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Topical Review

Review of online quality control for laser directed energy deposition (LDED) additive manufacturing

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Abstract

Laser directed energy deposition (LDED) is an emerging branch of metal-based additive manufacturing (AM) processes, offering unprecedented capabilities for high-performance fabrication with complex geometries and near-net shapes. This technology is gathering increasing attention from industries such as biomedical, automotive, and aerospace. However, achieving consistent part quality and desired material properties is challenging due to intricate processing parameters and potential process defects such as dynamic melt-pool behavior and localized heat accumulation. This paper reviews recent advances in on-line quality control, focusing on in-situ measurement and closed-loop control for efficient assurance of LDED-fabricated parts. The quality principles, encompassing accuracy and material performance, are summarized to lay a foundation for understanding the mechanisms of quality defects and influencing factors. This review explores and thoroughly compares advancements in indirect process measurements, such as optical, thermal, and acoustic monitoring with direct quality measurements, including laser-line scanning and operando synchrotron X-ray imaging. Depending on the sensing techniques, this paper highlights a hierarchical control strategy for

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adaptive parameter regulation on intra-layer and inter-layer scales. The requirements and performance of various state-of-the-art controllers are critically compared to indicate their suitable applications. The importance of machine learning in detecting process anomalies and predicting build quality based on sensory signals is also outlined. Future directions are proposed towards adaptive, automated, and intelligent quality control, with a focus on multi-modal monitoring, physics-informed neural networks for interpretable analysis, and multi-objective control applications.

Keywords: additive manufacturing, directed energy deposition, laser deposition, process monitoring, quality defects, quality control, machine learning

1. Introduction

In recent years, metal-based additive manufacturing (MAM) has garnered substantial traction across industries for its capacity to construct high-performance and high-value components with minimized material waste and optimized design flexibility. Unlike traditional manufacturing processes, which often rely on subtractive or casting methods, MAM enables a unique layer-by-layer fabrication approach, allowing for the creation of intricate geometries^[1], functionally graded structures^[2] and multiple material integration^[3]. These features make MAM a critical technology for industrial sectors such as aerospace^[4,5], automotive^[6] and biomedical engineering^[7].

Prominent MAM includes powder bed fusion (PBF) and directed energy deposition (DED). PBF generally involves selectively melting fine metal powder layers with a laser beam or electron beam and is thus able to achieve a high geometrical resolution and fine microstructure. However, the build rate of PBF is typically limited due to its small laser spot size, restricting its efficiency in producing large components^[8,9]. In contrast, DED employs a focused energy source to directly deposit material onto a substrate, offering faster deposition rates, a broader material choice, and the ability to add materials to existing structures. This flexibility allows DED to fabricate larger parts more quickly and makes it particularly valuable for applications such as component repairing^[10] and surface coating^[11]. According to ISO/ASTM 52900: 2021^[12], DED technologies can be further categorized into three primary types based on the energy source and feedstock type: wire-arc additive manufacturing (WAAM), electron-beam melting (EBM) additive manufacturing and laser directed energy deposition (LDED). WAAM^[13] utilizes an electric arc as a heat source and a metal wire as feedstock, enabling high deposition rates but typically offering low dimensional accuracy and surface quality. EBM^[14] uses an electron beam in a vacuum environment to produce high-density parts with minimal oxidation, while the need for a vacuum chamber incurs additional costs and restricts build size. This review will primarily focus on LDED, one of the most widely adopted DED technologies in industrial applications. Compared to WAAM, which is prone to arc instability, LDED offers better control of thermal input and higher precision in depositing

materials, thereby yielding a cleaner process with less material waste and superior quality on surface finish and material property. Nagalingam et al.^[15] benchmarked a comprehensive comparison regarding deposition strategies, process phenomena and quality aspects between LDED and WAAM.

LDED is a viable additive manufacturing (AM) process enabling the fabrication, repair, and enhancement of metal components made of advanced materials such as high-performance aluminum alloys^[16] and programmable maraging steel^[17]. This process employs a high-power laser as the heat source to generate a localized melt-pool on the substrate or previously deposited layer, into which metallic feedstock, either in powder or wire form, is continuously fed coaxially with the laser beam or from the side. The molten material rapidly solidifies due to steep thermal gradients, forming a bead-shaped track as it cools. Common choices of laser sources include fiber, diode, CO₂, and Nd:YAG lasers, each offering distinct advantages based on their wavelength, efficiency and beam quality. Depending on the feedstock form, LDED can be further divided into powder laser DED (P-LDED) and wire laser DED (W-LDED). A comparison of these two LDED variants can be found in Figure 1. While P-LDED offers greater flexibility in material blending and localized composition control, W-LDED provides higher deposition efficiency and reduced material waste. As LDED is layer-by-layer process, deposition strategy, e.g., raster, zig-zag, water-pouring, and contour-parallel paths^[15], has a significant influence on the thermal process by dictating heat transfer, cooling rates, and residual stress formation, ultimately affecting microstructural evolution and mechanical properties. Key process parameters in LDED include laser power, scanning speed, feed rate, and shielding gas flow. Understanding of these factors, including their intricate inter-relationships and effects on deposition quality, is essential for optimizing LDED and can be found in^[18].

Despite its advantages, LDED-based AM faces significant challenges regarding process repeatability^[19–21] and quality consistency^[22,23], limiting its broader application to mission-critical industries. Quality assurance in LDED involves addressing two key aspects, i.e., geometrical quality and mechanical quality. Geometrical quality includes surface roughness, dimensional accuracy, and adherence to specific design tolerances, which are crucial for the functional

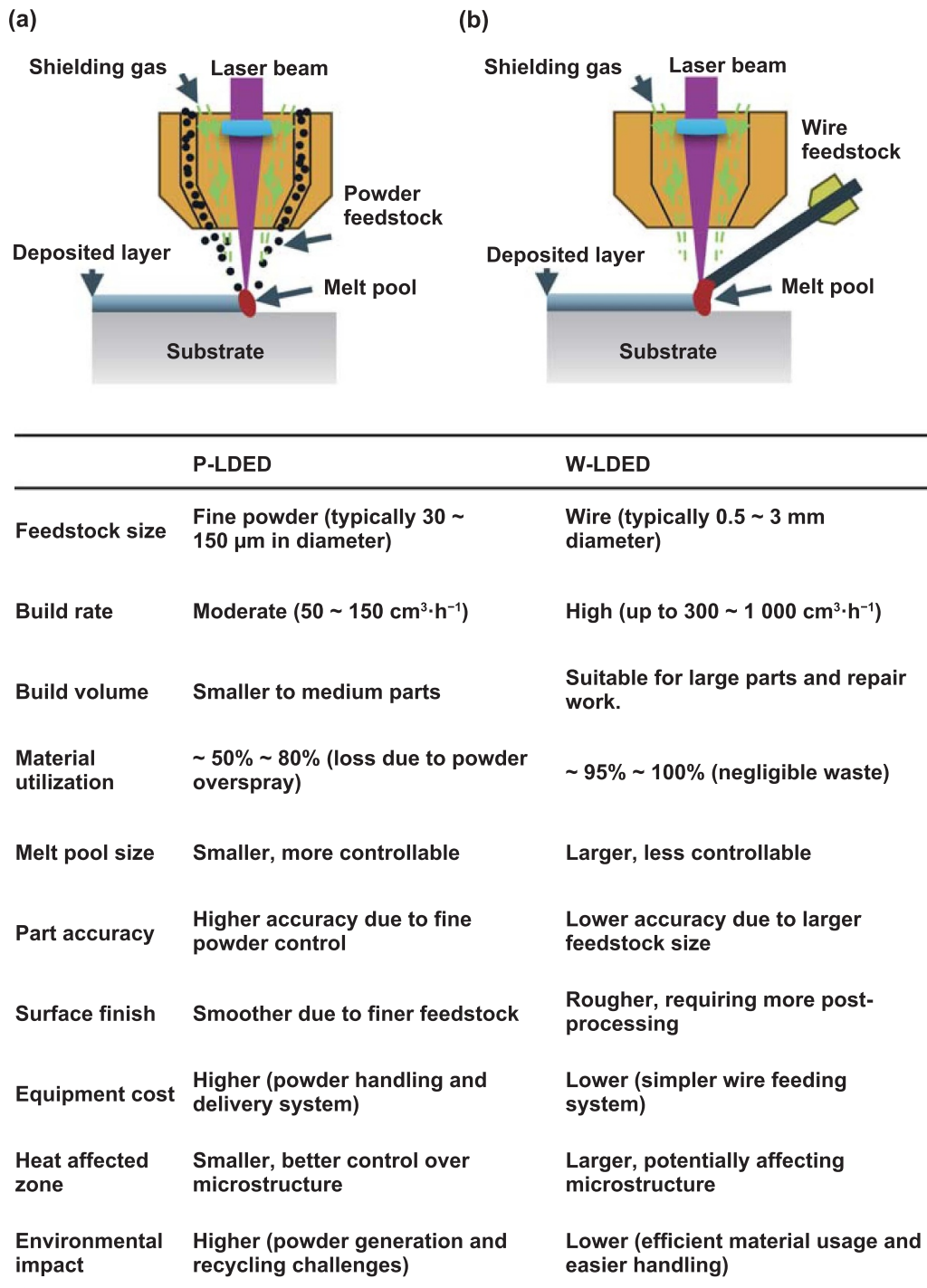


Figure 1. A comprehensive comparison of two variants of LDED. (a) Laser powder DED (P-LDED) and (b) laser wire DED (W-LDED).

fit of components. Mechanical quality, on the other hand, is concerned with the internal material structure and properties, such as tensile strength, fatigue resistance, and hardness. These attributes are essential to ensuring the durability and reliability of LDED-fabricated parts. Another critical concern is the formation of defects such as porosity, cracks, residual stress and geometric distortions, which are caused by e.g., high thermal gradients, complex laser-material interactions

and intrinsic variability in melt-pool dynamics associated with the LDED process. The inability to control these factors often results in a compromised performance with material inhomogeneity and degraded structural integrity in fabricated parts or even part failure. Current approaches to quality assurance in DED still largely rely on post-process inspections, which are costly, time-consuming and limited in detecting internal defects. Consequently, there is a pressing need for developing

robust and efficient control mechanisms that enable immediate intervention to enhance part quality and minimize production disruptions.

On-line quality control, which integrates in-situ measurement and adaptive control systems, represents a promising solution to optimizing DED built quality. In-situ measurement techniques monitor critical process signatures based on sensor signals, providing real-time insights into physical phenomena such as melt-pool dynamics and temperature history, or capture quality signatures, providing direct information about the built quality. Based on the feedback of measured signatures, adaptive control makes adjustments to process parameters on-the-fly, enabling proactive quality control and advancing toward autonomous DED systems. Although the on-line quality control is essential for mitigating the appearance of defects, two main challenges that may impede its further application still exist. The first is manipulation of the large amount of heterogeneous data from different sensory sources, making it difficult to efficiently and effectively extract signatures that can be ubiquitously useful across different process settings. The second is the complex relationship between these signatures and process parameters, making it hard to effectively control the DED process dynamics. Recent advances in machine learning (ML) have demonstrated great potential to address these challenges due to its unprecedented capability in processing big data and discovering underlying patterns within them^[24]. This review paper will provide an in-depth overview of popular ML techniques reported in DED process monitoring.

While a collection of reviews has focused on the in-situ measurement and control for AM processes, there are notable gaps in the literature, particularly in the context of LDED. For instance, Zhang et al.^[25] offered a comprehensive report on real-time monitoring with a narrative focus on image processing. Abouel Nour and Gupta^[26] examined in-situ monitoring techniques for identifying sub-surface and internal defects in MAM but did not incorporate progress for controlling them. Xia et al.^[27] reviewed the progress of monitoring and control in the field of WAAM and proposed a conclusive framework dictating the future research efforts from both academia and industry. Cai et al.^[8] and Chen et al.^[9] successively published reviews on in-situ monitoring and control systems in laser AM, including both PBF and DED. Comprehensive surveys on sensor-based monitoring techniques, such as melt-pool and acoustic emission (AE) monitoring and advanced closed-loop control algorithms, were conducted. However, post-processing of the monitored signals, especially with the assistance of ML was not explicitly addressed. This paper aims to bridge these gaps by providing an in-depth summarization of fundamental LDED quality principles, clarifying the underlying defect mechanisms, including their influencing factors and effects on as-built geometrical quality and material performances. Sensor-based measurement techniques for indicating the process and quality defects are covered, with a particular emphasis on data analysis based on state-of-the-art ML algorithms for post-processing of measurement results. Particularly, fusion of multi-source sensor signals and their associated data fusion techniques are highlighted.

Furthermore, this review explores advanced closed-loop techniques, both in real time and on a per-layer basis, for regulating the DED quality on line.

To ensure a comprehensive literature review, this paper adopted a systematic search strategy encompassing database selection, keyword design, and paper inclusion criteria. Major academic databases such as ScienceDirect, SpringerLink, IOPscience, Scopus, and IEEE Xplore digital library were utilized for literature acquisition. During the search process, carefully constructed keyword combinations with Boolean operators were applied to suit each thematic section; for example, ('directed energy deposition' OR 'laser metal deposition') AND ('process monitoring' OR 'in-situ monitoring') was used for Section 3. Retrieved papers were then screened for relevance to the specific discussion topics, and priority was given to the most recent and impactful studies, particularly those published between 2015 and 2025.

This paper is organized as follows. Section 2 briefly concludes the general principles to evaluate the quality of metal LDED AM products. Section 3 overviews the state-of-art sensing techniques nowadays adopted for quality monitoring of LDED AM processes. Section 4 introduces the analysis methodologies for processing the data measured by the sensors. Later in Section 5, the possibility of merging the sensing and analyzing techniques for online quality control is demonstrated. This review thoroughly concludes the current research on the relationship between LDED AM processes and part quality, with a focus on direct quality evaluation methods for surface geometry and material performance. The review can also provide new ideas for the development of future intelligent AM technologies.

2. Measures of LDED quality

Quality in LDED is a critical factor of the performance, reliability, and efficiency of manufactured parts. The quality of the manufactured components can mainly be defined in terms of mechanical and geometrical requirements. The manufacturing process of LDED involves complex interactions between laser energy, material deposition rates, scanning speed and thermal effects, all of which must be carefully controlled to achieve desired outcomes in terms of surface texture, dimensional accuracy, geometric tolerance, and mechanical properties. Additionally, surface defects, dimensional deviations, and insufficient mechanical performance can significantly affect the functions of parts, leading to increased friction, reduced fatigue life, and potential failure under high operational stresses. To address these challenges, this section investigates the principle of quality in LDED, the factors that influence print quality, and the associated defects, highlighting the need for in-situ monitoring and adaptive control to improve the quality of manufactured parts.

2.1. Geometrical quality

2.1.1. Geometrical properties. Geometrical quality in LDED is characterized by surface texture, dimensional

accuracy, and geometrical tolerances, as defined by standards such as ISO 286-1, ISO 2768-1, ISO 2768-2 and ISO 21920-2. These attributes are fundamental to ensuring the functional performance and reliability of fabricated components.

Surface texture is characterized by roughness, waviness, and form deviations^[28], which critically influence friction, wear, and subsequent process compatibility. For example, higher roughness in aerospace blades significantly reduces aerodynamic efficiency, highlighting the necessity of surface optimization^[29]. Optimizing surface texture also minimizes the need for post-processing refinements, improving the efficiency of the entire production process. Dimensional accuracy pertains to the degree of conformity between a component's built dimensions and its intended design specifications, which is essential for ensuring proper fit and functionality of the manufactured components in applications requiring high precision assembly^[30]. Geometric tolerance in LDED defines the permissible variations in a part's shape, orientation, and position compared to the ideal design. It includes parameters such as flatness, cylindricity, parallelism, perpendicularity, and concentricity, which are essential to minimize defects, reduce post-processing, and align with international standards. Therefore, controlling these geometric attributes during deposition not only ensures the functional reliability of components but also streamlines production by minimizing post-processing and reducing material waste.

In recent years, numerous studies have been carried out to optimize these geometrical attributes in LDED processes, though achieving results comparable to conventional manufacturing methods like CNC machining remains challenging. Studies have shown that process optimization, especially in laser power, scan speed, and feed rate, can significantly reduce surface roughness and build error^[31–33]. Advanced approaches integrate real-time monitoring and computational models to dynamically adjust laser input, achieving up to 40% improvement in dimensional consistency^[34]. For example, closed-loop control based on melt-pool feedback has proven effective in minimizing ripples and height deviation, particularly in multi-layer and complex path structures^[20]. In-situ systems have also demonstrated high precision in detecting deviation trends, enabling real-time correction aligned with CAD models^[35]. In addition, statistical prediction modeling and process optimization using response surface methodology (RSM) can also effectively optimize LDED parameters to achieve lower dimensional errors and tolerances for high-quality multi-layer cladding structures^[36]. However, the inherent variability in the LDED process necessitates in-situ monitoring systems to enable real-time control, ensuring that components meet design specifications in high-precision applications.

In addition to process optimization, international standards play a crucial role in evaluating and ensuring geometric quality in LDED. Organizations such as ISO and ASTM have established essential guidelines that directly support quality benchmarking and component qualification. As summarized in Table 1, standards like ISO 25178 and ISO 21920-2

provide methods for characterizing surface textures, roughness, and geometric tolerances, essential for precision manufacturing. Meanwhile, standards including ISO/ASTM 52915 and ISO/ASTM 52915 (AMF) focus specifically on AM system qualification and standardized data exchange, ensuring accurate representation and reproducibility of complex geometries. Additionally, standards such as ISO 286-1, ISO 2768-1, and ISO 2768-2 clearly define acceptable geometrical tolerances, covering critical aspects like linear dimensions, flatness, and parallelism. Although these standards form a foundational framework for dimensional consistency, surface quality, and interoperability in LDED, gaps still remain in the lack of regard for adaptive control of geometrical quality, which is also important for the geometrical quality of AM products.

2.1.2. Geometrical defects. Geometrical defects such as warping, inconsistent layer thickness, and dimensional shrinkage remain critical challenges in LDED. As summarized in Table 2, these defects typically originate from thermal distortions, material behaviors, and improper process parameter settings, such as laser power, scanning speed, and material feed rate. These defects negatively impact surface finish, dimensional accuracy, and mechanical integrity.

Warping is one of the most prevalent geometrical defects in LDED. As shown in Figure 2(a), it occurs due to residual stresses from rapid thermal cycling during deposition. Specifically, uneven thermal expansion and contraction distort the part, leading to warped surfaces that deviate from the intended geometry or delaminate from the substrate. Thin-walled or large parts are especially vulnerable due to limited heat dissipation. To solve these problems, substrate pre-heating, optimizing cooling rates, and employing cross-layer (X-Y) scanning strategies can effectively reduce warping by minimizing residual stresses^[41]. As depicted in Figure 2(b), surface roughness is another significant defect that introduces microscopic irregularities affecting surface quality. It typically arises from incomplete melting or improper layer fusion due to inadequate laser power, high feed rates, or improper scanning speeds. High surface roughness can increase friction, reduce fatigue life, and impair wear resistance. Addressing this defect requires optimized laser settings and real-time monitoring systems to maintain consistency^[42,43]. Waviness refers to medium-scale surface irregularities that are characterized by periodic peaks and valleys as depicted in Figure 2(c). It arises from non-uniform heat distribution during the deposition process, which is often caused by fluctuating laser power or scanning strategies that fail to maintain consistent overlap and energy input across the layers. Waviness impairs the dimensional accuracy and can lead to challenges in assembly or further processing. Optimizing scanning strategies, employing adaptive control mechanisms, and regulating heat input can effectively mitigate waviness^[44]. As depicted in Figure 2(d), inconsistent layer thickness leads to bulging, shrinking, or stepped geometries, disrupting the overall dimensional integrity of the component. It arises from fluctuations in laser

Table 1. Summary of geometrical related international standards in LDED.

Topic	Code	Title
Areal surface texture measurement	ISO 25178	Geometrical product specifications (GPS)—Areal surface texture measurement
Surface roughness and geometric tolerance	ISO 21920-2	Surface texture: profile method—terms, definitions, and surface texture parameters
Benchmarking DED systems' performance	ISO/ASTM 52902	Additive manufacturing—test artifacts for benchmarking
Additive manufacturing file (AMF) format	ISO/ASTM 52915	Additive manufacturing file format specification
Test methods and characteristics for additive manufacturing	ISO/ASTM 52927	Standardization of test methods for additive manufacturing processes
Additive manufacturing terminology	ISO/ASTM 52900: 2015	Additive manufacturing—general principles—terminology
Design requirements for additive manufacturing	ISO/ASTM 52910: 2018	Additive manufacturing—design—requirements, guidelines, and recommendations
Coordinate systems and test methodologies	ISO/ASTM 52921: 2013	Standard terminology for additive manufacturing—coordinate systems and test methodologies
Assessing geometric capability of Additive Manufacturing	ISO/ASTM 52902-19	Test artifacts—geometric capability assessment of additive manufacturing systems
Design guidelines for DED	ISO/ASTM 52922	Additive manufacturing—design—directed energy deposition of metals
DED of Metals Guide	ASTM F3187-16	Standard guide for directed energy deposition of metals

Table 2. Summary of geometrical defects in LDED.

Defects	Characteristics	Potential Causes	Consequences	References
Warping	Deformation of the part, resulting in curved or twisted surfaces.	Uneven thermal gradients, rapid cooling and solidification.	Poor dimensional accuracy, misaligned features, need for post-processing.	[23]
High surface roughness	Microscopic peaks and valleys on the surface, leading to uneven finish.	Incomplete melting of powder, improper fusion between layers, inadequate laser power.	Increased friction, reduced fatigue life, compromised wear resistance, need for polishing.	[36]
Waviness	Periodic peaks and valleys affecting the macroscopic contour of the part.	Uneven heat distribution during scanning, poor scanning path planning.	Impaired dimensional accuracy, increased surface friction, reduced part performance.	[37]
Inconsistent layer thickness	Variations in layer thickness resulting in bulging, shrinking, or stepped geometries.	Fluctuations in laser power, scanning speed, or powder feed rate, changes in build orientation.	Poor dimensional accuracy, surface roughness, uneven mechanical properties.	[38]
Dimensional shrinkage	Contraction of the part as it cools, leading to deviations from intended dimensions.	Rapid cooling, improper management of cooling rate, material shrinkage behavior.	Undersized features, poor fit, potential need for rework or remodeling.	[39]
Edge defects	Material overlay or underlay along edges of the part,	Material deposition discontinuity and unsuitable scanning paths.	Poor dimensional accuracy	[40]

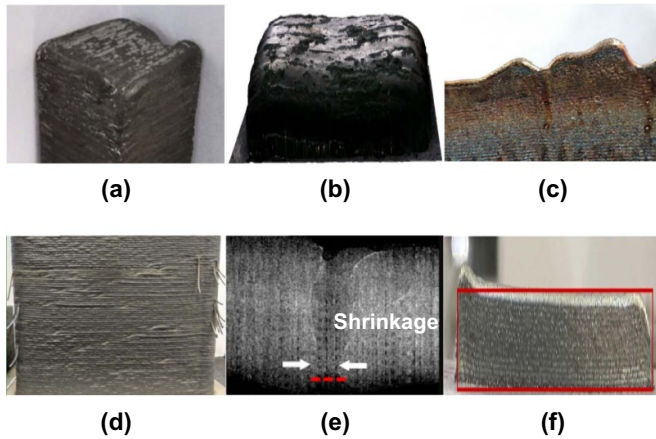


Figure 2. Common geometrical defects in LDED. (a) Warping. Reprinted from^[23], Copyright (2019), with permission from Elsevier. (b) High surface roughness. Reprinted from^[36], Copyright (2021), with permission from Elsevier. (c) Waviness. Reproduced from^[37], CC BY 4.0. (d) Inconsistent Layer Thickness. Reproduced from^[38], CC BY 4.0. (e) Dimensional shrinkage. Reprinted from^[39], Copyright (2024), with permission from Elsevier. (f) Edge defects. Reprinted from^[40], Copyright (2023), with permission from Elsevier.

power, scanning speed, or material feed rate, or unstable build conditions. Ensuring consistent energy input, material deposition rate, and layer adhesion is critical for preventing these variations and maintaining overall part quality^[45]. As presented in Figure 2(e), dimensional shrinkage refers to the contraction of the part upon cooling, leading to deviations from the intended dimensions. Shrinkage is mainly caused by inadequate cooling rate management. Predictive modeling to account for material shrinkage during the design phase and adjustment to process parameters, such as cooling rates, are essential to mitigate shrinkage and maintain dimensional accuracy^[39].

Despite the significant progress made in understanding and mitigating geometrical defects, achieving defect-free parts in LDED remains a challenge. The inherent variability in the process underscores the importance of integrating robust in-situ monitoring systems and real-time adaptive control techniques. These innovations are essential for improving process reliability, reducing post-processing requirements, and ensuring the broader adoption of LDED in different industries.

2.2. Mechanical quality

2.2.1. Mechanical properties. Besides geometrical quality, achieving optimal mechanical quality is also significant for LDED. Mechanical properties such as tensile strength, fatigue resistance, and hardness are primarily influenced by internal defects like porosity, cracks, and residual stress. Hence, detection and mitigation of these defects are crucial to ensure mechanical reliability. Recent research has focused on key areas such as process parameter optimization, microstructural control, post-processing techniques, and material development^[46,47]. Studies have shown that variables such as laser power, scanning speed, and material feed rate

have a particular influence on mechanical properties^[48,49]. Achieving the desired mechanical properties in LDED parts necessitates precise control over microstructural features, including grain size, phase distribution, and texture. Research has demonstrated that manipulating process parameters can enhance grain refinement and phase transformations, leading to improved mechanical performance^[50]. Post-processing methods, such as heat treatment and laser rescanning, have been investigated to further refine microstructures and alleviate residual stresses inherent in LDED processes. Heat treatments can homogenize microstructures, dissolve secondary phases, and relieve internal stresses, resulting in improved mechanical properties^[51]. Additionally, the development of novel alloys and composite materials tailored for LDED has emerged as a promising area of research. By designing material compositions optimized for LDED, it is possible to fabricate components with superior mechanical performance^[52]. Collectively, these studies contribute to a deeper understanding of the factors influencing the mechanical quality of LDED-fabricated parts and offer valuable directions for optimization.

In parallel, standardization frameworks provide benchmarks for mechanical quality assessment. Many of the existing standards converge in their emphasis on standardized terminology, mechanical test methods, and data reporting, ensuring comparability across diverse AM processes. For instance, as summarized in Table 3, while standards such as ISO 17296-3 and ISO/ASTM 52921 both highlight the importance of uniform metrics (e.g., tensile strength, elongation, and toughness), ISO 6892-1 and ISO/ASTM 52910 place greater focus on specific testing protocols and design considerations for metallic materials. This shared framework fosters reliability and consistency, yet it also reveals certain limitations.

Most notably, current standards often do not fully capture the unique complexities of LDED, for example, when evolving multi-material capabilities, high thermal gradients, and complicated interactions between different parameters. Furthermore, the rapid development of new alloys and hybrid manufacturing systems can outpace revisions to existing standards, resulting in gaps where no formal guidelines exist. As a result, certain parameters crucial to LDED (e.g., working parameters, deposition layer strategies, in-situ monitoring, or post-processing treatments) remain only partially standardized or are addressed too broadly. These challenges underscore the need for ongoing updates and greater harmonization among different standardization bodies. While the current standards provide a solid foundation, continued refinement is essential to fully realize LDED's potential in delivering robust, repeatable, and certifiable parts for demanding industries.

2.2.2. Mechanical defects. The LDED process is prone to various mechanical defects as summarized in both Figure 3 and Table 4, which can significantly affect the quality and performance of the final part. Among these, porosity is one of the most common defects, typically resulting from trapped gases in the melt-pool or incomplete melting and fusion of materials, as depicted in Figure 3(a). This defect compromises the mechanical strength of the part, making it more susceptible

Table 3. Summary of mechanical related international standards in LDED.

Topic	Code	Title
Mechanical properties and test methods	ISO 17296-3: 2014	Additive manufacturing—general principles—part 3: main characteristics and test methods
Testing terminology and methods	ISO/ASTM 52921: 2013	Standard terminology for additive manufacturing—coordinate systems and test methodologies
Standardized vocabulary for mechanical quality in additive manufacturing	ISO/ASTM 52900: 2021	Additive manufacturing—general principles—terminology
Tensile testing for metallic materials	ISO 6892-1: 2019	Metallic materials—tensile testing—part 1: method of test at room temperature
Design guidelines for additive manufacturing	ISO/ASTM 52910: 2018	Additive manufacturing—design—requirements, guidelines, and recommendations
Guidelines for DED of metals	ASTM F3187-16	Standard guide for directed energy deposition of metals

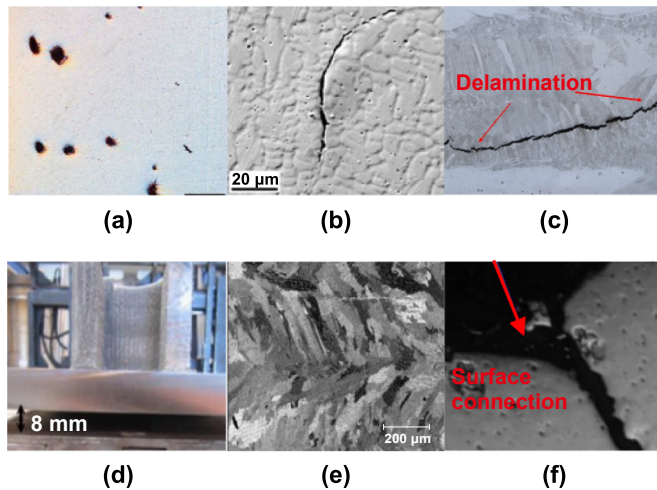


Figure 3. Common mechanical defects in LDED. (a) Porosity. Reprinted from^[60], Copyright (2021), with permission from Elsevier. (b) Cracking. Reprinted from^[55], Copyright (2020), with permission from Elsevier. (c) Delamination. Reproduced from^[61]. CC BY 4.0. (d) Distortion. Reprinted from^[58], Copyright (2015), with permission from Elsevier. (e) Microstructural Inhomogeneity. Reprinted from^[56], Copyright (2014), with permission from Elsevier. (f) Lack of Fusion. Reprinted from^[21], Copyright (2022), with permission from Elsevier.

to cracking under stress. Key factors contributing to porosity include insufficient laser power, excessively high scanning speeds, and improper shielding gas flow^[53]. Cracking, particularly thermal cracking, is another critical issue in LDED as presented in Figure 3(b). It arises from high thermal stresses caused by rapid heating and cooling cycles and is especially prevalent in high-strength alloys like Titanium and steel. Cracking significantly reduces ductility and toughness, impairing the mechanical performance of the part. Optimizing thermal gradients and implementing preheating techniques can effectively mitigate this problem^[54,55]. Residual stresses

arise from uneven thermal expansion and contraction during the deposition process. These stresses can lead to part warping, distortion, or delamination (Figures 3(c) and (d)), adversely affecting the component's performance in service. Moreover, the accumulation of residual stress can induce microstructural inhomogeneity (Figure 3(e)), such as the formation of columnar grains, resulting in anisotropic mechanical properties^[56]. To address residual stresses, post-process heat treatments such as annealing or stress-relief are commonly employed to enhance mechanical integrity. Layer delamination, characterized by the separation between deposited layers, arises from insufficient bonding. Factors such as low laser energy or inappropriate scanning speeds often contribute to this defect. Ensuring consistent energy input and adequate interlayer fusion is crucial for preventing delamination^[57]. As depicted in Figure 3(f), lack of fusion is another critical defect that occurs when inadequate energy fails to fully melt the previously deposited layers, resulting in weak bonding and reduced mechanical strength. This defect is often associated with insufficient laser power, high scanning speeds, or improper layer thickness settings^[58]. Oxidation poses a significant challenge, especially when processing reactive metals like Titanium or Aluminum. Inadequate shielding gas can result in oxygen reacting with the metal surface, forming oxides that degrade both mechanical properties and corrosion resistance^[59].

Addressing these defects necessitates meticulous control of process parameters and careful material selection to ensure optimal mechanical performance of the manufactured parts. However, the defects may still occur even with optimized process parameters due to the complexity and stochastic nature of the LDED process. Consequently, advancements in real-time monitoring systems and feedback control mechanisms are essential for mitigating these issues by dynamically adjusting process parameters to maintain high mechanical quality throughout the build process.

Table 4. Summary of mechanical defects in LDED.

Defects	Characteristics	Potential Causes	Consequences	References
Porosity	Voids within the part due to incomplete fusion or trapped gas, reducing part density	Inadequate laser power, improper powder feed rate, insufficient melting	Reduced mechanical strength, increased susceptibility to fatigue, and failure under load	[62]
Cracking	Fractures that occur during the build due to high thermal stresses, typically in high-strength alloys	Rapid cooling, high thermal gradients, improper thermal management	Brittleness, reduced ductility, increased risk of mechanical failure during operation	[55]
Layer delamination and distortions	Separation between deposited layers due to insufficient bonding	Low laser energy, improper scanning speeds, insufficient interlayer fusion	Weak interlayer bonding, poor mechanical performance, part failure under stress	[57]
Microstructural Inhomogeneity	Formation of columnar grains and dendritic structures leading to anisotropic properties	High cooling rates, improper thermal management, material composition	Anisotropic properties, reduced fatigue resistance, and toughness	[19]
Lack of fusion	Weak bonding between layers caused by insufficient melting	Suboptimal laser power, excessive scanning speed, incorrect layer thickness	Poor mechanical strength, reduced bonding between layers	[63]
Oxidation	Surface oxides due to inadequate shielding gas coverage, degrading mechanical properties	Inadequate shielding gas coverage during deposition	Degradation of mechanical properties and corrosion resistance	[59]

2.3. Factors affecting quality and its impact of final quality

The quality of components produced using LDED is influenced by the complex interaction of different factors like laser and process parameters, environmental conditions, and material properties, as summarized in Figure 4. Each of these factors plays a unique role in determining the geometrical and mechanical properties of the final components. This section reviews these factors and their interdependencies, highlighting areas for optimization and research.

Process parameters are among the most important factors that affect the quality of LDED. Laser parameters, as a key subset of process parameters, significantly influence the energy input and its interaction with feedstock materials. Specifically, laser power governs the amount of energy delivered to the material, directly affecting the melt-pool dynamics. While higher power ensures complete melting and improved bonding, excessive power risks overheating, distortion, and cracking^[49,64].

Beyond laser parameters, other process parameters also have a significant effect on LDED quality. Scanning speed, for example, controls the interaction time between the laser and material. Slower speeds improve bonding but increase the risk of overheating, while faster speeds reduce heat accumulation but risk incomplete fusion^[65]. Material feed rate affects the volume of material deposited, where higher rates can lead to incomplete melting and rough surfaces, while lower rates improve fusion and surface uniformity. Layer thickness

also plays an important role, with thinner layer thicknesses improving surface finish and dimensional accuracy but requiring longer processing times, which can be impractical for large-scale components. Hatch spacing must be carefully managed to ensure sufficient overlap between scan lines, balancing bonding strength, and heat management. Additionally, build orientation and deposition paths influence the thermal history of the material, affecting both dimensional accuracy and microstructural development^[66].

Feedstock characteristics, including particle or wire size, morphology, chemical composition, and thermal properties, play a critical role in the LDED process. In P-LDED, spherical particles with a narrow size distribution promote better flowability and packing density, resulting in uniform layer deposition and reduced porosity. Irregular particle shapes can lead to uneven melting, which increases porosity and weakens mechanical performance. Material composition affects the melting behavior and solidification process, influencing the resulting microstructure and mechanical performance. Additionally, the thermal properties of the material, such as thermal conductivity and heat capacity, influence cooling rates and grain structure development, thereby affecting both geometrical precision and mechanical integrity^[18,52].

Environmental factors, including humidity, temperature, and shielding gas quality, also play a non-negligible role. Moisture in powder can reduce flowability and introduce porosity, while inadequate shielding gas volume leads to oxidation and metallurgical defects^[67].

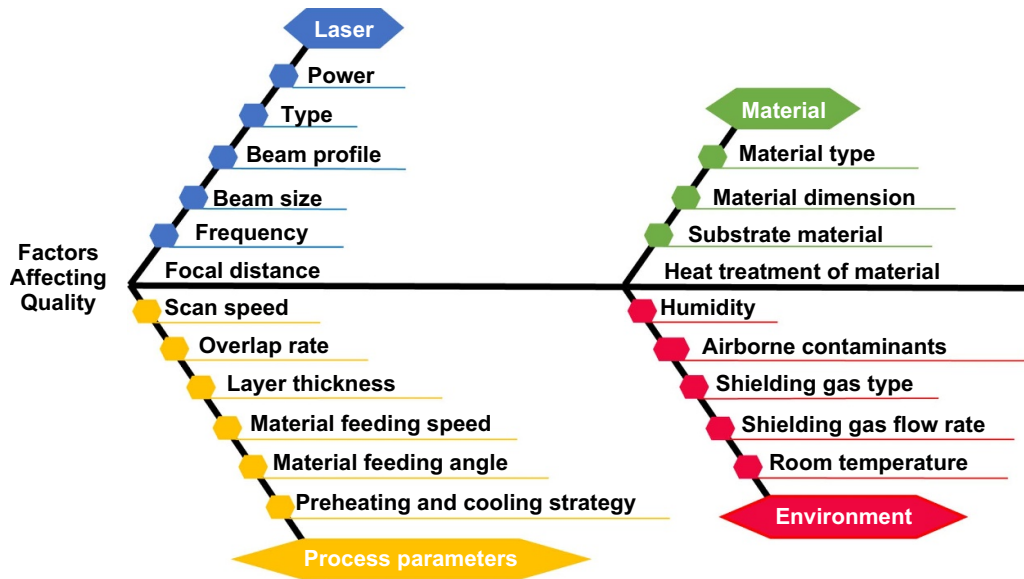


Figure 4. Factors affecting quality and its impact of final quality.

Critically, these process and material factors are also key inputs for real-time monitoring and control systems. For instance, fluctuations in melt-pool size due to scan speed or feed rate deviations can be detected via thermal or optical sensors, enabling closed-loop adjustment of laser power to maintain build stability and defect-free deposition.

2.4. Summary

The quality of parts produced via LDED is a critical consideration for high-stakes applications in industries such as aerospace, automotive, and medical devices. Achieving both optimal geometrical and mechanical quality requires precise control over several factors, including process parameters, material properties, thermal management, equipment, and process variability, etc. Considering that these parameters are interdependent and subject to variability during the deposition process, online quality control systems have emerged as a vital solution to automatic parameter regulation, enabling in-situ monitoring and adaptive control of the LDED process. Continued research into the complex relationships between process parameters and manufacturing quality, along with advancements in real-time monitoring and control technologies, will be key to improving the quality of LDED components and expanding the use of this technology in critical manufacturing sectors.

3. Signal sensing for in-situ measurement

Signal sensing-based in-situ measurement is critical in ensuring quality assurance for LDED by providing continuous data on key process parameters and quality attributes. Unlike traditional quality control methods, which rely on post-process

inspections, in-situ measurement offers the advantage of detecting and addressing defects as they occur, enabling proactive interventions and reducing reliance on costly rework. Different sensing methods offer unique advantages for specific monitoring scenarios in the LDED process. For instance, visual sensing techniques excel at capturing surface properties and geometric accuracy with high precision (± 0.01 mm), making them ideal for monitoring external features such as melt pool geometry and surface quality, but are limited to what can be directly observed and are constrained by the viewing angle^[9,68]. Thermal imaging is particularly valuable for monitoring temperature distribution and thermal gradients over large areas (accuracy of $(\pm 1)^\circ\text{C}$ – 2°C typical, spatial resolution $50\ \mu\text{m}$), enabling the identification of thermal anomalies that may lead to residual stresses or cracking^[69]. Acoustic emission techniques offer unique capabilities for real-time detection of micron-scale internal micro-defects such as cracks and pores, making them particularly useful for multi-material systems where interface quality is critical^[70,71]. Spectral signal monitoring offers specialized capabilities for analyzing chemical composition changes and phase transformations, but has more limited defect detection capabilities^[72,73]. For direct measurement, geometric sensing using laser line scanners provides high-resolution surface quality control (± 0.01 mm to $\pm 5\ \mu\text{m}$)^[74,75], while X-ray techniques offer excellent penetration for subsurface and internal microstructure analysis but are relatively complex and expensive to implement^[76]. A summary of literature on these techniques and their recommended application scenarios can be found in Table 5.

This section provides a detailed review of in-situ measurement techniques for LDED, focusing on their principles, applications, and limitations. In LDED, in-situ measurement techniques can be broadly classified into two categories: direct

Table 5. Overview of sensing methods, objects, and accuracy in LDED process monitoring.

Method	Signal type	Objects	Common defects	Device Type	Accuracy	Application scenarios/ advantages and disadvantages	References
Indirect measurement	Visual signals	Melt-pool dimension & geometry characteristics & Spatter & Plume & Deposited layer geometry characteristics	Surface quality, porosity, geometric deformation	CCD & CMOS & 3D camera system	± 0.01 mm	Suitable for surface monitoring with high accuracy, but cannot detect internal defects	[9,68,77–96]
	Thermal signals	Melt-pool temperature & Workpiece temperature & Melt-pool geometry characteristics & Plume	Thermal cracks, residual stress	Pyrometer & Photodiode & IR camera & NIR camera & hyperspectral line camera	≤ 100 °C ± 2 °C (± 1 °C typical); ≤ 100 °C ± 21 °C ($\pm 1\%$ typical)	Real-time temperature monitoring, high cost, suitable for temperature distribution analysis	[5,69,97–106]
	Acoustic & Ultrasonic signals	Internal Defects	Cracks and pores	Structural load acoustic emission sensor & Microphone & Fibre Bragg Grating sensor	Micron level	Can detect internal defects, suitable for multi-material systems	[70,71,107–124]
	Spectral signals	Plasma characteristics & Phase transformation & Defects & Spatter	Material composition deviation	Optical spectrometer	Dependence on spectral resolution	Suitable for chemical composition analysis, limited defect detection capabilities	[72,73,125–127]
Direct measurement	Geometric signals (3D data)	Surface morphology, geometric features	Depressions, protrusions, uneven layers	Laser line scanners, structured light, stereo vision	± 0.01 mm to ± 5 μ m	High-resolution surface quality control; limitations in thermal interference and ambient lighting	[74,75,78,128–130]
	X-Ray signals	Subsurface and internal microstructure	Porosity, phase transformation, residual stress	Synchrotron X-ray imaging and diffraction systems	Micron-level	High penetration for internal defects; high cost and complexity; limited industrial scalability	[76,131–133]

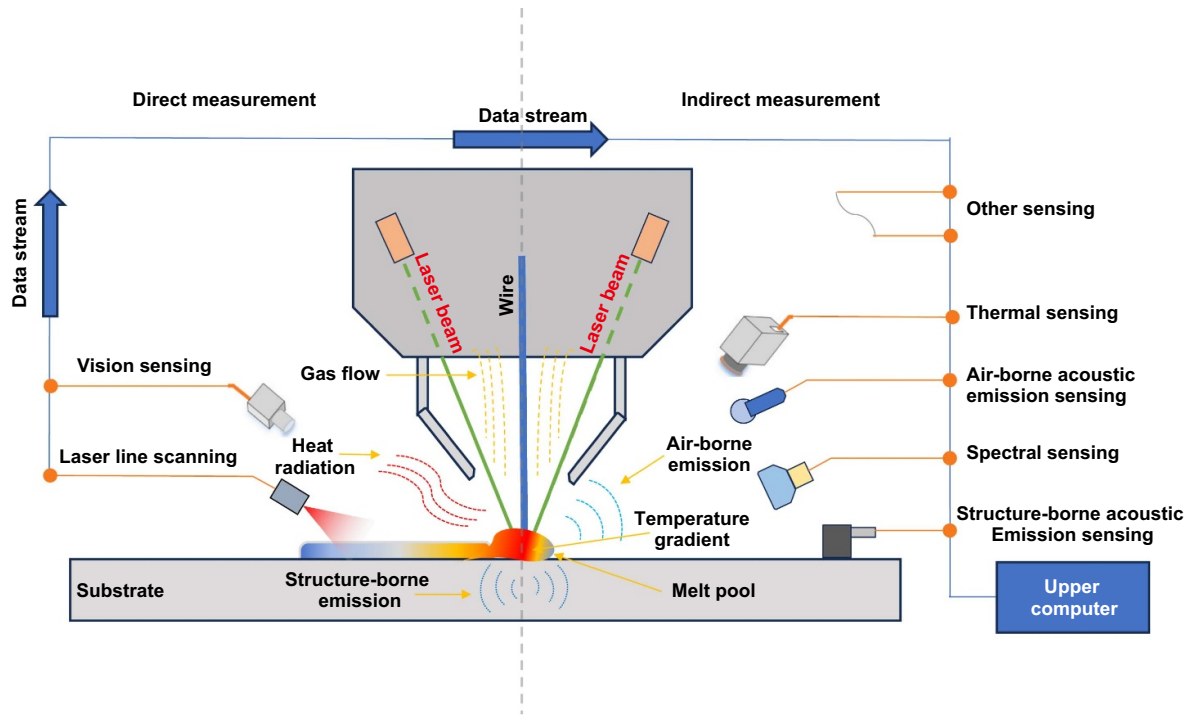


Figure 5. Schematic diagram of the generation and propagation of physical signals in W-LDED process.

measurement and indirect measurement. Indirect measurement methods observe real-time variations in process parameters, such as thermal gradient and cooling rate. By monitoring various signals, including optical, thermal, acoustic, and plasma signals, they provide valuable insights into multi-physical phenomena, e.g., melt-pool dynamics, laser-material interaction, and thermal cycles, that influence part quality. Indirect measurements are essential for intra-layer control strategies (as will be discussed in Section 5.1), where adjustments are made in real time during the deposition process. Direct measurement methods, such as laser line scanning, focus on directly assessing the quality of the deposited layers online. These techniques measure attributes like dimensional accuracy, geometrical consistency, and surface roughness, providing precise feedback on the actual outcomes of the deposition process. These measurements are particularly useful for inter-layer quality control (as will be discussed in Section 5.2), where the focus is on evaluating and correcting deviations before subsequent layers are deposited. Figure 5 illustrates these two measurement strategies and their corresponding sensing techniques during the W-LDED process.

3.1. Direct measurement

3.1.1. 3D scanning and point cloud acquisition. In the LDED process, in-situ measurement of point cloud data provides direct and accurate information about the surface quality of manufactured components. Unlike the indirect measurement methods, point cloud acquisition captures three-dimensional geometric information of the part during the build

process. This data is crucial for evaluating surface morphology and geometric features, enabling the identification of surface defects like depressions, protrusions, or uneven layers (as seen in Section 2.1.2).

Key features extracted from point cloud data include layer thickness, surface flatness, and geometric contours, all of which are directly related to the quality of the printed components. Uniform layer thickness is essential for maintaining dimensional accuracy in multi-layered builds, while surface flatness affects the deposition quality of subsequent layers. Deviations in these features often result from fluctuations in process variables such as material feed rate, laser power, or thermal gradients. By analyzing point cloud data, local defects can be detected, and dynamic adjustments to process parameters along the scanning path can be made to mitigate the impact of deviated surface quality^[74,78].

Point cloud data is typically acquired using technologies such as laser line scanning, structured light scanning, and stereo vision. Laser line scanning, based on triangulation principles, captures the reflected laser line from the component surface to measure height distribution. This method offers high resolution and fast data acquisition, but can be affected by thermal radiation emitted from the melt-pool and its surroundings^[74,75]. For example, Schmidt et al.^[125] developed an integrated LDED robotic processing system with laser line scanning, as illustrated in Figure 6(a). The proposed hand-eye calibration method improved the calibration accuracy between the laser scanner and the robot end-effector to below 0.5 mm. Additionally, the combination with the RandLA-Net network enabled precise surface defect classification and localization,

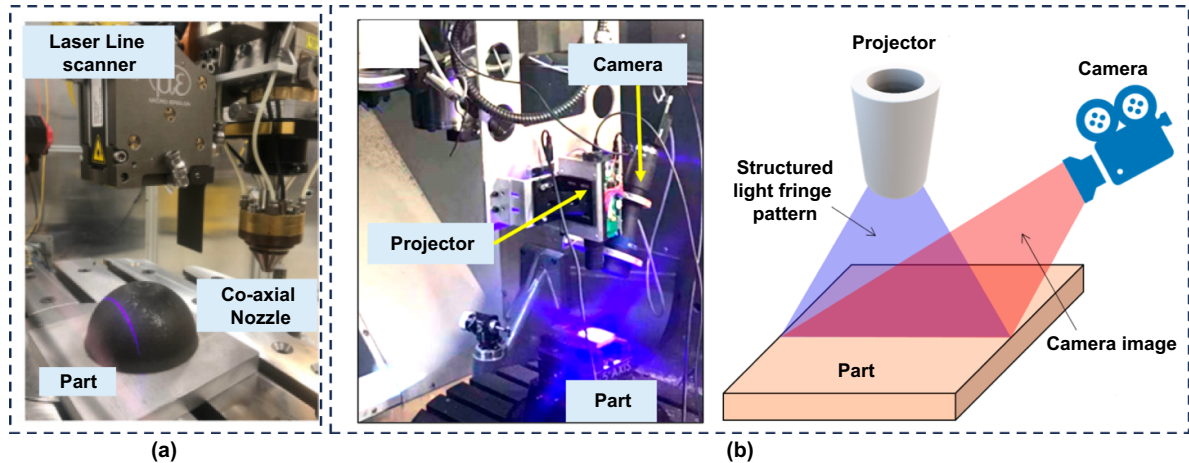


Figure 6. Direct measurement of LDED quality. (a) Mounted laser scanner sensor on the robotic processing system. Reprinted from^[75], Copyright (2022), with permission from Elsevier. (b) Actual setup and schematic representation of the structured light scanning method for measuring the surface characteristics. Reproduced from^[129]. CC BY 4.0.

achieving an average accuracy of 91.3% and a mean intersection over union of 83.3%.

Structured light scanning projects structured light patterns, such as stripes or grids, onto the surface and analyzes their deformation to reconstruct the 3D geometry. It is highly effective for precision measurements of complex surfaces but requires controlled lighting conditions and may be sensitive to ambient light interference^[128]. For instance, Mukherjee et al.^[129] employed a laboratory-constructed structured light scanning system, shown in Figure 6(b), to capture deformed phase lines during the LDED process and reconstruct 3D point clouds. Their system achieved high-precision measurements of surface roughness, skewness, and kurtosis of LDED parts, with an accuracy of $\pm 5 \mu\text{m}$.

Stereo vision, utilizing multiple cameras, calculates depth information through parallax differences between images. Li et al.^[130] implemented a pseudo-binocular vision system combining a high-speed visible light camera and a biprism to capture dynamic melt-pools and static tracks in LDED. The system enabled high-accuracy feature point extraction and matching, as well as melt-pool 3D reconstruction and point cloud filtering, experimental results demonstrated that, the system achieved imaging errors of 1.17%, 1.87%, and 1.11% for the length, width, and height of static L-DED tracks, respectively. For dynamic melt-pool measurements, the width and height errors were 2.26% and 2.48%, showcasing low system complexity and high imaging precision. While it covers larger areas and provides a broader field of view, stereo vision generally offers lower precision compared to laser-based methods, making it more suitable for coarse measurement applications^[75].

While each method has distinct advantages, they collectively contribute to enhancing defect detection and surface quality control in LDED manufacturing. Section 4.5 will delve into the advanced post-processing techniques for optimizing the utilization of point cloud data.

3.1.2. X-ray-based in-situ monitoring. X-ray techniques provide a unique advantage by enabling a direct observation of subsurface conditions and microstructural evolution during the LDED process. With their high penetration ability and real-time imaging potential, particularly through synchrotron X-rays, these methods have become indispensable for understanding the complex thermal history and dynamic material behaviour that significantly affect the microstructure and mechanical properties of the final component^[76,131].

X-ray monitoring captures critical quality-related features, such as melt-pool dynamics, defect evolution during solidification, residual stress, and phase transformation kinetics. Instabilities in the melt-pool, such as fluctuations or pore formation, are closely associated with surface roughness and internal defects like porosity, which directly influence mechanical performance and print quality^[131,132]. Additionally, X-ray techniques can track phase transformation behaviours, such as the transition from austenite to martensite, which are crucial for determining material hardness, toughness, and overall structural integrity^[133].

In-situ X-ray monitoring methods commonly include high-energy X-ray imaging and diffraction. Synchrotron sources, such as advanced photon source and PETRA III, deliver high spatiotemporal resolution, enabling real-time observations of melt-pool behaviour and defect evolution^[76,133]. These setups typically involve YAG lasers coupled with two-dimensional detectors to capture phase transformations and dynamics within the heat-affected zone. By achieving high frame rates and precise spatial resolution, X-ray systems provide detailed insights into complex thermal and fluid dynamics^[132,133].

The integration of X-ray technology into the broader framework of online quality control offers unparalleled advantages for ensuring component reliability, enabling a deeper understanding and optimization of process parameters. However, X-ray-based measurement methods face challenges, particularly regarding the high cost and complexity of integrating X-ray

Table 6. Key features observed in optical monitoring.

Feature	Causes	Indicators
Melt-pool dynamics	Localized laser heating; melting/solidification cycles	Layer height stability, dimensional accuracy, part density ^[84,87]
Spatter formation	Recoil pressure; melt-pool turbulence	Surface roughness, material loss ^[86]
Plume generation	Vaporization of material; ejection of particles	Energy utilization, process consistency ^[90]
Surface morphology	Variations in material deposition or energy input	Surface finish quality, potential defect sites ^[9]
Bead geometry	Fluctuations in feedstock flow or laser trajectory	Dimensional accuracy, bonding strength ^[89]
Particle dynamics	Disruptions in powder delivery or wire feed	Material utilization efficiency, uniformity of deposition ^[77]
Reflection intensity	Surface oxidation; melting	Energy absorption efficiency, metallurgical bonding quality ^[92]

systems into industrial settings. Advanced synchrotron facilities, while highly effective for research, are not yet scalable for widespread industrial use. However, ongoing advancements in equipment resolution and portability are paving the way for broader adoption of X-ray systems in industrial LDED applications. Future developments in post-processing strategies for X-ray data, as discussed in Section 4.5, will further enhance their role in optimizing manufacturing quality and process efficiency.

3.2. Indirect measurement

3.2.1. Optical sensing. Optical sensing techniques are among the most widely applied indirect in-situ measurement methods in LDED due to their non-invasive nature and high temporal resolution. Generally, these optical techniques leverage the interaction of light with the process to collect real-time signal data. These signals are often used to observe and characterize key parameters, such as melt-pool dynamics, surface morphology evolution, and powder flow behavior, enabling the detection of potential issues and the support of adaptive process control^[79,80]. Furthermore, advances in ML have significantly enhanced the potential of optical sensing, making it possible to recognize the internal defects of a printed part^[84,85], as will be discussed in Section 4.

The main features monitored by optical sensing in LDED include melt-pool dynamics, bead geometry, spatter formation, and plume generation, as summarized in Table 6. These observed features are pivotal to ensuring the stability of the LDED process and achieving consistent part quality. For example, monitoring melt-pool dynamics directly correlates with maintaining dimensional accuracy and avoiding defects such as porosity^[84,87]. Similarly, tracking spatter and plume formation enables early detection of disruptions that might degrade surface quality or reduce material efficiency. Spatter formation arises primarily due to recoil pressure and melt-pool turbulence, where high-energy laser-material interactions eject molten material from the surface. This not only affects material utilization efficiency but also contributes to surface contamination and potential defects in subsequent layers^[134]. Plume generation results from the vaporization of material and the ejection of fine particles into the surrounding atmosphere. Excessive plume formation can reduce energy absorption efficiency by scattering the laser beam and disrupt process consistency^[87,91]. By continuously observing and interpreting these signals, optical monitoring provides a foundation

for real-time process control, ensuring the reliable production of high-quality components.

The hardware setup for optical sensing in LDED is critical to its effectiveness, as it must meet the demanding requirements of high-temperature, high-glare, and particle-laden (specifically in P-LDED) environments. For example, high-resolution CCD and CMOS cameras are equipped with optical filters to isolate specific wavelengths, reducing interference from stray light or background noise^[92]. Two primary configurations are commonly employed for optical sensing, i.e., coaxial and off-axial setups, as illustrated in Figure 7. Specifically, coaxial optical systems align the camera or imaging devices with the laser beam or processing area centreline, offering a direct top-down view of the melt-pool. This alignment eliminates the need for complex geometric corrections, improving operational efficiency, and providing localized imaging of small-scale features with fine details. Tang et al.'s research indicates that coaxial cameras can capture visual features closely linked to metallurgical phenomena such as melting, cooling, and heat transfer states, making them a valuable tool in LDED monitoring^[68]. However, coaxial setups face several limitations: their observation is not able to capture the overall melt-pool morphology, especially the depth; they are more complex to integrate due to the required precise alignment with the laser axis; they are prone to contamination from spatter and glare. Off-axial optical systems, where the imaging device is positioned at an angle relative to the laser beam, are easier to install. They are flexible and versatile solutions for providing comprehensive views of the melt-pool and surrounding features by capturing them from different angles. However, their tilted perspective requires additional image correction and calibration to accurately measure the melt-pool size, increasing operational time and complexity^[90–92]. These layout strategies significantly influence the type and quality of data collected, shaping the monitoring results and the downstream analysis. The choice between coaxial and off-axial configurations depends on the specific requirements for the monitoring, including the desired field of view, resolution, and ease of integration. The melt-pool image serves as the primary object of optical monitoring in the LDED process, providing critical information about process stability and bead quality. Preprocessing of the raw melt-pool image is essential to extract geometric and morphological features that lay a foundation for real-time monitoring and advanced data analysis. As shown in Figure 8, common preliminary image processing techniques such as binarization, threshold segmentation, edge detection,

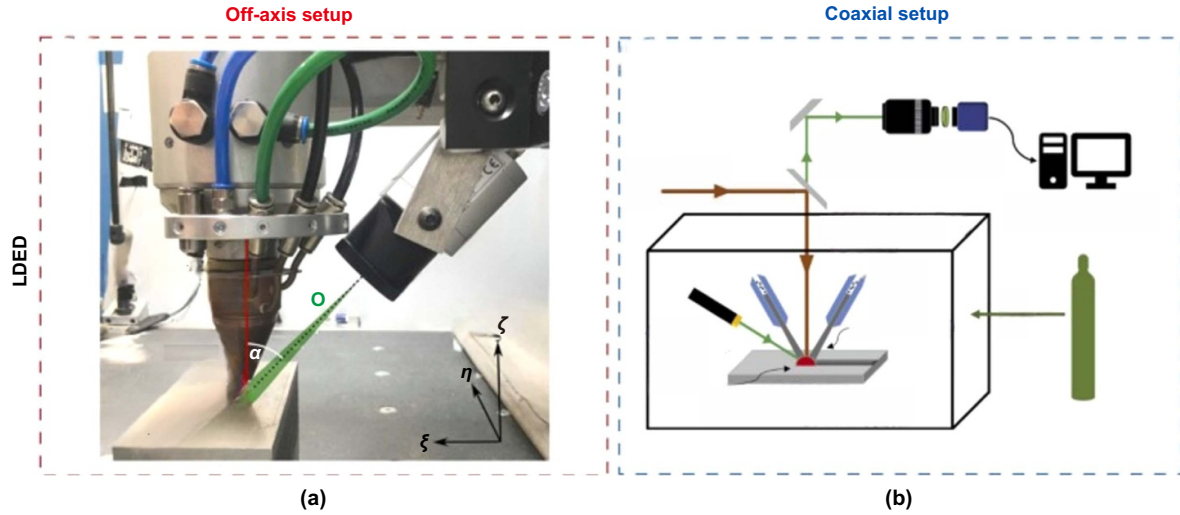


Figure 7. Comparison and visualization of off-axis and coaxial camera setups. (a) Off-axis camera mounting in LDED. Reproduced with permission from^[135]. CC BY-NC-ND 4.0. (b) Coaxial camera setup in LDED. Reprinted from^[136], Copyright (2019), with permission from Elsevier.

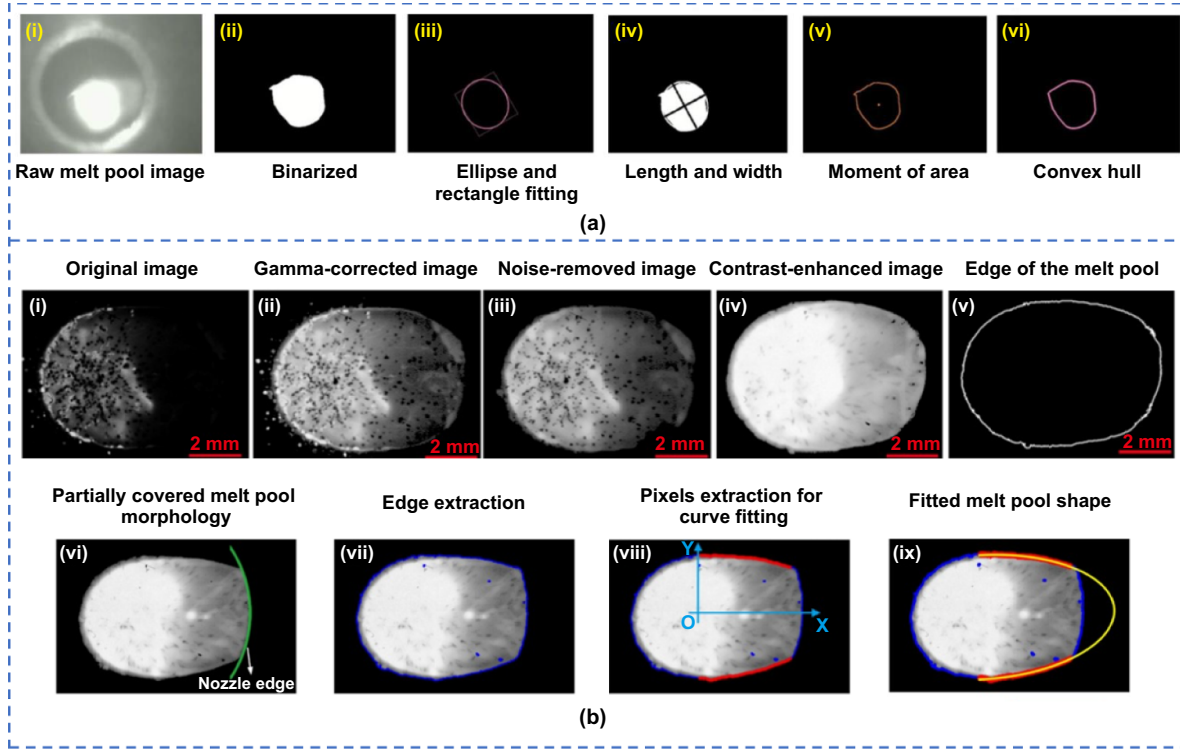


Figure 8. Melt-pool feature extraction. (a) Binarization and basic operations such as ellipse fitting and contour extraction from raw melt-pool images. Reprinted from^[94], Copyright (2023), with permission from Elsevier. (b) Feature extraction from grayscale melt-pool images using gamma correction, noise removal, and edge fitting. Reprinted from^[95], Copyright (2020), with permission from Elsevier.

and ellipse fitting are widely used to delineate the shape and size of the melt-pool.

In off-axis monitoring, additional corrections such as geometric distortion adjustment, are often required to restore accurate melt-pool morphology. For instance, Guerra et al.^[87] combined edge detection and centroid extraction to track layer height with an accuracy of 0.01 mm by aligning the

2D spatial coordinates with the real space. Coaxial monitoring, on the other hand, offers a direct and high-resolution view of the melt-pool, capturing detailed information about its shape, size, and oscillations. For example, Perani et al.^[89] utilized this setup to detect laser activation signals through pixel intensity analysis, ensuring process consistency. Such systems leverage the direct perspective provided by coaxial

Table 7. Key thermal features in LDED monitoring.

	Causes	Quality indicators
Melt-pool temperature	Laser-material interaction	Porosity, part density ^[97]
Thermal history	Heating and cooling cycles	Layer bonding, microstructure evolution ^[104]
Thermal gradient	Localized heat flow	Residual stress, microstructural properties ^[99]
Spatter thermal patterns	Material ejection during turbulence	Surface contamination, material efficiency ^[100]

setups to streamline feature extraction while maintaining accuracy^[9].

Surface morphology is another major focus of LDED optical monitoring. It is related to the layer quality and surface finish of the deposited material. It is a key quality indicator that affects the mechanical properties and deposition of subsequent layers. Optical monitoring can directly capture high-resolution images of the printed parts, thereby providing data support for subsequent analysis. For example, Ning et al.^[137] proposed a machine vision method combined with the YOLOv5s algorithm to automatically identify the melt-pool area, remove spatter interference, and extract the three-dimensional contour of the upper surface of the deposited layer with an error control within 0.25 mm. Combined with real-time monitoring and compensation, the flatness of thin-walled parts was increased to more than 90%, with a maximum increase of 22.8%.

The preliminary processing of optical data forms the basis for advanced data analysis and post-processing techniques, which will be explored in Section 4.1. These foundational algorithms ensure that optical monitoring systems can provide actionable insights into the LDED process, enabling robust and efficient process control.

3.2.2. Thermal sensing. Thermal radiation refers to the emission of electromagnetic waves generated by the interaction of the laser and the material during the LDED process. It is highly dynamic with non-uniform distribution across deposition positions and rapid change during the scanning process, and can be influenced by many factors, including laser power, scanning speed, and thermal conductivity of the material. Real-time sensing of the thermal radiation, either through localized melt-pool thermal profile^[97] or global thermal field distribution^[138], provides valuable insights into the thermal process, such as the melting and solidification of the feedstock materials, and thermally-induced material responses, such as microstructural evolution, grain refinement, and phase transformations. These insights are essential for understanding heat flow, energy utilization, and defect formation mechanisms, thereby optimizing material properties and ensuring the quality of LDED-fabricated components.

Unlike optical sensing, which emphasizes surface geometry and visual features, thermal sensing relies on specialized equipment like infrared cameras and pyrometers to detect heat radiation, with distinct post-processing techniques tailored for thermal analysis^[97,98]. This distinction highlights the unique contributions of thermal sensing to LDED monitoring and

quality control. To capture these critical thermal signals, various sensors and monitoring setups are employed, each with distinct advantages and limitations. Table 7 provides an overview of the most used equipment, including their principles, accuracy, frequency, limitations, and typical applications. The choice of sensor depends on the specific monitoring requirements. For example, MWIR cameras are widely used for melt-pool monitoring due to their high-speed imaging capabilities and coaxial placement compatibility, as shown in Figure 9. In contrast, thermocouples, while accurate for localized measurements, are less suitable for in-process applications due to their slower response time and intrusive nature.

Thermal features extracted from sensing signals such as melt-pool temperature (MPT) and thermal gradients offer particular implications for LDED mechanical quality. Table 8 summarizes the key thermal features, their causes and associated quality indicators. These features directly correlate with key quality metrics such as porosity, residual stress, and dimensional accuracy. For instance, monitoring thermal gradients promotes mitigation of residual stress, which could otherwise lead to part warping or failure. Similarly, analyzing spatter thermal patterns reveals inefficiencies in material usage and highlights potential issues of surface contamination^[69,98].

Thermal monitoring has been successfully applied to various aspects of LDED, from optimizing single-track deposition to ensuring quality in complex geometries. For instance, Siva Prasad et al. demonstrated the use of infrared cameras for analyzing single-track deposition in nickel-based superalloys, linking precise temperature control to improved layer quality^[99]. Similarly, Kim et al. developed a layer height estimation system using thermographic imaging combined with neural networks, achieving reliable results under complex deposition conditions^[69]. Despite these advances, thermal sensing in LDED faces several challenges: (1) sensor interference from spatter or plume; (2) the high cost of advanced imaging systems; (3) the computational demands of processing large volumes of thermal data^[101]. Therefore, post-processing based on the acquired thermodynamic data becomes necessary, such as prediction models and process optimization frameworks based on ML, which will be further discussed in Section 4.2.

3.2.3. Acoustic sensing. Visual and thermal signals are indispensable for monitoring external features and changes in the melt-pool during the LDED process^[107]. However, these methods are limited in detecting internal defects within

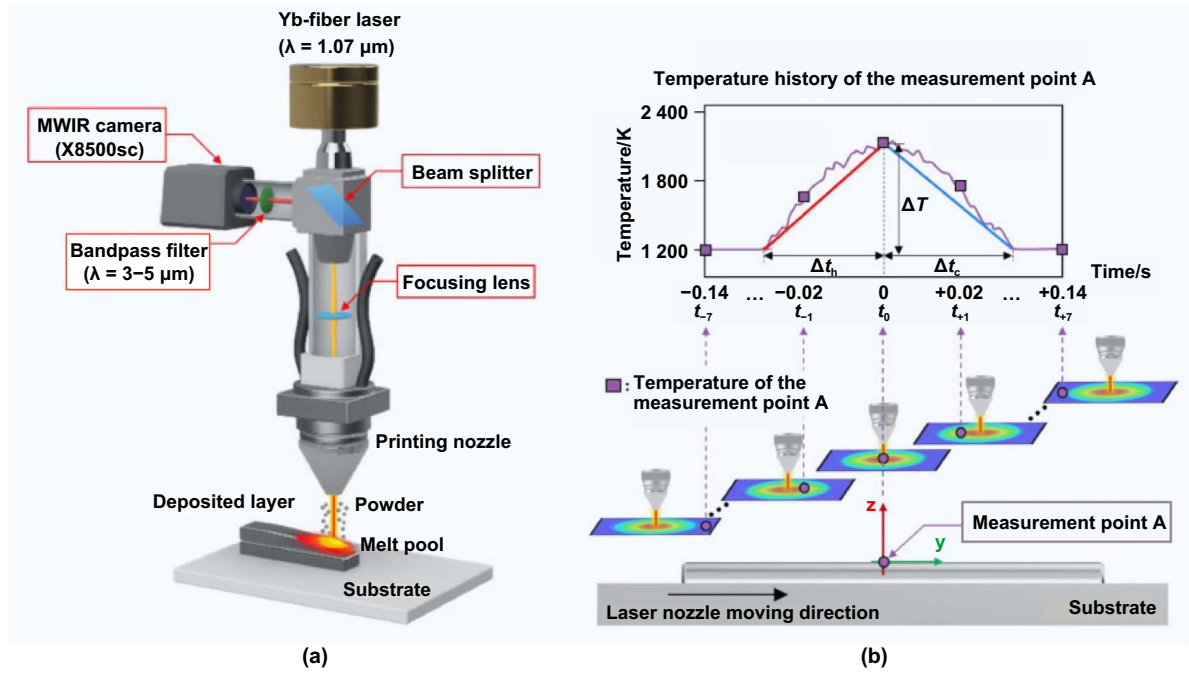


Figure 9. MWIR camera (Reprinted from^[69], Copyright (2023), with permission from Elsevier) for DED monitoring. (a) Coaxial thermographic setup for layer height estimation and (b) temperature history analysis showing heating and cooling cycles.

Table 8. Common thermal sensors and their specifications.

Sensor	Principle	Accuracy	Frequency	Limitations	Applications
MWIR infrared camera	Thermal radiation capture	$\pm 2^{\circ}\text{C}$	High speed	Plume interference	Melt-pool monitoring, layer height estimation ^[69]
LWIR infrared camera	Thermal radiation capture	$\pm 3^{\circ}\text{C}$	Moderate speed	Reduced spatial resolution	Thermal history analysis ^[99]
Pyrometer	Single-point IR detection	$\pm 1^{\circ}\text{C}$	Very high speed	Limited to localized regions	Peak temperature monitoring ^[97]
Thermocouple	Direct temperature sensing	$\pm 0.5^{\circ}\text{C}$	Low speed	Intrusive, slow response time	Baseline thermal measurements ^[103]

the printed components. In contrast, acoustic sensing, which encompasses techniques like AE, laser ultrasound, Rayleigh waves, and ultrasonic guided waves, offers unique capabilities for identifying internal defects such as cracks, porosity, and lack of fusion. By capturing transient acoustic signals with a broad frequency bandwidth generated during material deposition, acoustic monitoring provides valuable insights into defect formation and material integrity.

Acoustic signals in the LDED process arise from various physical mechanisms during material deposition. Stress waves are generated by the laser-material interaction, where rapid heating, melting, and vaporization induce vibrations that propagate through the material^[115]. These waves are further amplified by events such as material fracture or cracking, where localized failure occurs under thermal and mechanical loads^[112]. Additionally, wave propagation within the substrate and deposited layers allows energy to travel through the material, providing insights into subsurface conditions and

potential defect locations^[116]. These acoustic signals, characterized by their frequency and intensity, are critical for identifying internal defects such as cracks, pores, and lack of fusion, ensuring process stability and quality assurance^[108].

Unlike optical and thermal monitoring, acoustic monitoring relies on analyzing sound signals in the time and frequency domains to extract meaningful features that reflect process dynamics. Key features include amplitude and energy, which indicate the intensity of material deformation or cracking, providing early warnings of potential defects such as voids or cracks^[123]. The frequency content of acoustic signals correlates with defect types and sizes, enabling differentiation between microstructural anomalies and larger structural issues^[70]. Additionally, the signal duration and rise time offer insights into the nature of acoustic events, such as crack initiation, powder flow irregularities, or material detachment during deposition^[124]. Hauser et al.^[111] demonstrated the effectiveness of acoustic monitoring in their study of LDED

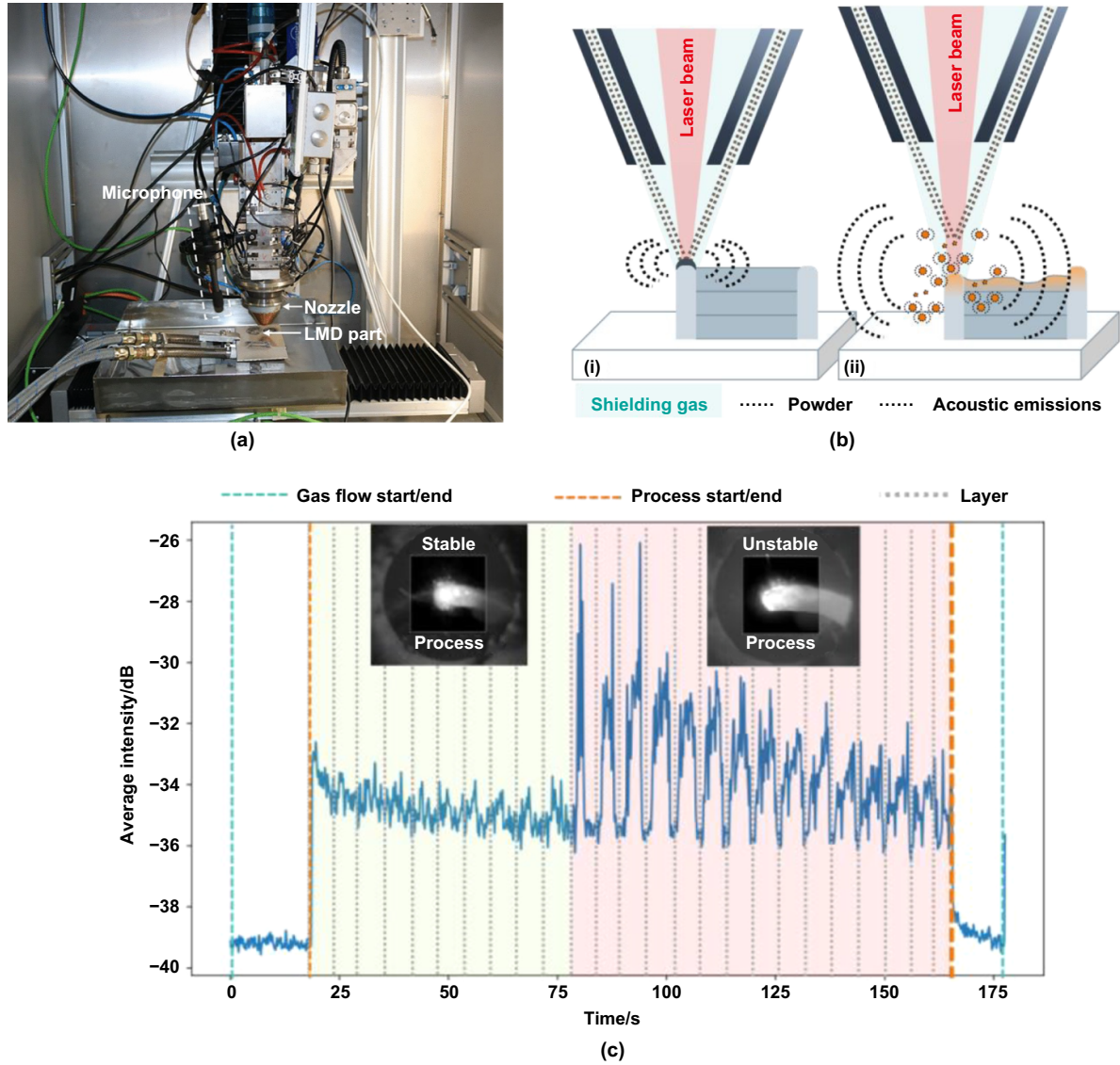


Figure 10. AE monitoring and signal feature recognition in the LDED process. Reproduced from^[111], CC BY 4.0. (a) Set-up of the LDED process cell. (b) Influence on the acoustic emissions in LDED for a stable processes and b unstable processes with an increase of sputters. (c) Average intensity of the characteristic Mel frequencies (1–10 kHz) for an unstable LDED process with its corresponding process camera images.

processes. As shown in Figure 10, they integrated microphones in the LDED process cell to monitor AEs, allowing for differentiation between stable and unstable processes. Their findings revealed that unstable processes, characterized by increased sputters, exhibited significant variations in Mel-frequency bands (1–10 kHz). These variations were directly correlated with defect occurrence and process quality^[70], confirming the relationship between acoustic signals and process stability.

Several acoustic sensing techniques are employed in LDED, each offering unique capabilities for defect detection and process stability monitoring. Table 9 summarizes these methods, highlighting their principles, accuracy, limitations, and typical applications. For instance, AE is widely used for detecting cracks and monitoring powder flow during the P-LDED process, while laser Rayleigh waves are

effective for surface defect detection. Ultrasonic guided waves enable subsurface analysis, offering high sensitivity for identifying internal defects, albeit with more complex setup requirements^[117,119].

Acoustic sensing has demonstrated considerable success in detecting defects and monitoring process stability. For instance, Rao et al. used full waveform inversion and reverse time migration to reconstruct internal defects in multi-material components, providing high-resolution imaging of material interfaces^[107]. Despite its advantages, acoustic monitoring faces challenges, including signal noise interference, complex sensor placement, and the high computational cost of processing acoustic data. Emerging techniques, such as combining ML with advanced signal processing methods, offer promising solutions to these challenges, enabling more precise and efficient monitoring, as will be discussed in Section 4.3.

Table 9. Acoustic sensing methods for LDED.

Method	Principle	Accuracy	Limitations	Applications	References
Acoustic Emission (AE)	Capture stress wave emissions	High (~ 0.1 mm)	Sensitive to noise interference	Crack detection, powder flow monitoring	[70,71,107,110–112, 115,116,123,124]
Laser Rayleigh waves	Monitor surface acoustic waves	Moderate	Limited to surface phenomena	Surface defect detection	[108,109]
Ultrasonic guided waves	Analyze wave propagation in material	High	Complex setup requirements	Subsurface defect detection	[117,119,120]

3.2.4. Spectral sensing. Spectral sensing, particularly through optical emission spectroscopy (OES), provides critical insights into the LDED process by capturing plasma signals emitted from excited metal elements. These signals reveal valuable information about plasma temperature, chemical composition, and melt-pool dynamics, supporting real-time process monitoring and quality control^[9]. This capability allows for the direct correlation of spectral data with material behaviour and process parameters, making spectroscopy an indispensable component in AM quality assurance.

Spectral signals in LDED originate from the laser-material interaction, where high-energy input excites atoms and ions in the plasma. These emissions, captured at specific wavelengths, provide details about temperature distributions, material composition, and deposition dynamics. For instance, the intensity of spectral lines such as Cr I or Mn I correlates with key parameters, including laser power, scan velocity, and powder feed rate, offering a real-time indicator of process conditions^[72,125]. This connection enables spectral signals to serve as proxies for quality metrics, including defect formation, porosity, and melt-pool stability. Spectral sensing has been utilized in various studies to monitor process dynamics and detect defects in real-time. Pignatelli et al.^[72] used UV-Vis spectroscopy to measure sub-millimeter defects. Schmidt et al.^[125] employed atomic emission spectroscopy (AES) to explore the effects of laser power and other parameters on the intensity of specific element lines. As illustrated in Figure 11, the correlation between spectral intensity and process parameters emphasizes the role of spectroscopy in linking process dynamics to surface quality.

Despite its advantages, spectral sensing faces challenges, particularly in terms of sensitivity to specific defect types and complex signal interpretation. However, the integration of spectroscopy with advanced analytics and ML offers great opportunities to overcome these challenges. By enhancing the precision and scope of defect detection, such innovations can further improve the quality control and optimization of LDED.

3.3. Fusion of multi-source sensing system

Multi-sensor fusion technology has emerged as a powerful strategy for achieving comprehensive process monitoring and quality control in the LDED process. By integrating signals from various modalities such as optical, thermal, acoustic, and spectral sources, multi-source systems provide a holistic

view of the process, comprehensively capturing both surface and subsurface phenomena. This fusion enables more accurate defect detection, better process stability assessment, and improved decision-making for quality control^[101,139]. Table 10 summarizes these fusion methods, detailing their key applications and advantages in LDED process monitoring. Generally, multi-sensor fusion methods can be categorized into three main types: low-level, mid-level, and high-level fusion^[140]. Low-level fusion primarily involves the direct combination and alignment of raw data or simply extracted data features from different sensors in time or space dimensions^[141]. It is usually used to obtain intuitive multi-dimensional visualization results or as input for higher-level data fusion, such as providing AI models as training data. For example, in optical-thermal fusion, it usually involves pixel-by-pixel registration of thermal images and visual images to create a composite visualization result in which temperature data is superimposed on structural features^[138]. As shown in Figure 12(a), Vandone et al.^[142] combined optical imaging and infrared thermography directly in the DED process. This approach utilized a high dynamic range (HDR) camera and dual-spectrum pyrometer to monitor the melt-pool morphology and temperature distribution in real time, and compared them with the axis position information from the CNC machine tool to ensure the precise temporal matching of optical data, infrared data and machine tool motion data, achieving a classification accuracy of 77% for identifying over- and under-deposition cases. Similarly, Kisielewicz et al.^[143] maintained stable liquid metal transfer in the LDED process by employing a multi-sensor system that integrated a visible light spectrometer and voltage and current measurements, showcasing the effectiveness of low-level fusion for dynamic process stabilization.

Mid-level fusion typically uses feature selection algorithms, principal component analysis, canonical correlation analysis, or machine learning techniques to identify the most informative features extracted from different sensor datasets to monitor and understand more complex process states^[146]. For example, when combining acoustic and optical data, mid-level fusion extracts temporal spectral features from acoustic emissions and spatial features from images, and then analyzes the correlation between these feature sets to detect anomalies that would not appear in either data stream alone. Chen and Moon^[144] implemented mid-level fusion,

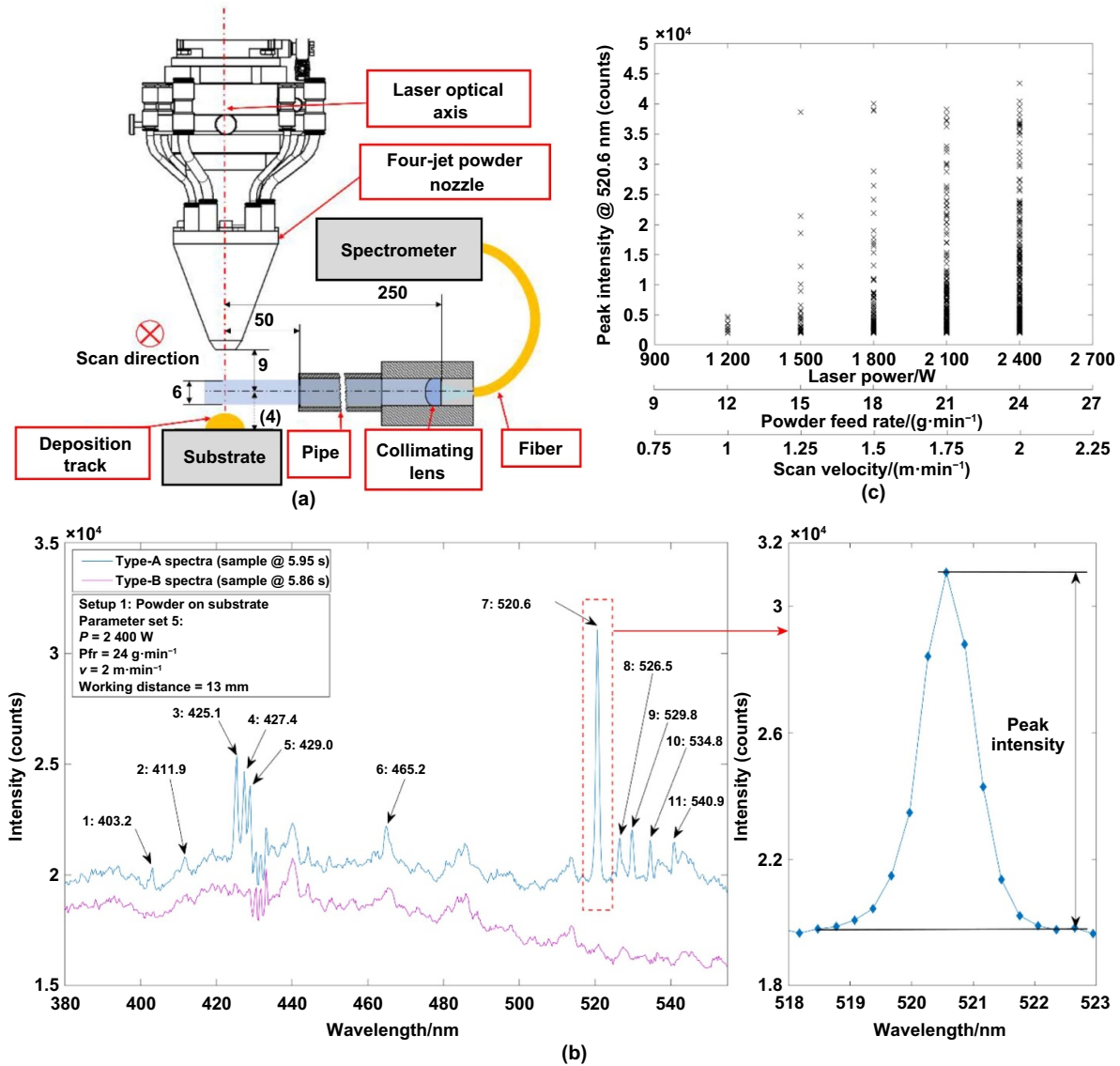


Figure 11. Spectral sensing and process parameter correlation in DED. Reproduced from^[125]. CC BY 4.0. (a) DED setup with a four-jet powder nozzle and spectrometer for real-time spectral monitoring. (b) Spectral intensity of Cr I, Mn I, and Co I lines, with a zoom on the Cr I peak at 520.6 nm. (c) Cr I peak intensity (520.6 nm) versus laser power, powder feed rate, and scan velocity.

using genetic algorithm optimization to extract spectral features such as spectral centroid mean from acoustic signals and spatial features such as contour area from the molten pool morphology for fusion. This method reduces the data dimension while retaining the complementary information provided by each sensor type, enabling real-time detection of internal defects such as cracks and porosity, demonstrating the potential of mid-level fusion in process quality optimization. Similarly, Haley et al.^[138] combined digital image correlation (DIC) with infrared thermography to simultaneously monitor the stress and temperature fields during the fabrication of complex geometries. As shown in Figure 12(b), their approach generated a three-dimensional strain map that was used for analyzing the impact of scanning strategies on the dynamic thermo-mechanical behavior of workpieces.

High-level fusion uses advanced computational methods such as machine learning or digital twins to integrate independent decisions or predictions from each sensor data stream, and then combines their outputs into a final quality prediction using ensemble methods or neural network inference^[147]. For example, Wasmer et al.^[148] integrated acoustic and photoemission spectroscopy with several mainstream ML algorithms to enable real-time prediction of cracks and porosity in functionally graded materials (FGMs) during the DED process. The approach utilized deep feature extraction from optical and acoustic signals to significantly enhance the accuracy of defect detection and chemical composition analysis. Furthermore, Chen et al.^[94] introduced a multi-sensor fusion-based digital twin (MFDT) framework, illustrated in Figure 12(c). This framework synchronizes multi-sensor data, including acoustic

Table 10. Summary of multi-source sensor fusion methods and their applications in DED process monitoring.

Fusion level	Sensor combination	Method description	Application example	Effects
Low-level Fusion	Optical imaging + Infrared thermography	Direct combination and processing of raw data	Vandone et al. ^[142] : used HDR camera and dual-spectrum pyrometer to monitor DED melt-pool	Classification accuracy of 77%
	Visible light spectrometry + Electrical sensors	Direct data processing to monitor interaction between melt-pool and wire	Kisielewicz et al. ^[143] : monitored melt-pool morphology evolution in hot-wire DED process	Revealed thermal history and morphology changes
Mid-level Fusion	DIC + Infrared thermography	Feature extraction and analysis for stress and temperature monitoring	Haley et al. ^[138] : generated 3D strain maps to analyze effects of scanning strategy	Real-time monitoring, 3D strain maps
	Multi-sensor (melt-pool morphology + Acoustic features)	Optimized feature extraction using genetic algorithm	Chen and Moon ^[144] : detected internal defects like cracks and porosity	Defect detection accuracy of 96.4%
High-level Fusion	Optical + Acoustic signals	Advanced modeling using deep learning	Akhavan et al. ^[145] : real-time defect prediction using convolutional neural network and AE data	Improved defect detection accuracy
	Spectral signals + Autoencoder	Multi-modal model with autoencoder and clustering algorithms	Garmendia et al. ^[78] : classified deposition quality of Al7075 alloy	High classification accuracy
	Multi-sensor (digital twin technology)	Digital Twin + Real-time model updating	Chen et al. ^[94] : real-time monitoring and defect prediction	Enhanced process intelligence

signals, thermal fields, and coaxial melt-pool images, with robot motion in real time. The synchronized data is then processed using ML models to create a virtual quality map of the printed part, enabling precise monitoring and defect prediction for the DED process.

Despite its advantages, the implementation of multi-source sensing systems faces several challenges. These include the complexity of sensor integration, synchronization of data acquisition, and the high computational cost of processing large datasets. Additionally, developing robust algorithms capable of effectively fusing multi-modal data remains a critical area of research, which will be discussed in Section 4.5.

3.4. Summary

In-situ monitoring methods are integral to ensuring the quality and reliability of the LDED process by enabling real-time observations and control. Indirect measurement techniques such as optical and thermal monitoring provide essential surface-level insights into melt-pool dynamics and temperature distribution, while acoustic sensing extends these capabilities to subsurface defect detection. Direct measurements such as laser scanning and operando synchrotron-based X-ray efficiently assess quality by capturing precise geometrical and microstructural information. Integrating multi-sensor

data further enhances defect detection and quality prediction. According to a survey by Tang et al.^[77], optical and thermal sensors have been widely adopted in many commercial LDED machine tools, such as those from DMG MORI®, DM3D Technology®, and Stratonics®, thanks to their affordability, straightforward implementation, and robust performance. In contrast, more advanced sensing techniques, including acoustic monitoring and X-ray imaging, remain largely confined to research due to challenges related to integration complexity, higher cost, and difficulties in signal interpretation within industrial environments.

While significant progress has been made for LDED, current in-situ monitoring techniques still face significant limitations. Data complexity from heterogeneous sensors (optical, thermal, acoustic) necessitates advanced algorithms for real-time analysis, often causing processing delays that hinder adaptive control. Integration hurdles arise from harsh process conditions (spatter, plasma plume, high temperature), which degrade sensor accuracy and complicate multi-modal synchronization. High costs of high-resolution systems, e.g., X-ray, clash with industry cost constraints. Addressing these limitations requires streamlined sensor fusion standardized frameworks and cost-effective solutions to achieve reliable, real-time quality assurance in LDED.

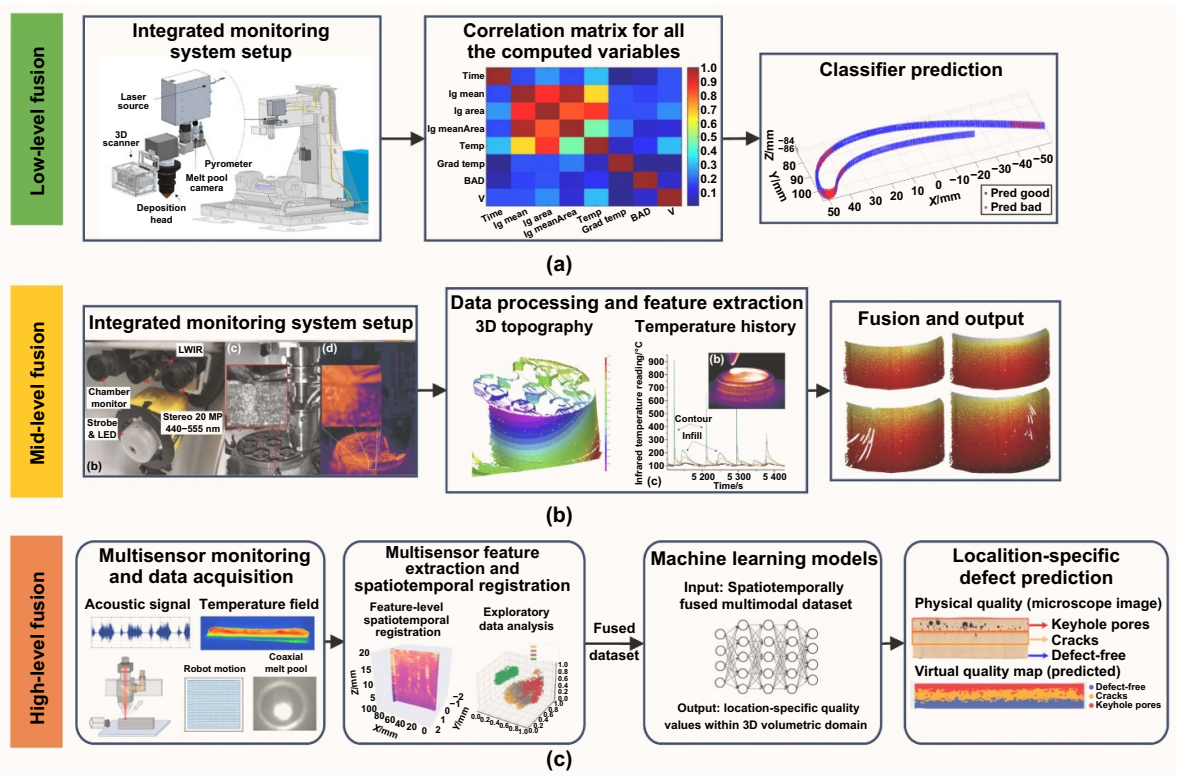


Figure 12. Multi-sensor data fusion classifications. (a) DED part quality assessment and monitoring system based on a camera and a bi-chromatic pyrometer. Reprinted from^[142], Copyright (2022), with permission from Elsevier. (b) DIC and infrared thermography for mid-level data fusion in DED process. Reproduced from^[138], CC BY 4.0. (c) Multi-sensor fusion-based digital twin (MFDT) framework for location-dependent defect prediction in robotic LDED. Reprinted from^[94], Copyright (2023), with permission from Elsevier.

4. Advanced analysis of in-situ measurement results

This section investigates post-processing of measurement results, which are obtained through in-situ sensing techniques introduced in Section 3. Traditional analytical methods can reveal relationships between the LDED process and the resulting components, yet these techniques often fall short in precision control. The multidimensional and highly dynamic nature of the LDED presents challenges in accurately managing process parameters and ensuring component quality^[24]. To address these challenges, researchers increasingly rely on ML methods to analyze LDED data. This section reviews the application of ML techniques in LDED quality analysis, compares datasets and their corresponding models, and evaluates their potential for defect prediction. Additionally, we critically examine the strengths and weaknesses of different models and provide insights into further research directions.

Previous researchers have reviewed the concepts of ML and related algorithms. Herzog et al. reviewed some classical algorithms in ML for LDED^[149], while Era et al.^[150] reviewed the current status of ML applications in LDED. This paper will not delve into specific algorithms. Instead, it will focus more on the process-quality domain of LDED, examining how ML can be used to handle data obtained during the LDED process or post-processing.

4.1. Visible image

In the LDED process, melt-pool images have become a primary focus of research due to their critical role in determining the quality of the final product. The dynamic behaviours of the melt-pool, including its size, shape, temperature distribution, and cooling rate, directly affect the microstructure of the deposited material, which in turn influences key properties of the final component, such as wearing performance, corrosion resistance, and other functional characteristics. However, the highly dynamic and nonlinear nature of the LDED process poses significant challenges for traditional physical models, which often struggle to accurately predict and control these complex variables. With the advancement in computer imaging technology, researchers are increasingly leveraging ML, particularly deep learning (DL) techniques, to analyze melt-pool images and gain deeper insights into melt-pool behavior.

4.1.1. Melt-pool visual feature extractions. Melt-pool visual features are critical for understanding the dynamic characteristics of the LDED process. Numerous research studies have been undertaken to extract physics-relevant features from melt-pool images to reflect the stability and quality of the LDED process^[130]. Generally, key melt-pool features can be

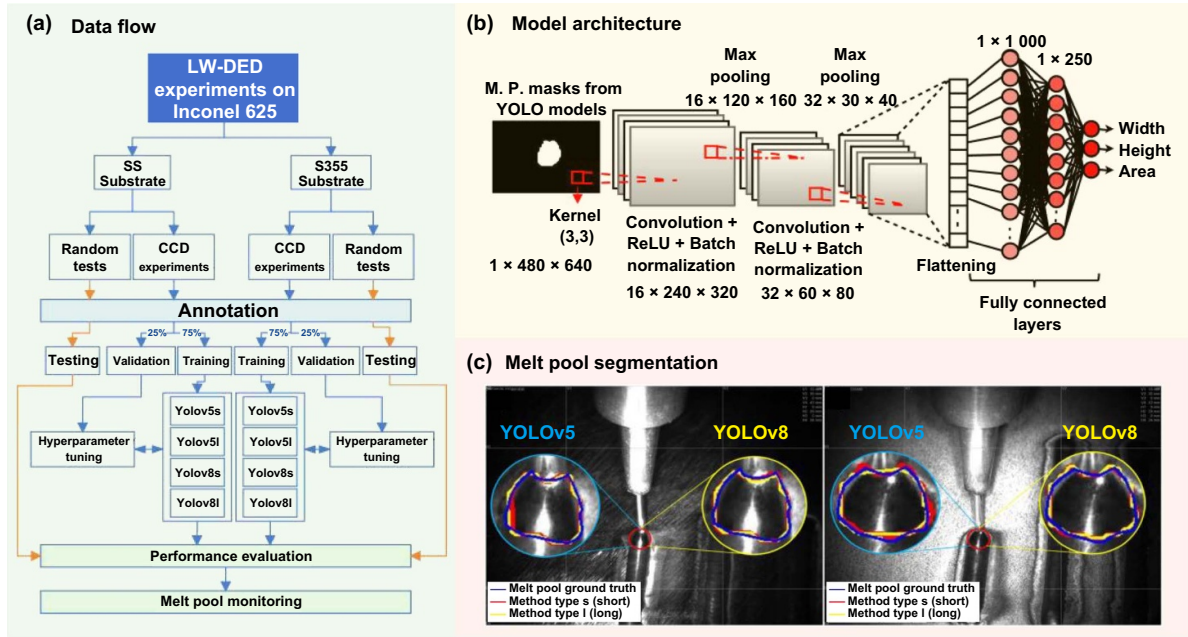


Figure 13. CNN-based melt pool detection and segmentation. Reproduced from^[154]. CC BY 4.0. (a) Dataset collection and melt pool monitoring procedure. (b) Architecture of the developed CNN-based model for bead geometry prediction. (c) Visual comparison of the result of proposed networks on sample experiments conducted on steel substrates S355 (left) and 316 L SS (right).

categorized into two types: (1) morphological features such as its area, width, and depth; (2) temperature features such as peak temperature and thermal history^[9,103].

To facilitate accurate feature extraction, advanced pre-processing techniques are commonly employed. These techniques include noise reduction, ellipse fitting, and coarse enhancement^[95,151]. For example, Sun et al.^[95] utilized a combination of edge detection and Boolean operations to enhance boundary precision in melt-pool images, achieving accurate feature quantification under varying process conditions. A review of these extraction methods has been provided in Section 3.

However, the quality of melt-pool images can be influenced by the rapid dynamics of the melt-pool and the harsh sensing environment, making traditional binary threshold-based extraction of melt-pool boundaries inaccurate (Section 3.1). To address this issue, ML techniques have been applied to enhance the ability to extract and analyze melt-pool features. Specifically, numerous computer vision-based algorithms were employed to accelerate and optimize melt-pool recognition^[152]. For example, Liu et al.^[153] proposed an image-enhancement generative adversarial network (GAN) to improve the contrast of melt-pool images.

Recently, Asadi et al.^[154] proposed a CNN-based process-quality data fusion framework for laser wire DED, which integrated in-situ process monitoring with ex-situ quality evaluation, as shown in Figure 13. In their work, YOLOv8-based instance segmentation was employed to accurately extract melt-pool geometrical features (e.g., area, width, and height) from high-speed coaxial vision images. These segmented features were statistically correlated with offline measured

bead geometries, including cross-sectional area, penetration depth, and heat-affected zone. The model achieved high segmentation accuracy (mAP up to 0.925) and real-time performance (over 114 FPS), enabling precise mapping between melt pool dynamics and final bead shape. Furthermore, a CNN model was developed using the segmentation masks to predict bead geometries, with mean squared error as low as 0.082 for area prediction. This integrated framework highlights the effectiveness of combining online visual data with post-process inspection to support real-time quality prediction and control in W-LDED.

4.1.2. Defect detection with melt-pool feature. Based on features extracted from melt-pool images, numerous ML algorithms have been applied to defect detection in LDED. The most commonly used approaches include classic ML algorithms, e.g., k-nearest neighbors (KNN), artificial neural network (ANN), support vector machine (SVM), DL within supervised learning e.g., convolutional neural network (CNN), recurrent neural network (RNN), and unsupervised learning e.g., self-organizing map (SOM), K-means clustering. A summary of the relevant studies is provided in Table 11.

In the early stages of exploring the relationship between melt-pool behavior and defect formation, classic ML played a critical role in classification tasks. For instance, Khanzadeh et al.^[155] applied methods like SVM, KNN, and decision trees (DT) to recognize patterns in melt-pool images and developed black-box models to predict porosity probability distributions based on melt-pool features, as illustrated in Figure 14. This data-driven approach did not rely on the material properties of the samples, making it versatile across different materials.

Table 11. Surgery of melt-pool based machine learning analysis in MAM.

ML category	ML algorithm	AM process	Dataset type	Objective	Performance	References
Supervised learning	SVM, KNN, DT, DA	P-LDED	Melt-pool thermal images	Localized porosity prediction	Accuracy: 96%	[155]
	CNN (ResNet)	P-LDED	Melt-pool thermal image	Laser power prediction	F1 score: 0.975	[156]
	m-CNN	P-LDED	Melt-pool image	Microstructure prediction	Error of α/β : 1.15%/3.67%	[157]
	XGBoost, LSTM	P-LDED	Melt-pool thermal image	Melt-pool temperature prediction	RMSE: 25.1/20.2, RE: 1.0%/0.8%, R2: 73.9%/31.3%	[103]
	ANN	P-LDED	Melt-pool image	Layer height, surface unevenness estimation	R ² : 12.62%	[69]
	CNN	P-LDED	Melt-pool image	Thermal infrared camera	Uniform microstructure	[136]
	CNN-GRU	P-LDED	Melt-pool image	Online defect prediction	Latency: 1.1 ms, Accuracy: 95.1%, F1 score: 95.2%	[158]
Semi-supervised learning	GAN, IEGAN	P-LDED	Melt-pool thermal image	Melt-pool segmentation	CII of GAN/IEGAN: 0.91/1.14	[153]
	Contrastive learning-CNN	P-LDED	Melt-pool image	Quality grades classification	Accuracy: 89%–97%	[152]
	KNN, CNN	PBF-LB/M	Melt-pool thermal image	Build condition classification	ROC AUC: 0.994	[159]
Unsupervised learning	SOM	P-LDED	Melt-pool thermal image	Localized porosity prediction	Accuracy: 96%	[160]
	Autoencoders	UA-DED	Melt-pool image	Melt-pool image reconstruction	Accuracy: 94.52%	[161]

Their work exemplifies the use of manual feature extraction and classification models for defect prediction. However, this method has inherent limitations, including its dependence on manual labelling and its inefficiency in addressing complex defect mechanisms or large datasets.

DL models, particularly CNNs, have addressed many of these limitations by automatically learning features from data without the need for manual extraction, and are more efficient in processing large data. For example, Zhang et al.^[136] trained a CNN model using melt-pool images captured by coaxial cameras to predict porosity in LDED, achieving a classification accuracy of 91.2%. In contrast, Guo et al.^[162] proposed a physics-driven CNN model that integrated thermal images from infrared cameras with physical features derived from finite element analysis, achieving 100% accuracy in porosity prediction. These studies highlight the performance differences between purely data-driven CNNs and hybrid approaches that incorporate domain knowledge, suggesting that integrating physics-based constraints can significantly enhance prediction accuracy and generalizability. By combining data-driven features

from thermographic images with physical features derived from finite element analysis, their algorithm achieved a remarkable 100% accuracy in porosity prediction.

Moreover, semi-supervised learning approaches have shown promise in leveraging both labelled and unlabelled data for defect detection. Pandiyan et al.^[152] employed a contrastive learning with a CNN model to perform binary classification of defects using coaxial melt-pool images. This approach effectively addressed the challenges associated with limited labelled datasets while maintaining high classification accuracy, illustrating the growing versatility of DL in LDED applications.

4.2. Thermal emission

LDED energy is introduced primarily through thermal input, making temperature a critical parameter in the process. Temperature data in LDED can be categorized into two types: MPT and local thermal history. MPT represents the dynamic, fluctuating thermal conditions within the melt-pool

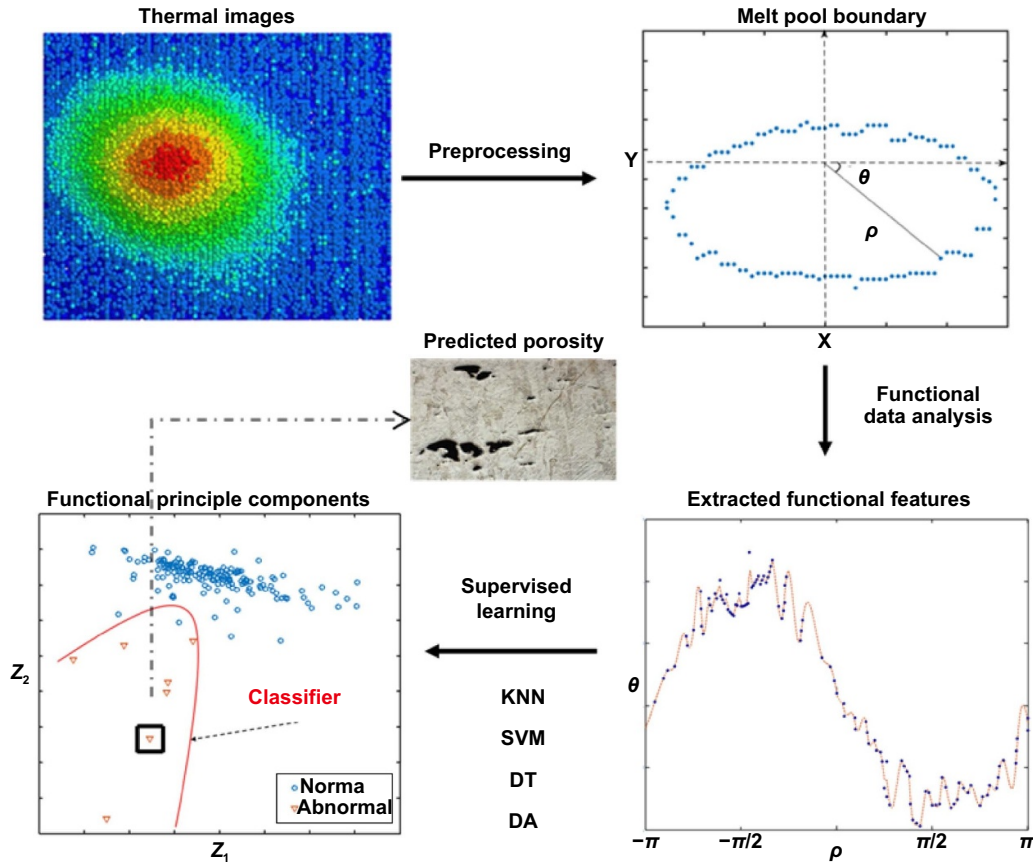


Figure 14. Demonstration of porosity prediction procedure using classic supervised machine learning. Reprinted from^[155], Copyright (2018), with permission from Elsevier.

as it moves across the material, whereas local thermal history refers to time-series temperature data recorded within a specified region of interest (ROI) at a fixed location^[163]. Since both MPT and local thermal history are inherently dynamic, numerous ML methods have been applied to analyze their relationship with the quality (or defects) of the final part.

4.2.1. Melt-pool temperature. In ML applications, MPT can be utilized as both an input and an output variable. For example, MPT was predicted as the output of an ML model in LDED processes, as shown in Figure 15(a). In a similar study^[103], thermographic images were employed to model the MPT, with melt-pool boundary temperature serving as the input data. Two learning models, eXtreme Gradient Boosting (XGBoost) and long-short term memory (LSTM), were employed for this task. While XGBoost demonstrated superior computational efficiency, LSTM outperformed in terms of prediction accuracy and robustness.

With the increasing adoption of advanced temperature measurement equipment in LDED^[77], recent research has shifted toward exploring the relationship between MPT and the microstructure or defects of the final part. For instance, Jamnikar et al.^[157] developed a multi-modality CNN (m-CNN) that incorporated both MPT and size information as input features. This model was used to predict α -lath thickness and β -grain length in thin-wall structures, as illustrated in

Figure 15(b). To prevent overfitting and network malfunction, most studies have implemented batch normalization. Notably, this study applied regularization to microstructural properties prediction, specifically for lath thickness and beta grain length, to enhance convergence in prediction performance. The microstructural model achieved a relative error (RE) of 1.15% for alpha lath thickness, 5.84% for beta grain length parallel to the build, and 3.73% for beta grain length perpendicular to the build. Furthermore, Khanzadeh et al.^[164] modelled the spatial surface features of melt-pool thermograms and applied a semi-supervised SOM to analyze the temperature distribution on the melt-pool surface, as depicted in Figure 15(c). This approach achieved a 96% prediction accuracy for porosity in Ti-6Al-4V thin walls, highlighting the effectiveness of temperature-based thermal features in predicting defects.

4.2.2. Thermal history. Thermal history in LDED significantly influences grain growth, residual stress formation, and the potential for microcracks, all of which are critical to the mechanical performance and reliability of the final part. Recognizing the importance of localized heating and cooling effects, Xie et al.^[163] proposed a mechanistic data-driven framework for evaluating the local thermal history of printed thin walls. Their framework integrated wavelet transforms with a CNN to predict the position-specific ultimate tensile

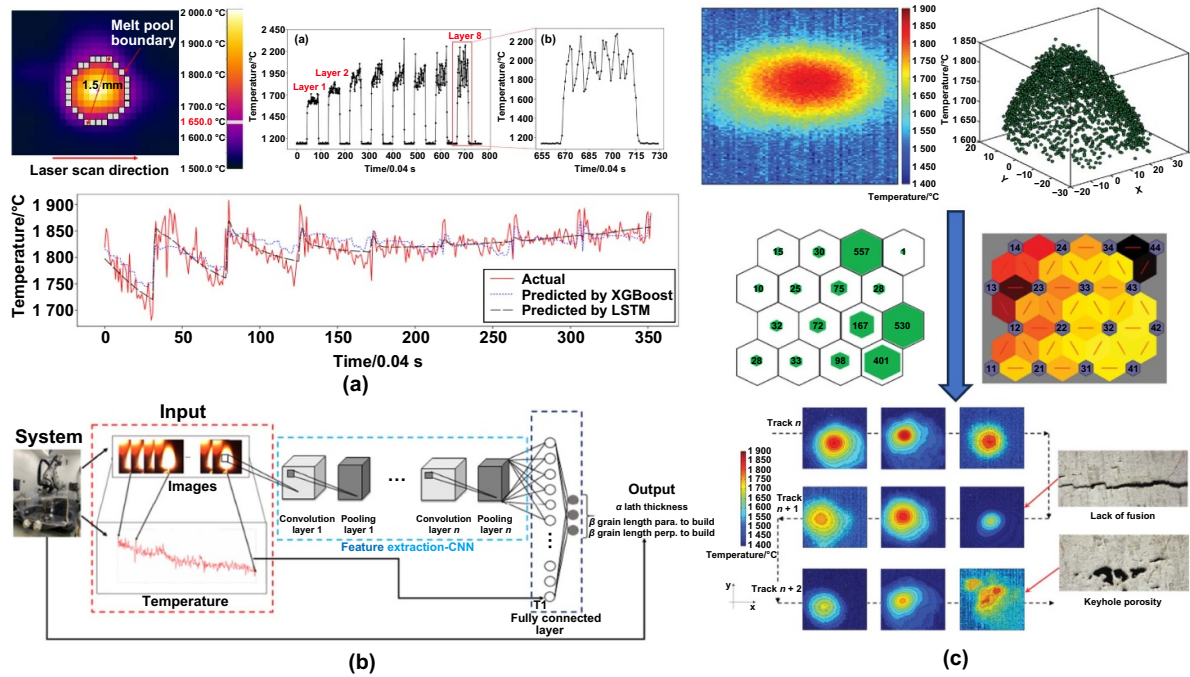


Figure 15. ML-assisted defect detection methods using melt-pool temperature (MPT). (a) MPT prediction by XGBoost and LSTM. Reprinted from [103], Copyright (2020), with permission from Elsevier. (b) Multi-modality CNN for microstructure properties prediction. Reprinted from [157], Copyright (2022), with permission from Elsevier. (c) Using self-organizing map to predict porosity by MPT. [164] [12 May 2017], reprinted by permission of the publisher (Taylor & Francis Ltd, www.tandfonline.com).

strength of the thin walls based on thermal history data, capturing the intricate relationship between thermal cycles and mechanical properties. Chen et al. [94] developed a fusion-based digital twin that leveraged thermal history data to predict in-situ part quality. By integrating multi-sensor information, this method enhances prediction accuracy for various defects such as keyholes and cracks. The ability to handle complex, multi-dimensional data positions this method as a robust tool for advancing high-precision defect prediction models in LDED.

In addition to ML-based techniques, Gaikwad et al. [165] demonstrated a hybrid approach using graph theory to calculate the transient thermal distribution in Titanium alloy thin walls. By combining simulated temperature data with real-time measurements from pyrometers, they trained a SVM model to predict defect occurrence. This hybrid model achieved an F-score of 90%, compared to 80% when using SVM alone without simulation data. This integration of physics-driven simulations with data-driven models highlights the advantages of combining white-box and black-box approaches, offering significant insights into thermally-induced processes in DED.

4.3. Acoustic emission

The integration of AE technology and ML in MAM is emerging as a crucial tool for real-time quality monitoring. These methods allow for in-situ signal capture without disrupting the AM process [166–168], offering a non-invasive and efficient approach to defect detection and process optimization. This

section explores the application of AE and ML in AM and highlights the advantages and challenges of these technologies in industrial contexts.

AE technology has proven particularly effective in detecting internal defects, such as porosity and cracks, with the assistance of ML for its analysis. For instance, Taheri et al. [166] demonstrated AE's ability to detect process anomalies in DED. By using K-means clustering to classify captured acoustic signals, they successfully identified issues like porosity and cracks, achieving an accuracy of 94%. This highlights AE's potential for non-destructive, real-time defect detection. The incorporation of DL, especially CNN, has further enhanced the efficiency and accuracy of AE signal processing compared to traditional ML methods. For example, while K-means clustering achieved 96% accuracy in Taheri et al.'s study, CNN-based models applied to wavelet-transformed AE features by Hossain and Taheri [166] reached 79%–84%, demonstrating comparable performance while offering greater adaptability to complex feature extraction.

One significant challenge in applying AE is interference from environmental noise, which can reduce model accuracy. Hossain and Taheri [166] addressed this issue in LDED by using wavelet transforms to extract frequency-domain features from AE signals. These features, classified using CNN, achieved 95%–96% accuracy. Similarly, Chen et al. [169] developed a DL-assisted denoising framework that enhanced the detection of porosity and micro-cracks, reducing false positives in DED processes.

Recent advancements in AE signal processing have further refined defect detection methods, particularly with

tailored CNN models. Chen et al.^[115] proposed a denoising method incorporating acoustic equalization, bandpass filtering, and harmonic-percussive source separation (HPSS). Their CNN model, based on Mel-frequency cepstral coefficients (MFCCs), achieved 89% accuracy in identifying defects. Additionally, Wasmer et al.^[148] extended the scope of monitoring by integrating AE with OES in DED. This multi-modal approach enhanced defect detection with models trained on AE data, achieving 79% accuracy and those using OES reaching 90%. These results underscore the advantages of combining multiple sensor inputs for more comprehensive quality control.

In summary, the combination of AE technology and ML offers significant potential for real-time monitoring in LDED, particularly in defect detection and process optimization. From traditional ML methods to advanced CNN and RL models, AE signal processing is rapidly evolving. However, further research is needed to address challenges such as noise interference and scalability for large-scale industrial applications. The development of multimodal monitoring systems represents a promising direction for achieving more precise and comprehensive quality control in LDED.

4.4. Other sources of analysis

4.4.1. Point cloud. In the layer-wise LDED quality control, point clouds, which are based on the geometric features of printed parts, are commonly employed. Point cloud data is frequently used for surface defect identification and defect calibration. However, the raw point cloud data is often contaminated with noises from the measurement or the process, including outliers and irrelevant surfaces. Consequently, analytical methods for processing this data primarily focus on data enhancement.

For point cloud denoising, one of the most commonly used techniques is the statistical outlier removal method^[170]. This method calculates the distance between each point and its nearest neighbor, compares it to the average distance of all points, and removes points that deviate significantly from the mean as outliers. For example, Lyu and Manoochehri^[171] utilized 2D depth images generated from laser line scanning in combination with CNN to classify surface defects, including over-extrusion and under-extrusion. Through pixel-level analysis, raised and indented areas were successfully identified in their study^[172]. Additionally, 3D point cloud data can be converted into 2D depth images to simplify computation and accelerate defect identification. Liu et al.^[173] proposed a window-based image processing method that pairs the depth information of pixels with corresponding local patches in the 3D point cloud, enabling the automatic detection of overbuilt and underbuilt areas.

Point cloud data has shown great potential for surface defect detection in LDED processes, yet several challenges and limitations remain. There is currently no widely accepted industry standard for evaluating part quality based on point cloud data. Moreover, research involving the use of

3D data for ML training is significantly less in number compared to studies using image data, which further limits the widespread adoption of point cloud data in LDED. Another major issue is improving resolution and reliability. While laser line scanning can identify surface defects, it may struggle to accurately detect small or subtle defects that do not significantly interfere with the projected laser line. Addressing these challenges requires the development of more advanced and robust algorithms capable of processing point cloud data effectively while accommodating the inherent variability of AM processes. Such advancements are crucial for ensuring reliable surface defect detection in real-world applications.

4.4.2. X-ray. Synchrotron X-ray monitoring has proven to be a valuable research tool in laser AM, offering critical insights into phenomena occurring during laser processing. Synchrotron X-ray monitoring allows for high-resolution imaging of the melt-pool, revealing the dynamic processes underlying material behavior during deposition^[174–176]. Since X-rays can provide precise, high-resolution, and fast detection of keyhole porosity^[177], their measurement data holds the potential for use as ground-truth labels in annotating in-situ monitoring data for ML applications. As illustrated in Figure 16, Ren et al.^[178] utilized infrared thermography guided by high-speed synchrotron X-ray imaging to detect keyhole formation in Ti-6Al-4V LPBF. By using high-energy X-rays to penetrate a single layer of the powder bed, the dynamics of sub-surface structures were revealed. Through combining imaging techniques with multi-physics simulations, various forms of keyhole oscillation were identified. Operando X-ray imaging data were annotated as ‘porosity’ and ‘non-porosity’, providing ground-truth labels for a supervised DL model. This model successfully detected keyhole porosity events with sub-millisecond time resolution. Similarly, Wolff et al.^[179] employed operando X-ray imaging in their piezo-driven LDED system, high-speed X-ray imaging data is used to train an LSTM-CNN model for in-situ defect prediction. The keyhole detection accuracy reaches 96.2% and 99.9% under time windows of 0.5 ms and 4 ms, respectively, to investigate laser-material interactions. High-speed X-ray imaging revealed how these interactions influenced powder flow and porosity formation. Pandiyan et al.^[180] trained an LSTM-CNN model on high-speed X-ray imaging data for in-situ defect prediction. Their study revealed how these interactions influence powder flow and porosity formation. The keyhole detection accuracy was 96.2% and 99.9% under 0.5 ms and 4 ms time windows, respectively.

Despite its exceptional capabilities, the widespread application of X-ray imaging in LDED faces challenges. The high cost and specialized customization of X-ray equipment significantly limit the volume of available data compared to other sensing modalities. This scarcity of data constrains the application of many data-driven analytical methods. Therefore, both the industry and researchers are eagerly awaiting the

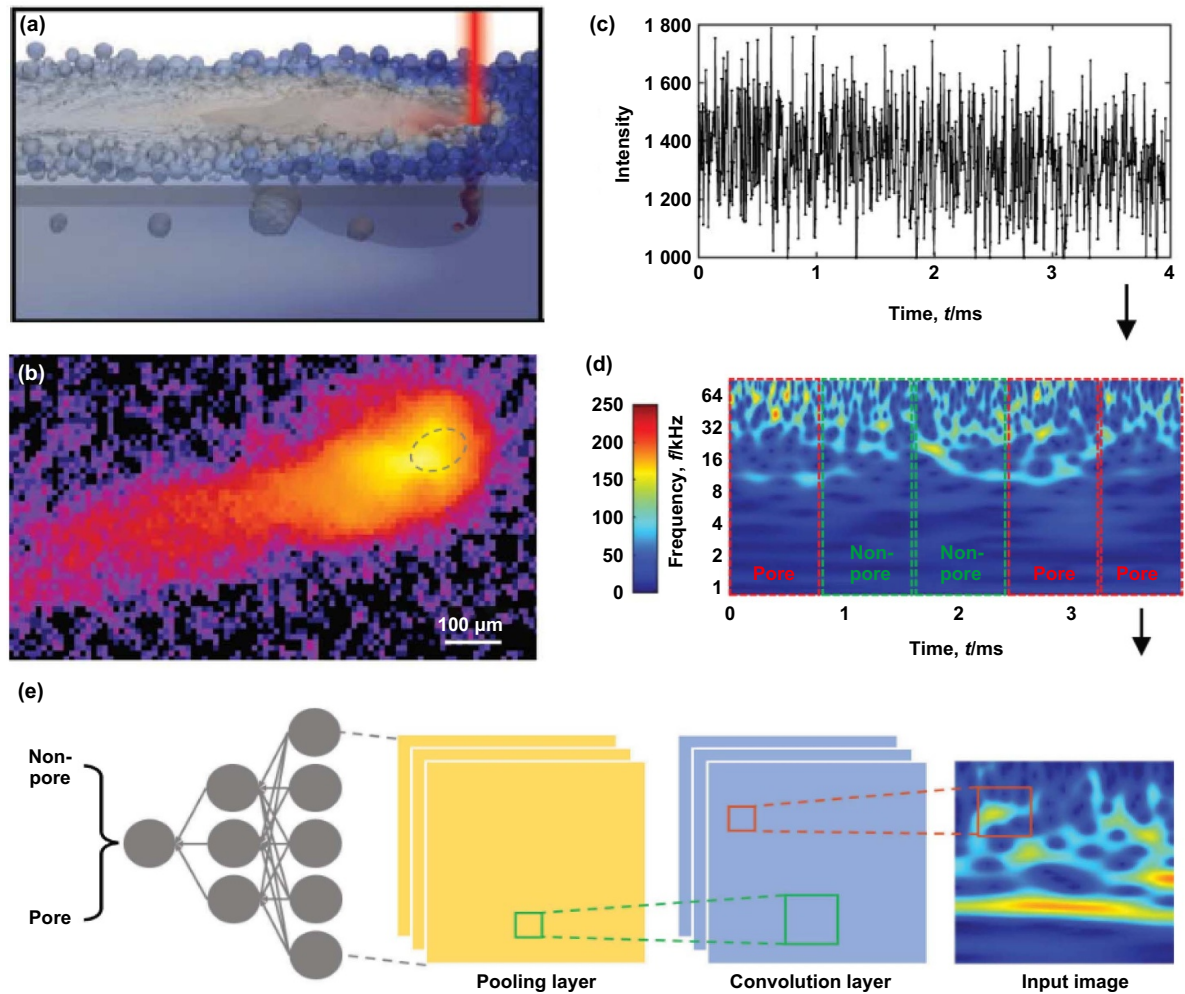


Figure 16. Real-time keyhole porosity detection by high-speed synchrotron X-ray. From^[178]. Reprinted with permission from AAAS. (a) Schematic of the laser melting of Ti-6Al-4V. (b) A representative angle top-view thermal image. (c) Typical time-series signal of the average emission intensity from the keyhole region. (d) Wavelet analysis performed over the time-series signals in (c). (e) Machine-learning approach with sectioned scalograms as input data.

availability of more high-quality X-ray datasets for LDED to unlock the potential of ML-based defect monitoring using X-ray data.

4.5. Data fusion

Data fusion offers a comprehensive approach by integrating multiple data sources, effectively addressing the limitations of individual data types, optimizing the signal-to-noise ratio, and enhancing the predictability of process outcomes^[101]. This section examines the advantages, technologies, and challenges of data fusion in LDED from three perspectives (Figure 17): process data fusion, process-quality data fusion, and process-simulation data fusion.

Process data fusion is the primary approach for data integration in DED, focusing on the synchronization and temporal alignment of multi-sensor data. The difficulty in achieving spatiotemporal alignment across diverse data sources impacts the reliability and robustness of defect monitoring and quality control. Kim et al.^[181] proposed a DL-based method to

estimate the melt-pool coordinates directly within the machine coordinate system from melt-pool images. This method eliminates the need for system-wide synchronization by using only the process settings and melt-pool images provided by the machine, offering a valuable alternative for spatial registration of in-situ monitoring data. Similarly, as shown in Figure 17(a), Chen et al.^[94] proposed a method to extract features from multi-sensor inputs and register them spatiotemporally with real-time robot tool centre point (TCP) positions, facilitating localized quality mapping. This system synchronizes and registers multi-sensor features, ML prediction outputs, and robot TCP data, using the ROS message filter module's approximate time synchronizer algorithm. By aligning messages from different sensing modalities based on timestamps, this method achieved significant improvements in defect prediction, with 96% accuracy, a 99% ROC-AUC score, and a 4.4% false positive rate, greatly surpassing traditional single-dataset approaches.

Process-quality data fusion combines online monitoring data with offline inspection data, enabling the integration of

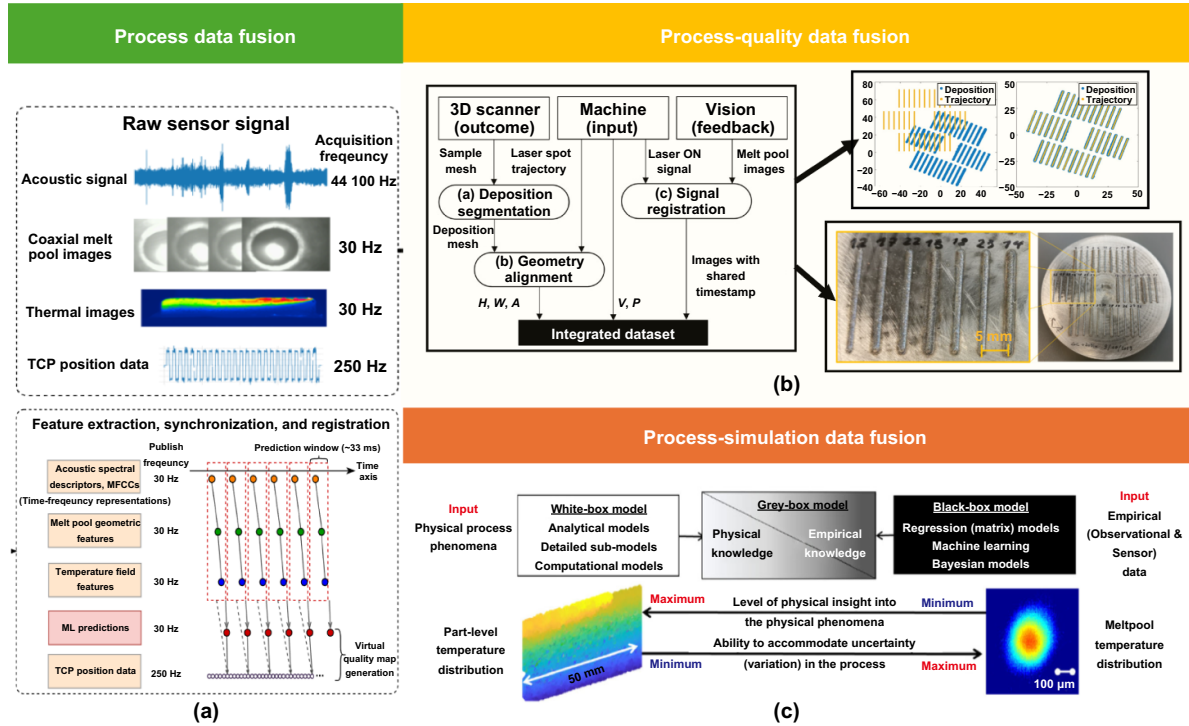


Figure 17. Data fusion. (a) Synchronization and registration of multi-sensor features, machine learning predictions, and real-time robot TCP positions. Reprinted from^[94], Copyright (2023), with permission from Elsevier. (b) Online and offline multimodal data registration. Reproduced from^[89]. CC BY 4.0. (c) Physics-driven model and data-driven model fusion in occurrence prediction by SVM.^[165] [3 July 2019], reprinted by permission of the publisher (Taylor & Francis Ltd, www.tandfonline.com).

real-time process insights and post-process evaluations. As shown in Figure 17(b), Perani et al.^[89] developed a process-quality data fusion framework for LDED that integrates real-time monitoring and offline quality measurements. Their method combines coaxial melt pool images and process inputs (e.g., laser power, scan speed) with 3D surface reconstructions obtained via fringe projection scanning. This fused dataset is then used to train a deep learning model composed of convolutional and dense neural networks to predict track geometry (e.g., width, height, cross-section) during deposition. The model successfully correlates process parameters and visual cues with local geometrical features, achieving near-real-time prediction (38 ms per instance), and shows potential for closed-loop control. This approach significantly enhances the ability to maintain target geometry even during process transients, making it highly promising for adaptive LDED process control.

Process-simulation data fusion integrates sensor data with physics-based simulation outputs, combining the predictive power of data-driven approaches with the interpretability of physical models. As shown in Figure 17(c), a study by Gaikwad et al.^[165] used thermal simulations, sensor data, and analytical techniques to detect defects during AM. This method employed a graph-theory-based thermal conduction model in conjunction with in-situ sensor data to predict defects, enhancing accuracy of defect prediction. Experimental results showed that using only sensor data or simulation data yielded F1 scores of 81.6% and 82.9%, respectively, whereas combining both approaches

increased the F1 score to 91%. Similarly, in^[162], Guo et al. combined a physics- finite element analysis (FEA) simulation of melt-pool parameters with a data-driven DL model to predict porosity during the printing process. This hybrid approach demonstrated significant advantages, leveraging the strengths of physics-driven models for interpretability and data-driven framework for handling complex datasets.

4.6. Summary

ML offers significant advantages in LDED, by enabling precise defect prediction and process optimization. ML applications span a wide range of areas, including image-based melt-pool monitoring, temperature analysis, and acoustic emission data for real-time quality assessment. Supervised, unsupervised, and semi-supervised ML approaches have demonstrated effectiveness in analyzing LDED data, with DL models achieving high accuracy in detecting critical defects such as porosity and cracks. However, in-situ monitoring using ML in LDED still faces challenges:

- **Data acquisition and quality:** LDED data is affected by noise, measurement errors, and environmental factors, leading to instability. The lack of standardized labeling limits supervised learning. The absence of high-quality datasets reduces model generalization, hindering its adaptability in complex manufacturing environments.

- Real-time data processing: LDED demands millisecond-level feedback, yet ML models' high computational complexity may introduce latency. Moreover, multi-sensor data synchronization and fusion are challenging, affecting real-time control. Efficient multimodal data processing is crucial for accurate predictions.
- Model generalization: variations in process parameters and materials affect LDED model generalization. Minor parameter changes impact build quality, while differing thermal properties reduce model applicability. Environmental factors further affect stability, making robustness crucial.
- Interpretability and industrial deployment: the black-box nature of ML models limits industrial adoption, reducing trust due to poor interpretability. Additionally, ML methods in LDED lack standardization, hindering large-scale deployment. Improving interpretability and reliability is essential.

Future research of ML-based analysis should focus on refining multimodal data integration and developing high-precision, adaptive models, contributing to the reliability and scalability of LDED monitoring in industrial applications.

5. On-line quality controller

Generally, control of LDED-built quality can be implemented in either an open-loop or a closed-loop manner. Open-loop control relies on prior knowledge, which can be obtained by engineering experience or simulation, to configure the DED process before printing. Depending on different manufacturing requirements, the configuration parameters can be tentatively adjusted as per the offline quality assessment or statistically optimized through the design of experiments. However, this strategy cannot account for the process variability, such as heat accumulation and material inhomogeneities, posing challenges for ensuring consistent quality, especially for complex structures with tight tolerances. In contrast, closed-loop control seeks to automatically adjust processing parameters during or between the layer scanning until the desired quality is achieved. This section examines closed-loop quality control in two distinct regimes, i.e., intra-layer process control and inter-layer tool path correction, depending on whether the parameters are modulated in real time or on a per-layer basis.

5.1. Intra-layer process control

The LDED process is prone to variations caused by deterministic drift and unpredictable disturbances such as thermal build-up and power fluctuations, respectively, which can adversely impact the quality and consistency of the built parts. Closed-loop process control, which monitors the dynamics and compensates for deviations in real time, is essential for maintaining process stability, repeatability, and overall printing quality.

A general scheme of the closed-loop process control system is presented in Figure 18. Two main elements, e.g., control variables and sensing outputs, are critical in designing a successful controller. The control variables represent the parameters which the system can adjust to influence the process.

Although many process parameters can affect deposition quality (refer to discussion in Section 2), laser power is often considered the primary variable for LDED processes^[11,19,160,182], as evidenced by the summarized survey in Table 12. This choice is justified by the following reasons: (i) laser power presents a direct physical effect on the melt-pool dynamics (as explained in Section 3.1); (ii) it can be adjusted almost instantaneously, offering a highly responsive control mechanism; (iii) it exerts minimal influence on the system's motion dynamics compared with scanning speed and feed rate. On the other hand, the powder or wire feed rate, despite influencing deposition quality, is rarely used as a feedback control variable due to the slow response of build geometry to its variations^[23]. Sensing outputs are pertaining to the real-time measurements that indicate the process stability and/or quality, providing essential feedback for the control loop. Common outputs, or process signatures, in LDED monitoring focus on melt-pool characteristics, including morphological features, such as width^[11,160,183,184], height^[185,186], and area^[187,188], and thermal features^[185,189], as these are directly linked to the quality of the deposition. Specifically, a stable and well-controlled melt-pool morphology ensures uniform bead geometry, consistent layer height, and minimal defects (as seen in Section 2.1.2), which are essential for achieving high geometrical accuracy. While the temperature distribution within the melt-pool governs the solidification rate and thermal gradients, which directly influence the microstructure of the deposited material. Faster cooling rates generally lead to finer microstructures, which can enhance mechanical properties such as hardness^[189,190]. It is worth noting that the sensing signals often require dedicated post-processing, such as advanced ML techniques introduced in Section 4, before they can be adopted as feedback signatures. This post-processing step can incur an extra time delay^[188,191], depending on the acquisition and real-time control hardware. The feedback signature is further compared with a reference value, yielding an error signal that dictates the controller actions.

LDED process controllers are typically designed using either model-free or model-based approaches, depending on whether a process model that represents the mathematical relationship between control variables and sensing outputs is needed. Different from numerical models^[192] for material removal mechanisms, the process model for control purposes is established through system identification^[193] to incorporate the dynamic characteristics of the LDED system. The comparison of model-free and model-based controllers is presented in Figure 19. Model-free controller eliminates the need for a detailed process model, thereby simplifying their implementation in discrete systems. A typical example of model-free LDED process controller is illustrated in Figure 20(a), where Smoqi et al.^[19] developed a rule-based controller to maintain a constant MPT during the P-LDED process. Laser power was adjusted based on real-time temperature deviations monitored by coaxial dual-wavelength imaging pyrometry and user-defined thresholds. This approach effectively compensated for disturbances, promoting microstructure homogeneity and reducing porosity in trapezoid-shaped stainless-steel parts. Similarly, Farshidianfar et al.^[190] used a PID controller to

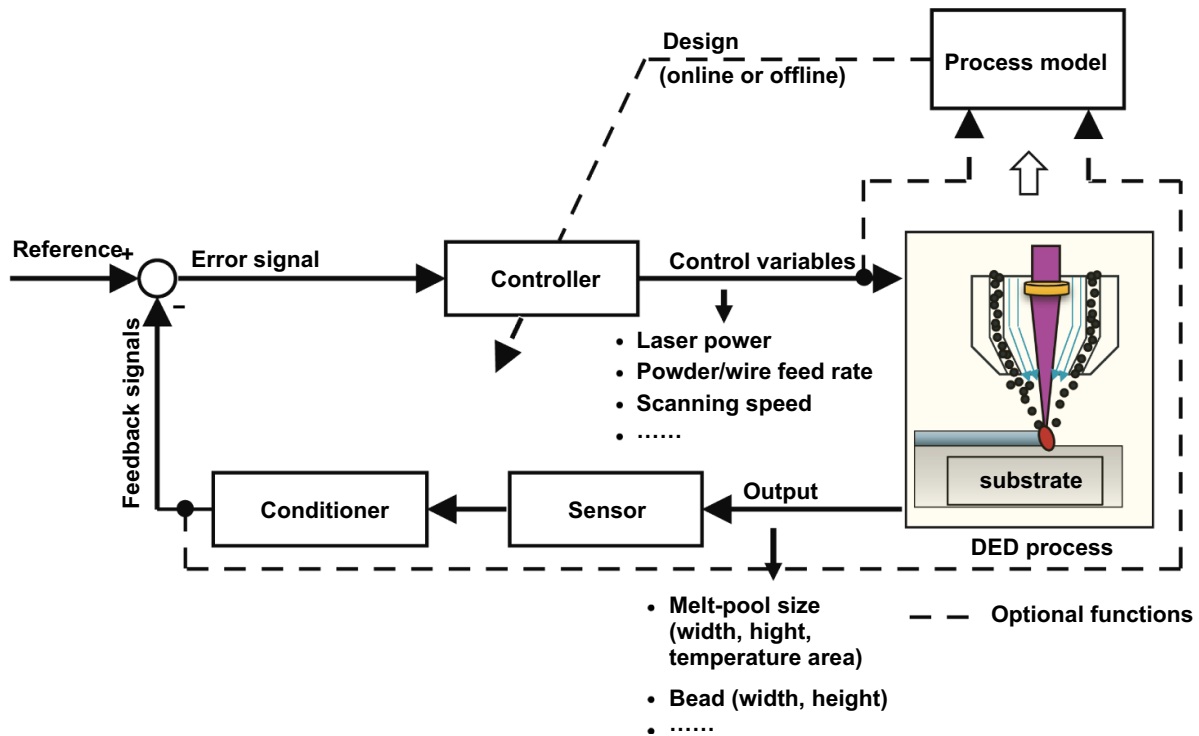


Figure 18. A general scheme for closed-loop LDED process control.

regulate cooling rates, successfully controlling microstructure and hardness. However, traditional model-free controllers have two main limitations: (1) they show limited control effects in handling multivariable and coupled interactions in LDED processes^[194]; (2) their effectiveness in non-linear and time-varying LDED processes remains unvalidated^[195]. In this respect, advanced control strategies with the integration of intelligent inference system have been explored. For instance, Xiong et al.^[196] proposed a two-dimensional Mamdani fuzzy controller, which was implemented through fuzzification, fuzzy reasoning, and defuzzification, to maintain the layer width in the process of printing 20-layered walls with variable widths. Mattera et al.^[194] applied reinforcement learning controller, which involved a neural network-driven deep deterministic policy and a reward function for the representation of desired quality outcome, for the complex printing environment. In both cases, flexible and informed control decisions were made to offer a superior capability in managing uncertainties and disturbances, achieving exceptional robustness and enhanced performance. However, the complex control logics often demand substantial computational resources and exploratory experiments.

Conversely, model-based controllers rely on process models obtained through system identification to design and regulate the controller structure and parameters. These controllers offer predictable and optimal control over process stability, ensuring high-precision and consistent printing quality. Rahmani Dehaghani et al.^[193] comprehensively investigated the relationship of parameter-signature-quality using

first- and second-order linear models, Hammerstein-Wiener models, and autoregressive with extra input (ARX) models to represent the mathematical relationship between parameters, e.g., laser power, wire feed speed, travel speed, and electrical power, and melt-pool characteristics. Two PID controllers were then implemented to directly or indirectly control the melt-pool width and bead width, respectively, depending on whether the signature-quality prediction model was considered in the control loop. However, these controllers often assume constant transfer functions, limiting their capability for handling a time-varying process. In this respect, Akbari and Kovacevic^[160] proposed an adaptive PI controller to maintain a constant melt-pool width during the P-LDED process, with the controller adaptively updated based on an identified first-order transfer model. This strategy effectively managed dynamic responses of the system such as the cooling rate as per the increasing deposition height, resulting in uniform and fine microstructure in thin-wall parts. A similar adaptive controller was reported by Chen et al.^[182], using the virtual reference feedback tuning (VRFT) algorithm for parameter auto-tuning, which was performed periodically in a constant time interval, as depicted in Figure 20(b). The digital controller was applied to print a semicylinder structure, yielding a flattened surface with little bulge area on the centre due to stable melt-pools under the effect of regulated heat input and localized heat accumulation throughout the fabrication process. To address rapidly changing system characteristics, more sophisticated model-based controllers such as adaptive sliding mode controller^[186] and self-learning single-neuron

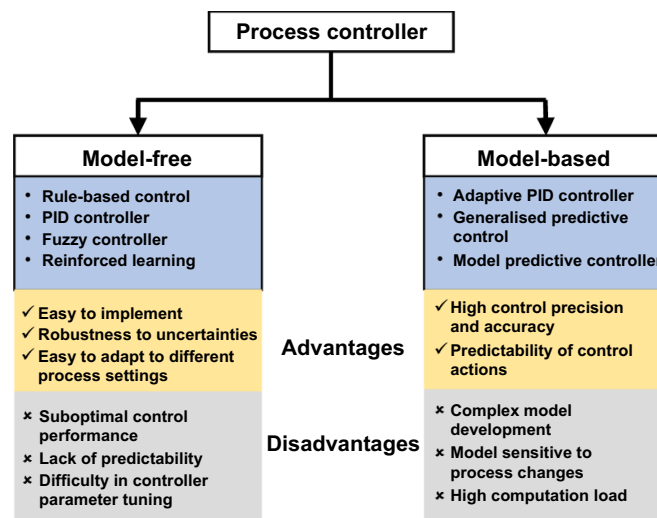
Table 12. A survey on intra-layer real-time controller applied for LDED process.

	Sub-process	Control variables	Sensing outputs	Monitoring sensors	Plant model	Controller	Quality remarks	References
Model-free process controller	P-LDED	Laser power	Melt-pool width	Infrared camera		PID controller	Surface roughness reduced by 57.5%, porosity by 52.5%, pitting potential (corrosion) increased by ~18.6%	[11]
	P-LDED	Laser power	Melt-pool temperature	Germanium photodiode sensor		PID controller with path-dependent set values	Homogenous microstructure and hardness for thin wall structures	[189]
	P-LDED	Laser power	Deposition height	Two optical deposition height sensors		Fuzzy controller	Averaged height error within 0.05 mm for ramp-shaped structures	[183]
	P-LDED	Laser power	Peak melt-pool temperature	Two-wavelength imaging pyrometer		Rule-based controller	Uniform microstructure and reduced volume percent porosity (0.036%–0.043% by control loop)	[19]
	P-LDED	Laser power	Melt-pool size/area	Infrared camera (off axis, side view)		PID controller	Uniform geometry in both vertical and horizontal bead cross-sections	[187]
	P-LDED	Scanning speed	Cooling rate	Thermal infrared camera		PID controller	Uniform microstructure and hardness profile across layers	[190]
Model-based process controller	P-LDED	Laser power	Melt-pool width	Coaxial CMOS camera	First-order model with parameters changing in the first 10 layers	Adaptive PI controller	Homogeneous and finer microstructure with slight increase in grain size	[160]

(Continued.)

Table 12. (Continued.)

Sub-process	Control variables	Sensing outputs	Monitoring sensors	Plant model	Controller	Quality remarks	References
P-LDED	Laser power	Melt-pool width	Coaxial CCD camera	Adaptive model (identified by VRFT)	Adaptive PID controller	Improved geometric accuracy (flatter surface and sharper edges)	[182]
P-LDED	Laser power	Melt-pool height and temperature	Dual-color pyrometer + Three high-speed CCD camera	state-space model (two-order)	Two-input single-output hybrid control system	Avoidance of distortion on trailing edges of turbine blades	[185]
P-LDED	Scanning speed	Melt-pool height	CCD Camera	First-order transfer function with time delay (state space realization)	Adaptive sliding mode controller	Desired flat deposition surface even with damaged surface slots	[186]

**Figure 19.** Comparison of model-based and model-free process controller.

controller^[197] have been reported. These intelligent controllers, capable of self-regulation, demonstrate adequate robustness in managing process variations, supporting long-term printing stability and high-precision deposition quality.

5.2. Inter-layer path-dependent deposition control

As the DED process builds layer by layer, the thermal conditions, such as the cooling rate^[190] and heat conduction mode^[160], can vary significantly. Hagenlocher et al.^[198] reported an increase of up to 400 K in the residual temperature after depositing 50 layers in W-LDED processing of Aluminium, through in-situ IR camera measurements. The heat accumulation accounted for inhomogeneous solidification conditions

and the formation of columnar grain structures. These process variances in temporal and spatial evolutions can lead to accumulated geometrical deviations and anisotropic mechanical properties in deposition quality, especially in multi-bead printing where beads are overlapped within each layer^[199]. For instance, Garmendia et al.^[23] reported that severe deposition height errors were propagated along increasing layers when printing hexahedrons with constant build parameters, which in turn negatively influenced melt-pool stability. Such layer-wise deviations can result in surface or subsurface defects that cannot be effectively compensated for by the aforementioned intra-layer controllers (as introduced in Section 5.1), potentially causing catastrophic failures in the LDED printing process.

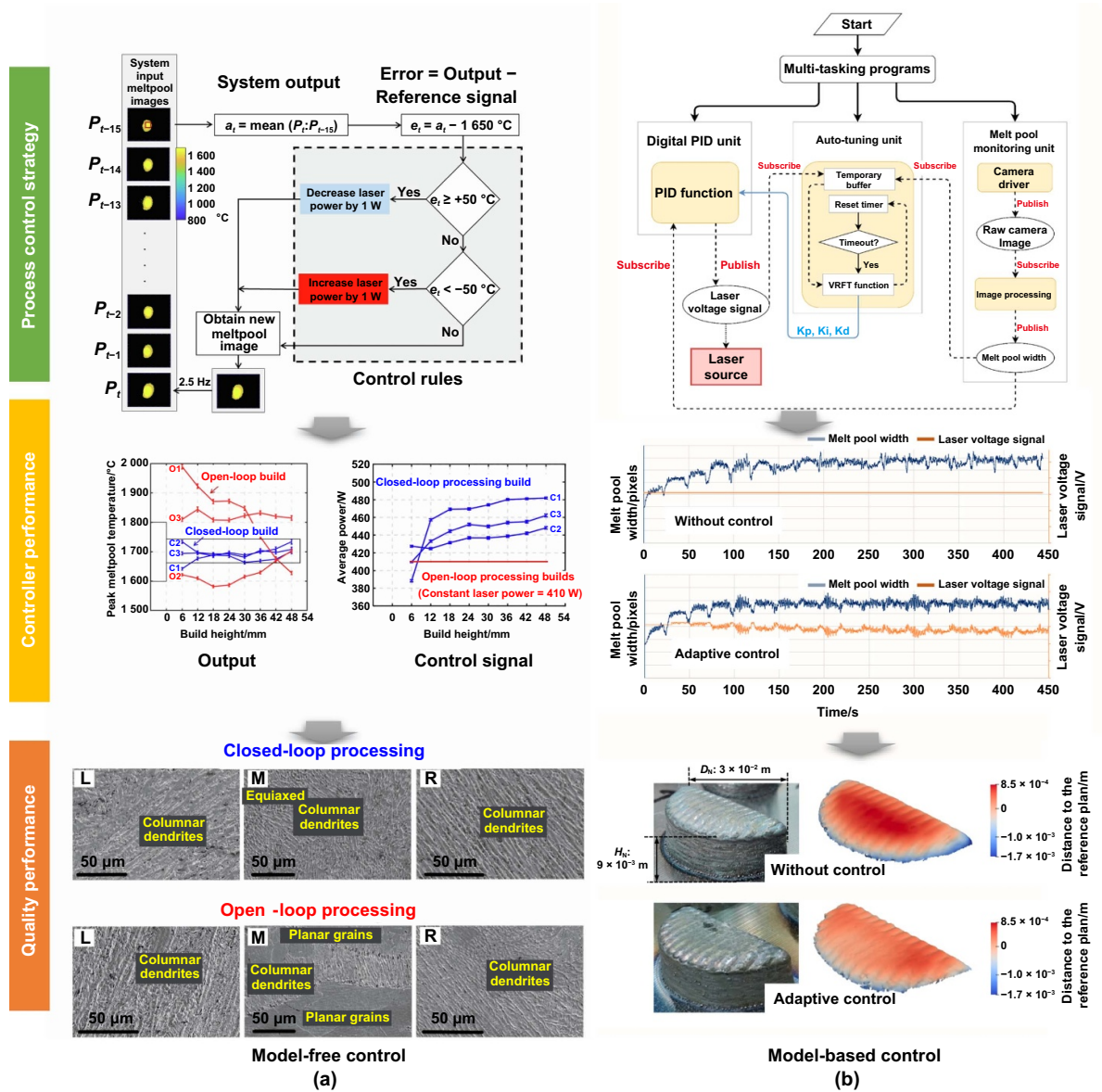


Figure 20. Intra-layer LDED quality control: (a) model-free control. Reprinted from^[19], Copyright (2022), with permission from Elsevier and (b) model-based control. Reproduced from^[182], CC BY 4.0, from controller design to track of controller performance and quality performance.

To mitigate the layer-wise deviations, digital controllers designed for correcting the tool path^[22,78] or optimizing the path-dependent manufacturing parameters^[199–202] are essential, particularly for W-LDED processes that are prone to geometric inaccuracies and microstructural inhomogeneities^[193]. Unlike the real-time process controllers, path-dependent controllers act on subsequent layers based on the quality of previously deposited layers. These layer-wise deposition beads are often measured by in-situ optical scanning sensors (Section 3.1.1) such as laser line scanner^[23,78] or structure light scanner^[22,203]. It is worth mentioning that the deposition process needs to be suspended regularly for these measurements^[23], even though scanner sensors are integrated into the DED system. A summary of path-dependent controllers is provided in Table 13.

To mitigate build failures and surface quality degradation in the P-LDED process, Xu et al.^[22] introduced an inter-layer

dimensional correction method using an on-machine laser line scanner. The scanned 3D point cloud underwent post-processing, including noise filtering and clustering, to detect the deviation boundaries for bulge defects. The correction involved selectively switching the laser power on or off, depending on whether the tool path segments were outside or inside the defect boundary regions, respectively.

Although the basic laser manipulation effectively eradicated the trailing dimensional defects, it showed limited control capabilities for more complex structures. Advanced path-dependent correction strategies involve mathematically informed adjustments to deposition trajectories based on measured dimensional deviations for each layer. For example, Garmendia et al.^[78] proposed a layer-wise height control strategy for the W-LDED process, reconfiguring the tool path based on measurements from previously deposited layer profiles. As illustrated in Figure 21(a), this strategy

Table 13. A survey on inter-layer quality controller applied for LDED process.

Sub-processes	Control variables	Sensing outputs	Measurement techniques	Controller	References
P-LDED	Tool-path generation	Layer height profile (point cloud)	Structured light scanner		[23]
P-LDED	Tool-path generation (correction or repairing)	Dimensional deviations (3D point cloud)	Laser line scanner		[22]
P-LDED	Powder feed rate	Layer height (mean value), through nozzle working distance	CCD camera	PID controller	[204]
W-LDED	Wire feed-rate (path dependent)	Layer height (profile)	Coaxial optical coherence tomography	PI controller	[200]
W-LDED	Trajectory (deposition path) + Scanning speed (local)	Layer height (mean + profile)	Structured light scanner	Path-based correction model (scanned profile)	[78]
W-LDED	Wire feed-rate (path dependent)	Layer height (profile)	Resistance measurement system	Iterative learning controller	[201]
W-LDED	Wire feed-rate (path dependent)	Layer height (profile)	Laser scanner	Iterative learning controller	[203]

comprised both mean and local height corrections, which were chronologically applied to generate a more accurate theoretical geometry model for each sliced layer as well as to tune the intra-layer scanning speed along the subsequent point-to-point deposition trajectories, respectively. This approach was validated using an artificial pocket-shaped defect sample, proving effective for repairing deposition defects. However, this adjustment assumed a linear relationship between scanning speed and point-wise height deviations. This assumption can be violated under different process settings.

To address the process variability, Bernauer et al.^[205] developed a set of closed-loop PI controllers to maintain a constant distance between the deposition surface and the printer head. These controllers were implemented within an interconnected system architecture, as depicted in Figure 21(b). The system consisted of a 3D laser scanner for measurement, an industrial PC with a programmable logiccontroller for data processing, and a MATLAB program for generating control actions. The position-dependent control strategy involved segmenting each thin-walled layer, with each segment being controlled independently by a PI controller using the heights of the previously deposited layers. Compared to the open-loop system, this closed-loop strategy demonstrated superior performance in maintaining consistent deposition quality, even under deterministic and abrupt disturbances, as shown in tests with inclined planes and machined grooves, respectively.

5.3. Summary

This section reviews closed-loop control strategies for real-time and per-layer regulation of LDED quality, with a primary focus on geometrical aspects such as melt-pool morphology and deposition height, typically monitored through in-situ

visual sensors and on-machine optical scanners. Most reported controllers are single-input, single-output systems, particularly PID controllers, valued for their simplicity and computational efficiency, with laser power commonly used as the control variable. However, advanced controllers capable of managing multiple process parameters, adapting to dynamic changes, and enhancing robustness remain limited.

6. Future research directions and conclusions

6.1. Future research directions

Despite the significant advancements in online quality enhancement, several challenges persist, limiting its broader industrial application: (1) the underlying mechanisms of defect formation are not yet fully elucidated, which impedes the development of predictive models capable of mitigating these issues; (2) the vast array of data generated during the process, often derived from multi-modal sensing systems, lacks unified processing frameworks, resulting in fragmented insights that fail to capture the full complexity of the system; (3) the intricate relationship between process and quality signatures, which are inherently nonlinear and multi-scale, makes it difficult to establish precise correlations or design adaptive control strategies; (4) balancing multiple and conflicting objectives, such as optimizing surface finish, build speed, and material properties, further complicates control efforts, particularly in scenarios requiring real-time adjustments; (5) these challenges are exacerbated by the absence of a universal industrial platform for implementing monitoring and control strategies, which has led to the proliferation of bespoke solutions that lack scalability and cross-system compatibility.

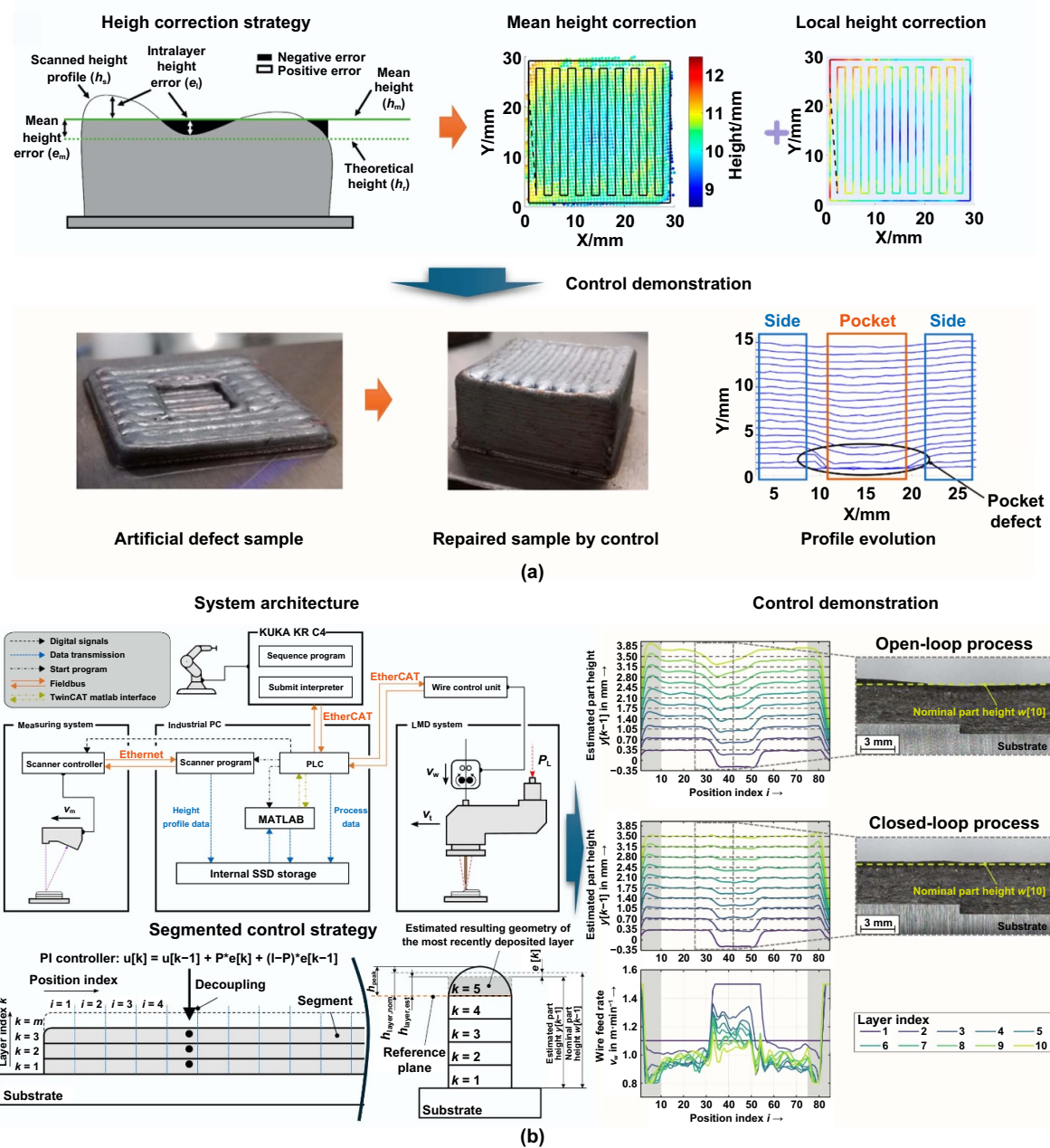


Figure 21. Interlayer quality control based on online tool path correction, which is implemented through (a) scanning speed optimization. Reproduced from^[78]. CC BY 4.0. and (b) wire feed-rate optimization. Reproduced from^[205]. CC BY 4.0.

Overcoming these interwoven challenges requires a concerted effort to integrate advancements in process understanding, data analytics, and control design into a cohesive, standardized framework that can meet the demands of modern industrial applications. Looking forward, several key areas within monitoring and control, as shown in Figure 22, can be explored to advance LDED toward industrial-level quality and efficiency standards.

6.1.1. Sensor-based monitoring. Future research on sensor-based monitoring must contribute to establishing robust standards, advancing process signatures, improving

multi-sensor data integration, and integrating physics-informed ML models. Several promising avenues are outlined below:

One critical area is the establishment of standards for defects and quality tolerances in LDED. Despite the widespread adoption of sensor-based monitoring, there is currently no universally accepted framework for defining defect types, tolerances, or quality benchmarks across diverse industrial applications. This lack of standardization hinders consistent quality evaluation and prevents the development of broadly applicable monitoring protocols. Establishing international standards and application-specific quality criteria will provide manufacturers and researchers with clear benchmarks,

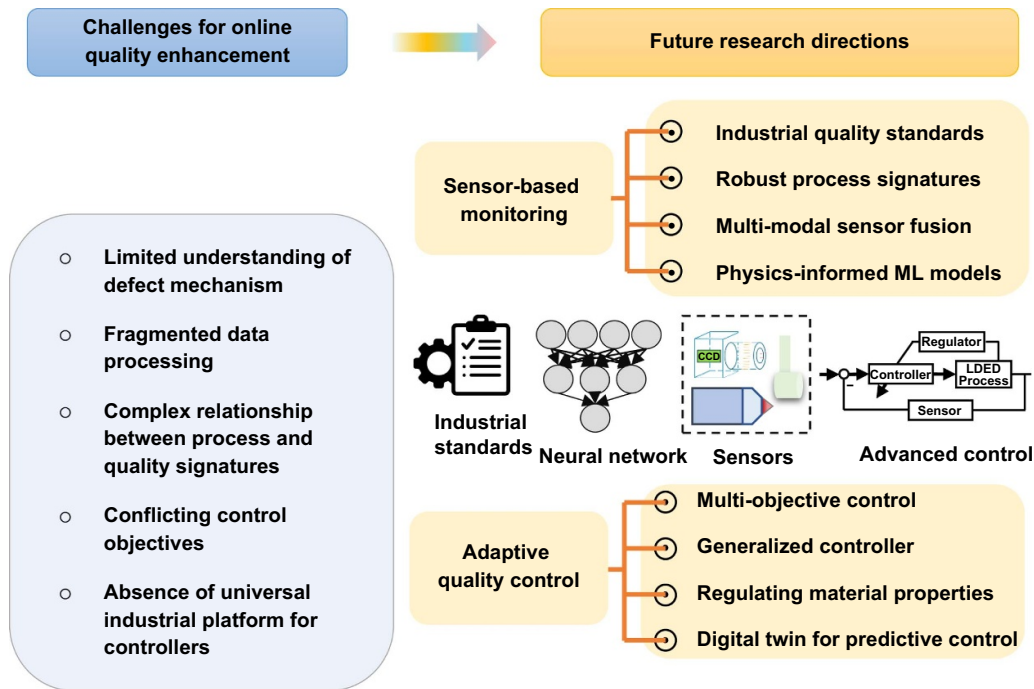


Figure 22. Present challenges for online LDED quality control and proposed future research directions with monitoring and control to address these challenges.

fostering greater consistency in the evaluation and adoption of LDED technologies.

Another promising avenue lies in the development of interpretable and robust process signatures. Current monitoring approaches often rely on basic signatures such as melt-pool width, height, or area to assess process stability. While useful, these metrics fail to capture the complex and transient dynamics inherent in LDED processes. Future research should focus on identifying process signatures that are more sensitive to real-time variations and directly linked to defect formation mechanisms. Such signatures should be designed for real-time extraction and processing, enabling immediate feedback and adjustments to improve part quality. Enhanced interpretability of these signatures would also facilitate broader adoption and more effective communication between automated systems and human operators.

The integration of multiple sensor modalities represents another key direction through multi-modal sensor data fusion. With the increasing availability of diverse sensing technologies, including thermal imaging, optical cameras, acoustic emissions, and spectral analysis, future systems must focus on effectively combining data streams across these modalities. Multi-modal fusion, particularly when supported by ML, can generate a more comprehensive understanding of process behavior, improving the reliability and accuracy of defect detection. By reducing data redundancy and enabling insights across scales and dimensions, efficient data fusion frameworks will enhance the scalability of sensor-based monitoring systems for industrial applications.

Finally, exploring physics-informed ML models offers significant potential to advance sensor-based monitoring in LDED. While conventional ML models excel at identifying

patterns within large datasets, their reliance on empirical data alone often limits their generalization across varying process conditions. Physics-informed ML approaches, which integrate established physical laws into data-driven models, can provide higher predictive accuracy and adaptability. These hybrid models balance empirical insights with theoretical principles, making them more robust to variations in process dynamics and better suited for complex LDED environments.

6.1.2. Adaptive quality control. Future research on adaptive quality control must focus on developing robust, multi-objective, and material-agnostic controllers capable of dynamically adjusting to varying process conditions and quality requirements. Several promising avenues are outlined below:

One critical direction is the development of control strategies for complex geometries and multi-layer structures. Current controllers are primarily validated on simplified geometries or single-track samples, such as pocket^[78] and cylinder^[203], leaving their efficacy for more intricate builds largely unverified. As the complexity of LDED applications grows, adaptive controllers must be capable of maintaining consistent quality across layers and tracks, where inter-layer variations and thermal effects introduce non-linearities. Robust control strategies that incorporate dynamic process feedback and layer-by-layer quality assessment will be essential for scaling LDED to industrial applications involving intricate geometries.

Multi-objective control represents another significant research priority. Achieving optimal quality in LDED requires simultaneous regulation of multiple factors, such as dimensional accuracy, surface finish, and material properties.

Several hybrid controllers have been developed to manage these multi-variable aspects. For example, Song et al.^[185] demonstrated the use of a rule-based deposition controller in combination with a generalized predictive controller to stabilize layer growth and MPT, respectively. Similarly, Gibson et al.^[5] attempted to control melt-pool size and average laser simultaneously by adjusting laser power in real time while modulating print speed and nominal deposition rate on a per-layer basis. By dynamically balancing competing quality objectives such as stabilizing MPT while ensuring uniform layer growth, these controllers can address the interdependencies between quality parameters. Incorporating advanced ML into these systems could further enhance their ability to manage complex, multi-variable relationships in real-time, optimizing performance across diverse build conditions.

The direct regulation of material properties is a transformative goal for LDED adaptive control. While stabilizing MPT has shown promise in reducing thermal accumulation and promoting microstructural homogeneity^[11,189,190], real-time control of microstructural features and material properties remains underexplored. Future research could leverage surrogate modeling techniques to predict material performance based on in-situ process data, enabling automated regulation of location-dependent properties. This approach would bridge the gap between process monitoring and quality control, ensuring that material properties align with application-specific requirements.

Developing generalized controllers for diverse materials and applications is another critical focus area. Most existing controllers are designed for specific materials or processes, limiting their versatility and industrial applicability. Future work should aim to design material-agnostic controllers that can be adapted to varying material properties and structural requirements without extensive recalibration. These generalized controllers should also comply with industrial standards for hardware interoperability, robustness to process variability, and operational safety. Benchmarking frameworks that evaluate the performance of such controllers across different setups and use cases will be instrumental in their development and adoption. As a typical example of exploration, Regulin and Barucci^[191] conducted a comparative study to benchmark different control approaches for regulating the melt-pool width in DED, critically assessing their tracking performance.

While the proposed future directions of multi-objective and general-purpose controllers offer promising pathways toward intelligent LDED systems, their practical implementation introduces several challenges. Chief among these is the computational complexity associated with real-time multi-sensor data processing, high-fidelity modeling, and dynamic decision-making, all of which demand significant processing power and efficient algorithm design. Furthermore, ensuring hardware compatibility across diverse sensing and actuation platforms remains a major hurdle, particularly when integrating legacy systems with new, data-intensive modules. Latency in data acquisition and feedback loops can also compromise control accuracy, especially in high-speed deposition scenarios. Additionally, the lack of standardized communication protocols and system architectures complicates modularity

and scalability. These bottlenecks highlight the need for co-design approaches that consider both software optimization and hardware capabilities to ensure that intelligent control systems remain feasible and reliable for industrial deployment.

Finally, digital twin technology holds immense potential for advancing adaptive quality control in LDED. By integrating real-time sensor data with high-fidelity predictive models, digital twins can simulate process behavior and material properties dynamically. This capability would allow for proactive process adjustments, reducing the likelihood of defects and maximizing overall efficiency. Incorporating ML into digital twins can further enhance their predictive accuracy, enabling them to model complex interactions between process parameters and part quality. Future research should focus on refining these systems to ensure seamless integration with real-time monitoring and control platforms, paving the way for autonomous, intelligent manufacturing systems.

6.2. Conclusions

LDED has proven to be a powerful technology for producing high-performance parts with complex geometries and unique material properties. However, LDED faces ongoing challenges in maintaining consistent quality and repeatability due to the high variability in melt-pool dynamics and process conditions. This review has highlighted recent advancements in on-line quality control, focusing on in-situ measurement and adaptive control methods that allow for real-time adjustment of process parameters to improve quality. Monitoring approaches such as optical, thermal, and acoustic sensing have shown potential in capturing critical quality signatures, providing the foundation for a closed-loop control that can address common issues such as porosity, cracking, and residual stress in LDED parts. ML techniques are further enhancing these monitoring systems by enabling predictive modeling and adaptive quality control that align with the goals of zero-defect manufacturing.

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References

- [1] Tan C L, Deng C, Li S, Abena A, Jamshidi P, Essa K, Wu L K, Xu G H, Attallah M M and Liu J. 2022. Mechanical property and biological behaviour of additive manufactured TiNi functionally graded lattice structure. *Int. J. Extrem. Manuf.* **4**, 045003.
- [2] Zhang C et al. 2019. Additive manufacturing of functionally graded materials: a review. *Mater. Sci. Eng. A* **764**, 138209.
- [3] Nazir A, Gokcekaya O, Md Masum Billah K, Ertugrul O, Jiang J C, Sun J Y and Hussain S. 2023. Multi-material additive manufacturing: a systematic review of

- design, properties, applications, challenges, and 3D printing of materials and cellular metamaterials. *Mater. Des.* **226**, 111661.
- [4] Blakey-Milner B, Gradl P, Snedden G, Brooks M, Pitot J, Lopez E, Leary M, Berto F and Du Plessis A. 2021. Metal additive manufacturing in aerospace: a review. *Mater. Des.* **209**, 110008.
- [5] Gibson B T, Bandari Y K, Richardson B S, Henry W C, Vetland E J, Sundermann T W and Love L J. 2020. Melt pool size control through multiple closed-loop modalities in laser-wire directed energy deposition of Ti-6Al-4V. *Addit. Manuf.* **32**, 100993.
- [6] Köhler M, Sun L, Hensel J, Pallaspuro S, Kömi J, Dilger K and Zhang Z L. 2021. Comparative study of deposition patterns for DED-Arc additive manufacturing of Al-4046. *Mater. Des.* **210**, 110122.
- [7] Mobarak M H, Islam M A, Hossain N, Al Mahmud M Z, Rayhan M T, Nishi N J and Chowdhury M A. 2023. Recent advances of additive manufacturing in implant fabrication—a review. *Appl. Surf. Sci. Adv.* **18**, 100462.
- [8] Cai Y H, Xiong J, Chen H and Zhang G J. 2023. A review of *in-situ* monitoring and process control system in metal-based laser additive manufacturing. *J. Manuf. Syst.* **70**, 309–326.
- [9] Chen L Q, Bi G J, Yao X L, Su J L, Tan C L, Feng W H, Benakis M, Chew Y and Moon S K. 2024. *In-situ* process monitoring and adaptive quality enhancement in laser additive manufacturing: a critical review. *J. Manuf. Syst.* **74**, 527–574.
- [10] Saboori A, Aversa A, Marchese G, Biamino S, Lombardi M and Fino P. 2019. Application of directed energy deposition-based additive manufacturing in repair. *Appl. Sci.* **9**, 3316.
- [11] Su Y Y, Wang C Y, Xu X, Luo K Y and Lu J Z. 2023. Pore defects and corrosion behavior of AISI 316L stainless steel fabricated by laser directed energy deposition under closed-loop control. *Surf. Coat. Technol.* **463**, 129527.
- [12] ISO. 2021. ISO/ASTM 52900: 2021(en) Additive manufacturing—General principles—Fundamentals and vocabulary. (Geneva: International Organization for Standardization)
- [13] Costello S C A, Cunningham C R, Xu F D, Shokrani A, Dhokia V and Newman S T. 2023. The state-of-the-art of wire arc directed energy deposition (WA-DED) as an additive manufacturing process for large metallic component manufacture. *Int. J. Comput. Int. Manuf.* **36**, 469–510.
- [14] Negi S, Nambolan A A, Kapil S, Joshi P S, Manivannan R, Karunakaran K P and Bhargava P. 2019. Review on electron beam based additive manufacturing. *Rapid Prototyp. J.* **26**, 485–498.
- [15] Nagalingam A P, Shamir M, Tureyen E B, Sharman A R C, Poyraz O, Yasa E and Hughes J. 2025. Recent progress in wire-arc and wire-laser directed energy deposition (DED) of titanium and aluminium alloys. *Int. J. Adv. Manuf. Technol.* **136**, 2035–2073.
- [16] Liu T S, Chen P, Qiu F, Yang H Y, Jin N T Y, Chew Y, Wang D, Li R D, Jiang Q C and Tan C L. 2024. Review on laser directed energy deposited aluminum alloys. *Int. J. Extrem. Manuf.* **6**, 022004.
- [17] Su J L, Li Q, Teng J, Ng F L, Shen Z L, Goh M H, Jiang F L, Sing S L, Yang T and Tan C L. 2025. Programmable mechanical properties of additively manufactured novel steel. *Int. J. Extrem. Manuf.* **7**, 015001.
- [18] Ghanadi N and Pasebani S. 2024. A review on wire-laser directed energy deposition: parameter control, process stability, and future research paths. *J. Manuf. Mater. Process.* **8**, 84.
- [19] Smoqi Z, Bevans B D, Gaikwad A, Craig J, Abul-Haj A, Roeder B, Macy B, Shield J E and Rao P. 2022. Closed-loop control of meltpool temperature in directed energy deposition. *Mater. Des.* **215**, 110508.
- [20] Ertay D S, Naiel M A, Vlasea M and Fieguth P. 2021. Process performance evaluation and classification via *in-situ* melt pool monitoring in directed energy deposition. *CIRP J. Manuf. Sci. Technol.* **35**, 298–314.
- [21] Dos Santos Paes L E, Pereira M, Xavier F A, Weingaertner W L and Vilarinho L O. 2022. Lack of fusion mitigation in directed energy deposition with laser (DED-L) additive manufacturing through laser remelting. *J. Manuf. Process.* **73**, 67–77.
- [22] Xu P, Yao X L, Chen L Q, Zhao C Y, Liu K, Moon S K and Bi G J. 2022. In-process adaptive dimension correction strategy for laser aided additive manufacturing using laser line scanning. *J. Mater. Process. Technol.* **303**, 117544.
- [23] Garmendia I, Pujana J, Lamikiz A, Madarieta M and Leunda J. 2019. Structured light-based height control for laser metal deposition. *J. Manuf. Process.* **42**, 20–27.
- [24] Gunasegaram D R, Barnard A S, Matthews M J, Jared B H, Andreaco A M, Bartsch K and Murphy A B. 2024. Machine learning-assisted *in-situ* adaptive strategies for the control of defects and anomalies in metal additive manufacturing. *Addit. Manuf.* **81**, 104013.
- [25] Zhang Y K, Shen S N, Li H and Hu Y W. 2022. Review of *in situ* and real-time monitoring of metal additive manufacturing based on image processing. *Int. J. Adv. Manuf. Technol.* **123**, 1–20.
- [26] AbouelNour Y and Gupta N. 2022. *In-situ* monitoring of sub-surface and internal defects in additive manufacturing: a review. *Mater. Des.* **222**, 111063.
- [27] Xia C Y, Pan Z X, Polden J, Li H J, Xu Y L, Chen S B and Zhang Y M. 2020. A review on wire arc additive manufacturing: monitoring, control and a framework of automated system. *J. Manuf. Syst.* **57**, 31–45.
- [28] Bhushan B. 2013. *Introduction to Tribology*. 2nd edn. (Wiley, Chichester, West Sussex, United Kingdom) (<https://doi.org/10.1002/9781118403259>)
- [29] Lim S, Ko Y, Hong D, Kim M and Song S J. 2025. Impact of additive manufacturing surface roughness on the aerodynamic performance of axial compressor blades. *Int. J. Aeronaut. Space Sci.* **26**, 42–49.
- [30] Ertay D S, Vlasea M and Erkorkmaz K. 2020. Thermomechanical and geometry model for directed energy deposition with 2D/3D toolpaths. *Addit. Manuf.* **35**, 101294.
- [31] Chen Y H et al. 2021. *In situ* X-ray quantification of melt pool behaviour during directed energy deposition additive manufacturing of stainless steel. *Mater. Lett.* **286**, 129205.
- [32] Craig O, Bois-Brochu A and Plucknett K. 2021. Geometry and surface characteristics of H13 hot-work tool steel manufactured using laser-directed energy deposition. *Int. J. Adv. Manuf. Technol.* **116**, 699–718.
- [33] Haley J C, Schoenung J M and Lavernia E J. 2019. Modelling particle impact on the melt pool and wettability effects in laser directed energy deposition additive manufacturing. *Mater. Sci. Eng. A* **761**, 138052.
- [34] Wang Q, Li J Y, Nassar A R, Reutzel E W and Mitchell W F. 2021. Model-based feedforward control of part height in directed energy deposition. *Materials* **14**, 337.
- [35] Binaga E, Yang L, Sohn H and Cheng J C P. 2022. Online geometry monitoring during directed energy deposition additive manufacturing using laser line scanning. *Precis. Eng.* **73**, 104–114.
- [36] Guo C G, He S Z, Yue H T, Li Q and Hao G B. 2021. Prediction modelling and process optimization for forming multi-layer cladding structures with laser directed energy deposition. *Opt. Laser Technol.* **134**, 106607.
- [37] Balhara H, Karthikeyan A, Hanchate A, Nakkina T G and Bukkapatnam S T S. 2023. Imaging systems and techniques for fusion-based metal additive manufacturing: a review. *Front. Manuf. Technol.* **3**, 1271190.

- [38] Odermatt A E, Dorn F, Ventzke V and Kashaev N. 2022. Coaxial laser directed energy deposition with wire of thin-walled duplex stainless steel parts: process discontinuities and their impact on the mechanical properties. *CIRP J. Manuf. Sci. Technol.* **37**, 443–453.
- [39] Xu J L, Wang X, Yao C X, Zou D M, Xiong R, Xiao R S, Huang T and Zhang B B. 2024. A dual *in-situ* monitoring of multiphase dynamics during laser wire fusion process with synchrotron radiation and visible light. *J. Manuf. Process.* **131**, 2528–2534.
- [40] Wang Y H, Hu K X, Li W D and Wang L H. 2023. Prediction of melt pool width and layer height for laser directed energy deposition enabled by physics-driven temporal convolutional network. *J. Manuf. Syst.* **69**, 1–17.
- [41] Mehrabi O, Seyedkashi S M H and Moradi M. 2024. Effect of the scanning strategy in the laser directed energy deposition process of SS316L-Inconel 625 FGM bulk. *Int. J. Adv. Manuf. Technol.* **135**, 5747–5761.
- [42] Kim H, Cong W L, Zhang H C and Liu Z C. 2017. Laser engineered net shaping of nickel-based superalloy Inconel 718 powders onto AISI 4140 alloy steel substrates: interface bond and fracture failure mechanism. *Materials* **10**, 341.
- [43] Svetlizky D, Das M, Zheng B L, Vyatskikh A L, Bose S, Bandyopadhyay A, Schoenung J M, Lavernia E J and Eliaz N. 2021. Directed energy deposition (DED) additive manufacturing: physical characteristics, defects, challenges and applications. *Mater. Today* **49**, 271–295.
- [44] Chandra S and Rao B C. 2017. A study of process parameters on workpiece anisotropy in the laser engineered net shaping (LENSTM) process. *J. Phys. D: Appl. Phys.* **50**, 225303.
- [45] Wang S H, Zhu L D, Dun Y, Yang Z C, Fuh J Y H and Yan W T. 2021. Multi-physics modeling of direct energy deposition process of thin-walled structures: defect analysis. *Comput. Mech.* **67**, 1229–1242.
- [46] Mahamood R M and Akinlabi E T. 2017. Scanning speed and powder flow rate influence on the properties of laser metal deposition of titanium alloy. *Int. J. Adv. Manuf. Technol.* **91**, 2419–2426.
- [47] Ge J, Pillay S and Ning H B. 2023. Post-process treatments for additive-manufactured metallic structures: a comprehensive review. *J. Mater. Eng. Perform.* **32**, 7073–7122.
- [48] Mahamood R M, Akinlabi E T and Akinlabi S. 2015. Laser power and scanning speed influence on the mechanical property of laser metal deposited titanium-alloy. *Lasers Manuf. Mater. Process.* **2**, 43–55.
- [49] Kim T G and Shim D S. 2021. Effect of laser power and powder feed rate on interfacial crack and mechanical/microstructural characterizations in repairing of 630 stainless steel using direct energy deposition. *Mater. Sci. Eng. A* **828**, 142004.
- [50] Ahn D G. 2021. Directed energy deposition (DED) process: state of the art. *Int. J. Precis. Eng. Manuf. Green Technol.* **8**, 703–742.
- [51] Park Y K, Nam H J, Park Y H and Lee W. 2024. Laser rescanning for enhancing mechanical properties of laser-directed energy-deposited high-manganese steels. *Micromachines* **15**, 176.
- [52] Piscopo G and Iuliano L. 2022. Current research and industrial application of laser powder directed energy deposition. *Int. J. Adv. Manuf. Technol.* **119**, 6893–6917.
- [53] Wang S H, Ning J S, Zhu L D, Yang Z C, Yan W T, Dun Y, Xue P S, Xu P H, Bose S and Bandyopadhyay A. 2022. Role of porosity defects in metal 3D printing: formation mechanisms, impacts on properties and mitigation strategies. *Mater. Today* **59**, 133–160.
- [54] Chen Y, Lu F G, Zhang K, Nie P L, Elmi Hosseini S R, Feng K and Li Z G. 2016. Dendritic microstructure and hot cracking of laser additive manufactured Inconel 718 under improved base cooling. *J. Alloys Compd.* **670**, 312–321.
- [55] Kies F, Wilms M B, Pirch N, Pradeep K G, Schleifenbaum J H and Haase C. 2020. Defect formation and prevention in directed energy deposition of high-manganese steels and the effect on mechanical properties. *Mater. Sci. Eng. A* **772**, 138688.
- [56] Parimi L L, Ravi G A, Clark D and Attallah M M. 2014. Microstructural and texture development in direct laser fabricated IN718. *Mater. Charact.* **89**, 102–111.
- [57] Qin L Y, Wang K, Li X D, Zhou S Y and Yang G. 2022. Review of the formation mechanisms and control methods of geometrical defects in laser deposition manufacturing. *Chin. J. Mech. Eng.: Addit. Manuf. Front.* **1**, 100052.
- [58] Qiu C L, Ravi G A, Dance C, Ranson A, Dilworth S and Attallah M M. 2015. Fabrication of large Ti–6Al–4V structures by direct laser deposition. *J. Alloys Compd.* **629**, 351–361.
- [59] Zhang L, Zhai W G, Zhao K, Bi G J, Chen X Q and Zhou W. 2024. Oxidation behavior and resultant deposition efficiency and material properties of laser aided additively manufactured stainless steel 316 L. *J. Manuf. Process.* **115**, 352–364.
- [60] Liu M, Kumar A, Bukkapatnam S and Kuttolamadom M. 2021. A review of the anomalies in directed energy deposition (DED) processes & potential solutions—part quality & defects. *Proc. Manuf.* **53**, 507–518.
- [61] Rott M, Li Y, Koukolíková M, Šípová M, Salvetr P, Nový Z, Wolf G and Džugan J. 2023. *In-situ* directed energy deposition of Al based low density steel for automotive applications. *Sci. Rep.* **13**, 21911.
- [62] Gualtieri T and Bandyopadhyay A. 2018. Additive manufacturing of compositionally gradient metal-ceramic structures: stainless steel to vanadium carbide. *Mater. Des.* **139**, 419–428.
- [63] Liu M and Kuttolamadom M. 2020. Nano-scale hardness and abrasion resistance of directed energy deposited Co-Cr-Mo biomedical alloy. In *ASME 2020 15th International Manufacturing Science and Engineering Conference V001T05A022*. (ASME) (<https://doi.org/10.1115/MSEC2020-8455>)
- [64] Lee Y, Kim E S, Park S, Park J M, Seol J B, Kim H S, Lee T, Sung H and Kim J G. 2022. Effects of laser power on the microstructure evolution and mechanical properties of Ti–6Al–4V alloy manufactured by direct energy deposition. *Met. Mater. Int.* **28**, 197–204.
- [65] Barragan G, Rojas Perilla D A, Grass Nuñez J, Mariani F and Coelho R. 2021. Characterization and optimization of process parameters for directed energy deposition powder-fed laser system. *J. Mater. Eng. Perform.* **30**, 5297–5306.
- [66] Sun G F, Zhou R, Lu J Z and Mazumder J. 2015. Evaluation of defect density, microstructure, residual stress, elastic modulus, hardness and strength of laser-deposited AISI 4340 steel. *Acta Mater.* **84**, 172–189.
- [67] Majumdar J D, Madapana D and Manna I. 2021. 3-D printing by laser-assisted direct energy deposition (LDED): the present status. *Trans. Indian Natl Acad. Eng.* **6**, 933–953.
- [68] Tang Z J, Liu W W, Zhu L N, Liu Z C, Yan Z R, Lin D, Zhang Z and Zhang H C. 2021. Investigation on coaxial visual characteristics of molten pool in laser-based directed energy deposition of AISI 316L steel. *J. Mater. Process. Technol.* **290**, 116996.
- [69] Kim S, Jeon I and Sohn H. 2023. Infrared thermographic imaging based real-time layer height estimation during directed energy deposition. *Opt. Lasers Eng.* **168**, 107661.
- [70] Ito K, Kusano M, Demura M and Watanabe M. 2021. Detection and location of microdefects during selective laser melting by wireless acoustic emission measurement. *Addit. Manuf.* **40**, 101915.

- [71] Ramalho A, Santos T G, Bevans B, Smoqi Z, Rao P and Oliveira J P. 2022. Effect of contaminations on the acoustic emissions during wire and arc additive manufacturing of 316L stainless steel. *Addit. Manuf.* **51**, 102585.
- [72] Pignatelli G, Strasse A, Gumenyuk A and Gornushkin I. 2022. Online monitoring of 3D printing of steel via optical emission spectroscopy. *Mater. Test.* **64**, 24–32.
- [73] Lough C S, Escano L I, Qu M L, Smith C C, Landers R G, Bristow D A, Chen L Y and Kinzel E C. 2020. *In-situ* optical emission spectroscopy of selective laser melting. *J. Manuf. Process.* **53**, 336–341.
- [74] Tang S Y, Wang G L and Zhang H O. 2019. *In situ* 3D monitoring and control of geometric signatures in wire and arc additive manufacturing. *Surf. Topogr.: Metrol. Prop.* **7**, 025013.
- [75] Kaji F, Nguyen-Huu H, Budhwani A, Narayanan J A, Zimny M and Toyserkani E. 2022. A deep-learning-based *in-situ* surface anomaly detection methodology for laser directed energy deposition via powder feeding. *J. Manuf. Process.* **81**, 624–637.
- [76] Ioannidou C, König H H, Semjatov N, Ackelid U, Staron P, Körner C, Hedström P and Lindwall G. 2022. *In-situ* synchrotron X-ray analysis of metal Additive Manufacturing: current state, opportunities and challenges. *Mater. Des.* **219**, 110790.
- [77] Tang Z J, Liu W W, Wang Y W, Saleheen K M, Liu Z C, Peng S T, Zhang Z and Zhang H C. 2020. A review on *in situ* monitoring technology for directed energy deposition of metals. *Int. J. Adv. Manuf. Technol.* **108**, 3437–3463.
- [78] Garmendia I, Pujana J, Lamikiz A, Flores J and Madarieta M. 2019. Development of an intra-layer adaptive toolpath generation control procedure in the laser metal wire deposition process. *Materials* **12**, 352.
- [79] Shamsaei N, Yadollahi A, Bian L K and Thompson S M. 2015. An overview of Direct Laser Deposition for additive manufacturing; Part II: mechanical behavior, process parameter optimization and control. *Addit. Manuf.* **8**, 12–35.
- [80] Mani M, Lane B M, Donmez M A, Feng S C and Moylan S P. 2017. A review on measurement science needs for real-time control of additive manufacturing metal powder bed fusion processes. *Int. J. Prod. Res.* **55**, 1400–1418.
- [81] Heralić A, Christiansson A K, Ottosson M and Lennartson B. 2010. Increased stability in laser metal wire deposition through feedback from optical measurements. *Opt. Laser Eng.* **48**, 478–485.
- [82] Takushima S, Shinohara N, Morita D, Kawano H, Mizutani Y and Takaya Y. 2021. In-process height displacement measurement using crossed line beams for process control of laser wire deposition. *Int. J. Autom. Technol.* **15**, 715–727.
- [83] Liu S, Liu W, Harooni M, Ma J J and Kovacevic R. 2014. Real-time monitoring of laser hot-wire cladding of Inconel 625. *Opt. Laser Technol.* **62**, 124–134.
- [84] Bourlesas N, Tzimanis K, Sabatakakis K, Bikas H and Stavropoulos P. 2024. Over-deposition assessment of Direct Energy Deposition (DED) using melt pool geometric features and Machine Learning. *Proc. CIRP* **124**, 797–802.
- [85] Ukwaththa J, Herath S and Meddage D P P. 2024. A review of machine learning (ML) and explainable artificial intelligence (XAI) methods in additive manufacturing (3D printing). *Mater. Today Commun.* **41**, 110294.
- [86] Liu R S and Yang H. 2023. Multimodal probabilistic modeling of melt pool geometry variations in additive manufacturing. *Addit. Manuf.* **61**, 103375.
- [87] Guerra M G, Mazzarisi M, Latte M, Lavecchia F, Campanelli S and Galantucci L M. 2024. Off-axis monitoring of the melt pool spatial information in Laser Metal Deposition process. *Proc. CIRP* **121**, 144–149.
- [88] Assad A, Bevans B D, Potter W, Rao P, Cormier D, Deschamps F, Hamilton J D and Rivero I V. 2024. Process mapping and anomaly detection in laser wire directed energy deposition additive manufacturing using *in-situ* imaging and process-aware machine learning. *Mater. Des.* **245**, 113281.
- [89] Perani M, Baraldo S, Decker M, Vandone A, Valente A and Paoli B. 2023. Track geometry prediction for Laser Metal Deposition based on on-line artificial vision and deep neural networks. *Robot. Comput. Int. Manuf.* **79**, 102445.
- [90] Raj A, Owen C, Stegman B, Abdel-Khalik H, Zhang X H and Sutherland J W. 2023. Predicting mechanical properties from co-axial melt pool monitoring signals in laser powder bed fusion. *J. Manuf. Process.* **101**, 181–194.
- [91] Raj A, Huang D L, Stegman B, Abdel-Khalik H, Zhang X H and Sutherland J W. 2023. Modeling spatial variations in co-axial melt pool monitoring signals in laser powder bed fusion. *J. Manuf. Process.* **89**, 24–38.
- [92] Errico V, Campanelli S L, Angelastro A, Dassisti M, Mazzarisi M and Bonserio C. 2021. Coaxial monitoring of AISI 316L thin walls fabricated by direct metal laser deposition. *Materials* **14**, 673.
- [93] Fischer F G, Birk N, Rooney L, Jauer L and Schleifenbaum J H. 2021. Optical process monitoring in Laser Powder Bed Fusion using a recoater-based line camera. *Addit. Manuf.* **47**, 102218.
- [94] Chen L Q, Bi G J, Yao X L, Tan C L, Su J L, Ng N P H, Chew Y, Liu K and Moon S K. 2023. Multisensor fusion-based digital twin for localized quality prediction in robotic laser-directed energy deposition. *Robot. Comput. Int. Manuf.* **84**, 102581.
- [95] Sun Z, Guo W and Li L. 2020. In-process measurement of melt pool cross-sectional geometry and grain orientation in a laser directed energy deposition additive manufacturing process. *Opt. Laser Technol.* **129**, 106280.
- [96] Kanko J A, Sibley A P and Fraser J M. 2016. *In situ* morphology-based defect detection of selective laser melting through inline coherent imaging. *J. Mater. Process. Technol.* **231**, 488–500.
- [97] Kayacan M Y and Yılmaz N. 2020. An investigation on the measurement of instantaneous temperatures in laser assisted additive manufacturing by thermal imagers. *Measurement* **160**, 107825.
- [98] Wei J C, He Y, Wang F, He Y Y, Rong X X, Chen M J, Wang Y, Yue H H and Liu J Y. 2023. Convolutional neural network assisted infrared imaging technology: an enhanced online processing state monitoring method for laser powder bed fusion. *Infrared Phys. Technol.* **131**, 104661.
- [99] Siva Prasad H, Brueckner F and Kaplan A F H. 2020. Powder incorporation and spatter formation in high deposition rate blown powder directed energy deposition. *Addit. Manuf.* **35**, 101413.
- [100] Hartmann S, Vykhartar B, Möbs N, Kelbassa I and Mayr P. 2024. IoT-based data mining framework for stability assessment of the laser-directed energy deposition process. *Processes* **12**, 1180.
- [101] Kong L B, Peng X, Chen Y, Wang P and Xu M. 2020. Multi-sensor measurement and data fusion technology for manufacturing process monitoring: a literature review. *Int. J. Extrem. Manuf.* **2**, 022001.
- [102] D'Accardi E, Chiappini F, Giannasi A, Guerrini M, Maggiani G, Palumbo D and Galletti U. 2024. Online monitoring of direct laser metal deposition process by means of infrared thermography. *Prog. Addit. Manuf.* **9**, 983–1001.
- [103] Zhang Z Y, Liu Z C and Wu D Z. 2021. Prediction of melt pool temperature in directed energy deposition using machine learning. *Addit. Manuf.* **37**, 101692.

- [104] Chandrasekar S, Coble J B, List F, Carver K, Beauchamp S, Godfrey A, Paquit V and Babu S S. 2022. Similarity analysis for thermal signature comparison in metal additive manufacturing. *Mater. Des.* **224**, 111261.
- [105] Ren K, Chew Y, Zhang Y F, Fuh J Y H and Bi G J. 2020. Thermal field prediction for laser scanning paths in laser aided additive manufacturing by physics-based machine learning. *Comput. Methods Appl. Mech. Eng.* **362**, 112734.
- [106] Flores J, Saez I G and Cabanes Axpe I. 2020. Thermal monitoring and control by infrared camera in the manufacture of parts with laser metal deposition. *Dyna* **95**, 360–364.
- [107] Rao J, Sing S L, Lim J C W, Yeong W Y, Yang J Z, Fan Z and Hazell P. 2022. Detection and characterisation of defects in directed energy deposited multi-material components using full waveform inversion and reverse time migration. *Virtual Phys. Prototyp.* **17**, 1047–1057.
- [108] Bakre C, Meyer T, Jamieson C, Nassar A R, Reutzel E W and Lissenden C J. 2022. *In-situ* laser ultrasound-based Rayleigh wave process monitoring of DED-AM metals. *J. Nondestruct. Eval.* **33**, 218–242.
- [109] Bakre C, Afzalimir S H, Jamieson C, Nassar A, Reutzel E W and Lissenden C J. 2022. Laser generated broadband Rayleigh waveform evolution for metal additive manufacturing process monitoring. *Appl. Sci.* **12**, 12208.
- [110] Wang H J, Li B and Xuan F Z. 2022. Acoustic emission for *in situ* process monitoring of selective laser melting additive manufacturing based on machine learning and improved variational modal decomposition. *Int. J. Adv. Manuf. Technol.* **122**, 2277–2292.
- [111] Hauser T, Reisch R T, Kamps T, Kaplan A F H and Volpp J. 2022. Acoustic emissions in directed energy deposition processes. *Int. J. Adv. Manuf. Technol.* **119**, 3517–3532.
- [112] Tempelman J R, Wachtor A J, Flynn E B, Depond P J, Forien J B, Guss G M, Calta N P and Matthews M J. 2022. Detection of keyhole pore formations in laser powder-bed fusion using acoustic process monitoring measurements. *Addit. Manuf.* **55**, 102735.
- [113] Yang Z C, Zhu L D, Wang S H, Ning J S, Dun Y, Meng G R, Xue P S, Xu P H and Xin B. 2021. Effects of ultrasound on multilayer forming mechanism of Inconel 718 in directed energy deposition. *Addit. Manuf.* **48**, 102462.
- [114] Li S H, Chen B, Tan C W and Song X G. 2024. *In situ* identification of laser directed energy deposition condition based on acoustic emission. *Opt. Laser Technol.* **169**, 110152.
- [115] Chen L Q, Yao X L, Tan C L, He W Y, Su J L, Weng F, Chew Y, Ng N P H and Moon S K. 2023. *In-situ* crack and keyhole pore detection in laser directed energy deposition through acoustic signal and deep learning. *Addit. Manuf.* **69**, 103547.
- [116] Pandiyan V, Wróbel R, Leinenbach C and Shevchik S. 2023. Optimizing *in-situ* monitoring for laser powder bed fusion process: deciphering acoustic emission and sensor sensitivity with explainable machine learning. *J. Mater. Process. Technol.* **321**, 118144.
- [117] Liu P P, Yang L, Yi K, Kundu T and Sohn H. 2023. Application of nonlinear ultrasonic analysis for *in situ* monitoring of metal additive manufacturing. *Struct Health Monit.* **22**, 1760–1775.
- [118] Bevans B, Ramalho A, Smoqi Z, Gaikwad A, Santos T G, Rao P and Oliveira J P. 2023. Monitoring and flaw detection during wire-based directed energy deposition using *in-situ* acoustic sensing and wavelet graph signal analysis. *Mater. Des.* **225**, 111480.
- [119] Wen F Z, Gao S M, Song X and Shi F. 2024. Piezoelectric-laser ultrasonic inspection and monitoring of thin-walled structure fabricated by directed energy deposition process based on guided waves. *Ultrasonics* **138**, 107255.
- [120] Davis G et al. 2023. Near-surface defect detection in additively manufactured components using laser induced phased arrays with surface acoustic wave crosstalk suppression. *Mater. Des.* **236**, 112453.
- [121] Kouprianoff D, Yadroitsava I, Du Plessis A, Luwes N and Yadroitsev I. 2021. Monitoring of laser powder bed fusion by acoustic emission: investigation of single tracks and layers. *Front. Mech. Eng.* **7**, 678076.
- [122] Chabot A, Rauch M and Hascoët J Y. 2021. Novel control model of Contact-Tip-to-Work Distance (CTWD) for sound monitoring of arc-based DED processes based on spectral analysis. *Int. J. Adv. Manuf. Technol.* **116**, 3463–3472.
- [123] Ansari M J, Arcondoulis E J G, Roccisano A, Schulz C, Schlaefer T and Hall C. 2024. Optimized analytical approach for the detection of process-induced defects using acoustic emission during directed energy deposition process. *Addit. Manuf.* **86**, 104218.
- [124] Whiting J, Springer A and Sciammarella F. 2018. Real-time acoustic emission monitoring of powder mass flow rate for directed energy deposition. *Addit. Manuf.* **23**, 312–318.
- [125] Schmidt M, Huke P, Gerhard C and Partes K. 2021. In-line observation of laser cladding processes via atomic emission spectroscopy. *Materials* **14**, 4401.
- [126] Dunbar A J and Nassar A R. 2018. Assessment of optical emission analysis for in-process monitoring of powder bed fusion additive manufacturing. *Virtual Phys. Prototyp.* **13**, 14–19.
- [127] Ren W J, Wen G R, Zhang Z F and Mazumder J. 2022. Quality monitoring in additive manufacturing using emission spectroscopy and unsupervised deep learning. *Mater. Manuf. Process.* **37**, 1339–1346.
- [128] Chen L Q, Yao X L, Xu P, Moon S K and Bi G. 2021. Rapid surface defect identification for additive manufacturing with *in-situ* point cloud processing and machine learning. *Virtual Phys. Prototyp.* **16**, 50–67.
- [129] Mukherjee T, Shen W J, Liao Y L and Li B W. 2024. Improving deposited surface quality in additive manufacturing using structured light scanning characterization and mechanistic modeling. *J. Manuf. Mater. Process.* **8**, 124.
- [130] Li H P, Hu L, Ye J H, Wei W, Gao X Y, Qian Z and Long Y. 2024. A high-precision *in-situ* monitoring system for laser directed energy deposition melt pool 3D morphology based on deep learning. *J. Intell. Manuf.* **1–20**.
- [131] Guo Q L, Qu M L, Escano L I, Hojjatzadeh S M H, Young Z, Fezzaa K and Chen L Y. 2022. Revealing melt flow instabilities in laser powder bed fusion additive manufacturing of aluminum alloy via *in-situ* high-speed X-ray imaging. *Int. J. Mach. Tools Manuf.* **175**, 103861.
- [132] Fleming T G, Rees D T, Marussi S, Connolley T, Atwood R C, Jones M A, Fraser J M, Leung C L A and Lee P D. 2023. *In situ* correlative observation of humping-induced cracking in directed energy deposition of nickel-based superalloys. *Addit. Manuf.* **71**, 103579.
- [133] Silveira A C D F, Fechte-Heinen R and Epp J. 2023. Microstructure evolution during laser-directed energy deposition of tool steel by *in situ* synchrotron X-ray diffraction. *Addit. Manuf.* **63**, 103408.
- [134] Zhang Y J, Hong G S, Ye D S, Zhu K P and Fuh J Y H. 2018. Extraction and evaluation of melt pool, plume and spatter information for powder-bed fusion AM process monitoring. *Mater. Des.* **156**, 458–469.

- [135] Thiele M, Dillkötter D, Stoppok J, Mönningmann M and Esen C. 2020. Laser metal deposition controlling: melt pool temperature and target/actual height difference monitoring. *Proc. CIRP* **94**, 441–444.
- [136] Zhang B, Liu S Y and Shin Y C. 2019. In-Process monitoring of porosity during laser additive manufacturing process. *Addit. Manuf.* **28**, 497–505.
- [137] Ning J S et al. 2024. Height consistency compensation in laser-directed energy deposition of thin-walled parts. *Int. J. Mech. Sci.* **266**, 108963.
- [138] Haley J, Leach C, Jordan B, Dehoff R and Paquit V. 2021. *In-situ* digital image correlation and thermal monitoring in directed energy deposition additive manufacturing. *Opt. Express* **29**, 9927.
- [139] Wang R X. 2023. *Multi-physics Sensing and Real-time Quality Control in Metal Additive Manufacturing*. (Virginia Polytechnic Institute and State University, Blacksburg).
- [140] Rodionova O and Pomerantsev A. 2023. Multi-block DD-SIMCA as a high-level data fusion tool. *Anal. Chim. Acta* **1265**, 341328.
- [141] Ma T C, Shen J X, Song D and Xu F Y. 2023. Multi-sensor and multi-level information fusion model for compressor blade crack detection. *Measurement* **222**, 113622.
- [142] Vandone A and Valente A. 2022. AI based monitoring system for DED part quality evaluation. *Proc. CIRP* **107**, 635–640.
- [143] Kisielewicz A, Mi Y, Sikström F and Ancona A. 2023. Multi sensor monitoring of the wire-melt pool interaction in hot-wire directed energy deposition using laser beam. *IOP Conf. Ser.: Mater. Sci. Eng.* **1296**, 012011.
- [144] Chen L Q and Moon S K. 2024. *In-situ* defect detection in laser-directed energy deposition with machine learning and multi-sensor fusion. *J. Mech. Sci. Technol.* **38**, 4477–4484.
- [145] Akhavan J, Xu K, Vallabh C K and Manoochehri S. Real-time print tracking in metal additive manufacturing using acoustic emission sensors and vision transformer algorithms. In *ASME 2024 19th International Manufacturing Science and Engineering Conference V002T07A009*. (ASME, Knoxville, Tennessee, USA) (<https://doi.org/10.1115/MSEC2024-125391>)
- [146] Lin K, Li Y H, Sun J C, Zhou D S and Zhang Q. 2020. Multi-sensor fusion for body sensor network in medical human-robot interaction scenario. *Inf. Fusion* **57**, 15–26.
- [147] Beddar-Wiesing S and Bieshaar M. 2020. Multi-sensor data and knowledge fusion—a proposal for a terminology definition. (arXiv:2001.04171).
- [148] Wasmer K, Wüst M, Cui D, Masinelli G, Pandiyan V and Shevchik S. 2023. Monitoring of functionally graded material during laser directed energy deposition by acoustic emission and optical emission spectroscopy using artificial intelligence. *Virtual Phys. Prototyp.* **18**, e2189599.
- [149] Herzog T, Brandt M, Trinchi A, Sola A and Molotnikov A. 2024. Process monitoring and machine learning for defect detection in laser-based metal additive manufacturing. *J. Intell. Manuf.* **35**, 1407–1437.
- [150] Era I Z, Farahani M A, Wuest T and Liu Z C. 2023. Machine learning in Directed Energy Deposition (DED) additive manufacturing: a state-of-the-art review. *Manuf. Lett.* **35**, 689–700.
- [151] Ye J Y, Bab-Hadiashar A, Hoseinnezhad R, Alam N, Vargas-Uscategui A, Patel M and Cole I. 2023. Predictions of *in-situ* melt pool geometric signatures via machine learning techniques for laser metal deposition. *Int. J. Comput. Integr. Manuf.* **36**, 1345–1361.
- [152] Pandiyan V, Cui D, Le-Quang T, Deshpande P, Wasmer K and Shevchik S. 2022. *In situ* quality monitoring in direct energy deposition process using co-axial process zone imaging and deep contrastive learning. *J. Manuf. Process.* **81**, 1064–1075.
- [153] Liu W B, Wang Z D, Tian L L, Lauria S and Liu X H. 2021. Melt pool segmentation for additive manufacturing: a generative adversarial network approach. *Comput. Electr. Eng.* **92**, 107183.
- [154] Asadi R, Queguineur A, Wiikinkoski O, Mokhtarian H, Aihkialo T, Revuelta A and Ituarte I F. 2024. Process monitoring by deep neural networks in directed energy deposition: CNN-based detection, segmentation, and statistical analysis of melt pools. *Robot. Comput. Int. Manuf.* **87**, 102710.
- [155] Khanzadeh M, Chowdhury S, Marufuzzaman M, Tschopp M A and Bian L K. 2018. Porosity prediction: supervised-learning of thermal history for direct laser deposition. *J. Manuf. Syst.* **47**, 69–82.
- [156] Gonzalez-Val C, Pallas A, Panadeiro V and Rodriguez A. 2020. A convolutional approach to quality monitoring for laser manufacturing. *J. Intell. Manuf.* **31**, 789–795.
- [157] Jamnikar N D, Liu S, Brice C and Zhang X L. 2022. *In situ* microstructure property prediction by modeling molten pool-quality relations for wire-feed laser additive manufacturing. *J. Manuf. Process.* **79**, 803–814.
- [158] Knaak C, Von Eßen J, Kröger M, Schulze F, Abels P and Gillner A. 2021. A spatio-temporal ensemble deep learning architecture for real-time defect detection during laser welding on low power embedded computing boards. *Sensors* **21**, 4205.
- [159] Larsen S and Hooper P A. 2022. Deep semi-supervised learning of dynamics for anomaly detection in laser powder bed fusion. *J. Intell. Manuf.* **33**, 457–471.
- [160] Akbari M and Kovacevic R. 2019. Closed loop control of melt pool width in robotized laser powder-directed energy deposition process. *Int. J. Adv. Manuf. Technol.* **104**, 2887–2898.
- [161] Yang Z C, Zhu L D, Dun Y, Ning J S, Wang S H, Xue P S, Xu P H, Yu M, Yan B L and Xin B. 2023. *In-situ* monitoring of the melt pool dynamics in ultrasound-assisted metal 3D printing using machine learning. *Virtual Phys. Prototyp.* **18**, e2251453.
- [162] Guo W G, Tian Q, Guo S H and Guo Y B. 2020. A physics-driven deep learning model for process-porosity causal relationship and porosity prediction with interpretability in laser metal deposition. *CIRP Ann.* **69**, 205–208.
- [163] Xie X Y, Bennett J, Saha S, Lu Y, Cao J, Liu W K and Gan Z T. 2021. Mechanistic data-driven prediction of as-built mechanical properties in metal additive manufacturing. *npj Comput. Mater.* **7**, 86.
- [164] Khanzadeh M, Chowdhury S, Tschopp M A, Doude H R, Marufuzzaman M and Bian L K. 2019. *In-situ* monitoring of melt pool images for porosity prediction in directed energy deposition processes. *IJSE Trans.* **51**, 437–455.
- [165] Gaikwad A, Yavari R, Montazeri M, Cole K, Bian L K and Rao P. 2020. Toward the digital twin of additive manufacturing: integrating thermal simulations, sensing, and analytics to detect process faults. *IJSE Trans.* **52**, 1204–1217.
- [166] Taheri H, Koester L W, Bigelow T A, Faierson E J and Bond L J. 2019. *In situ* additive manufacturing process monitoring with an acoustic technique: clustering performance evaluation using K-means algorithm. *J. Manuf. Sci. Eng.* **141**, 041011.
- [167] Wasmer K, Le-Quang T, Meylan B and Shevchik S A. 2019. *In situ* quality monitoring in AM using acoustic emission: a reinforcement learning approach. *J. Mater. Eng. Perform.* **28**, 666–672.
- [168] Hossain M S and Taheri H. 2021. *In-situ* process monitoring for metal additive manufacturing through acoustic techniques using wavelet and convolutional neural network (CNN). *Int. J. Adv. Manuf. Technol.* **116**, 3473–3488.

- [169] Chen L Q, Yao X L and Moon S K. 2022. *In-situ* acoustic monitoring of direct energy deposition process with deep learning-assisted signal denoising. *Mater. Today: Proc.* **70**, 136–142.
- [170] Lyu J, Akhavan Taheri Boroujeni J and Manoochchri S. 2021. *In-situ* laser-based process monitoring and in-plane surface anomaly identification for additive manufacturing using point cloud and machine learning. In *ASME 2021 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference* (ASME) (<https://doi.org/10.1115/DETC2021-69436>)
- [171] Lyu J and Manoochchri S. 2021. Online convolutional neural network-based anomaly detection and quality control for fused filament fabrication process. *Virtual Phys. Prototyp.* **16**, 160–177.
- [172] Chen L Q, Yao X L, Xu P, Moon S K and Bi G J. 2020. Surface monitoring for additive manufacturing with *in-situ* point cloud processing. In *2020 6th International Conference on Control, Automation and Robotics (ICCAR)* (IEEE, Singapore, Singapore) pp 196–201.
- [173] Liu C N, Wang R R, Ho I, Kong Z J, Williams C, Babu S and Joslin C. 2023. Toward online layer-wise surface morphology measurement in additive manufacturing using a deep learning-based approach. *J. Intell. Manuf.* **34**, 2673–2689.
- [174] Martin A A et al. 2019. Ultrafast dynamics of laser-metal interactions in additive manufacturing alloys captured by *in situ* X-ray imaging. *Mater. Today Adv.* **1**, 100002.
- [175] Richter B, Blanke N, Werner C, Parab N D, Sun T, Vollertsen F and Pfeifferkorn F E. 2019. High-speed X-ray investigation of melt dynamics during continuous-wave laser remelting of selective laser melted Co-Cr alloy. *CIRP Ann.* **68**, 229–232.
- [176] Wolff S J, Wang H, Gould B, Parab N, Wu Z H, Zhao C, Greco A and Sun T. 2021. *In situ* X-ray imaging of pore formation mechanisms and dynamics in laser powder-blown directed energy deposition additive manufacturing. *Int. J. Mach. Tool Manuf.* **166**, 103743.
- [177] Hamidi Nasab M et al. 2023. Harmonizing sound and light: x-ray imaging unveils acoustic signatures of stochastic inter-regime instabilities during laser melting. *Nat. Commun.* **14**, 8008.
- [178] Ren Z S, Gao L, Clark S J, Fezzaa K, Shevchenko P, Choi A, Everhart W, Rollett A D, Chen L Y and Sun T. 2023. Machine learning-aided real-time detection of keyhole pore generation in laser powder bed fusion. *Science* **379**, 89–94.
- [179] Wolff S J, Wu H, Parab N, Zhao C, Ehmann K F, Sun T and Cao J. 2019. *In-situ* high-speed X-ray imaging of piezo-driven directed energy deposition additive manufacturing. *Sci. Rep.* **9**, 962.
- [180] Pandiyan V et al. 2022. Deep learning-based monitoring of laser powder bed fusion process on variable time-scales using heterogeneous sensing and *operando* X-ray radiography guidance. *Addit. Manuf.* **58**, 103007.
- [181] Kim J, Yang Z, Ko H, Cho H and Lu Y. 2023. Deep learning-based data registration of melt-pool-monitoring images for laser powder bed fusion additive manufacturing. *J. Manuf. Syst.* **68**, 117–129.
- [182] Chen L Q, Yao X L, Chew Y, Weng F, Moon S K and Bi G J. 2020. Data-driven adaptive control for laser-based additive manufacturing with automatic controller tuning. *Appl. Sci.* **10**, 7967.
- [183] Hua Y and Choi J. 2005. Adaptive direct metal/material deposition process using a fuzzy logic-based controller. *J. Laser Appl.* **17**, 200–210.
- [184] Moralejo S, Penaranda X, Nieto S, Barrios A, Arrizubieta I, Tabernero I and Figueras J. 2017. A feedforward controller for tuning laser cladding melt pool geometry in real time. *Int. J. Adv. Manuf. Technol.* **89**, 821–831.
- [185] Song L J, Bagavath-Singh V, Dutta B and Mazumder J. 2012. Control of melt pool temperature and deposition height during direct metal deposition process. *Int. J. Adv. Manuf. Technol.* **58**, 247–256.
- [186] Zeinali M and Khajepour A. 2010. Height control in laser cladding using adaptive sliding mode technique: theory and experiment. *J. Manuf. Sci. Eng.* **132**, 041016.
- [187] Ding Y Y, Warton J and Kovacevic R. 2016. Development of sensing and control system for robotized laser-based direct metal addition system. *Addit. Manuf.* **10**, 24–35.
- [188] Liu Y B, Wang L P and Brandt M. 2019. Model predictive control of laser metal deposition. *Int. J. Adv. Manuf. Technol.* **105**, 1055–1067.
- [189] Bi G J, Gasser A, Wissenbach K, Drenker A and Poprawe R. 2006. Characterization of the process control for the direct laser metallic powder deposition. *Surf. Coat. Technol.* **201**, 2676–2683.
- [190] Farshidianfar M H, Khodabakhshi F, Khajepour A and Gerlich A P. 2021. Closed-loop control of microstructure and mechanical properties in additive manufacturing by directed energy deposition. *Mater. Sci. Eng. A* **803**, 140483.
- [191] Regulin D and Barucci R. 2023. A benchmark of approaches for closed loop control of melt pool shape in DED. *Int. J. Adv. Manuf. Technol.* **126**, 829–843.
- [192] Sun Z, Guo W and Li L. 2020. Numerical modelling of heat transfer, mass transport and microstructure formation in a high deposition rate laser directed energy deposition process. *Addit. Manuf.* **33**, 101175.
- [193] Rahmani Dehaghani M, Sahraeidolatkhaneh A, Nilsen M, Sikström F, Sajadi P, Tang Y F and Wang G G. 2024. System identification and closed-loop control of laser hot-wire directed energy deposition using the parameter-signature-quality modeling scheme. *J. Manuf. Process.* **112**, 1–13.
- [194] Mattera G, Caggiano A and Nele L. 2025. Optimal data-driven control of manufacturing processes using reinforcement learning: an application to wire arc additive manufacturing. *J. Intell. Manuf.* **36**, 1291–1310.
- [195] Shi T, Lu B H, Shen T, Zhang R, Shi S H and Fu G Y. 2018. Closed-loop control of variable width deposition in laser metal deposition. *Int. J. Adv. Manuf. Technol.* **97**, 4167–4178.
- [196] Xiong J, Chen H, Zheng S M and Zhang G J. 2022. Feedback control of variable width in gas metal arc-based additive manufacturing. *J. Manuf. Process.* **76**, 11–20.
- [197] Xiong J, Yin Z Q and Zhang W H. 2016. Closed-loop control of variable layer width for thin-walled parts in wire and arc additive manufacturing. *J. Mater. Process. Technol.* **233**, 100–106.
- [198] Hagenlocher C, O'Toole P, Xu W, Brandt M, Easton M and Molotnikov A. 2022. The effect of heat accumulation on the local grain structure in laser-directed energy deposition of aluminium. *Metals* **12**, 1601.
- [199] Li Y Z, Li X L, Zhang G J, Horváth I and Han Q L. 2021. Interlayer closed-loop control of forming geometries for wire and arc additive manufacturing based on fuzzy-logic inference. *J. Manuf. Process.* **63**, 35–47.
- [200] Becker D, Boley S, Eisseler R, Stehle T, Möhring H C, Onuseit V, Hoffeld M and Graf T. 2021. Influence of a closed-loop controlled laser metal wire deposition process of S Al 5356 on the quality of manufactured parts before and after subsequent machining. *Prod. Eng. Res. Dev.* **15**, 489–507.
- [201] Hagqvist P, Heralić A, Christiansson A K and Lennartson B. 2015. Resistance based iterative learning control of additive manufacturing with wire. *Mechatronics* **31**, 116–123.
- [202] Xiong J, Zhang Y Y and Pi Y P. 2021. Control of deposition height in WAAM using visual inspection of previous and current layers. *J. Intell. Manuf.* **32**, 2209–2217.

- [203] Heralić A, Christiansson A K and Lennartson B. 2012. Height control of laser metal-wire deposition based on iterative learning control and 3D scanning. *Opt. Laser Eng.* **50**, 1230–1241.
- [204] Zhou V, Odum K, Soshi M and Yamazaki K. 2022. Development of a height control system using a dynamic powder splitter for directed energy deposition (DED) additive manufacturing. *Prog. Addit. Manuf.* **7**, 1085–1092.
- [205] Bernauer C, Leitner P, Zapata A, Garkusha P, Grabmann S, Schmoeller M and Zaeh M F. 2024. Segmentation-based closed-loop layer height control for enhancing stability and dimensional accuracy in wire-based laser metal deposition. *Robot. Comput. Int. Manuf.* **86**, 102683.