physics interactions and variations in process parameters limit the generalisation capability of these models. Defect formation and part quality in LAM are influenced by the melt-pool morphology, material properties, powder characteristics, and geometric configurations. This complexity hinders the models trained under specific conditions from being transferred directly to different process environments or material systems. In addition, differences in equipment setup, sensor configuration, and data acquisition conditions in industrial settings further challenge model reproducibility and scalability.

Therefore, future research should focus on developing robust generalisation strategies that can flexibly accommodate variations in process conditions and multi-physics behaviours while maintaining a stable predictive performance across different manufacturing environments.

6. Outlook

PIML approaches can mitigate the computational cost limitations of conventional analytical models and the generalisation constraints of purely data-driven models by combining physics-based modelling with data-driven learning. However, in L-PBF and L-DED, most current PIML models remain limited to prediction and evaluation. For these models to translate into effective defect control in actual manufacturing environments, several directions for further development are needed (Figure 24).

1 Closed Loop: PIML-Driven Process Control

Defects such as porosity and residual stress in L-PBF and L-DED are not fixed once formed. They continue to evolve depending on heat input, melt pool stability, cooling history, and interlayer heat accumulation. Therefore, even the most accurate predictive model remains limited to post hoc diagnosis unless its predictions are reflected in real time in the process conditions of the subsequent scan or layer. In other words, accurate monitoring and defect classification during the manufacturing process are not enough on their own. A closed-loop framework is also required, in which predicted defect information is fed back into the process parameters and scanning strategies of the subsequent scan or layer to mitigate or prevent further defect development. Only then can PIML-based monitoring translate into genuine improvements in manufacturing quality.

This direction has already been demonstrated in purely data-driven approaches. Zhang et al. [274] proposed a multimodal spatiotemporal network (MST-Net) for five-axis L-DED that predicts bead geometry from coaxial melt pool images, control parameters, and positional variables. To capture the temporal dependency and asymmetry of melt pool formation and evolution, asymmetric weights were assigned to past and future contexts. Prediction-based closed-loop control was applied in practice, reducing the average error by 45% and the RMSE by 48.5%. These results demonstrate that a closed-loop structure linking prediction and control can achieve meaningful quality improvement. Incorporating physical information into this structure is expected to enable a similar level of closed-loop control with less data and across a wider range of process conditions.

However, realising this will require further progress in closed-loop model development, computational efficiency, and prediction accuracy. As discussed in Section 5.2, in-line correction requires a response time of approximately 100 μ s [271]. Neural operator

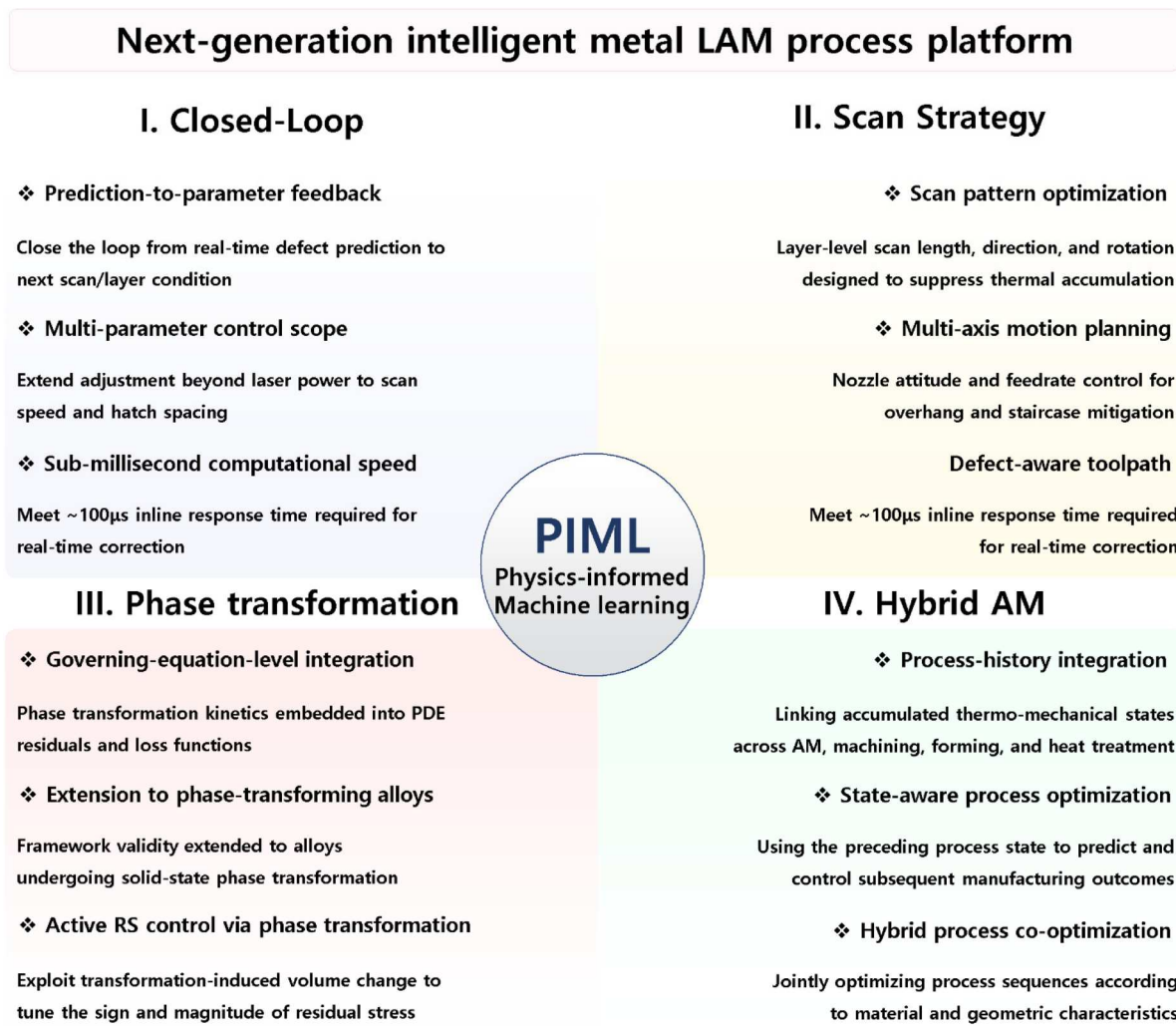


Figure 24. Outlook for the development of PIML for LAM.

approaches such as DeepONet and FNO are drawing attention as potential solutions to this time constraint. That said, no case has yet been found in which such PIML approaches are directly integrated into a feedback loop structure. Whether a full closed loop linking prediction and control can meet the actual response speed required for in-line correction remains to be verified in future work.

A PIML-based feedback loop of this kind is expected to contribute differently across the full process lifecycle. Before fabrication, a loop that repeats prediction and correction could refine process conditions in advance, reducing computational cost. During the process, detected defects could be linked directly to the adjustment of the next scan or layer, reducing defects as they occur. After the process, accumulated feedback history could serve as a means of quality inspection, enabling the identification of the stage at which a problem arose. If prediction, response, and post hoc verification are connected in this way across the full process

lifecycle, PIML-based feedback loops could evolve beyond simple defect detection tools into a key technology for actively managing quality throughout the LAM process. This represents an essential research direction for accelerating industrial adoption of LAM.

II. Physics-Informed Scan Strategy and Motion Planning

Scan path and scan strategy variables are also highly important in both L-PBF and L-DED processes. Beyond single-track, single-layer builds, scan strategy in multi-track, multilayer fabrication has drawn attention as a major factor driving defects such as porosity and residual stress. In L-PBF, PIML research addressing this issue is actively progressing, including physics-guided scan path optimisation and physics-based thermal models used to optimise scan sequencing.

Multi-axis L-DED systems, by contrast, have drawn attention due to their potential for fabricating large, complex parts, but research on scan and motion

strategies remains far more limited than in L-PBF. Multi-axis L-DED requires the nozzle to continuously change orientation while moving, and conventional discrete multi-directional slicing methods lead to overhang problems and staircase artifacts. He et al. [275] attributed this to the fact that L-DED, due to its fundamentally different material extrusion and layer formation mechanisms, permits a much smaller allowable overhang angle. For powder-jet based deposition, when the nozzle direction aligns with the surface normal, even a slight overhang can allow laser beam leakage, hindering melt pool formation. To address this, they proposed a feed-rate-preserving motion planning method specific to five-axis L-DED. This method matches the nozzle's actual angular velocity to its programmed angular velocity to maintain feed rate while adjusting deposition height, thereby enabling stable deposition. This was implemented together with orientation path optimisation that avoids singularities and ensures smooth motion under per-axis velocity constraints.

However, combining this kind of kinematic optimisation with a physics-informed approach could open a new path forward. Such an approach would also learn defect formation tendencies driven by heat accumulation. This would make it possible to jointly address shape feasibility and porosity or residual stress defects, starting from the scan strategy design stage. Therefore, physics-informed optimisation of motion and scan strategies is expected to be an important direction for future research. This applies especially to applications such as multi-track, multilayer L-DED that demand precise process control, going beyond existing kinematic approaches or individual experimental comparisons of scan strategies.

III. Coupling Phase Transformation and Residual Stress in PIML

Residual stress in L-PBF and L-DED has two physical origins: thermomechanical deformation (TGM) and volumetric change due to solid-state phase transformation. However, most studies applying PIML have focused on indirect prediction and control through the temperature field. The materials targeted for validation have likewise been limited to those in which solid-state phase transformation does not occur. Even in the small number of PIML studies that explicitly address phase-transformation physics, the objectives remain focused on other properties such as microstructure or hardness rather than residual stress. Some studies do mention both phase transformation and residual stress together. However, even in these studies, the connection between the two remains a post hoc explanation

based on correlations between observed values, rather than a physics-based calculation. Phase transformation can govern not only the magnitude but also the sign of the residual stress. Yet a PIML framework that incorporates it into the governing equations or loss function is still absent in both processes. Material groups for which residual stress management is particularly important in industrial applications, such as martensitic steels, tool steels, and β -phase titanium alloys, mostly involve solid-state phase transformation. Given this, the physical validity of the current temperature-field-centered PIML framework remains uncertain when it is extended to these material groups. PIML that accounts for such phase transformation is expected to contribute in different forms across the process lifecycle. In the pre-process stage, process conditions can be refined in advance by incorporating the stress-offsetting or stress-enhancing effects of phase transformation. During processing, residual stress, which is difficult to measure directly, can be indirectly estimated through the progression of phase transformation and used for control. In the post-process stage, the causal relationships linking transformation history to the final microstructure, residual stress, and fatigue properties can be learned and leveraged to optimise post-process conditions. Ultimately, establishing a PIML framework that integrally addresses phase transformation and residual stress remains an unresolved research direction. Resolving it is essential to extend PIML's industrial applicability to the material groups for which residual stress management is critical.

IV. PIML in Hybrid Manufacturing

In high-value-added industries such as aerospace, energy, and defense, demand for advanced manufacturing technologies is rapidly increasing. These technologies must simultaneously secure a high degree of design freedom and structural reliability. Hybrid LAM is a technology that combines LAM with existing processes such as mechanical surface treatment [276,277], machining [278–281], and heat treatment [282,283]. Through this, it is drawing attention as an alternative for overcoming the inherent limitations of a single LAM process, such as high surface roughness, accumulated residual stress, pore defects, and property anisotropy.

In L-PBF- and L-DED-based hybrid LAM, each unit process shares a thermomechanical history and is strongly coupled. The thermal history, porosity, residual stress, and microstructure accumulated during the deposition stage carry over into subsequent machining and forming processes. There, they govern the deformation behaviour, geometric error, and final

mechanical properties. Conversely, when deposition proceeds on a substrate that has already been machined or formed, the initial state of the substrate alters melt pool stability and interfacial bonding quality. This directly affects the pattern of defect formation. Therefore, rather than optimising each process independently, an integrated approach that continuously treats the thermomechanical history accumulating across process boundaries is needed. At this point, PIML which naturally links the history between processes using physical constraints, emerges as a promising key technology.

A representative example of this trend is the study by He et al. [237], discussed earlier in Section 4.2.2. They introduced 5-axis contact on-machine inspection (OMI) into a hybrid process alternating between L-DED and machining. They processed sparse measurement data between AM-SM transition sequences with a PINN and reconstructed it into a full deformation field. This allowed them to demonstrate that stress redistribution and shape distortion caused by machining can be captured in real time. This case is significant in that it demonstrated, based on measured data, that PIML can link accumulated residual stress and shape history beyond a single process. The research group proposed extending this reconstruction technique to a neural network linking process parameters and deformation. This concept involves predicting deformation from part geometry and process conditions and further performing inverse-design-based process compensation. It has the potential to develop into an integrated hybrid PIML that links history through to the forming and heat treatment stages in the future.

In contrast, the other PIML studies reviewed here (Sections 4.1-4.2) are all skewed toward a single process, either L-PBF or L-DED. They addressed only one of prediction, monitoring, or evaluation, and no case extending the scope to forming, machining, or heat treatment was identified. Developing a new model for each process stage is not the priority. What matters more is continuously carrying forward the evolutionary history of defects, residual stress, and microstructure under physical constraints. This kind of expansion of PIML has substantive implications for the industrial application of hybrid LAM.

If such expansion is achieved, the state at the deposition stage can be utilised as the initial condition for the subsequent process. This enables not only integrated prediction and control of final part quality but also the redesign of the hybrid process sequence itself according to the material group and geometric characteristics. Ultimately, building a PIML framework that crosses process boundaries will be a key to elevating

hybrid LAM from a simple combination of processes into an intelligent, integrated manufacturing system.

7. Conclusions

L-PBF and L-DED have established themselves as key technologies for the direct fabrication of complex, high-performance metal components. They are now widely employed in fields demanding high reliability, such as aerospace, energy, mobility, and defense. However, complex thermal histories and melt pool behaviour can give rise to defects such as porosity, residual-stress-induced cracking, and distortion. These defects degrade the dimensional accuracy, mechanical strength, fatigue life, and long-term reliability of the final component. This review has integratively presented the defect formation mechanisms of the L-PBF and L-DED processes together with trends in PIML research. This supports the potential for extension toward intelligent quality control across the entire process chain.

L-PBF and L-DED differ in process conditions and data-acquisition environments, and accordingly the considerations relevant to applying PIML also differ. The two processes exhibited clear differences along three axes, namely governing physics and physical constraints, scale, computational cost, data-acquisition, and measurement environments. The utilisation patterns of the three PIML approaches, namely Physics-based Feature Engineering, Physics-based Simulation-assisted Machine Learning, and Physics-constrained Learning, also differed across the pre-process, in-process, and post-process stages. Therefore, rather than any single approach being universally superior, the PIML type suited to the target prediction accuracy, available computational resources, and data-acquisition conditions should be selectively adopted.

At the same time, several challenges remain for the practical deployment of PIML. Dataset scale and labelling protocols vary considerably across studies, hindering direct comparison of reported results. In addition, formulation errors in physical constraints and data bias directly affect convergence stability and predictive accuracy. The term real-time itself is used with inconsistent meaning across studies, ranging from millisecond-scale response to layer-scale response on the order of tens of seconds to minutes. Moreover, the computational speed required for real-time monitoring often still falls short of the actual process time scale. Most studies are confined to the local melt pool region, and this leads to scalability limitations: computational complexity and memory requirements increase sharply when the approach is extended to full-scale components. The balance between physics-based constraints and data-driven learning also remains an unresolved challenge.

So does the generalisation capability of models trained under specific process conditions.

This review presents four directions for the future development of PIML. The first is closed-loop control that feeds predicted defect information back into the process parameters of the subsequent scan or layer. The second is physics-informed scan path and motion planning. The third is a framework that couples phase transformation with residual stress. The fourth is history linkage across process boundaries in hybrid manufacturing environments. Realisation of these directions is expected to advance PIML into a core technology of an intelligent process control platform supporting the fabrication of high-reliability components in the aerospace, energy, defense, and mobility sectors.

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Author contributions

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Data availability statement

No new data was generated or analysed in support of this research. All data discussed in this review are available in the cited references.

References

- [1] Pradeep PI, Kumar VA, Sriranganath A, et al. Characterization and qualification of LPBF additively manufactured AISI-316L stainless steel brackets for aerospace application. *Trans Indian Natl Acad Eng.* 2020;5:603–616. doi:10.1007/s41403-020-00159-x
- [2] Sun J, Huang G, Gu D, et al. Effect of laser energy density on temperature field, forming quality, and performance of LPBF-fabricated nickel-based superalloy composites. *J Manuf Sci Eng.* 2025;147:071007. doi:10.1115/1.4068162
- [3] Liu T-S, Chen P, Qiu F, et al. Review on laser directed energy deposited aluminum alloys. *Int J Extreme Manuf.* 2024;6:022004. doi:10.1088/2631-7990/ad16bb
- [4] Tüzemen GB, Yurtkuran E, Babacan N, et al. Shaping the future of energy: breakthrough additive manufacturing (3D) technologies for renewables. *Int J Energy Res.* 2026;2026:5032104. doi:10.1155/er/5032104
- [5] Li S, Chen B, Tan C, et al. Study on recyclability of 316L stainless steel powder by using laser directed energy deposition. *J Mater Eng Perform.* 2022;31:400–409. doi:10.1007/s11665-021-06150-z
- [6] Singh SN, Deoghare AB. Laser shock peening of laser based directed energy deposition and powder bed fusion additively manufactured parts: a review. *Met Mater Int.* 2023;29:1563–1585. doi:10.1007/s12540-022-01334-1
- [7] Cepeda-Jiménez CM, Potenza F, Magalini E, et al. Effect of energy density on the microstructure and texture evolution of Ti-6Al-4V manufactured by laser powder bed fusion. *Mater Charact.* 2020;163:110238. doi:10.1016/j.matchar.2020.110238
- [8] Schmidt M, Merklein M, Bourell D, et al. Laser based additive manufacturing in industry and academia. *Cirp Ann.* 2017;66:561–583. doi:10.1016/j.cirp.2017.05.011
- [9] Cozzolino E, Tiley AJ, Ramirez AJ, et al. Energy efficiency of Gaussian and ring profiles for LPBF of nickel alloy 718. *Int J Adv Manuf Technol.* 2024;132:3093–3104. doi:10.1007/s00170-024-13511-0
- [10] Li K, Zhan J, Wang Y, et al. Application of data-driven methods for laser powder bed fusion of Ni-based superalloys: A review. *J Manuf Process.* 2025;133:285–321. doi:10.1016/j.jmapro.2024.11.053
- [11] Wu D, Lv W, Li Z, et al. Investigation on melt growth (Mg, Co, Ni, Cu, Zn) O oxide ceramics prepared by laser directed energy deposition. *Ceram Int.* 2024;50:52228–52239. doi:10.1016/j.ceramint.2024.10.029
- [12] Majumdar JD, Madapana D, Manna I. 3-D printing by laser-assisted direct energy deposition (LDED): The present status. *Trans Indian Natl Acad Eng.* 2021;6:933–953. doi:10.1007/s41403-021-00252-9
- [13] Liu G, Su Y, Pi X, et al. Achieving high strength 316L stainless steel by laser directed energy deposition-ultrasonic rolling hybrid process. *Mater Sci Eng A.* 2024;903:146665. doi:10.1016/j.msea.2024.146665
- [14] Ai Y, Du C, Wang Y, et al. Controlling laser-powder interaction process and molten pool dynamic behaviors during laser directed energy deposition process by laser beam defocusing. *Phys Fluids.* 2025;37:043123. doi:10.1063/5.0260111
- [15] Mohanraj J, Sahu J. Numerical prediction of residual stress and distortion for laser powder bed fusion

- (LPBF) AM process of Ti-6Al-4V. *Simul Model Pract Theory*. 2025;140:103094. doi:10.1016/j.simpat.2025.103094
- [16] Svetlizky D, Das M, Zheng B, et al. Directed energy deposition (DED) additive manufacturing: physical characteristics, defects, challenges and applications. *Mater Today*. 2021;49:271–295. doi:10.1016/j.mattod.2021.03.020
- [17] Mo B, Li T, Deng L, et al. Mechanisms and influencing factors of defect formations during laser-based directed energy deposition with coaxial powder feeding: a review. *Virtual Phys Prototyp*. 2024;19:e2404155. doi:10.1080/17452759.2024.2404155
- [18] Kumar LJ, Nair CK. Laser metal deposition repair applications for Inconel 718 alloy. *Mater Today Proc*. 2017;4:11068–11077. doi:10.1016/j.matpr.2017.08.068
- [19] Thompson SM, Bian L, Shamsaei N, et al. An overview of direct laser deposition for additive manufacturing; Part I: transport phenomena, modeling and diagnostics. *Addit Manuf*. 2015;8:36–62. doi:10.1016/j.addma.2015.07.001
- [20] Liu M, Kumar A, Bukkapatnam S, et al. A review of the anomalies in directed energy deposition (DED) processes & potential solutions-part quality & defects. *Procedia Manuf*. 2021;53:507–518. doi:10.1016/j.promfg.2021.06.093
- [21] Lorusso M, Trevisan F, Calignano F, et al. A357 alloy by LPBF for industry applications. *Materials*. 2020;13:1488. doi:10.3390/ma13071488
- [22] Zheng Z, Peng L, Wang D. Defect analysis of 316 L stainless steel prepared by LPBF additive manufacturing processes. *Coatings*. 2021;11:1562. doi:10.3390/coatings11121562
- [23] Ren W, Xu L, Qin C, et al. Laser directed energy deposition additive manufacturing of Al7075 alloy: process development, microstructure, and porosity. *J Mater Res Technol*. 2024;33:2093–2100. doi:10.1016/j.jmrt.2024.09.170
- [24] Serrano-Munoz I, Fritsch T, Mishurova T, et al. On the interplay of microstructure and residual stress in LPBF IN718. *J Mater Sci*. 2021;56:5845–5867. doi:10.1007/s10853-020-05553-y
- [25] Chai Y, Li D, Miao L, et al. Residual stress and distortion prediction for laser directed energy deposition based on cyclic heat transfer model. *IEEE Access*. 2024;12:27723–27738. doi:10.1109/ACCESS.2024.3365141
- [26] Serrano-Munoz I, Ulbricht A, Fritsch T, et al. Scanning manufacturing parameters determining the residual stress state in LPBF IN718 small parts. *Adv Eng Mater*. 2021;23:2100158. doi:10.1002/adem.202100158
- [27] Guaglione F, Caprio L, Previtali B, et al. Single point exposure LPBF for the production of biodegradable Zn-alloy lattice structures. *Addit Manuf*. 2021;48:102426. doi:10.1016/j.addma.2021.102426
- [28] Liu W, Zeng B, Xiong W, et al. Unraveling the mechanism of energy utilization efficiency regulating melt pool dimensions and tensile properties of 316L stainless steel in laser directed energy deposition. *J Manuf Mater Process*. 2026;10:61. doi:10.3390/jmmp10020061
- [29] Chen M, Zhang J, Qu Q, et al. Cavity-induced bubbles and pore formation of laser direct energy deposited titanium alloy: influence of powder melting degree. *Addit Manuf*. 2025;105:104792. doi:10.1016/j.addma.2025.104792
- [30] Du C, Zhao Y, Jiang J, et al. Pore defects in laser powder bed fusion: formation mechanism, control method, and perspectives. *J Alloys Compd*. 2023;944:169215. doi:10.1016/j.jallcom.2023.169215
- [31] Snow Z, Nassar AR, Reutzel EW. Invited review article: review of the formation and impact of flaws in powder bed fusion additive manufacturing. *Addit Manuf*. 2020;36:101457. doi:10.1016/j.addma.2020.101457
- [32] Mercelis P, Kruth J-P. Residual stresses in selective laser sintering and selective laser melting. *Rapid Prototyp J*. 2006;12:254–265. doi:10.1108/13552540610707013
- [33] Catchpole-Smith S, Aboulkhair N, Parry L, et al. Fractal scan strategies for selective laser melting of ‘unweldable’ nickel superalloys. *Addit Manuf*. 2017;15:113–122. doi:10.1016/j.addma.2017.02.002
- [34] Wu D, Tian J, Liao M, et al. Study on the effect of variable laser power on residual stress distribution in laser directed energy deposition of Ti6Al4V. *CIRP J Manuf Sci Technol*. 2024;55:322–332. doi:10.1016/j.cirpj.2024.10.011
- [35] Hu X, Zeng G, Chang L, et al. Stress evolution and cracking mechanism in remelted region of laser direct energy deposition additively manufactured FeCoCrNiAl high entropy alloys. *Eng Fail Anal*. 2026;192:110810. doi:10.1016/j.engfailanal.2026.110810
- [36] Pant P, Salvemini F, Proper S, et al. A study of the influence of novel scan strategies on residual stress and microstructure of L-shaped LPBF IN718 samples. *Mater Des*. 2022;214:110386. doi:10.1016/j.matdes.2022.110386
- [37] Liao X, Lu X, Ji Z, et al. Thermo-mechanical evolution and control of residual stress and distortion in hybrid investment casting-additive manufactured Ti6Al4V components. *Addit Manuf Front*. 2026; 200316. doi:10.1016/j.amf.2026.200316
- [38] Chen Y, Liu G, Yin S, et al. Effect of ball milling on microstructure, porosity and mechanical properties of laser directed energy deposited Inconel 718 superalloy. *J Alloys Compd*. 2025;1036:181709. doi:10.1016/j.jallcom.2025.181709
- [39] Raj R, Chiu LNS, Huang A, et al. Analysing thermo-mechanical effects of in-situ micro-rolling in single-bead laser-directed energy deposition via finite element modelling. *Prog Addit Manuf*. 2025;10:6229–6248. doi:10.1007/s40964-025-00967-z
- [40] Jin Q-Y, Kang D, Ha K, et al. Simulation of annealing process on AISI 316 L stainless steel fabricated via laser powder bed fusion using finite element method with creep. *Addit Manuf*. 2022;60:103255. doi:10.1016/j.addma.2022.103255
- [41] Li Z, Gut A, Burda I, et al. Investigation of individual lack-of-fusion defects in the fatigue performance of laser-powder bed fusion Ti6Al4V alloys: A finite element analysis. *Theor Appl Fract Mech*. 2024;134:104735. doi:10.1016/j.tafmec.2024.104735
- [42] Ostolaza M, Urresti A, Arrizubieta JI, et al. Cfd simulation for the modelling of the powder flow on continuous coaxial nozzles in the laser DED process. *Procedia CIRP*. 2022;111:282–286. doi:10.1016/j.procir.2022.08.022
- [43] Ostolaza M, Arrizubieta JI, Lamikiz A. Cfd modelling of the powder segregation in multi-material laser directed

- energy deposition. *Int J Therm Sci.* **2024**;198:108885. doi:[10.1016/j.jthermalsci.2024.108885](https://doi.org/10.1016/j.jthermalsci.2024.108885)
- [44] Fotovvati B, Chou K. Multi-layer thermo-fluid modeling of powder bed fusion (PBF) process. *J Manuf Process.* **2022**;83:203–211. doi:[10.1016/j.jmapro.2022.09.003](https://doi.org/10.1016/j.jmapro.2022.09.003)
- [45] Xiang H, Chen J. Integrated simulation framework for metal additive manufacturing: powder deposition, melt pool dynamics and microstructure evolution with example of Ti-6Al-4V. *Mater Today Commun.* **2025**;47:113206. doi:[10.1016/j.mtcomm.2025.113206](https://doi.org/10.1016/j.mtcomm.2025.113206)
- [46] Moges T, Ameta G, Witherell P. A review of model inaccuracy and parameter uncertainty in laser powder bed fusion models and simulations. *J Manuf Sci Eng.* **2019**;141:040801. doi:[10.1115/1.4042789](https://doi.org/10.1115/1.4042789)
- [47] Qin J, Hu F, Liu Y, et al. Research and application of machine learning for additive manufacturing. *Addit Manuf.* **2022**;52:102691. doi:[10.1016/j.addma.2022.102691](https://doi.org/10.1016/j.addma.2022.102691)
- [48] Meng L, McWilliams B, Jarosinski W, et al. Machine learning in additive manufacturing: a review. *JOM.* **2020**;72:2363–2377. doi:[10.1007/s11837-020-04155-y](https://doi.org/10.1007/s11837-020-04155-y)
- [49] Moradi A, Tajalli S, Taghian M, et al. Enhancing additive manufacturing quality and productivity using machine learning: a study on laser powder bed fusion of AISI 316L-2.5%Cu. *Prog Addit Manuf.* **2026**;11:1969–1987. doi:[10.1007/s40964-025-01452-3](https://doi.org/10.1007/s40964-025-01452-3)
- [50] Seifoddini A, Azad A, Mosallanejad MH, et al. Multi-objective process parameter optimization using a hybrid reinforcement/machine learning model in metal additive manufacturing. *Adv Manuf.* **2026**. doi:[10.1007/s40436-026-00596-x](https://doi.org/10.1007/s40436-026-00596-x)
- [51] Leng J, Zuo K, Xu C, et al. Physics-informed machine learning in intelligent manufacturing: a review. *J Intell Manuf.* **2026**;37:2215–2257. doi:[10.1007/s10845-025-02641-1](https://doi.org/10.1007/s10845-025-02641-1)
- [52] Wang C, Tan XP, Tor SB, et al. Machine learning in additive manufacturing: state-of-the-art and perspectives. *Addit Manuf.* **2020**;36:101538. doi:[10.1016/j.addma.2020.101538](https://doi.org/10.1016/j.addma.2020.101538)
- [53] Demiral M, Otkur M. From mechanics to machine learning in additive manufacturing: a review of deformation, fatigue, and fracture. *Technologies.* **2026**;14:218. doi:[10.3390/technologies14040218](https://doi.org/10.3390/technologies14040218)
- [54] Pan L, Li G, Zhu T, et al. Physics-Informed machine learning in design and manufacturing: status and challenges. *J Comput Inf Sci Eng.* **2025**;25:120804. doi:[10.1115/1.4070100](https://doi.org/10.1115/1.4070100)
- [55] Duan C, Wu D. Predicting stress-strain behaviors of additively manufactured materials via loss-based and activation-based physics-informed machine learning, (2026). doi:[10.48550/arXiv.2603.14489](https://doi.org/10.48550/arXiv.2603.14489)
- [56] Monu MCC, McCarthy E, Madathil AP, et al. Esaform benchmark 2025: predicting stainless steel PBF-LB part density using statistical, data-driven, and physics-informed machine learning models derived from process parameters and in-situ monitoring data. *Int J Mater Form.* **2026**;19:31. doi:[10.1007/s12289-026-01995-y](https://doi.org/10.1007/s12289-026-01995-y)
- [57] Zhang J, Yin C, Farbiz F, et al. Advancing machine learning applications for in-situ monitoring and control in laser-based metal additive manufacturing: a state-of-the-art review. *Virtual Phys Prototyp.* **2025**;20:e2592732. doi:[10.1080/17452759.2025.2592732](https://doi.org/10.1080/17452759.2025.2592732)
- [58] Pilane LR, Botes A, Reddy K, et al. Machine learning based process optimisation in laser metal deposition: a systematic review. *Sci Afr.* **2026**;31:e03169. doi:[10.1016/j.sciaf.2025.e03169](https://doi.org/10.1016/j.sciaf.2025.e03169)
- [59] Guo S, Agarwal M, Cooper C, et al. Machine learning for metal additive manufacturing: towards a physics-informed data-driven paradigm. *J Manuf Syst.* **2022**;62:145–163. doi:[10.1016/j.jmsy.2021.11.003](https://doi.org/10.1016/j.jmsy.2021.11.003)
- [60] Faegh M, Ghungrad S, Oliveira JP, et al. A review on physics-informed machine learning for process-structure-property modeling in additive manufacturing. *J Manuf Process.* **2025**;133:524–555. doi:[10.1016/j.jmapro.2024.11.066](https://doi.org/10.1016/j.jmapro.2024.11.066)
- [61] Parsazadeh M, Sharma S, Dahotre N. Towards the next generation of machine learning models in additive manufacturing: A review of process dependent material evolution. *Prog Mater Sci.* **2023**;135:101102. doi:[10.1016/j.pmatsci.2023.101102](https://doi.org/10.1016/j.pmatsci.2023.101102)
- [62] Farrag A, Yang Y, Cao N, et al. Physics-Informed machine learning for metal additive manufacturing. *Prog Addit Manuf.* **2025**;10:171–185. doi:[10.1007/s40964-024-00612-1](https://doi.org/10.1007/s40964-024-00612-1)
- [63] Patel D, Sharma R, Guo YB. Computational, data-driven, and physics-informed machine learning approaches for microstructure modeling in metal additive manufacturing. *Annu Rev Heat Transf.* **2025**;28:339–378. doi:[10.48550/arXiv.2505.01424](https://doi.org/10.48550/arXiv.2505.01424)
- [64] Ra D, Lee J, Lee M, et al. Physics-informed machine learning across manufacturing processes: recent advances, challenges, and directions. *J Manuf Syst.* **2026**;85:72–95. doi:[10.1016/j.jmsy.2026.01.002](https://doi.org/10.1016/j.jmsy.2026.01.002)
- [65] Pascual A, Ortega N, Plaza S, et al. Analysis of the influence of L-PBF porosity on the mechanical behavior of AISi10Mg by XRCT-based FEM. *J Mater Res Technol.* **2023**;22:958–981. doi:[10.1016/j.jmrt.2022.11.172](https://doi.org/10.1016/j.jmrt.2022.11.172)
- [66] Park J, Choma T, Kalicki B, et al. Effect of Hf and Ce addition on microstructure and mechanical properties of L-DED processed AISI 316L stainless steel. *J Mater Res Technol.* **2026**;41:6906–6918. doi:[10.1016/j.jmrt.2026.03.016](https://doi.org/10.1016/j.jmrt.2026.03.016)
- [67] Afroz L, Qian M, Forsmark J, et al. Fatigue life of laser powder bed fusion (L-PBF) AISi10Mg alloy: effects of surface roughness and porosity. *Prog Addit Manuf.* **2025**;10:2423–2441. doi:[10.1007/s40964-024-00759-x](https://doi.org/10.1007/s40964-024-00759-x)
- [68] Moon S, Ma R, Attardo R, et al. Impact of surface and pore characteristics on fatigue life of laser powder bed fusion Ti-6Al-4V alloy described by neural network models. *Sci Rep.* **2021**;11:20424. doi:[10.1038/s41598-021-99959-6](https://doi.org/10.1038/s41598-021-99959-6)
- [69] António M, Fernandes R, Jesus JD, et al. Influence of low-temperature stress-relieving treatment in the fatigue life of components produced by laser powder Bed fusion in AISi10Mg. *Appl Sci.* **2024**;15:112. doi:[10.3390/app15010112](https://doi.org/10.3390/app15010112)
- [70] Wang H, Pfefferkorn FE, Wolff SJ. Investigation of pore formation mechanisms induced by spherical-powder delivery in directed energy deposition using in situ high-speed X-ray imaging. *Addit Manuf Lett.* **2022**;3:100050. doi:[10.1016/j.addlet.2022.100050](https://doi.org/10.1016/j.addlet.2022.100050)

- [71] Hojjatzadeh SMH, Parab ND, Guo Q, et al. Direct observation of pore formation mechanisms during LPBF additive manufacturing process and high energy density laser welding. *Int J Mach Tools Manuf.* 2020;153:103555. doi:10.1016/j.ijmachtools.2020.103555
- [72] Le KQ, Tang C, Wong CH. On the study of keyhole-mode melting in selective laser melting process. *Int J Therm Sci.* 2019;145:105992. doi:10.1016/j.ijthermalsci.2019.105992
- [73] Guo L, Wang H, Liu H, et al. Understanding keyhole induced-porosities in laser powder bed fusion of aluminum and elimination strategy. *Int J Mach Tools Manuf.* 2023;184:103977. doi:10.1016/j.ijmachtools.2022.103977
- [74] Du Plessis A. Effects of process parameters on porosity in laser powder bed fusion revealed by X-ray tomography. *Addit Manuf.* 2019;30:100871. doi:10.1016/j.addma.2019.100871
- [75] Shrestha S, Chou K. Formation of keyhole and lack of fusion pores during the laser powder bed fusion process. *Manuf Lett.* 2022;32:19–23. doi:10.1016/j.mfglet.2022.01.005
- [76] Huang Y, Fleming TG, Clark SJ, et al. Keyhole fluctuation and pore formation mechanisms during laser powder bed fusion additive manufacturing. *Nat Commun.* 2022;13:1170. doi:10.1038/s41467-022-28694-x
- [77] Bayat M, Thanki A, Mohanty S, et al. Keyhole-induced porosities in laser-based powder bed fusion (L-PBF) of Ti6Al4V: high-fidelity modelling and experimental validation. *Addit Manuf.* 2019;30:100835. doi:10.1016/j.addma.2019.100835
- [78] Guo L, Liu H, Wang H, et al. Identifying the keyhole stability and pore formation mechanisms in laser powder bed fusion additive manufacturing. *J Mater Process Technol.* 2023;321:118153. doi:10.1016/j.jmatprotec.2023.118153
- [79] Hua S, Pan Y, Guo Q, et al. Laser induced keyhole reshaping in laser powder bed fusion of aluminum alloy. *Addit Manuf.* 2025;111:104993. doi:10.1016/j.addma.2025.104993
- [80] Ur Rehman A, Mahmood MA, Pitir F, et al. Keyhole formation by laser drilling in laser powder Bed fusion of Ti6Al4V biomedical alloy: mesoscopic computational fluid dynamics simulation versus mathematical modelling using empirical validation. *Nanomaterials.* 2021;11:3284. doi:10.3390/nano11123284
- [81] Zhao C, Parab ND, Li X, et al. Critical instability at moving keyhole tip generates porosity in laser melting. *Science.* 2020;370:1080–1086. doi:10.1126/science.abd1587
- [82] Katagiri J, Nomoto S, Kusano M, et al. Influence of high Reynolds number flow inside molten pool on keyhole instability-induced pore formation process in laser powder bed fusion. *Mater Today Commun.* 2025;44:111756. doi:10.1016/j.mtcomm.2025.111756
- [83] Psihoyos HO, Lampeas GN. Density-based optimization of the laser powder bed fusion process based on a modelling framework. *Alloys.* 2023;2:55–76. doi:10.3390/alloys2010004
- [84] Harkin R, Wu H, Nikam S, et al. Evaluation of the role of hatch-spacing variation in a lack-of-fusion defect prediction criterion for laser-based powder bed fusion processes. *Int J Adv Manuf Technol.* 2023;126:659–673. doi:10.1007/s00170-023-11163-0
- [85] Lei W, Jiabao H, Shuoqing S, et al. Part-scale multi-physics model for laser powder bed fusion process. *Cell Rep Phys Sci.* 2025;6:102674. doi:10.1016/j.xcrp.2025.102674
- [86] Yang X, Li Y, Li B. Formation mechanisms of lack of fusion and keyhole-induced pore defects in laser powder bed fusion process: A numerical study. *Int J Therm Sci.* 2023;188:108221. doi:10.1016/j.ijthermalsci.2023.108221
- [87] Rezaeifar H, Elbestawi M. Porosity formation mitigation in laser powder bed fusion process using a control approach. *Opt Laser Technol.* 2022;147:107611. doi:10.1016/j.optlastec.2021.107611
- [88] Smoqi Z, Gaikwad A, Bevens B, et al. Monitoring and prediction of porosity in laser powder bed fusion using physics-informed melt pool signatures and machine learning. *J Mater Process Technol.* 2022;304:117550. doi:10.1016/j.jmatprotec.2022.117550
- [89] Zhang K, Bhagavath S, Marussi S, et al. Pore-lean directed energy deposition additive manufacturing through laser power modulation. *Acta Mater.* 2025;301:121515. doi:10.1016/j.actamat.2025.121515
- [90] Hosseini S, Shmatok A, Prorok B, et al. Criticality of volumetric defect structure on fatigue properties of stainless steel 316L fabricated by laser powder direct energy deposition. *J Manuf Process.* 2024;127:259–273. doi:10.1016/j.jmapro.2024.07.130
- [91] Urresti A, Escolar A, Arrizubieta JI, et al. Gas-flow-controlled porosity engineering in DED-LB and its influence on the mechanical response of 15CDV6 steel. *J Mater Res Technol.* 2026;43:1607–1617. doi:10.1016/j.jmrt.2026.06.152
- [92] Zhao T, Wang Y, Xu T, et al. Some factors affecting porosity in directed energy deposition of AlMgScZr-alloys. *Opt Laser Technol.* 2021;143:107337. doi:10.1016/j.optlastec.2021.107337
- [93] Dos Santos Paes LE, Pereira M, Xavier FA, et al. Lack of fusion mitigation in directed energy deposition with laser (DED-L) additive manufacturing through laser remelting. *Process.* 2022;73:67–77. doi:10.1016/j.jmapro.2021.10.052
- [94] Manoj J, Ravi KR. Real-time melting regime classification in direct energy deposition using quantitative plasma plume morphology. *Mater Lett.* 2026;421:141121. doi:10.1016/j.matlet.2026.141121
- [95] Pandiyan V, Cui D, Le-Quang T, et al. In situ quality monitoring in direct energy deposition process using co-axial process zone imaging and deep contrastive learning. *J Manuf Process.* 2022;81:1064–1075. doi:10.1016/j.jmapro.2022.07.033
- [96] Khanzadeh M, Tian W, Yadollahi A, et al. Dual process monitoring of metal-based additive manufacturing using tensor decomposition of thermal image streams. *Addit Manuf.* 2018;23:443–456. doi:10.1016/j.addma.2018.08.014
- [97] Jeon I, Liu P, Sohn H. Real-time melt pool depth estimation and control during metal-directed energy deposition for porosity reduction. *Int J Adv Manuf Technol.* 2023. doi:10.1007/s00170-023-11689-3

- [98] Zhang K, Chen Y, Marussi S, et al. Pore evolution mechanisms during directed energy deposition additive manufacturing. *Nat Commun.* 2024;15:1715. doi:10.1038/s41467-024-45913-9
- [99] Chen H, Sun Y, Wang S, et al. Numerical analysis of powder-induced gas porosity in directed energy deposition: formation, evolution, and mitigation. *Addit Manuf.* 2025;107:104815. doi:10.1016/j.addma.2025.104815
- [100] Menon N, Basak A. Prediction of melt pool geometry by fusing experimental and simulation data. *Int J Mech Sci.* 2024;263:108786. doi:10.1016/j.ijmecsci.2023.108786
- [101] Silvestri AT, Squillace A. Assessment of deposition strategy and overlap in laser-directed energy deposition of H13 tool steel. *Prog Addit Manuf.* 2025;10:11595–11610. doi:10.1007/s40964-025-01304-0
- [102] Chen C, Chang S, Zhu J, et al. Residual stress of typical parts in laser powder bed fusion. *J Manuf Process.* 2020;59:621–628. doi:10.1016/j.jmapro.2020.10.009
- [103] Tran HT, Chen Q, Mohan J, et al. A new method for predicting cracking at the interface between solid and lattice support during laser powder bed fusion additive manufacturing. *Addit Manuf.* 2020;32:101050. doi:10.1016/j.addma.2020.101050
- [104] Lu X, Chen C, Zhang G, et al. Thermo-mechanical simulation of annealing heat treatment of Ni-based GH4099 superalloy made by laser powder bed fusion. *Addit Manuf.* 2023;73:103703. doi:10.1016/j.addma.2023.103703
- [105] Lu X, Chiumenti M, Cervera M, et al. Warpage analysis and control of thin-walled structures manufactured by laser powder bed fusion. *Metals (Basel).* 2021;11:686. doi:10.3390/met11050686
- [106] Chen S, Gao H, Zhang Y, et al. Review on residual stresses in metal additive manufacturing: formation mechanisms, parameter dependencies, prediction and control approaches. *J Mater Res Technol.* 2022;17:2950–2974. doi:10.1016/j.jmrt.2022.02.054
- [107] Withers PJ, Bhadeshia HKDH. Residual stress. Part 1 – Measurement techniques. *Mater Sci Technol.* 2001;17:355–365. doi:10.1179/026708301101509980
- [108] Prakash R, Kumar B. Residual stress in metal additive manufacturing: influencing parameters, measurements, and control approaches. *J Mater Sci.* 2026;61:1399–1437. doi:10.1007/s10853-025-11963-7
- [109] DebRoy T, Khan K, Mukherjee T, et al. Residual stress and distortion in fusion welding and fusion-based additive manufacturing: measurements, mechanisms and control strategies. *Prog Mater Sci.* 2026;159:101651. doi:10.1016/j.pmatsci.2025.101651
- [110] Malakizadi A, Mallipeddi D, Dadbakhsh S, et al. Post-processing of additively manufactured metallic alloys – A review. *Int J Mach Tools Manuf.* 2022;179:103908. doi:10.1016/j.ijmachtools.2022.103908
- [111] Demeneghi G, Gradl P, Mayeur JR, et al. GRCop-42: comparison between laser powder bed fusion and laser powder direct energy deposition. *Addit Manuf Lett.* 2024;10:100224. doi:10.1016/j.addlet.2024.100224
- [112] Inácio RA, Mesquita-Guimarães J, Félix LMR, et al. Comparative analysis of directed energy deposition and powder bed fusion mechanical properties. *J Alloys Compd.* 2026;1065:188142. doi:10.1016/j.jallcom.2026.188142
- [113] Iveković A, Montero-Sistiaga ML, Vleugels J, et al. Crack mitigation in laser powder bed fusion processed hastelloy X using a combined numerical-experimental approach. *J Alloys Compd.* 2021;864:158803. doi:10.1016/j.jallcom.2021.158803
- [114] Okugawa M, Saito K, Yoshima H, et al. Solute segregation in a rapidly solidified Hastelloy-X Ni-based superalloy during laser powder bed fusion investigated by phase-field and computational thermal-fluid dynamics simulations. *Addit Manuf.* 2024;84:104079. doi:10.1016/j.addma.2024.104079
- [115] Wang J, Zhu R, Liu Y, et al. Understanding melt pool characteristics in laser powder bed fusion: An overview of single- and multi-track melt pools for process optimization. *Adv Powder Mater.* 2023;2:100137. doi:10.1016/j.apmate.2023.100137
- [116] Liu Y, Shi J, Wang Y, et al. And mitigation of residual stresses in additively manufactured metallic materials: A review. *Adv Eng Mater.* 2023;25:2300489. doi:10.1002/adem.202300489
- [117] Levkulich NC, Semiatin SL, Gockel JE, et al. The effect of process parameters on residual stress evolution and distortion in the laser powder bed fusion of Ti-6Al-4V. *Addit Manuf.* 2019;28:475–484. doi:10.1016/j.addma.2019.05.015
- [118] Ramineni L, Almotari A, Ali M, et al. Residual stress mapping in heat-assisted additive manufacturing of IN 718: An X-Ray diffraction study. *J Mater Eng Perform.* 2024;33:4124–4135. doi:10.1007/s11665-024-09269-x
- [119] Manikandan P, Venkatesan K. The influence of linear energy density on density, defect formation, residual stress, microstructure, and texture in 310 austenitic stainless steel by laser powder bed fusion. *J Manuf Process.* 2024;131:2191–2207. doi:10.1016/j.jmapro.2024.10.022
- [120] Serrano-Munoz I, Mishurova T, Thiede T, et al. The residual stress in as-built laser powder bed fusion IN718 alloy as a consequence of the scanning strategy induced microstructure. *Sci Rep.* 2020;10:14645. doi:10.1038/s41598-020-71112-9
- [121] Palmeri D, Pollara G, Licari R, et al. Finite element method in L-PBF of Ti-6Al-4V: influence of laser power and scan speed on residual stress and part distortion. *Metals.* 2023;13:1907. doi:10.3390/met13111907
- [122] Mishurova T, Artzt K, Haubrich J, et al. Exploring the correlation between subsurface residual stresses and manufacturing parameters in laser powder bed fused Ti-6Al-4V. *Metals.* 2019;9:261. doi:10.3390/met9020261
- [123] Tangestani R, Chakraborty A, Sabiston T, et al. Buckling mechanism simulation for thin-wall components made by laser powder bed fusion. *Key Eng Mater.* 2023;964:1–6. doi:10.4028/p-12DUdU
- [124] Huang Y, Guo Y, Su R, et al. Learning based toolpath planner on diverse graphs for 3D printing. *ACM Trans Graph.* 2024;43:1–16. doi:10.1145/3687933
- [125] Narvan M, Ghasemi A, Fereiduni E, et al. Part deflection and residual stresses in laser powder bed fusion of H13 tool steel. *Mater Des.* 2021;204:109659. doi:10.1016/j.matdes.2021.109659

- [126] Richter J, Bartzsch G, Scherbring S, et al. Metastable CrMnNi steels processed by laser powder bed fusion: experimental assessment of elementary mechanisms contributing to microstructure, properties and residual stress. *Sci Rep.* **2022**;12:21862. doi:10.1038/s41598-022-26052-x
- [127] Krakhmalev P, Yadroitsava I, Fredriksson G, et al. In situ heat treatment in selective laser melted martensitic AISI 420 stainless steels. *Mater Des.* **2015**;87:380–385. doi:10.1016/j.matdes.2015.08.045
- [128] Wu L, Das S, Gridin W, et al. Hot work tool steel processed by laser powder bed fusion: a review on most relevant influencing factors. *Adv Eng Mater.* **2021**;23:2100049. doi:10.1002/adem.202100049
- [129] An S, Eo D-R, Lim H, et al. Prediction of martensitic transformation and residual stress field on 17–4 PH stainless steel fabricated by laser powder bed fusion. *Addit Manuf.* **2024**;91:104339. doi:10.1016/j.addma.2024.104339
- [130] Zhang W, Yang M, Mao W, et al. The effect of productive and quality deposition strategies on residual stress for Directed Energy Deposition (DED) process. *Manuf Lett.* **2024**;41:868–878. doi:10.1016/j.mfglet.2024.09.107
- [131] Fan W, Peng Y, Zhang S, et al. On the powder chilling effect in laser based directed energy deposition. *Addit Manuf.* **2025**;105:104789. doi:10.1016/j.addma.2025.104789
- [132] Fan W, Peng Y, Qi Y, et al. Partially melted powder in laser based directed energy deposition: formation mechanism and its influence on microstructure. *Int J Mach Tools Manuf.* **2023**;192:104072. doi:10.1016/j.ijmachtools.2023.104072
- [133] Lv C, Wang J, Li H, et al. Dynamics of the laser–powder interaction in the Ti6Al4V powder feeding process of laser-directed energy deposition additive manufacturing. *J Mater Res Technol.* **2023**;27:6376–6385. doi:10.1016/j.jmrt.2023.11.099
- [134] Polyzos E, Pulju H, Mäkel P, et al. Measuring and predicting the effects of residual stresses from full-field data in laser-directed energy deposition. *Materials.* **2023**;16:1444. doi:10.3390/ma16041444
- [135] Yang Z, Yang J, Gu X, et al. Achieving balanced mechanical and thermal expansion properties of invar alloy prepared by hybrid laser directed energy deposition and post-heat treatment. *J Mater Res Technol.* **2025**;36:8543–8557. doi:10.1016/j.jmrt.2025.05.074
- [136] Yang S, Clare AT, Bennett C, et al. Informing directed energy deposition strategies through understanding the evolution of residual stress. *Addit Manuf.* **2024**;79:103907. doi:10.1016/j.addma.2023.103907
- [137] Mukherjee T, Zhang W, DebRoy T. An improved prediction of residual stresses and distortion in additive manufacturing. *Comput Mater Sci.* **2017**;126:360–372. doi:10.1016/j.commatsci.2016.10.003
- [138] Ivanov S, Artinov A, Zemlyakov E, et al. Spatiotemporal evolution of stress field during direct laser deposition of multilayer thin wall of Ti-6Al-4V. *Materials.* **2021**;15:263. doi:10.3390/ma15010263
- [139] Chen B, Dong B, Bian Y, et al. Investigation of thermal behavior of powder stream and molten pool during laser-based directed energy deposition. *Powder Technol.* **2024**;434:119385. doi:10.1016/j.powtec.2024.119385
- [140] Tan H, Fang Y, Zhong C, et al. Investigation of heating behavior of laser beam on powder stream in directed energy deposition. *Surf Coat Technol.* **2020**;397:126061. doi:10.1016/j.surfcoat.2020.126061
- [141] Babuska TF, Krick BA, Susan DF, et al. Comparison of powder bed fusion and directed energy deposition for tailoring mechanical properties of traditionally brittle alloys. *Manuf Lett.* **2021**;28:30–34. doi:10.1016/j.mfglet.2021.02.003
- [142] Hamdi H, Sadatabhari S, Tajik A, et al. From melt pool to performance: A review of microstructural engineering in the additive manufacturing of nickel-based superalloys. *Results Eng.* **2025**;28:107402. doi:10.1016/j.rineng.2025.107402
- [143] Mithal A, Maharjan N, Tan NYJ, et al. Understanding residual stress evolution in directed energy deposition With interlayer deformation. *J Manuf Sci Eng.* **2024**;146:111002. doi:10.1115/1.4066333
- [144] Saboori A, Piscopo G, Lai M, et al. An investigation on the effect of deposition pattern on the microstructure, mechanical properties and residual stress of 316L produced by directed energy deposition. *Mater Sci Eng A.* **2020**;780:139179. doi:10.1016/j.msea.2020.139179
- [145] Wang J, Zhang J, Liu G, et al. Effects of scanning strategies on residual stress and deformation by high-power direct energy deposition: island size and laser jump strategy between islands. *J Manuf Process.* **2022**;75:23–40. doi:10.1016/j.jmapro.2021.12.054
- [146] Denlinger ER, Heigel JC, Michaleris P, et al. Effect of interlayer dwell time on distortion and residual stress in additive manufacturing of titanium and nickel alloys. *J Mater Process Technol.* **2015**;215:123–131. doi:10.1016/j.jmatprotec.2014.07.030
- [147] Platz J, Aurich J, Bergmann B, et al. Residual stress determination in additively manufactured steels under different composition ratios and processing states. *Prod Eng.* **2026**;20:11. doi:10.1007/s11740-025-01377-4
- [148] Chen W, Xu L, Han Y, et al. Control of residual stress in metal additive manufacturing by low-temperature solid-state phase transformation: An experimental and numerical study. *Addit Manuf.* **2021**;42:102016. doi:10.1016/j.addma.2021.102016
- [149] Samaei A, Leonor JP, Gan Z, et al. Benchmark study of melt pool and keyhole dynamics, laser absorptance, and porosity in additive manufacturing of Ti-6Al-4V. *Prog Addit Manuf.* **2025**;10:491–515. doi:10.1007/s40964-024-00637-6
- [150] Wang L, Zhang Y, Chia HY, et al. Mechanism of keyhole pore formation in metal additive manufacturing. *Npj Comput Mater.* **2022**;8:22. doi:10.1038/s41524-022-00699-6
- [151] Yang J, Schlenger LM, Nasab MH, et al. Experimental quantification of inward marangoni convection and its impact on keyhole threshold in laser powder bed fusion of stainless steel. *Addit Manuf.* **2024**;84:104092. doi:10.1016/j.addma.2024.104092
- [152] Promoppatum P, Uthaisangsuk V. Part scale estimation of residual stress development in laser powder bed fusion additive manufacturing of Inconel 718. *Finite*

- Elem Anal Des. 2021;189:103528. doi:[10.1016/j.finel.2021.103528](https://doi.org/10.1016/j.finel.2021.103528)
- [153] Bruggeman K, Klingbeil N, Palazotto A. Residual stress generation in additive manufacturing of complex lattice geometries. *J Mater Eng Perform*. 2024;33:4088–4105. doi:[10.1007/s11665-024-09229-5](https://doi.org/10.1007/s11665-024-09229-5)
- [154] Georgilas K, Guo H, Ahmad B, et al. Residual stresses in alloy IN718 produced through modulated laser powder Bed fusion. *Exp Mech*. 2024;64:181–195. doi:[10.1007/s11340-023-01018-w](https://doi.org/10.1007/s11340-023-01018-w)
- [155] Zou X, Yan Z, Zou K, et al. Residual stress control of 316 L stainless steel using pulsed-wave laser additive manufacturing. *Opt Laser Technol*. 2022;150:107910. doi:[10.1016/j.optlastec.2022.107910](https://doi.org/10.1016/j.optlastec.2022.107910)
- [156] Ghanavati R, Naffakh-Moosavy H, Moradi M, et al. Residual stresses and distortion in additively-manufactured SS316L-IN718 multi-material by laser-directed energy deposition: A validated numerical-statistical approach. *J Manuf Process*. 2023;108:292–309. doi:[10.1016/j.jmapro.2023.11.018](https://doi.org/10.1016/j.jmapro.2023.11.018)
- [157] Yang S, Clare AT, Jin X. Understanding residual stress in functionally graded directed energy deposition. *Addit Manuf*. 2024;96:104581. doi:[10.1016/j.addma.2024.104581](https://doi.org/10.1016/j.addma.2024.104581)
- [158] Park G-W, Song S, Park M, et al. Effect of residual stress on pore formation in multi-materials deposited via directed energy deposition. *Addit Manuf*. 2024;81:104016. doi:[10.1016/j.addma.2024.104016](https://doi.org/10.1016/j.addma.2024.104016)
- [159] Chen Y, Wang Y, Lu Y, et al. A multiscale model for efficiently simulating laser powder bed fusion process with detailed microstructure and mechanical performance results. *Mater Sci Eng A*. 2024;918:147435. doi:[10.1016/j.msea.2024.147435](https://doi.org/10.1016/j.msea.2024.147435)
- [160] Ni W, Liu L, Feng S. Influence of laser energy density on microstructural development in laser powder bed fusion: A cellular automaton approach. *Opt Laser Technol*. 2026;193:114296. doi:[10.1016/j.optlastec.2025.114296](https://doi.org/10.1016/j.optlastec.2025.114296)
- [161] Vo V-L, Tran H-C, Li Y-J, et al. Numerical and experimental analysis of effects of processing conditions on melt pool stability of CuCr1Zr parts produced by laser powder bed fusion (L-PBF). *Opt Laser Technol*. 2025;181:111801. doi:[10.1016/j.optlastec.2024.111801](https://doi.org/10.1016/j.optlastec.2024.111801)
- [162] Chung M, Lee K-H, Park J, et al. A fully computational approach for the prediction of melt pool generation of the directed energy deposition process. *J Mech Sci Technol*. 2025;39:6847–6862. doi:[10.1007/s12206-025-1029-0](https://doi.org/10.1007/s12206-025-1029-0)
- [163] Selim Ahmed M, Hodgir R, Mujumdar S, et al. Computational modeling of multi-track multi-layer laser directed energy deposition process. *Manuf Lett*. 2024;41:983–991. doi:[10.1016/j.mfglet.2024.09.122](https://doi.org/10.1016/j.mfglet.2024.09.122)
- [164] Wei M, Ding WJ, Vastola G, et al. Quantitative study on the dynamics of melt pool and keyhole and their controlling factors in metal laser melting. *Addit Manuf*. 2022;54:102779. doi:[10.1016/j.addma.2022.102779](https://doi.org/10.1016/j.addma.2022.102779)
- [165] Sun Z, Chueh Y-H, Li L. Multiphase mesoscopic simulation of multiple and functionally gradient materials laser powder bed fusion additive manufacturing processes. *Addit Manuf*. 2020;35:101448. doi:[10.1016/j.addma.2020.101448](https://doi.org/10.1016/j.addma.2020.101448)
- [166] Duan G, Sakai M. Numerical investigation of gas entrapment in metal additive manufacturing using a quasi-sharp-interface particle method. *Int J Heat Mass Transf*. 2022;199:123451. doi:[10.1016/j.ijheatmasstransfer.2022.123451](https://doi.org/10.1016/j.ijheatmasstransfer.2022.123451)
- [167] Li C, Liu JF, Fang XY, et al. Efficient predictive model of part distortion and residual stress in selective laser melting. *Addit Manuf*. 2017;17:157–168. doi:[10.1016/j.addma.2017.08.014](https://doi.org/10.1016/j.addma.2017.08.014)
- [168] Qu M, Guo Q, Escano LI, et al. Mitigating keyhole pore formation by nanoparticles during laser powder bed fusion additive manufacturing. *Addit Manuf Lett*. 2022;3:100068. doi:[10.1016/j.addlet.2022.100068](https://doi.org/10.1016/j.addlet.2022.100068)
- [169] Gobert C, Reutzel EW, Petrich J, et al. Application of supervised machine learning for defect detection during metallic powder bed fusion additive manufacturing using high resolution imaging. *Addit Manuf*. 2018;21:517–528. doi:[10.1016/j.addma.2018.04.005](https://doi.org/10.1016/j.addma.2018.04.005)
- [170] Mochi VH, Núñez HHL, Ribeiro KSB, et al. Real-time prediction of deposited bead width in L-DED using semi-supervised transfer learning. *Int J Adv Manuf Technol*. 2023;129:5643–5654. doi:[10.1007/s00170-023-12658-6](https://doi.org/10.1007/s00170-023-12658-6)
- [171] Li H, Hu L, Ye J, et al. A high-precision in-situ monitoring system for laser directed energy deposition melt pool 3D morphology based on deep learning. *J Intell Manuf*. 2025;36:5525–5544. doi:[10.1007/s10845-024-02526-9](https://doi.org/10.1007/s10845-024-02526-9)
- [172] Gordon JV, Narra SP, Cunningham RW, et al. Defect structure process maps for laser powder bed fusion additive manufacturing. *Addit Manuf*. 2020;36:101552. doi:[10.1016/j.addma.2020.101552](https://doi.org/10.1016/j.addma.2020.101552)
- [173] Paulson NH, Gould B, Wolff SJ, et al. Correlations between thermal history and keyhole porosity in laser powder bed fusion. *Addit Manuf*. 2020;34:101213. doi:[10.1016/j.addma.2020.101213](https://doi.org/10.1016/j.addma.2020.101213)
- [174] Wang R, Wang R, Dou C, et al. Sub-surface thermal measurement in additive manufacturing via machine learning-enabled high-resolution fiber optic sensing. *Nat Commun*. 2024;15:7568. doi:[10.1038/s41467-024-51235-7](https://doi.org/10.1038/s41467-024-51235-7)
- [175] Montazeri M, Nassar AR, Dunbar AJ, et al. In-process monitoring of porosity in additive manufacturing using optical emission spectroscopy. *IIEE Trans*. 2020;52:500–515. doi:[10.1080/24725854.2019.1659525](https://doi.org/10.1080/24725854.2019.1659525)
- [176] Chen L, Yao X, Tan C, et al. In-situ crack and keyhole pore detection in laser directed energy deposition through acoustic signal and deep learning. *Addit Manuf*. 2023;69:103547. doi:[10.1016/j.addma.2023.103547](https://doi.org/10.1016/j.addma.2023.103547)
- [177] Feng S, Chen Z, Bircher B, et al. Predicting laser powder bed fusion defects through in-process monitoring data and machine learning. *Mater Des*. 2022;222:111115. doi:[10.1016/j.matdes.2022.111115](https://doi.org/10.1016/j.matdes.2022.111115)
- [178] Du Y, Mukherjee T, DebRoy T. Physics-informed machine learning and mechanistic modeling of additive manufacturing to reduce defects. *Appl Mater Today*. 2021;24:101123. doi:[10.1016/j.apmt.2021.101123](https://doi.org/10.1016/j.apmt.2021.101123)
- [179] Gaikwad A, Giera B, Guss GM, et al. Heterogeneous sensing and scientific machine learning for quality assurance in laser powder bed fusion – A single-track study. *Addit Manuf*. 2020;36:101659. doi:[10.1016/j.addma.2020.101659](https://doi.org/10.1016/j.addma.2020.101659)

- [180] Xie X, Bennett J, Saha S, et al. Mechanistic data-driven prediction of as-built mechanical properties in metal additive manufacturing. *NPJ Comput Mater.* 2021;7:86. doi:10.1038/s41524-021-00555-z
- [181] Li Y, Mojumder S, Lu Y, et al. Statistical parameterized physics-based machine learning digital shadow models for laser powder bed fusion process. *Addit Manuf.* 2024;87:104214. doi:10.1016/j.addma.2024.104214
- [182] Gawade V, Singh V. Leveraging simulated and empirical data-driven insight to supervised-learning for porosity prediction in laser metal deposition. *J Manuf Syst.* 2022;62:875–885. doi:10.1016/j.jmsy.2021.07.013
- [183] Liao S, Xue T, Jeong J, et al. Hybrid thermal modeling of additive manufacturing processes using physics-informed neural networks for temperature prediction and parameter identification. *Comput Mech.* 2023;72:499–512. doi:10.1007/s00466-022-02257-9
- [184] Liao S, Webster S, Huang D, et al. Simulation-guided variable laser power design for melt pool depth control in directed energy deposition. *Addit Manuf.* 2022;56:102912. doi:10.1016/j.addma.2022.102912
- [185] Weisz-Patrault D, Margerit P, Constantinescu A. Residual stresses in thin walled-structures manufactured by directed energy deposition: In-situ measurements, fast thermo-mechanical simulation and buckling. *Addit Manuf.* 2022;56:102903. doi:10.1016/j.addma.2022.102903
- [186] Wang K, Xie D, Lv F, et al. Stability of molten pool and microstructure evolution of Ti-6Al-4V during laser powder bed fusion with a flat-top beam. *Addit Manuf.* 2023;75:103756. doi:10.1016/j.addma.2023.103756
- [187] Lindström V, Lupo G, Yang J, et al. A simple scaling model for balling defect formation during laser powder bed fusion. *Addit Manuf.* 2023;63:103431. doi:10.1016/j.addma.2023.103431
- [188] Woo SS, Lee KY, Baek GY, et al. Residual stress variations in substrate (AISI D2) during directed energy deposition process of high-speed tool steel (AISI M4) powder. *J Alloys Metall Syst.* 2024;6:100080. doi:10.1016/j.jalmes.2024.100080
- [189] Zhang J, Shang X, Wei Q, et al. Mechanism and quantification of melt pool morphology evolution in single-track fabrication by laser directed energy deposition. *J Manuf Process.* 2025;156:556–568. doi:10.1016/j.jmapro.2025.10.097
- [190] Sui F, He X, Dong C. A dedicated multiphysics model optimizes lack of fusion defects through various scanning paths in L-PBF process. *Int J Therm Sci.* 2025;210:109611. doi:10.1016/j.ijthermalsci.2024.109611
- [191] Prabhune B, Panicker N, Jordan B, et al. Multi-physics melt pool modeling and process optimization for laser direct energy deposition of Nb-based refractory C103: defect formation, geometric precision, and process mapping. *J Manuf Process.* 2025;154:444–461. doi:10.1016/j.jmapro.2025.09.082
- [192] Bayat M, Rothfelder R, Schwarzkopf K, et al. Exploring spatial beam shaping in laser powder bed fusion: high-fidelity simulation and in-situ monitoring. *Addit Manuf.* 2024;93:104420. doi:10.1016/j.addma.2024.104420
- [193] Oster S, Scheuschner N, Chand K, et al. Local porosity prediction in metal powder bed fusion using in-situ thermography: A comparative study of machine learning techniques. *Addit Manuf.* 2024;95:104502. doi:10.1016/j.addma.2024.104502
- [194] Mojumder S, Halder P, Tonge T. Multimodal learning of melt pool dynamics in laser powder bed fusion. *Prog Addit Manuf.* 2026;11:2801–2814. doi:10.1007/s40964-025-01496-5
- [195] Raihan AS, Harper A, Era IZ, et al. A data-efficient sequential learning framework for melt pool defect classification in laser powder bed fusion. *J Manuf Process.* 2025;145:201–210. doi:10.1016/j.jmapro.2025.03.118
- [196] Tao Z, Thanki A, Goossens L, et al. Data-driven keyhole pore detection in laser powder bed fusion: integrating process insights with X-CT. *J Manuf Process.* 2025;142:293–316. doi:10.1016/j.jmapro.2025.03.107
- [197] Karthikeyan A, Balhara H, Hanchate A, et al. In-situ surface porosity prediction in hybrid-directed energy deposition (DED) process using explainable multimodal sensor fusion. *J Manuf Process.* 2025;156:904–919. doi:10.1016/j.jmapro.2025.10.080
- [198] Era IZ, Zhou F, Raihan AS, et al. In-situ melt pool characterization via thermal imaging for defect detection in directed energy deposition using vision transformers. *J Manuf Process.* 2025;145:11–21. doi:10.1016/j.jmapro.2025.03.123
- [199] Shen T, Li B, Ren F, et al. A monitoring framework for predicting laser directed energy deposition property. *Int J Mech Sci.* 2025;307:110861. doi:10.1016/j.ijmecsci.2025.110861
- [200] Qin M, Ding J, Qu S, et al. Deep reinforcement learning based toolpath generation for thermal uniformity in laser powder bed fusion process. *Addit Manuf.* 2024;79:103937. doi:10.1016/j.addma.2023.103937
- [201] Zhang R, Strickland J, Hou X, et al. Rapid residual stress simulation and distortion mitigation in laser additive manufacturing through machine learning. *Addit Manuf.* 2025;102:104721. doi:10.1016/j.addma.2025.104721
- [202] Vulimiri PS, Riley S, Dugast FX, et al. A mean-variance estimation bidirectional convolutional long short-term memory surrogate model predicting residual stress and model error for laser powder bed fusion. *Addit Manuf.* 2025;97:104591. doi:10.1016/j.addma.2024.104591
- [203] Kim S-Y, Oh Y-S, Kim D-K, et al. Prediction of residual stress in additively manufactured 18Ni300 maraging steel using GAN-based deep learning method. *J Mater Res Technol.* 2026;41:1703–1715. doi:10.1016/j.jmrt.2026.01.126
- [204] Simson D, Paul CP, Subbu SK. Experimental study and neural network model based prediction of layer thickness influence on LPBF IN625 single track geometry. *Opt Laser Technol.* 2024;173:110543. doi:10.1016/j.optlastec.2024.110543
- [205] Kunkel N, Thölken D, Behler K. Deep learning-based automated defect classification for powder bed fusion – laser beam, *Eur. J Mater.* 2024;4:2427401. doi:10.1080/26889277.2024.2427401

- [206] Mao Y, Lin X, Zhu H, et al. Physics-guided spatiotemporal approach for melt pool size prediction in laser powder bed fusion. *Virtual Phys Prototyp.* 2024;19:e2427243. doi:10.1080/17452759.2024.2427243
- [207] Sharma R, Raissi M, Guo Y. Physics-informed deep learning of gas flow-melt pool multi-physical dynamics during powder bed fusion. *CIRP Ann.* 2023;72:161–164. doi:10.1016/j.cirp.2023.04.005
- [208] Yang W, Qiu Y, Liu W, et al. Defect prediction in laser powder bed fusion with the combination of simulated melt pool images and thermal images. *J Manuf Process.* 2023;106:214–222. doi:10.1016/j.jmapro.2023.10.006
- [209] Cao X, Duan C, Luo X, et al. Physics-informed machine learning approach for molten pool morphology prediction and process evaluation in directed energy deposition of 12CrNi2 alloy steel. *J Manuf Process.* 2024;119:806–826. doi:10.1016/j.jmapro.2024.04.023
- [210] Ye J, Patel M, Alam N, et al. A dimensionless group-incorporating artificial neural network (DI-ANN) model for single-track depth prediction of SS316L for laser-directed energy deposition (L-DED). *Int J Adv Manuf Technol.* 2024;135:3529–3545. doi:10.1007/s00170-024-14696-0
- [211] Hosseini E, Scheel P, Müller O, et al. Single-track thermal analysis of laser powder bed fusion process: parametric solution through physics-informed neural networks. *Comput Methods Appl Mech Eng.* 2023;410:116019. doi:10.1016/j.cma.2023.116019
- [212] Scheel P, Hosseini E. Pulse approach: a physics-guided machine learning model for thermal analysis in laser-based powder bed fusion of metals. *Prog Addit Manuf.* 2025;10:1405–1420. doi:10.1007/s40964-024-00713-x
- [213] Yang Y. Micro-mechanism informed neural networks for process-property prediction in laser powder Bed fusion. *Artif Intell Eng.* 2026;2:158–179. doi:10.1049/aie2.70015
- [214] Xu W, Jiang Y, Ran X, et al. In-situ residual stress mitigation of laser powder bed fusion Ti-6.5Al-2Zr-1Mo-1V using an active learning framework. *J Mater Sci Technol.* 2026;275:212–223. doi:10.1016/j.jmst.2026.02.052
- [215] Li S, Wang G, Di Y, et al. A physics-informed neural network framework to predict 3D temperature field without labeled data in process of laser metal deposition. *Eng Appl Artif Intell.* 2023;120:105908. doi:10.1016/j.engappai.2023.105908
- [216] Peng B, Panesar A. Multi-layer thermal history prediction framework for directed energy deposition based on extended physics-informed neural networks (XPINN). *Addit Manuf.* 2025;110:104953. doi:10.1016/j.addma.2025.104953
- [217] Kushwaha S, Park J, Koric S, et al. Advanced deep operator networks to predict multiphysics solution fields in materials processing and additive manufacturing. *Addit Manuf.* 2024;88:104266. doi:10.1016/j.addma.2024.104266
- [218] Zhang Y, Fu D, Zou Y, et al. Thermal-microstructure prediction and process optimization in laser directed energy deposition of Ti-6Al-4V alloy using multiscale physics and surrogate modeling. *J Mater Res Technol.* 2026;43:2991–3008. doi:10.1016/j.jmrt.2026.06.241
- [219] Matilainen V-P, Piili H, Salminen A, et al. Preliminary investigation of keyhole phenomena during single layer fabrication in laser additive manufacturing of stainless steel. *Phys Procedia.* 2015;78:377–387. doi:10.1016/j.phpro.2015.11.052
- [220] Hinnebusch S, Anderson D, Bostan B, et al. In-Situ infrared camera monitoring for defect and anomaly detection in laser powder Bed fusion: calibration, data mapping, and feature extraction. *Appl Sci.* 2026;16:3378. doi:10.3390/app16073378
- [221] Zheng L, Zhang Q, Cao H, et al. Melt pool boundary extraction and its width prediction from infrared images in selective laser melting. *Mater Des.* 2019;183:108110. doi:10.1016/j.matdes.2019.108110
- [222] Cao L, Hu W, Zhou T, et al. Monitoring of single-track melting states based on photodiode signal during laser powder Bed fusion. *Sensors.* 2023;23:9793. doi:10.3390/s23249793
- [223] Khanzadeh M, Chowdhury S, Marufuzzaman M, et al. Porosity prediction: supervised-learning of thermal history for direct laser deposition. *J Manuf Syst.* 2018;47:69–82. doi:10.1016/j.jmsy.2018.04.001
- [224] Cunningham R, Narra SP, Montgomery C, et al. Synchrotron-Based X-ray microtomography characterization of the effect of processing variables on porosity formation in laser power-bed additive manufacturing of Ti-6Al-4V. *JOM.* 2017;69:479–484. doi:10.1007/s11837-016-2234-1
- [225] Dilip JJS, Zhang S, Teng C, et al. Influence of processing parameters on the evolution of melt pool, porosity, and microstructures in Ti-6Al-4V alloy parts fabricated by selective laser melting. *Prog Addit Manuf.* 2017;2:157–167. doi:10.1007/s40964-017-0030-2
- [226] Mao Z, Feng W, Ma H, et al. Continuous online flaws detection with photodiode signal and melt pool temperature based on deep learning in laser powder bed fusion. *Opt Laser Technol.* 2023;158:108877. doi:10.1016/j.optlastec.2022.108877
- [227] Cao L, Guo W, He B, et al. In-situ monitoring of the small changes in process parameters with multi-sensor fusion during LPBF. *Meas Sci Technol.* 2024;35:106114. doi:10.1088/1361-6501/ad5ea5
- [228] Kishor G, Sharma YK, Mugada KK, et al. A review on in-situ monitoring; process control and residual stress prediction using machine learning methods in metal-based laser additive manufacturing. *Prog Addit Manuf.* 2026;11:3485–3521. doi:10.1007/s40964-026-01532-y
- [229] Zhang Y, Ren H, Yan H, et al. In situ study of surface morphology formation mechanism during laser powder bed fusion. *Appl Sci.* 2025;15:2550. doi:10.3390/app15052550
- [230] Mao Y, Yan J, Lin X, et al. A physics-guided multi-source data fusion model for LPBF process monitoring: from data generation to melting state recognition. *Addit Manuf.* 2026;122:105200. doi:10.1016/j.addma.2026.105200
- [231] Zhang J, Jafary-Zadeh M, Laskowski R, et al. Insights beneath the surface: physics-guided multi-task learning for in situ defect detection in laser powder bed fusion. *J Manuf Process.* 2026;169:126–136. doi:10.1016/j.jmapro.2026.04.032

- [232] Wang J, Lu Y. In-situ monitoring of 3D melt pool temperature field and layer-wise parameter optimization in LPBF via a data-model interactive approach. *J Manuf Process*. 2025;156:627–644. doi:10.1016/j.jmapro.2025.10.107
- [233] Yu M, Zhu L, Yang Z, et al. In-situ monitoring and ensemble learning for micro-pore distribution prediction in laser-directed energy deposition. *Eng Appl Artif Intell*. 2026;174:114496. doi:10.1016/j.engappai.2026.114496
- [234] Niu J, Li Y, Qi X, et al. An image-physics dual-driven machine learning framework for cross-sectional geometry prediction in laser direct energy deposition. *Opt Laser Technol*. 2025;192:114150. doi:10.1016/j.optlastec.2025.114150
- [235] Alfattani R, Hotami MM. Digital twin-driven multiscale modelling for real-time defect prediction in metal additive manufacturing. *Sci Rep*. 2026. doi:10.1038/s41598-026-58348-7
- [236] Li H, Roh B-M, Xiao X. In-situ laser powder bed fusion: real-time assessment of residual stress through thermal gradient analysis. *Int J Interact Des Manuf IJIDeM*. 2025;19:5417–5430. doi:10.1007/s12008-024-02146-w
- [237] He D, Lau TY, Hao J, et al. PINN-based reconstruction of deformation fields in hybrid additive-subtractive manufacturing of metal cavity parts. *J Manuf Syst*. 2026;87:1–16. doi:10.1016/j.jmsy.2026.05.001
- [238] Wang J, Zhang D, Wu B, et al. Prediction of distortion induced by machining residual stresses in thin-walled components. *Int J Adv Manuf Technol*. 2018;95:4153–4162. doi:10.1007/s00170-017-1358-y
- [239] Yang S, Tang Z, Ye Y, et al. A PINN-EWMA framework with uncertainty quantification for high-fidelity temperature field modeling and early defect warning in directed energy deposition of thin-walled structures. *Reliab Eng Syst Saf*. 2026;267:111834. doi:10.1016/j.res.2025.111834
- [240] Duan C, Xu H, Luo X, et al. Infrared-thermography-driven prediction of thermal behavior in directed energy deposition via a physics-guided spatio-temporal neural network. *Int J Therm Sci*. 2026;228:110998. doi:10.1016/j.ijthermalsci.2026.110998
- [241] Bevans BD, Carrington A, Riensche A, et al. Digital twins for rapid in-situ qualification of part quality in laser powder bed fusion additive manufacturing. *Addit Manuf*. 2024;93:104415. doi:10.1016/j.addma.2024.104415
- [242] Yang S, Zhang Z, Guo R, et al. Physics-informed machine learning for high-cycle fatigue of AM Ti6Al4V: life prediction and correlation analysis. *Int J Fatigue*. 2026;203:109296. doi:10.1016/j.ijfatigue.2025.109296
- [243] Zhu Z, Wang R, Li N, et al. Physics-informed machine learning for mapping of composition and mechanical properties in 316L/AICrFeNi multi-material alloys fabricated by directed energy deposition. *Virtual Phys Prototyp*. 2026;21:e2648350. doi:10.1080/17452759.2026.2648350
- [244] Cooper C, Zhang J, Huang J, et al. Tensile strength prediction in directed energy deposition through physics-informed machine learning and shapley additive explanations. *J Mater Process Technol*. 2023;315:117908. doi:10.1016/j.jmatprotec.2023.117908
- [245] Hills MA, Becker TH. Fatigue strength prediction of additively manufactured Ti-6Al-4V: A defect-based physics-informed neural network. *Mater Today Commun*. 2026;52:115035. doi:10.1016/j.mtcomm.2026.115035
- [246] Ince A. Physics-informed deep neural network framework for prediction of fatigue crack growth in LPBF-manufactured metallic alloys. *Int J Fatigue*. 2026;208:109522. doi:10.1016/j.ijfatigue.2026.109522
- [247] Bartošák M, Halamka J, Beránek L, et al. Using physics-informed neural networks to predict the lifetime of laser powder bed fusion processed 316L stainless steel under multiaxial low-cycle fatigue loading. *Int J Fatigue*. 2025;190:108608. doi:10.1016/j.ijfatigue.2024.108608
- [248] Wang H, Li B, Xuan F-Z. Fatigue-life prediction of additively manufactured metals by continuous damage mechanics (CDM)-informed machine learning with sensitive features. *Int J Fatigue*. 2022;164:107147. doi:10.1016/j.ijfatigue.2022.107147
- [249] Shaaban M, Al-Hamidi Y, El-Borgi S, et al. Machine learning-driven in situ defect monitoring and real-time process control in directed energy deposition: techniques, challenges, and future prospects. *Mater Today Commun*. 2026;51:114767. doi:10.1016/j.mtcomm.2026.114767
- [250] Pazireh S, Mirazimzadeh SE, Urbanic J. A review of machine learning applications on direct energy deposition additive manufacturing—A trend study. *Metals*. 2025;15:966. doi:10.3390/met15090966
- [251] Liu R, Liu S, Zhang X. A physics-informed machine learning model for porosity analysis in laser powder bed fusion additive manufacturing. *Int J Adv Manuf Technol*. 2021;113:1943–1958. doi:10.1007/s00170-021-06640-3
- [252] Zhao M, Wei H, Mao Y, et al. Predictions of additive manufacturing process parameters and molten pool dimensions with a physics-informed deep learning model. *Engineering*. 2023;23:181–195. doi:10.1016/j.eng.2022.09.015
- [253] Ko H, Lu Y, Yang Z, et al. A framework driven by physics-guided machine learning for process-structure-property causal analytics in additive manufacturing. *J Manuf Syst*. 2023;67:213–228. doi:10.1016/j.jmsy.2022.09.010
- [254] Xie Z, Chen F, Wang L, et al. Data-driven prediction of keyhole features in metal additive manufacturing based on physics-based simulation. *J Intell Manuf*. 2024;35:2313–2326. doi:10.1007/s10845-023-02157-6
- [255] Prasanna GL, Patel S, Priya P. Physics-Informed data-driven determination of printability maps of industrial alloys for laser powder bed fusion process with understandings from numerical modeling. *Integrating Mater Manuf Innov*. 2026;15:359–377. doi:10.1007/s40192-026-00448-3
- [256] Karkaria V, Goeckner A, Zha R, et al. Towards a digital twin framework in additive manufacturing: machine learning and Bayesian optimization for time series process optimization. *J Manuf Syst*. 2024;75:322–332. doi:10.1016/j.jmsy.2024.04.023
- [257] Xiang H, Ji Y, Zhan Z, et al. A physics-informed neural network framework for multi-parameter calibration of DED thermal models. *J Mater Res*. 2026;41:1078–1091. doi:10.1557/s43578-026-01812-x

- [258] Ghungrad S, Faegh M, Gould B, et al. Architecture-Driven physics-informed deep learning for temperature prediction in laser powder Bed fusion additive manufacturing With limited data. *J Manuf Sci Eng.* **2023**;145:081007. doi:[10.1115/1.4062237](https://doi.org/10.1115/1.4062237)
- [259] Sharma R, Guo YB, Raissi M, et al. Physics-Informed machine learning of argon gas-driven melt pool dynamics. *J Manuf Sci Eng.* **2024**;146:081008. doi:[10.1115/1.4065457](https://doi.org/10.1115/1.4065457)
- [260] Han X, Qian Z, Gao X, et al. Three-Dimensional modeling and analysis of directed energy deposition melt pools based on physical information neural networks. *Appl Sci.* **2025**;15:9401. doi:[10.3390/app15179401](https://doi.org/10.3390/app15179401)
- [261] Liu L, Di Y, Wang G, et al. Framework on laser deposition digital system with monitoring-based prediction and process control. *Measurement.* **2026**;280:121799. doi:[10.1016/j.measurement.2026.121799](https://doi.org/10.1016/j.measurement.2026.121799)
- [262] Peng S, Yang S, Gao B, et al. Prediction of 3D temperature field through single 2D temperature data based on transfer learning-based PINN model in laser-based directed energy deposition. *J Manuf Process.* **2025**;138:140–156. doi:[10.1016/j.jmapro.2025.02.015](https://doi.org/10.1016/j.jmapro.2025.02.015)
- [263] Riensche A, Deshmukh K, Carrington A, et al. And shape-agnostic physics-guided thermal history control to improve part quality in laser powder bed fusion additive manufacturing. *J Manuf Sci Eng.* **2025**;147:081005. doi:[10.1115/1.4068695](https://doi.org/10.1115/1.4068695)
- [264] Roh B-M, Xiao X. Ontology-Driven Physics Informed Neural Network (O-PINN) of interpretable melt pool behavior for real-time process anomalies' prognosis/diagnosis. *Int J Adv Manuf Technol.* **2026**;142:3353–3371. doi:[10.1007/s00170-025-17207-x](https://doi.org/10.1007/s00170-025-17207-x)
- [265] Boer J, Magolon M, Elbestawi M. On machine learning control in lpbf additive manufacturing. *Int J Adv Manuf Technol.* **2026**;144:7273–7287. doi:[10.1007/s00170-026-18294-0](https://doi.org/10.1007/s00170-026-18294-0)
- [266] Yu H, Hu Y, Kang G, et al. High-cycle fatigue life prediction of L-PBF AlSi10Mg alloys: a domain knowledge-guided symbolic regression approach. *Philos Trans R Soc Math Phys Eng Sci.* **2024**;382:20220383. doi:[10.1098/rsta.2022.0383](https://doi.org/10.1098/rsta.2022.0383)
- [267] Wang H, Li B, Lei L, et al. Uncertainty-aware fatigue-life prediction of additively manufactured Hastelloy X superalloy using a physics-informed probabilistic neural network. *Reliab Eng Syst Saf.* **2024**;243:109852. doi:[10.1016/j.ress.2023.109852](https://doi.org/10.1016/j.ress.2023.109852)
- [268] Feng F, Zhu T, Yang B, et al. A physics-informed neural network approach for predicting fatigue life of SLM 316L stainless steel based on defect features. *Int J Fatigue.* **2024**;188:108486. doi:[10.1016/j.ijfatigue.2024.108486](https://doi.org/10.1016/j.ijfatigue.2024.108486)
- [269] Wang H, Li B, Lei L, et al. Multi-physics information-integrated neural network for fatigue life prediction of additively manufactured Hastelloy X superalloy. *Virtual Phys Prototyp.* **2024**;19:e2368652. doi:[10.1080/17452759.2024.2368652](https://doi.org/10.1080/17452759.2024.2368652)
- [270] Bobbili VSR, Chandrasekhara Sastry C, Krishnaiah J, et al. Physics-informed neural networks for predicting high-strain-rate energy absorption in additively manufactured lattice materials. *Prog Addit Manuf.* **2026**;11:2095–2121. doi:[10.1007/s40964-025-01460-3](https://doi.org/10.1007/s40964-025-01460-3)
- [271] Yeung H. Toward real-time feedback control for powder bed fusion additive manufacturing. *Addit Manuf.* **2025**;114:105041. doi:[10.1016/j.addma.2025.105041](https://doi.org/10.1016/j.addma.2025.105041)
- [272] Liu N, Li X, Rajanna MR, et al. Deep neural operator enabled digital twin modeling for additive manufacturing. *Adv. Comput Sci Eng.* **2024**;2:174–201. doi:[10.3934/acse.2024010](https://doi.org/10.3934/acse.2024010)
- [273] Tian M, Mu H, Ding D, et al. Real-time distortion prediction in metallic additive manufacturing via a physics-informed deep operator network. *J Ind Inf Integr.* **2026**;52:101126. doi:[10.1016/j.jii.2026.101126](https://doi.org/10.1016/j.jii.2026.101126)
- [274] Zhang W, Wang Y, Chen Y, et al. Ded bead geometry and profile prediction with multimodal spatio-temporal neural networks. *Addit Manuf.* **2025**;110:104952. doi:[10.1016/j.addma.2025.104952](https://doi.org/10.1016/j.addma.2025.104952)
- [275] He D, Deng X, Chen Y, et al. Feedrate-preserved motion planning for five-axis directed energy deposition of free-form metal parts. *Addit Manuf.* **2024**;89:104302. doi:[10.1016/j.addma.2024.104302](https://doi.org/10.1016/j.addma.2024.104302)
- [276] Liu J, Zhao S, Zhang X, et al. A laser-shock-enabled hybrid additive manufacturing strategy with molten pool modulation of Fe-based alloy. *J Manuf Process.* **2022**;82:657–664. doi:[10.1016/j.jmapro.2022.08.043](https://doi.org/10.1016/j.jmapro.2022.08.043)
- [277] Zhang X, Huang S, Li D, et al. An approach to improve the microstructure and mechanical properties: A hybrid manufacturing of laser directed energy deposition and shot peening. *Addit Manuf.* **2022**;55:102686. doi:[10.1016/j.addma.2022.102686](https://doi.org/10.1016/j.addma.2022.102686)
- [278] Jo J, Kim H, Han D, et al. Effect of chip-induced powder size distribution on 18Ni maraging steel in hybrid additive manufacturing. *Mater Des.* **2026**;261:115324. doi:[10.1016/j.matdes.2025.115324](https://doi.org/10.1016/j.matdes.2025.115324)
- [279] Chen Y, Wang Y, Lu Y, et al. Process research of the powder bed-based 5-axis additive/subtractive hybrid manufacturing for internal features. *Addit Manuf.* **2025**;106:104812. doi:[10.1016/j.addma.2025.104812](https://doi.org/10.1016/j.addma.2025.104812)
- [280] Malej S, Godec M, Donik Č, et al. Hybrid additive manufacturing of Ti6Al4V with powder-bed fusion and direct-energy deposition. *Mater Sci Eng A.* **2023**;878:145229. doi:[10.1016/j.msea.2023.145229](https://doi.org/10.1016/j.msea.2023.145229)
- [281] Dai G, Yan Q, Niu F, et al. Refined microstructure and enhanced mechanical performance of hybrid additive manufacturing Al-Cu-Mg alloys by multi-cycle friction stirring processing. *J Manuf Process.* **2024**;112:248–262. doi:[10.1016/j.jmapro.2024.01.032](https://doi.org/10.1016/j.jmapro.2024.01.032)
- [282] Bidare P, Jiménez A, Abdelkhalek SM, et al. Hybrid additive manufacturing of AISI H13 through interlayer machining and laser re-melting. *Mater Today Commun.* **2023**;37:107042. doi:[10.1016/j.mtcomm.2023.107042](https://doi.org/10.1016/j.mtcomm.2023.107042)
- [283] Mashhadikarimi M, Aghayar Y, Moazzen P, et al. Hybrid additive manufactured tool steels: microstructural modifications and mechanical enhancements through heat treatments. *Materialia.* **2025**;44:102552. doi:[10.1016/j.mtla.2025.102552](https://doi.org/10.1016/j.mtla.2025.102552)