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Topical Review

New era towards autonomous additive manufacturing: a review of recent trends and future perspectives

Haolin Fan^{1,2} , Chenshu Liu¹ , Shijie Bian¹ , Changyu Ma¹ , Junlin Huang² , Xuan Liu² , Marshall Doyle¹, Thomas Lu³ , Edward Chow³ , Liany Chen⁴ , Jerry Ying Hsi Fuh² , Wen Feng Lu²  and Bingbing Li^{1,2,*} 

¹ Autonomy Research Center for STEAHM (ARCS), California State University Northridge, 18111 Nordhoff St, Northridge, CA 91330, United States of America

² Department of Mechanical Engineering, National University of Singapore, 9 Engineering Drive 1, Singapore 117575, Singapore

³ Jet Propulsion Laboratory, California Institute of Technology, 4800 Oak Grove Dr, Pasadena, CA 91109, United States of America

⁴ Department of Mechanical Engineering, University of Wisconsin-Madison, 1513 University Ave, Madison, WI 53706, United States of America

E-mail: bingbing.li@csun.edu

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Abstract

The additive manufacturing (AM) landscape has significantly transformed in alignment with Industry 4.0 principles, primarily driven by the integration of artificial intelligence (AI) and digital twins (DT). However, current intelligent AM (IAM) systems face limitations such as fragmented AI tool usage and suboptimal human-machine interaction. This paper reviews existing IAM solutions, emphasizing control, monitoring, process autonomy, and end-to-end integration, and identifies key limitations, such as the absence of a high-level controller for global decision-making. To address these gaps, we propose a transition from IAM to autonomous AM, featuring a hierarchical framework with four integrated layers: knowledge, generative solution, operational, and cognitive. In the cognitive layer, AI agents notably enable machines to independently observe, analyze, plan, and execute operations that traditionally require human intervention. These capabilities streamline production processes and expand the possibilities for innovation, particularly in sectors like in-space manufacturing. Additionally, this paper discusses the role of AI in self-optimization and lifelong learning, positing that the future of AM will be characterized by a symbiotic relationship between human expertise and advanced autonomy, fostering a more adaptive, resilient manufacturing ecosystem.

* Author to whom any correspondence should be addressed.



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Nomenclature

AAM	Autonomous additive manufacturing	MDP	Markov decision process
AE	Acoustic emission	MEX	Material extrusion
AHP	Analytical hierarchy process	MJT	Material jetting
AI	Artificial intelligence	ML	Machine learning
AM	Additive manufacturing	MLP	Multi-layer perception
AMaaS	Additive manufacturing as a service	MMDF	Multimodal data fusion
ANN	Artificial neural network	MR	Mixed reality
AR	Augmented reality	MRI	Magnetic resonance imaging
BASNet	Boundary-aware segmentation network	NDT	Non-destructive testing
BJT	Binder jetting	NER	Named entity recognition
BN	Bayesian network	NeRF	Neural reflectance field
CAN	Conditional adversarial network	NLP	Natural language processing
CFD	Computational fluid dynamics	NO	Neural operators
CMfg	Cloud manufacturing	OES	Optical emission spectroscopy
CNN	Convolutional neural network	PBF	Powder bed fusion
CPS	Cyber physical system	PINN	Physics-informed neural network
CV	Computer vision	PSO	Particle swarm optimization
DED	Directed energy deposition	PSP	Process-structure-property
DfAM	Design for additive manufacturing	PSPP	Process-structure-properties-performance
DL	Deep learning	RAG	Retrieval augmented generation
DNN	Deep neural networks	RFR	Random forest regressor
DOF	Degrees of freedom	RL	Reinforcement learning
DRL	Deep reinforcement learning	RNN	Recurrent neural network
DT	Digital twins	SCNN	Spectral convolutional neural network
FBG	Fiber Bragg grating	SHL	Sheet lamination
FDM	Fused deposition modeling	SLM	Selective laser melting
FEM	Finite element method	SLS	Selective laser sintering
FL	Federated learning	SNN	Shallow neural networks
GAN	Generative adversarial network	SVM	Support vector machine
GBR	Gradient boosting regressor	TL	Transfer learning
GP	Gaussian process	TO	Topology optimization
GPR	Gaussian process regression	TSDF	Truncated signed distance field
GS	Gaussian splatting	TSP	Traveling salesman problem
HEA	High entropy alloy	VLM	Vision language model
HMI	Human machine interaction	VPP	Vat photopolymerization
HNN	Hopfield neural network	VR	Virtual reality
IAM	Intelligent additive manufacturing	WAAM	Wire arc additive manufacturing
ICME	Integrated computational materials engineering	XCT	X-ray computed tomography
ICP	Iterative closest point	XGBoost	Extreme gradient boosting
IKG	Industrial knowledge graph		
IoT	Internet of Things		
IoU	Intersection over Union		
ISM	In-space manufacturing		
KD-Tree	K-dimensional tree		
KB-ANN	Knowledge-based artificial neural network		
KG	Knowledge graph		
KNN	K nearest neighbors		
LightGBM	Light gradient boosted machine		
LLM	Large language model		
LMM	Large multimodal model		
LPBF	Laser powder bed fusion		
LSTM	Long short-term memory		
MDKG	Multi-domain knowledge graph		
MAFN	Multi-modal attention fusion network		
MARL	Multi-agent reinforcement learning		

1. Introduction

Over the past decade, AM has significantly transformed the manufacturing landscape by enabling the production of complex and customized products. AM processes have evolved quickly within the seven standard classifications established by the ASTM and ISO standards committee (ISO/ASTM 52900:2021): BJT, DED, MEX (also known as FDM), MJT, PBF, SHL, and VPP. These advancements are driven by innovations in multi-materials including polymers [1], composites [2], ceramics [3, 4], biomaterials [5, 6], sands [7], and metal alloys [8, 9], etc, as well as creations and improvements in multi-scale (macro, micro, and nano) AM processes including

4D printing [10], bioprinting for organs [11], nano-printing [12], and electronics printing [13], etc. This has broadened the scope of AM applications in sectors like medical [14, 15], dental [16], aerospace [17], defense [18], automotive [19], food [20], energy [21], construction [22], and semiconductor [23] industries. This transformation aligns with the principles of Industry 4.0, which emphasizes the integration of the IoT, data science, and CPS to enhance automation and connectivity in manufacturing [24].

Moreover, the convergence of material science and AI has further accelerated progress in AM, particularly in processes heavily influenced by material properties, such as metal AM. AI has become an essential tool in material science, aiding tasks like discovering new materials or modifying existing materials to possess great printability and desired properties for AM [25], microscopic image analysis for prediction [26], which supports the understanding of material nature and improves the materials characterization. This enhanced understanding contributes to better performance in parts produced through AM and more accurate predictions of fatigue life [27]. These advancements have paved the way for the development of IAM, which focuses on optimizing AM decision-making for the whole life cycle, including material science and development for AM [28].

IAM systems leverage the growing capabilities of AI, particularly its ability to produce optimal results, which are revolutionizing the field of AM. AI encompasses various fields and techniques, including ML/DL, CV, NLP, and robotics. These techniques analyze patterns, make intelligent decisions, solve complex problems, and augment human capabilities. Despite these advancements, the application of AI in AM remains fragmented, with individual tools often used independently for tasks such as *in-situ* monitoring, design optimization, or process automation. This lack of a comprehensive framework limits the full potential of AM, as the correct selection and application of AI tools for specific purposes remains challenging. Moreover, current research predominantly focuses on isolated applications like design optimization [29] and process monitoring [30], with less attention given to system-level integration.

Although hybrid intelligent solutions, such as frameworks based on DT [31, 32], have been proposed for monitoring, modeling, control, and simulation, they are not yet widely implemented, and IAM systems still rely on human intervention. This reliance limits IAM's ability to function as a fully integrated, autonomous solution, resulting in a fragmented approach that lacks a holistic view of the manufacturing process. Additionally, the multi-source and heterogeneous nature of data in IAM poses significant challenges for seamless system integration [33]. This challenge is further compounded by the reliance on open-loop control for higher-level decision-making, which restricts proactive management and optimization. While feedback control loops are present internally, such as in *in-situ* monitoring [34], IAM lacks a fully closed-loop system capable of autonomously addressing robustness and resilience issues. These limitations underscore the need for a more robust, resilient, and autonomous manufacturing solution.

To address these challenges, this article proposes an AAM framework that moves beyond the limitations of current IAM systems, specifically fragmentation, limited adaptability, and dependence on human intervention. The proposed AAM framework consists of key layers representing an integrated solution: knowledge, predictive, operational, and cognitive layers. The knowledge layer extracts knowledge from sensory data, physical models and simulations, and historical libraries, which are then pre-processed and fed into the generative solution. Here, advanced AI technologies such as multi-sensor fusion, multimodal fusion, LLMs, and KGs are used to produce predictive models for supporting future decision-making. The operational layer focuses on module validation or function-level implementation, addressing the question, 'How to realize the AAM system?' The cognitive layer features AI agents capable of independently and cooperatively observing, analyzing, reasoning, planning, acting, and reflecting. These capabilities enhance the efficiency and precision of manufacturing processes and broaden the scope of possible applications. AI agents significantly impact production workflows by streamlining processes and participating in every stage of the AM process, from observing and planning to coordinating tools and analyzing outcomes for better decision support. Furthermore, these agents automate routine tasks such as batch printing, freeing human operators to focus on more complex and innovative aspects of manufacturing.

This review highlights the current advancements in IAM and provides a roadmap for achieving true autonomy by integrating these tools into a cohesive framework. The aim of this work is to propose an innovative and practically implementable AAM framework that addresses the fragmentation in IAM. By enhancing autonomy, adaptability, and resilience, this framework aims to advance the AM ecosystem. We begin by discussing three types of autonomy that serve as cornerstones within the AAM system. Then, we propose the concept of AAM, distinct from IAM, as a hierarchical framework leveraging AI agents. The proposed AAM framework emphasizes autonomous decision-making, utilizing advanced techniques such as KGs and AI agents to create a streamlined workflow. Through a comprehensive analysis of current advancements and case studies, this paper offers insights into how AI and AI agents are ushering in a new era of autonomous future manufacturing solutions. These advancements pave the way for a more innovative, flexible, and adaptive approach to the industry, particularly in complex environments like ISM.

The remainder of this paper is organized as follows. Section 2 discusses control autonomy, focusing on robotic-assisted AM and automated toolpath planning. Section 3 reviews the state of monitoring techniques, including *ex-situ* and *in-situ* monitoring, and multi-sensor data fusion. Section 4 introduces process autonomy within AM, covering aspects from model preparation to autonomous post-processing. Section 5 discusses higher-level process integration. Section 6 presents our proposed AAM system with detailed explanations. Finally, section 7 summarizes the findings of the paper with a vision of AAM systems.

2. Control autonomy

The development of control autonomy marks a significant advancement in automating complex, high-level tasks within AM processes. Unlike conventional manufacturing workflows, which are often rigid and lack adaptability, control autonomy enables AM systems to respond dynamically to complex geometries and adapt material processing strategies. This flexibility is crucial for producing intricate or highly customized parts, where precision and specific control over processes are required to meet the desired performance criteria.

An important consideration in this discussion is the broader trend toward advanced manufacturing paradigms, such as the ‘multi-x’ approach, which involves multi-material, multi-process, and multi-dimensional capabilities [35]. While comprehensive reviews [36, 37] delve into these advances, it is critical to understand that such trends highlight the growing complexity challenges that AM systems must overcome. Control autonomy plays a pivotal role in addressing these challenges by allowing AM systems to seamlessly switch between different materials, processes, or dimensions within a single production cycle [38]. Despite this broad context, this section will narrow its focus to two core innovations that illustrate the transformative power of control autonomy: robotic-assisted AM and automated toolpath design. These technologies push the boundaries of traditional AM, adding new layers of flexibility and intelligence to production workflows.

2.1. Robotic-assisted AM

Robotic systems have become increasingly prominent in the realm of AI and autonomous systems, and their application in AM is no exception. Traditional AM configurations often operate within the constraints of three DOF. For example, within extrusion-based AM processes, the extrusion head typically travels along a horizontal plane (2 DOF) while the build plate adjusts height in the vertical direction (1 DOF). In some configurations, the extrusion head moves along the z -axis (1 DOF) while the build plate handles the remaining two DOFs [39]. Despite advancements like multi-gantry and multi-nozzle technologies, which enhance efficiency, each component’s workspace remains limited. The evolution of AM has shifted from desktop-level printers to advanced systems incorporating robotics, enhancing freedom and flexibility. This shift has opened new possibilities in AM, including extrusion-based processes such as FDM and 3D concrete printing, as well as metal AM processes like DED and its popular type WAAM [40]. The integration of robotic technology in these processes enables the creation of large-scale, intricate structures with reduced waste and minimal post-processing requirements. The adoption of robotic systems in AM has resolved many limitations associated with traditional manufacturing. These systems can precisely manipulate various components, reducing manual intervention and improving overall efficiency. The increased autonomy of these systems allows for greater design flexibility and spatial scales and reduces the time and resources required for production.

A significant advantage of robotic AM systems is their ability to work in continuous free-form spaces, creating geometrically complex designs at high quality that would be challenging to achieve with conventional methods. Various robotic systems are used in AM, including fixed multi-axis robotic arms with designated end-effectors for different AM tasks. For example, Kaji *et al* [41] introduced an adaptive trajectory planning technique for manufacturing tubular components with variable overhang angles using a robotic DED process. This method utilizes non-parallel slicing and dynamic adjustments in scanning speed and tool orientation, allowing for the construction of complex shapes without support for hanging parts. Their study demonstrated the successful production of bent pipes (with 45 degrees and 90 degrees bends) with high dimensional accuracy and density, illustrating the potential of robotic systems in producing defect-free, complex components through DED.

Alternatively, instead of having the robot print on a fixed platform from different directions, another robot-assisted fabrication scheme uses an extruder with 3 DOF may lay down material on a build plate mounted on a robotic arm with high DOF, although this method is less efficient due to potential gravity-related adhesion issues. For example, Wu *et al* [42] introduced RoboFDM, a robotic system designed for 3D printing without the need for support structures. RoboFDM uses a robotic arm with 6 DOF for platform motion and a 3 DOF extruder to form PLA filaments. Unlike traditional FDM, RoboFDM prints models along various directions by decomposing them into support-free parts. Experiments successfully demonstrated the system’s ability to print freeform objects without support. Using similar logic, Bhatt *et al* [43] introduced a supportless extrusion-based AM process for manufacturing thin shell parts, which traditionally require support structures in conventional material extrusion processes. In addition to the 3 DOF flexibility of the extrusion tool, the building platform also reorients with 3 DOF, eliminating the need for support, and saving time and material while avoiding surface degradation. Figure 1 illustrates more integration of industrial robotics in AM processes such as construction, aerospace, and automotive.

However, while these fixed-platform robotic systems offer advantages in supportless printing, they face inherent limitations regarding scalability due to the constraints of rigid workspaces. To address the issue, researchers have explored various solutions, the most popular of which is the use of mobile robotic printing. For example, Tiryaki *et al* [47] proposed a mobile printing system designed to overcome scalability challenges. Unlike previous systems that could only print while stationary, their proposed scheme enables ‘printing-while-moving’, allowing single-piece structures of arbitrary size to be printed in one go. Effective path planning for robots is essential to ensure fluent printing-in-motion processes. Sustarevas *et al* [49, 51] developed a high-level planning algorithm for robot-base paths and further evaluated the effectiveness of the path planning algorithms by integrating them in long-duration path planning with a short-horizon model predictive controller. The system, Armstone,

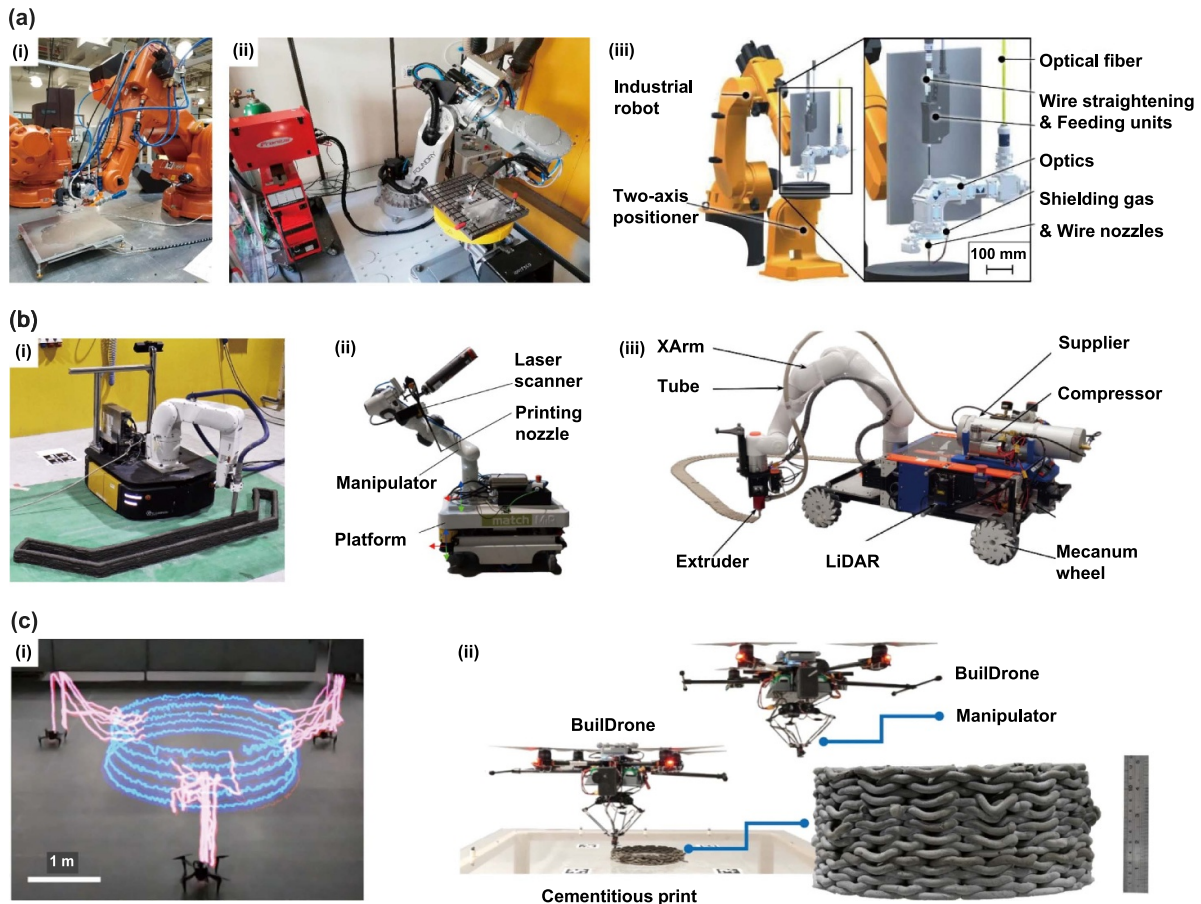


Figure 1. Robotics systems in AM for enhanced autonomy. (a) Utilization of a single industrial robot across various AM methods. (i) A 6-DOF ABB robot arm employed for high-DOF extrusion-based AM Reprinted from [44], © 2021 Elsevier B.V. All rights reserved. (ii) A 6-axis COMAU NJ130 robot and a 2-axis tilt-turn table used for wire arc AM Reproduced with permission from [45]. CC BY-NC-ND 4.0. (iii) A six-axis KUKA robot utilized in the DED process Reproduced with permission from [46]. CC BY-NC-ND 4.0. (b) Advancements in mobile robotics for increased flexibility. (i) A 6-DOF Denso VS-087 robot manipulator mounted on a mobile base for the FDM process © (2019) IEEE. Reprinted, with permission, from [47]. (ii) A MiR 100 mobile platform equipped with a 7-axis Franka Emika manipulator for construction tasks Reproduced with permission from [48]. CC BY-NC-ND 4.0. (iii) A mobile robot platform employing Mecanum wheels for holonomic motion in large-scale AM © (2022) IEEE. Reprinted, with permission, from [49]. (c) Emerging trends in multi-robot collaboration for large-scale and efficient AM. (i) Virtual fabrication and simulation of a surface of revolution with a parabolic profile, achieved using three or more printing robots Adapted from [50], with permission from Springer Nature. (ii) An autonomous aerial-AM framework employing multiple UAVs for collaborative, large-scale, extrusion-based AM. Adapted from [50], with permission from Springer Nature.

successfully executed a 250 m multi-layer print, five times longer than any previous printing-in-motion system. These mobile robotics offer increased flexibility by allowing systems to move beyond static workspaces, making them particularly valuable in construction and large-scale manufacturing, where producing components larger than the static range of a fixed robotic system is critical. To further improve the accuracy of mobile robots used in large-scale AM, Lachmayer *et al* [48] proposed a robust alternative using a high-precision 2D line laser mounted on the robot's end-effector, which detects surface contours regardless of material or lighting. This method can effectively address the challenge in force control or vision-based techniques such as no contact force and varying lighting conditions. Instead, the depth data sensed by the laser can control the robot's trajectory and adjust speed for consistent material application.

While robotic arms offer multi-axis printing and eliminate the need for support structures in complex objects, they face challenges in design and control complexity. Issues like arm singularities and structural vibrations can negatively affect printing quality and accuracy. Additionally, even though mobile robots enable printing in large, hard-to-reach areas, their precision in positioning the printhead is limited by localization uncertainties. For example, aerial robots, affected by propeller vibrations, struggle with accuracy, while ground-based robots may suffer from issues like vibrations due to specific wheel configurations (e.g. Mecanum wheels). To mitigate these risks, research has extended control autonomy through collaborative robotics [52], which reduces the complexity of individual robot tasks and compensates for the limitations of single robots. For example, Zhang *et al* [50] utilized collaborative aerial robotics, providing an unbounded action

space and allowing for the construction of complex structures in previously inaccessible locations. This technology has potential applications in building infrastructure, remote site construction, and other domains where traditional manufacturing methods face logistical and spatial limitations.

However, it is important to note that robot-assisted AM remains unsuitable for certain processes, such as BJT and PBF, which rely on large, highly specialized machines and controlled environments. These processes do not lend themselves to the mobility and flexibility offered by robotic systems, as they typically depend on tightly controlled parameters and massive equipment to ensure precision and quality. This limitation underscores the gap in applying robotic AM to highly specialized manufacturing techniques, pointing to an area where further research is necessary to extend control autonomy across a broader range of AM processes.

2.2. Automatic toolpath design

Automatic toolpath design is another critical factor for enhancing the precision and efficiency of AM processes [53], complementing the control autonomy provided by robotic systems. By precisely controlling the print head, toolpath design ensures that digital designs are accurately translated into physical objects. As highlighted by Tian *et al* [54], the main goals of toolpath optimization are to improve surface quality, reduce geometric errors, and increase time efficiency. Effective toolpath optimization directly impacts the durability and quality of manufactured structures by enabling the creation of fully dense objects without unintentional voids. Additionally, it significantly improves time efficiency by minimizing non-productive movements. For example, Volpato *et al* [55] developed algorithms that minimize the repositioning distance of the extrusion head in MEX. Their approach, which combines the nearest insertion heuristic with 2-opt optimization, demonstrated that build times could be substantially reduced by optimizing head movements, with the complexity of the object's geometry influencing the extent of these improvements. Toolpath optimization also facilitates the production of objects with variable shell thickness and dynamic resolution. For instance, Gharehpapagh *et al* [56] proposed an adaptive toolpath generation method using a rectangular-orifice nozzle, which adjusts bead width to improve accuracy. Their method achieved a shell thickness range from 0.45 mm to 0.9 mm, effectively allowing the nozzle to print lines twice as wide, demonstrating the flexibility and precision this approach provides.

Traditionally, numerical modeling techniques, such as the FEM and TO, have been used for toolpath optimization [57, 58]. In conventional TO processes, the applied loads, boundary conditions, and structural information of the part are defined upfront, after which FEM is employed to calculate material distribution. However, Sales *et al* [59] identified several limitations of TO in this context. First, TO is computationally intensive, which becomes impractical when applied

to every layer during process planning. Second, while TO generates discrete outputs, extrusion-based AM requires continuous toolpaths, making conversion from TO results complex and inefficient. Additionally, speeding up TO by using a coarse discretization reduces the resolution of the output, further complicating the toolpath generation. Ren *et al* [60] also noted the challenges of evaluating different toolpaths, which often depend on labor-intensive experiments or costly high-fidelity simulations. Given the time demands of numerical modeling, conducting both simulation and optimization in parallel is impractical, particularly as structural complexity grows. While brute-force simulations can optimize toolpaths for simple structures, this approach becomes computationally prohibitive for more complex designs. Therefore, more efficient computational strategies are needed to navigate this growing complexity.

Recent advancements in automatic toolpath design have shifted from relying solely on traditional methods to integrating ML techniques. These ML algorithms build on the foundations of traditional approaches, using them as reference points to navigate the vast search space associated with complex optimization problems. The primary objectives of these ML-driven approaches include: (i) leveraging surrogate modeling to achieve simulations that are faster than physics-based models, thus offering process evolution for the largely unexplored domain of realistically sized layers of arbitrary shape [61]; (ii) reverse engineering composite material parts to capture the geometry and reconstruct the toolpath [62]; (iii) optimizing toolpaths to avoid the accumulation of internal residual stress [63], predicting the optimal toolpath that minimizes the average thermal gradient [64], and improving the thermo-mechanical properties such as in WAAM [65]. A detailed comparison of different ML algorithms for toolpath design and optimization, categorized by data efficiency, optimization capability, and real-time adaptation, is summarized in table 1. Data efficiency refers to models handling limited or synthetic data; optimization capability highlights those excelling in decision-making, and real-time adaptation covers models that dynamically adjust to new data.

In addition to advancements in ML techniques, table 1 highlights the varied performance outcomes of toolpath optimization objectives, which depend on the material and AM process used. For example, thermal management is a critical concern due to the high energy input and resulting thermal gradients in metal-based AM processes like WAAM. Inadequate heat control can cause macro-level defects such as warping and cracking, which negatively affect the mechanical properties of the printed part. Poor heat control can affect material solidification and lead to porosity at the micro-level, further compromising part performance. Therefore, optimizing heat distribution and minimizing residual stresses is essential for maintaining both part quality and dimensional accuracy. Toolpath strategies for metal AM processes focus on the precise timing of material deposition to effectively manage heat dissipation

Table 1. Comparison of ML models for AM processes based on key advantages in autonomous toolpath design and optimization^a.

References	Objective	AM process	ML algorithm	DE	OC	RA
Li <i>et al</i> [66]	Improves consistency and geometric accuracy	FDM	CAN	✓		
Zhou <i>et al</i> [67]	Selects filling path for lattice structures	FDM	SVM	✓		
Dong <i>et al</i> [68]	Reduces path length, printing time, and improves quality	FDM	HNN		✓	
Nguyen <i>et al</i> [69]	Reduces defects in rib-web structures	WAAM	ANN	✓		
Zhou <i>et al</i> [65]	Optimizes thermal-mechanical properties	WAAM	Genetic evolution		✓	
Kunchala <i>et al</i> [70]	Enhances weld bead deposition and surface quality	WAAM	Hybrid-TLBO & SVM		✓	
Petrik <i>et al</i> [71]	Fully automates path planning for thin walls	WAAM	DRL	✓	✓	✓
Sideris <i>et al</i> [72]	Maintains consistent preheat temperature	WAAM	Monte Carlo tree search		✓	
Stathatos <i>et al</i> [61]	Simulates real-time temperature and density	Laser-aided AM	ANN			✓
Ren <i>et al</i> [73]	Predicts temperature and selects optimal toolpath	Laser-aided AM	FEM & RNN	✓		
Kim <i>et al</i> [64]	Minimizes average thermal gradient	SLS	DL		✓	
Qin <i>et al</i> [74]	Minimizes thermal gradients for reduced deformation	SLM	KNN	✓		
Qin <i>et al</i> [63]	Avoids thermal accumulation regions	SLM	DRL	✓	✓	✓
Ikeuchi <i>et al</i> [75]	Improves geometric control in single-track profiles	Cold Spray AM	ANN			✓
Ikeuchi <i>et al</i> [76]	Predicts overlapping track profiles for quality improvement	Cold Spray AM	GPR	✓		

^a Note: **DE** is Data Efficiency, **OC** is Optimization Capability, and **RA** is Real-time Adaptation

and reduce deformation during cooling. In contrast, extrusion-based AM processes, such as FDM, prioritize surface quality and geometric accuracy over thermal management. Parameters like deposition speed and layer height significantly influence surface finish and dimensional precision. Since polymers used in FDM are less prone to thermal stress compared to metals, the primary focus of toolpath strategies in these processes is on optimizing print speed and path smoothness to minimize geometric deviations and improve surface quality. Additionally, controlling extrusion width and material flow is crucial for avoiding voids and ensuring consistent layer adhesion. These differences underscore the need to tailor toolpath designs

to the specific material and AM process to achieve optimal performance.

It is also worth noting that while ML-driven solutions offer significantly greater computational efficiency than traditional physics-based simulations, the challenge of acquiring large, high-quality datasets for training these models remains a limitation. RL, a promising ML technique, addresses this issue by interacting with its environment and learning adaptively. Unlike supervised learning algorithms or population-based optimization methods (e.g. genetic algorithms), which rely on large, labeled datasets or pre-defined data, RL learns through trial and error. It receives feedback in the form of rewards

for its actions, allowing it to adapt and optimize in real-time without the need for a fixed dataset. This makes RL particularly effective in environments where conditions or tasks change over time, such as in AM processes. The unique advantages of RL, as detailed in table 1, further underscore its value in this context.

The adaptive nature of RL makes it especially suitable for generating optimal toolpaths in AM processes. RL agents can identify paths that minimize print head lifts and overall print time, resulting in more efficient and optimized printing processes [77]. For example, Petrik and Bambach [71] successfully applied RL to path planning in the specialized WAAM process. In their work, the RL agent was responsible for planning the deposition path, adjusting welding speed, and regulating wire feed rates with minimal human input and parameterization. The learned policies from this RL model were not only effective but also generalizable to other geometries, demonstrating the flexibility and adaptability of RL in diverse AM scenarios.

In summary, alongside robotic systems, toolpath planning and optimization play a critical role in enhancing control autonomy in AM. By leveraging ML techniques, significant improvements can be achieved in the efficiency and accuracy of toolpath generation. These advancements enhance the precision and reliability of the manufacturing processes and contribute to the development of more optimized and autonomous AM systems.

3. Monitoring autonomy

While substantial progress has been made at the macro-level in terms of control autonomy, the detailed micro-level aspects of the AM process continue to present significant challenges. Defects such as porosity, cracks, delamination, and distortion are prevalent in the microscale. These defects often originate during the layered material deposition process, where inconsistencies in layer adhesion, thermal stresses, nanoparticle movements, and material properties can lead to significant flaws in the final product. Such defects can propagate from one layer to subsequent layers, potentially causing the entire build to fail. Therefore, monitoring and controlling these defects is critical to improving the repeatability, reliability, and quality of AM-produced parts.

Traditionally, time-consuming *ex-situ* monitoring methods (e.g. metallographic examinations) are used post-production to detect defects, which are destructive in most cases. While recent ML advancements have improved the accuracy of defect detection in *ex-situ* methods, they remain reactive, addressing defects only after the part is built, leading to delays and added costs due to rework. In contrast, *in-situ* monitoring combined with ML enables real-time defect detection during the manufacturing process. This proactive approach allows immediate adjustments to printing parameters, enhancing efficiency, preventing defect propagation, and improving overall part quality. The following comparison in table 2 summarizes the key differences between ML-enhanced *ex-situ* and *in-situ* monitoring methods.

3.1. Ex-situ monitoring techniques

Current practices for detecting process-induced defects primarily rely on post-production inspections to ensure that printed parts have acceptably low defect concentrations. This approach, known as *ex-situ* or post-event monitoring, includes both destructive and NDT methods. While providing valuable insights into the effects of processing parameters on microstructure and mechanical properties, destructive testing is often impractical for all parts due to its nature of causing damage. Conversely, NDT methods such as ultrasonic testing, XCT, and MRI are generally preferred as they assess part quality without causing damage [78]. However, these inspections are time-consuming and expensive, especially for large or complex parts, which only provide a snapshot of the final product's condition rather than continuous monitoring throughout the production process.

Among NDT methods, XCT is particularly valuable for validating and evaluating *in-situ* results. XCT can detect geometric accuracy on all surfaces, including complex and internal features, and investigate internal defects such as porosity and cracks [79]. Despite its benefits, XCT is time-consuming and expensive, with the quality of results varying based on the setup, part size, and geometry [80]. For instance, achieving high spatial resolution in XCT requires generating extensive data sets, which can limit the scan volume and increase acquisition time. Additionally, x-ray penetration depends on part size and density, which can affect image quality. The manual thresholding required to produce usable images and segmentation labels from XCT scans further hinders scalability, making it challenging to apply these methods in high-throughput production environments.

Recent advancements in AI offer promising solutions to the challenges of detecting process-induced defects in AM. For example, Wong *et al* [81] developed an automatic porosity defect segmentation method for metal AM using a deep CNN architecture with XCT images. In their experiments, they utilized a publicly available dataset of AM XCT specimens containing artificially generated pores and cracks of varying positions and geometries, which were processed through concatenation to form 3D volumetric images. The authors employed CNN-based architectures, specifically 2D U-Net [82] and 3D U-Net [83] for training and segmentation of defect regions in the XCT specimens. This *ex-situ* defect identification method achieved high-precision segmentation of AM porosity in XCT images, with a reported IoU value of 0.993. Similarly, Zamiela *et al* [84] proposed a DL-based sensor fusion method utilizing the U-Net architecture to enhance the prediction accuracy of porosity in laser-based AM. Their method integrates thermal history images, generated from melt pool images using K-means regression, with *ex-situ* ultrasonic images within the latent space of the encoded features. By combining these two types of data in the U-Net architecture, the approach significantly improves the accuracy of porosity detection, leveraging the complementary strengths of thermal and ultrasonic imaging.

Table 2. Comparison between ML-enhanced *ex-situ* monitoring and ML-enhanced *in-situ* monitoring in AM processes.

Aspect	ML-enhanced <i>ex-situ</i> monitoring	ML-enhanced <i>in-situ</i> monitoring
Defect detection timing	Post-production (after the part is built)	Real-time or near-real-time during the build
Nature of testing	Destructive (e.g. metallography) or nondestructive (e.g. XCT)	Non-destructive
Resource and time efficiency	Time-consuming and labor-intensive due to delayed analysis	Automated and continuous, minimizing delays
Process impact	Defects detected only after production is complete	Proactive: detects and corrects defects immediately
Scalability	Limited scalability, especially for large or complex parts	Highly scalable, suitable for high-throughput production
Cost	Expensive due to rework and testing processes	Cost-effective due to reduced rework and minimal waste
Accuracy	High precision, especially with ML-enhanced detection, but delayed until post-process	High precision with real-time optimization and adjustments

These advancements illustrate how ML techniques have significantly improved post-production defect detection. Furthermore, researchers have identified the benefits of combining *ex-situ* monitoring with *in-situ* monitoring for more comprehensive defect detection [85]. For instance, Abouelnour and Gupta [86] proposed a method for real-time defect detection during the FDM process using image-based techniques while validating the *in-situ* results with *ex-situ* ultrasonic tensile testing. The authors noted that while *ex-situ* monitoring is valuable for material characterization, integrating it with *in-situ* monitoring can significantly enhance the accuracy and quality of defect detection, which is pivotal to the commercialization of AM technologies.

Therefore, to further enhance the quality and reliability of AM processes, there is a growing trend towards leveraging ML techniques for more automated, precise, effective, and flexible *in-situ* monitoring. By enabling real-time examination and adaptive adjustments of printing parameters, these advancements aim to ensure higher precision and consistency throughout the production process.

3.2. *In-situ* monitoring techniques

AM faces significant challenges due to its inherent randomness, low reproducibility, especially in metal AM, and the difficulty of post-production defect detection. To mitigate these issues, real-time or near-real-time monitoring of part quality is essential. Recent advancements in AI-driven visual and signal processing, along with hardware development, have made *in-situ* monitoring technologies increasingly vital for AM. These systems use a variety of sensors and imaging technologies to collect real-time data, enabling the detection and correction of defects as they occur. This proactive approach reduces the likelihood of significant flaws in the final product, enhancing overall manufacturing quality. By analyzing multi-modal data during the printing process, these systems provide automated monitoring, process control, fault detection, and quality assurance, significantly improving the efficiency and reliability of AM processes [34].

The key feature of *in-situ* monitoring lies in its ability to detect and adjust in real-time, rather than post-production, making immediate decision-making and corrections crucial. This on-the-fly data processing, coupled with the application of ML, enhances autonomy and ensures continuous optimization with precision throughout the printing process. In this subsection, we will discuss recent work that utilized AI for *in-situ* monitoring of AM processes. Table 3 presents a comprehensive overview of various sensory methods used for this purpose.

3.2.1. Visual processing. Automatic *in-situ* monitoring in AM processes relies heavily on visual data captured by high-resolution cameras strategically placed within the printing workspace. Central to this system is CV, a branch of AI that allows computers to interpret visual data similarly to human vision. CV analyzes captured images and converts raw visual input into actionable insights, enhancing monitoring efficiency and enabling real-time adjustments [113–115]. This capability is vital for promptly detecting and correcting errors during the printing process, thus maintaining quality and efficiency. Additionally, CV provides detailed, non-invasive observations of the printing process, reducing the need for manual intervention and advancing autonomy. Integrating CV into AM monitoring represents a significant step toward fully autonomous AM systems. Figure 2 illustrates some notable examples of AI applications in visual processing for *in-situ* monitoring in AM.

2D Image Processing. 2D images collected from cameras during the AM processes are essential for defect detection and quality control in *in-situ* monitoring. Cannizzaro *et al* [88] exemplified this approach by using a CV to enhance real-time monitoring and defect detection in metal AM. Their system includes an off-axis camera mounted atop the machine, which captures clear, uninterrupted images of each printed layer, free from mechanical disturbances during the process. The visual data are subsequently processed using two sophisticated CV models to transform raw images into actionable insights.

Table 3. Comparison of sensory methods for *in-situ* monitoring in AM process.

Sensory method	Advantages	Limitations	Typical applications
2D images	Inexpensive and easy to set up [87]; provides rapid visual information [88]; broader compatibility with various ML techniques [89]	Limited subsurface and internal feature detection [34, 90]; performance is affected by lighting, camera placement, and environmental factors [85]; requires careful calibration to avoid environmental disturbances [87]	Infill layer deformation detection [87]; real-time parameter correction [89]; defect segmentation and classification [88] etc.
3D point cloud	High fidelity and resolution; captures comprehensive spatial data for real-time comparisons [91]	High computational cost due to large data sets; limited sensitivity to minor defects [92]; complex and costly setup [92]	Surface roughness detection [93]; defect detection [92]; geometric accuracy assessments [94] etc.
Radiography	Non-contact, non-invasive; suitable for subsurface defect detection such as pores [95]; can penetrate dense materials [96]	Time-consuming and expensive for large-scale production [85, 97]; limited resolution for larger/thicker components [79]; high equipment cost and complexity [98]	More useful for metal AM: defect detection [95]; real-time monitoring of subsurface structures [96] etc.
Thermography	Non-contact, non-intrusive method [34]; effective for detecting surface thermal anomalies [99]; can rapidly scan large areas	Low surface penetration [97]; ineffective for detecting internal defects [34, 99]; susceptible to environmental noise from temperature fluctuations [85]	Surface-level defect monitoring [85]; real-time melt pool temperature monitoring [99] etc.
Acoustic emission	Capable of detecting internal faults and providing volumetric information [78, 85]; cost-effective hardware [100]	Highly sensitive to environmental and process-generated noise [101]; sensor placement is critical and requires careful setup [102]; complex signal analysis required [101]	Detection of crack formation and propagation [103, 104]; pore detection [101, 105]; monitoring of faulty nozzle height [106] etc.
Spectroscopic signals	Quick data collection and analysis [107]; effective for real-time monitoring [108]; provides insights into mechanical and chemical conditions [109, 110]; Captures essential physical details useful for process understanding [111]	Primarily applicable to metal AM processes; complex data requires advanced ML techniques [109]; noisy signals often require calibration and filtering [112]	Real-time <i>in-situ</i> monitoring of porosity levels during the LPBF process [112]; monitoring pore formation in metal AM [109]; optimization of local process conditions in metal AM [108]

First, a U-net architecture, which is a DL model for semantic segmentation, partitions images into segments to distinguish defects from the background at the pixel level. This capability is vital for accurately monitoring the dimensions and integrity of each layer as it is formed, allowing for the capture and detection of defects of high variability in shapes and dimensions that are typical in AM defects.

Second, they use a GAN to augment their dataset with synthetic images of potential defects, addressing the challenge of insufficient training data in specialized applications. The GAN enhances the robustness and accuracy of defect detection by generating realistic images of various defect types. This data augmentation approach tackles the common challenge of insufficient training data for ML models in highly specialized

applications such as AM. Their system achieves a defect detection and classification accuracy of at least 79% across various defect types (including holes, spattering, incandescence, etc), with image processing operations taking less than one second. This work serves as a representative example of how visual processing using visible cameras and CV can be useful for defect detection and *in-situ* monitoring.

Similar work further explores the application of CV and image processing to support *in-situ* monitoring of AM processes. For example, Petsiuk and Pearce [87] introduced an open-source CV-based system that employs cameras to conduct layer-wise analysis of the FDM process. Their system utilized multiple-stage monocular image examinations, including side view height validation to detect critical printing

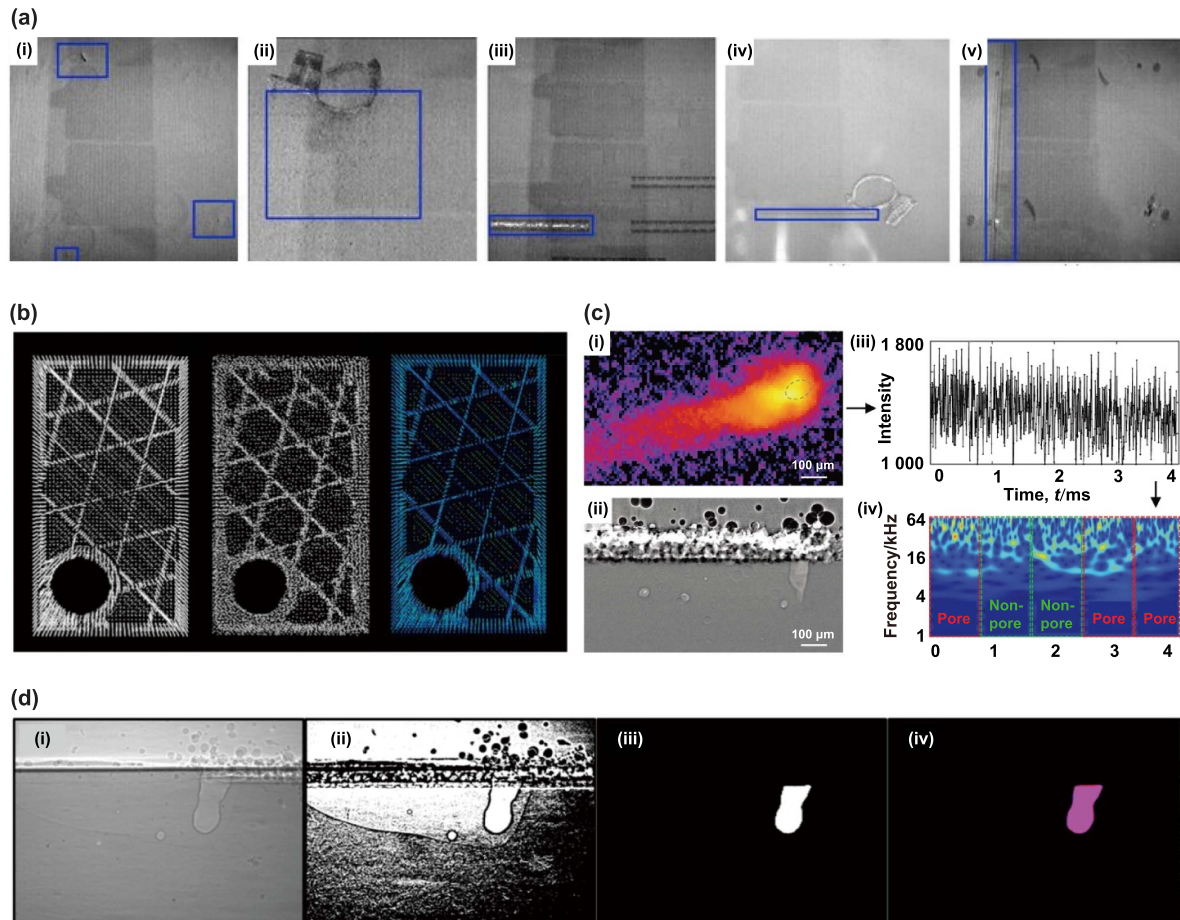


Figure 2. Methodologies for *in-situ* monitoring of AM processes using visual processing. (a) *In-situ* defect detection using an off-axis 2D camera. (i) Holes, (ii) spattering, (iii) incandescence, (iv) horizontal defects, (v) vertical defects © (2022) IEEE. Reprinted, with permission, from [88]. (b) Real-time vision-based method to evaluate AM process performance Adapted from [94], with permission from Springer Nature. Defect detection by comparing the theoretical point cloud from the CAD model (left) with the reconstructed point cloud from the printed part (middle). The resulting difference (right) reveals any errors or defects. (c) Real-time detection of keyhole pores in the LPBF process (i)–(iv) From [99]. Reprinted with permission from AAAS. Defect detection by applying ML to (iv) scalograms generated from (iii) the time-series signal of the average emission intensity from (i) thermal imaging, with (ii) representing an x-ray image for labeling. (d) Deep learning-based keyhole segmentation in LPBF Reproduced from [95]. CC BY 4.0. Defect detection through post-processing (i) raw x-ray images into (ii) normalized and standardized images, followed by image segmentation to identify (iii) ground truth-labeled defects, comparing the ground truth with the prediction in (iv).

failures by examining the height of printed parts, global trajectory correction to identify mismatches between reference borders and printed outline, local texture analysis to detect irregular sections of textures within the layer infill, and targeted failures and corrective actions, where detected failures are mapped to printer actions for real-time adjustments and corrections. Throughout the stages of their system, the authors adopted open-source CV libraries and algorithms such as multi-template matching and ICP to track printing errors and generate corrective actions based on the visual information collected from the top-view and pseudo-side view of a camera placed on the printer. This approach was validated experimentally, showing substantial improvements in print reliability by providing real-time adjustments through visual processing.

Building on advancements in visual processing for *in-situ* monitoring, Brion and Pattinson [89] introduced a comprehensive framework for *in-situ* monitoring of the FDM

process, significantly advancing real-time error correction and adaptability. The framework starts with constructing a robust dataset of 1.2 million images from 192 distinct parts, annotated with four critical printing parameters: flow rate, lateral speed, z offset, and hot-end temperature. This extensive dataset facilitated the development of a multi-head deep residual attention network with a shared backbone for feature extraction and four output heads, each classifying one parameter as low, good, or high. This design enables simultaneous output, allowing the network to understand parameter interdependencies and identify multiple solutions for the same error. To enhance parameter adjustment capabilities, the authors integrated an online correction pipeline into the feedback control loop, incorporating proportional parameter updates, toolpath splitting, and optimized prediction thresholding, resulting in a tenfold improvement in correction speed and response time. For instance, the system adjusts

parameters based on a calculated probability derived from average prediction results based on the image of the extruder's nozzle region. Despite being trained only on extruded PLA parts, the system demonstrated exceptional generalizability to unseen printer types, various camera positions, different materials, and even direct ink write extrusion processes, all using affordable equipment like standard consumer webcams and Raspberry Pi units. This study highlights the significant potential of visual processing for *in-situ* monitoring, offering a practical, cost-effective solution suitable for diverse industrial applications, especially benefiting smaller operations with limited budgets.

In summary, 2D image processing offers several practical advantages for AM *in-situ* monitoring. The straightforward use of cameras provides a simple yet highly flexible solution, allowing seamless integration into various AM systems without disrupting the printing process. This ease of deployment enables rapid adaptation to diverse manufacturing environments with minimal modifications to existing setups, making it a cost-effective approach. Additionally, 2D images, as a fundamental data type in CV, are highly compatible with a broad range of established ML methodologies, which offer optimization and automation capabilities for the enhancement of accuracy and efficiency in real-time *in-situ* monitoring applications.

Despite its advantages, 2D image processing has notable limitations, the most significant being its inability to penetrate materials. This restricts the system to monitoring only the visible surface, such as the melt pool or the outermost printed layers, which limits its ability to detect internal defects, often critical to ensuring the final part's quality [85]. Additionally, the performance of 2D image processing is highly dependent on practical factors like lighting conditions and camera positioning, which can affect the quality and reliability of monitoring. However, CV techniques significantly enhance the utility of 2D image processing by enabling real-time defect detection and quality control.

Looking forward, several advancements and emerging trends in sensory technology for *in-situ* monitoring deserve attention. One emerging trend is the importance of high-quality datasets in supervised learning, as it often relies on large volumes of labeled data. Acquiring such datasets can be time-consuming and labor-intensive, making techniques related to unsupervised or semi-supervised learning promising alternatives. For instance, Manivannan [116] achieved a state-of-the-art accuracy of 98% with only 25% of the labeled training data in the SLS process. Similarly, Song *et al* [117] proposed an unsupervised method for anomaly detection in the WAAM process, significantly improving recall rates and achieving an $F1$ score of 86.3% on the test set. Other related works include [118–120]. Another key development is the transition from offline models to online models, which bring greater adaptability to AM processes, allowing for more dynamic control [121]. Lastly, advancements in hardware, such as adaptive dark-field illumination systems that produce

high-contrast images, are also driving improvements in monitoring capabilities [122].

3D Point Cloud Processing. Apart from 2D images collected from cameras, 3D point clouds have become promising visual data sources for *in-situ* monitoring in AM, offering comprehensive spatial details essential for evaluating the precision and quality of manufactured objects.

In a study by Charalampous *et al* [94], a vision-based system was developed to enhance the monitoring of the FDM process. This system facilitates real-time comparisons between printed objects and their corresponding digital 3D models. It uses a high-resolution 3D structural light scanner to capture detailed point clouds of the objects' external surfaces during the printing process. This method provides a thorough external view essential for geometric accuracy assessments. The point clouds captured for each layer undergo several processing stages to detect discrepancies precisely. Initially, raw point clouds are filtered and segmented using threshold cutoffs and Euclidean clustering, isolating the printed object from the build plate and other non-relevant elements. This segmentation focuses the analysis solely on the target component. Subsequently, the segmented point clouds are aligned with the digital model's point cloud using the ICP algorithm, ensuring accurate comparisons. Rather than using complex and computationally intensive methods, the authors employed a more conventional approach with the K-D Tree for rapid point comparison. This method allows for efficient and precise comparisons, enabling the detection of dimensional deviations between the printed part and the digital model in real time. Experimental validation using geometrically complex objects, such as a spur gear and a centrifugal impeller, demonstrated the system's capability to monitor and identify deviations effectively, confirming its efficacy in handling the intricacies of AM processes. This underscores the pivotal role of 3D point cloud processing in *in-situ* monitoring.

Another study by Ye *et al* [91] leveraged DL with 3D point cloud processing for *in-situ* layer-wise monitoring of the FDM process. Initially, an online scanning system using a structured light scanner captured 3D point clouds of each printed layer. These point clouds were preprocessed and registered with prior layers using a Gaussian mixture model to ensure accurate alignment. Recognizing that global patterns from the entire point cloud might not fully capture minute printing defects, the authors adopted a multi-dimensional indexing approach to partition the point cloud into local regions. To address limitations in traditional 3D point cloud deviation measurement, they proposed measuring the affinity between these point clouds using kernel correlation. This method determines the affinity between local regions of the captured point cloud and the reference point cloud. The vectorized representations of these affinity measurements were then fed into a deep cascade model consisting of random forests to perform classification and facilitate *in-situ* anomaly detection. This innovative approach

demonstrates the effective application of AI for real-time monitoring and quality assurance, highlighting the potential of advanced DL techniques to improve defect detection in AM processes.

Numerous other studies have explored the combination of ML with 3D point cloud processing for *in-situ* monitoring and defect detection in AM processes. For instance, Akhavan *et al* [123] developed a hybrid convolutional auto-encoder decoder DL model to assess and control the quality of FDM-manufactured parts in real time. During their experimentation, a laser scanner captured the top surface point clouds of each printed layer. These raw point cloud datasets were denoised and transformed into 2D depth images for computational efficiency. The HCAE model, consisting of multiple stacked layers of CNNs and inception modules, performed feature extraction and unsupervised training. The model's outputs generated control signals via a G-code manipulation algorithm, enabling real-time process adjustments such as modifying print speed and feed rate. In another study by Chen *et al* [124], ML techniques were applied to 3D point cloud data for *in-situ* surface defect identification during DED processes. A laser profiler, mounted on top of the printing robotic arm adjacent to the laser head, captured the 3D point cloud of the printed surface. The raw point cloud data were denoised using a statistical outlier filter, and random sample consensus segmentation [125] was performed to isolate regions of interest corresponding to the target surface. Multiple ML techniques, including KNN, SVM, and neural network, were employed to extract features from the 3D point cloud data and classify surface defects into four predefined types: no defect, bulge defect, dent defect, and wavy defect. This approach enabled real-time identification and classification of surface defects, enhancing the quality control and reliability of the DED process.

In conclusion, the key advantage of 3D point clouds lies in their ability to capture comprehensive spatial data, providing a detailed and accurate representation of an object's external geometry. Unlike 2D image processing, which is limited to capturing a single surface, 3D point clouds offer a full spatial view, enabling real-time comparisons with digital models such as CAD designs. This capability allows for immediate detection of deviations from predefined models, offering a significant advantage over traditional post-production inspections, particularly in layer-by-layer deposition methods like FDM. However, implementing 3D scanning systems can be expensive and complex, and the large data sets generated require substantial computational resources, which may limit their use in specific applications. ML is increasingly being integrated with 3D point cloud processing to overcome these challenges, enhancing real-time defect detection and quality control. In addition to advancements in algorithms [123, 126], recent research is exploring the potential of 4D reconstruction, which incorporates spatial-temporal information from AM processes to expand the capabilities of 3D point clouds further. For example, Chew *et al* [127] proposed a framework for cold-spray AM by fusing dynamically captured spatiotemporal 3D data. This approach effectively manages dynamic scenes with continuously evolving objects, enabling

the detection of errors in layer height and changes in surface roughness.

Radiography & Thermography. Radiography, particularly x-ray imaging and CT scans, has become a pivotal tool in laser-based metal AM [96, 128–130]. Its ability to penetrate metal powder and substrates while maintaining an ultra-fast capture frame rate makes it ideal for overcoming the challenges of monitoring internal structures and dynamics, which conventional 2D imaging cannot achieve. In a notable study by Dong *et al* [95], the authors explored the processing of x-ray images using advanced DL and CV techniques to enable automated *in-situ* monitoring of the LPBF process, also known as SLM, specifically for detecting keyholes and potential defects. During the visual data collection phase of this study, x-rays were directed at the active machinery during the fusion process. The imaging of keyhole and pore shapes was transformed into visible light using a scintillator and recorded by a high-speed camera. Subsequently, these images underwent post-processing through standardization and normalization to ensure uniform resolution and binary color scales across all images. The ground truths of the keyhole regions were manually labeled to support ML model training. Finally, the authors employed the BASNet [131], an encoder-decoder-based DNN, to perform semantic segmentation. This approach achieved more than 90% segmentation accuracy for keyhole boundaries, highlighting the effective synergy between CV and x-ray image processing for *in-situ* monitoring.

Building upon the concept of *in-situ* keyhole and pore formation detection during LPBF, Ren *et al* [99] proposed an alternative approach that combines radiography with thermography. The motivation behind this study was the observation that intense thermal conditions during the printing process can induce structural defects. In this approach, the authors simultaneously collected x-ray images of internal sub-surface structure dynamics and thermal images of the melt pool. Here, the x-ray images served as the ground truth for model training, while the thermal images facilitated pore-formation predictions. By training a CNN on thermal image-derived scalograms, segmented into Pore and Non-pore categories based on x-ray insights, the authors achieved near-perfect prediction accuracy within sub-millisecond temporal resolution. This integration of x-ray with thermal imaging is crucial as it leverages the precise internal structural visibility offered by x-ray imaging to create superior ground truth segmentation maps. This, in turn, enhances the ML model's training effectiveness, further validated by the detailed surface temperature profiles extracted by thermal imaging.

In summary, radiography, particularly x-ray imaging and CT scans, is highly effective for penetrating metal powders and substrates, allowing real-time monitoring of internal and microscopic structures, such as keyholes and pores. This makes it particularly suitable for processes like LPBF [85]. However, a key limitation of x-ray radiography is its reduced resolution for large or thick objects, making it less effective for detecting cracks and time-consuming for data acquisition and analysis. Additionally, as part size increases, the sensitivity of

the technique degrades, potentially preventing the detection of critical defects in larger AM components [79, 98]. In contrast, thermography excels at detecting surface-level and shallow defects by capturing thermal signals during the AM process. It offers real-time insights into melt pool dynamics without disrupting the workflow [85]. However, its major drawback is the inability to detect internal defects, as it only provides information on the part's external thermal characteristics [34]. When combined, thermography and radiography complement each other: thermography captures external surface data, while radiography offers crucial insights into internal structures. Together, they create a comprehensive *in-situ* monitoring system for detecting both internal and external defects.

Another notable trend in these sensory methods, similar to 2D imaging, is integrating semi-supervised or unsupervised learning [132]. For instance, Li *et al* [133] developed AM-SegNet, a model for high-resolution x-ray image segmentation and quantification. This model utilizes lightweight convolutional blocks and a custom attention mechanism to achieve highly accurate semantic segmentation (approximately 96%) with fast processing speeds ($<4 \text{ ms}\cdot\text{frame}^{-1}$). The segmentation results can be used for quantifying key features, such as keyholes and pores, and for multimodal correlation analysis. This also highlights a trend toward developing lightweight models for real-time monitoring. Additionally, TL [134] is under investigation, and the potential for training foundational models that can be applied across various AM processes is a promising area for further exploration.

3.2.2. Signal processing. In addition to the visual information captured by cameras, other digital signals, such as acoustic and spectroscopic data, play a crucial role in the *in-situ* monitoring of AM processes. These signals offer complementary insights that are instrumental in detecting and correcting defects, thereby enhancing the overall effectiveness of the monitoring system [135]. Moreover, signal-based monitoring systems offer a practical advantage, as processing these one-dimensional data streams typically requires less computational power compared to visual data, making them more efficient for real-time applications [85]. Figure 3 illustrates exemplary works that have applied AI with signal processing for *in-situ* monitoring of AM processes. The technical details of these applications are discussed below.

AE. Acoustic signals are renowned for their high sensitivity and temporal resolution, making them ideal for capturing subtle sound variations during AM processes. These one-dimensional signals can be processed rapidly and are compatible with various AI techniques. Furthermore, acoustic signals are not constrained by material type or location and are free from radiation hazards, significantly enhancing their utility in detecting anomalies that visual inspections might miss [102]. This versatility makes them particularly advantageous for real-time, non-invasive monitoring in AM.

In the study by Shevchik *et al* [101], AE signals were combined with ML techniques for *in-situ* quality monitoring

during the SLM process. The researchers deliberately adjusted process parameters to generate pores of varying concentrations. During the SLM process for each configuration, airborne AE signals were captured using a FBG sensor, which detected the compression and extension of the fiber core induced by sound waves. To address the limitations of CNNs in processing irregular signals, the authors adopted SCNNs [137], which effectively classified AE signals into quality categories in realtime.

Similarly, Taheri *et al* [138] applied acoustic signal processing for *in-situ* monitoring of DED processes. Acoustic signals were collected using a commercial AE research system equipped with acoustic transducers. These signals were recorded under various operating conditions, including normal operation and abnormal conditions such as low laser power or improper powder feed. Spectral features were extracted from the acoustic waveform signals using Fourier transformation and homomorphic deconvolution filtering, providing a detailed representation of the waveform patterns. These features were classified using the K-means clustering algorithm, with ground truth labels corresponding to the different operating conditions. This methodology enabled real-time identification of operational behaviors, allowing for the detection and differentiation between normal and abnormal process states during *in-situ* monitoring of the DED process.

In another study, Wang *et al* [136] also leveraged ML using AE for *in-situ* monitoring of the SLM process. The authors performed experiments with different process parameters, such as laser power and scanning speed. AE signals generated from the interaction between the laser, powder bed, and substrate were collected using a four-channel AE acquisition system (Ver. SAEU3H), with each sensor placed in a corner of the printing area for comprehensive coverage. To establish the ground truths, the printed parts were meticulously analyzed using optical microscopes and classified into low, medium, or high printing qualities based on porosity levels. The collected AE signals were denoised using variational modal decomposition with the whale optimization algorithm. The extracted features were fed into a fully connected MLP and an SVM, with the SVM demonstrating superior performance in mapping AE signals to the respective printing qualities.

Advancements in DL have significantly enhanced the monitoring of metal AM processes. For instance, Pandiyan *et al* [139] developed an unsupervised domain adaptation DL technique to improve the robustness of ML models in identifying regimes in the LPBF process. This study specifically addressed challenges related to changes in data distribution caused by varying laser-material interactions. AE signatures from the LPBF process, involving lack of fusion pores, conduction mode, and keyhole pores, were recorded using two different 316 l stainless steel powder distributions ($>45 \mu\text{m}$ and $<45 \mu\text{m}$) under distinct parameter sets. By applying associative domain adaptation-based training on the proposed CNN-based neural network, the study successfully inferred class labels for an unlabeled AE data distribution based on knowledge from a labeled distribution. This method improved the model's generalization capability, resulting in high prediction

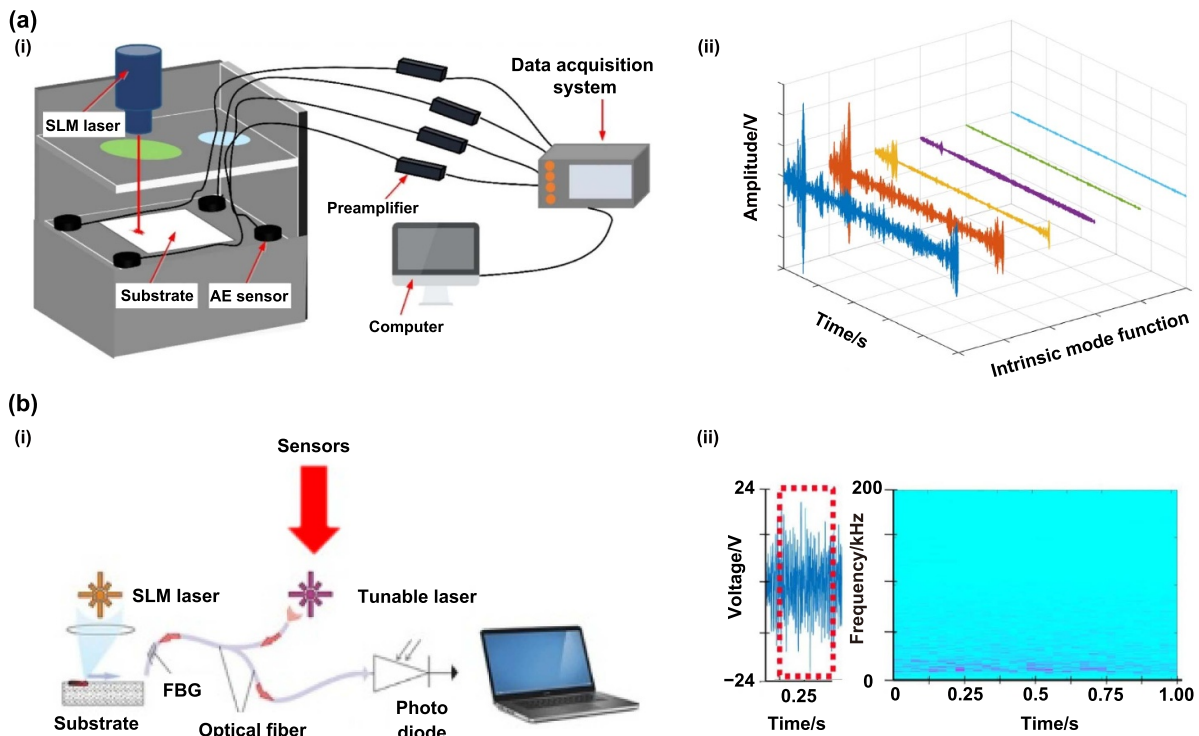


Figure 3. Methodologies for *in-situ* monitoring of AM processes using digital signal processing. (a) Quality prediction through ML processing of AE signals (a) (i), (ii) Adapted from [136], with permission from Springer Nature. (i) AE sensors capture real-time elastic wave signals generated by interactions among the laser, powder bed, and substrate during the SLM process. These signals are amplified by a preamplifier, recorded via a data acquisition system, and visualized on a computer for feature extraction and ML processing. (ii) The proposed method decomposes AE signals into waveforms that closely resemble the original signals while preserving richer feature information, improving interpretability and suitability for ML model training. (b) Acoustic emission monitoring using spectral convolutional neural networks (b) (i), (ii) Reprinted from [101], © 2017 Elsevier B.V. All rights reserved. (i) The proposed framework is equipped with a FBG sensor to detect airborne AE signals. (ii) Defect identification through ML processing of AE signals: (left) an example fragment of an AE signal corresponding to a high-quality printed layer, with the red region indicating a running window. (right) The corresponding spectrogram is generated and passed into a spectral convolutional neural network for pattern extraction and learning.

accuracies of 98.3% and 94.8%, effectively handling domain shifts in the LPBF process.

These studies collectively highlight the integration of acoustic signal processing with ML techniques to derive actionable quality monitoring insights, which shows great potential applicability across various AM processes. This combination not only enhances the detection of anomalies but also facilitates the differentiation between normal and abnormal operational states, ultimately contributing to more reliable and higher-quality AM outputs.

In terms of practical advantages, AE signals are highly sensitive to subtle variations, offering high temporal resolution and the ability to detect internal faults, such as cracks or material inconsistencies, that are undetectable by visual or thermal methods [78]. Additionally, AE is a non-invasive monitoring technique that is not constrained by material type and, unlike radiography, is free from radiation hazards. However, AE faces practical limitations, particularly in manufacturing environments where signals can be difficult to interpret due to noise and irregular patterns caused by environmental factors, system interference, and inherent process-generated noise [85]. To overcome these challenges, advanced signal processing

techniques, such as spectral analysis and denoising algorithms, are often required to extract meaningful features. Furthermore, AE monitoring systems tend to be more complex to implement, as they require precise sensor placement for effective coverage, which adds complexity compared to simpler visual monitoring methods. A promising direction in the AE sensory method is the use of explainable AI to interpret the underlying physics of acoustic signals [139]. For example, Song *et al* [140] studied AE signals during laser spot welding on powder beds, identifying distinct signals linked to cooling-induced tensile cracks, powder impact, and thermal expansion of the substrate. By connecting specific signal characteristics to underlying physical events, explainable AI provides a clearer understanding of AE signals, improving their interpretability and enhancing the overall reliability of AE monitoring systems.

Spectroscopic signals. Spectroscopic signals, such as those obtained from OES, measure the spectral content of light emitted during AM processes. These signals are particularly valuable in laser-based AM techniques like LPBF or DED, where they provide detailed insights into the chemistry and

relative intensities of the vaporized species in the process zone. Specifically, as high-energy lasers irradiate metallic powders, the intense heat causes material vaporization, producing a plasma cloud above the molten pool. This plasma emits photons at specific wavelengths due to atomic line emission and thermal radiation. By capturing and analyzing this emission, deeper insights into the thermal and chemical dynamics of the process can be achieved [141]. When integrated with AI-driven signal processing techniques, OES becomes a powerful tool for *in-situ* monitoring, enabling real-time detection of local conditions. This capability is essential for identifying defects and optimizing overall system performance [108].

In a study by Sun *et al* [109], OES signals were used to monitor microscopic pore formation in metal AM. The emitted spectra capture the energy intensities of photons released as metal atoms absorb laser energy, causing electrons to transition between different energy levels. These spectra were recorded using a spectrometer, and the data were then processed through a deep autoencoder neural network. This network incorporated CNN layers for feature extraction and LSTM layers for compressing features in the time domain. A semi-supervised spectral clustering algorithm was then applied to categorize the processed features, assigning binary quality labels, either good or bad, based on whether the pore defect density surpassed a set threshold. The feasibility of the study was validated using an experimental dataset where four parts were produced by a DED machine under different process parameters.

In another study by Montazeri *et al* [112], the authors applied OES combined with ML for *in-situ* monitoring of porosity presence and severity in the LPBF process. During data collection, four cylindrical disc samples were built using an LPBF machine, each exhibiting distinct porosity levels as verified by x-ray CT, providing ground-truth data. During the build process, OES signals were captured by a photodetector-based multi-spectral sensor. These one-dimensional multi-spectral signals were then transformed into weighted, undirected graph representations, characterized by vertices (representing spectral features), edges (representing relationships between features), and weights (indicating signal intensity relationships). From these graphs, graph Fourier coefficients were extracted as features. The authors experimented with various ML classification algorithms, including Decision Trees, KNN, and SNN, to classify porosity levels based on the graph Fourier coefficients. The experimental results demonstrated that the KNN model with the graph Fourier coefficients as features achieved approximately 10% higher F-score than other ML models using statistical features and could perform the classification in less than 0.5 s. This study further highlights the effectiveness of using OES signals and AI for rapid and accurate *in-situ* monitoring in AM.

In summary, integrating advanced spectroscopic signal processing techniques, particularly OES, with AI-driven methods has significantly advanced quality monitoring in various AM processes. These combined approaches enhance the real-time detection of defects and enable optimization of process parameters, demonstrating their potential for broader application

across the AM industry. However, while these advances are promising, the effective fusion of heterogeneous sensor data, such as combining spectroscopic, acoustic, and thermal signals, remains a key challenge. For example, Liu *et al* [142] proposed a method that integrates acoustic and thermal information to infer key morphological features of the LPBF melt pool and detect defects. Although the study demonstrated potential correlations between features, it did not offer a comprehensive method for fusing multi-sensor data, highlighting a critical area for future research.

The future of OES-based monitoring in AM will likely see advancements in unsupervised learning models and the integration of physics-driven explainable AI systems. These innovations will enhance the interpretation of complex spectral data and provide more transparent, physics-based decision-making processes. Ren *et al* [141] emphasized that spectral signals are not only easy to collect but also contain critical physical information about the material's state during processing. This physical-rich data, when combined with explainable AI models, can yield predictions that are both accurate and grounded in physical phenomena. However, the challenges surrounding multi-sensor data fusion persist. To fully realize the potential of *in-situ* monitoring, future research must focus on developing sophisticated methods for integrating various sensory inputs, providing deeper insights into the real-time dynamics of defect formation and material behavior in AM.

3.3. Multi-sensor data fusion

The aforementioned monitoring methods often rely on data from a single sensor, which requires the extraction of hand-crafted features. These features may not always align with monitoring objectives, leading to a decrease in the performance of monitoring algorithms when the features are inappropriate or inadequate. Additionally, manually extracting features from raw sensor data is time-consuming and demands extensive expert knowledge.

To address these limitations, multi-sensor data fusion has emerged as a more effective and comprehensive approach. By integrating data from multiple sensors, this method captures a broader range of process parameters, thereby providing more distinctive and representative features. This integration enables cross-validation of the prediction, which enhances the accuracy and reliability of monitoring systems and reduces the dependency on human intervention. In the context of AM, multi-sensor data fusion presents significant advancements over traditional single-sensor systems. By enriching the data, this approach enhances the consistency and generalization of models, leading to improved authenticity. Consequently, multi-sensor fusion provides a holistic view of the monitored processes, substantially increasing the accuracy and reliability of autonomous monitoring in AM. The fusion of multi-sensor data also increases the robustness of the monitoring system, as it continues to provide valuable insights even if one sensor fails or is compromised. By integrating different sensor modalities, such as visual, optical, radiographic, acoustic, and

thermal sensors, multi-sensor fusion offers a more comprehensive picture of the manufacturing process than single-sensor approaches [143, 144].

As stated before, the trend towards *in-situ* monitoring is gaining traction as it supports the AM process more effectively. Multi-sensor systems improve monitoring capabilities, reliability, and confidence while reducing data ambiguity and expanding spatial and temporal coverage. For instance, Vandone *et al* [145] developed an AM process control approach based on multi-sensor data fusion. They integrated real-time monitoring data, offline experiment data, and post-process inspection data to create a robust control model for the DED process, adjusting process parameters to meet specific dimensional, mechanical, and quality targets. Similarly, Chen *et al* [125] demonstrated localized quality prediction in a robotic DED process under a DT framework by fusing sensory data from a coaxial melt pool vision camera, a microphone, and an off-axis short wavelength infrared thermal camera. These examples highlight the improved performance compared to single-sensor data prediction.

The heterogeneity of fused data, which can be temporal or spatial and referenced at various resolutions, necessitates advanced processing techniques. The rise of ML has significantly enhanced multi-sensor data fusion. For example, Grasso *et al* [147] utilized SVM combined with a control charting scheme applied to multiple sensor data streams to detect defects and process faults related to the stability of embedded signals. Moretti *et al* [148] integrated multiple heterogeneous sensors into the FDM process, using multi-sensor data fusion technologies for online monitoring of manufacturing processes and part quality. Petrich *et al* [143] proposed a comprehensive framework combining layer-wise electro-optical imagery, acoustic monitoring, multi-spectral emissions, and scan vector trajectory information for LPBF process monitoring. A neural network was used to fuse all available modalities and discriminate flaws from nominal build conditions using only *in-situ* data, investigating the contribution of each sensor's data to the monitoring results. Li *et al* [149] developed a CNN-based approach to combine acoustic and photodiode signals for *in-situ* quality monitoring during the SLM process. Their research demonstrated that integrating these two sensors provided more effective results compared to a broader approach [146] that included layer-wise images along with AE and photodiode signals. This finding suggests that focusing on the most relevant sensors can enhance monitoring performance, even when additional sensor data is available. Examples of using ML in multi-sensor data fusion for monitoring are illustrated in figure 4.

Despite the immense potential of multi-sensor data fusion in AM, several challenges must be addressed for effective implementation. Firstly, sensor imprecision can lead to measurement errors and inaccurate data. The heterogeneous nature of sensory data, with varying resolutions and time scales, adds complexity, and incorrect sensor configurations can further degrade data quality. Secondly, ambiguous

environmental conditions and spurious data require robust systems to manage noise and inconsistencies. Conflicting data from multiple sensors can complicate the determination of the true state of the monitored process. Thirdly, the low repeatability and reproducibility of metal AM processes mean that data fusion cannot be generalized effectively, adding significant uncertainty.

Addressing these challenges necessitates advanced algorithms and robust data processing techniques, including improved sensor calibration, enhanced data preprocessing methods, and sophisticated fusion algorithms. Standardized protocols for sensor integration and data fusion will also enhance the reliability and accuracy of multi-sensor systems in AM. In summary, while multi-sensor data fusion offers great promise for improving monitoring and control in AM processes, overcoming these technical and environmental challenges is crucial for successful implementation.

4. Process autonomy

Process autonomy represents the culmination of integrating various automated components within the AM workflow, ideally achieving end-to-end manufacturing autonomy. This category builds on macro-level control autonomy, which extends AM capabilities to higher DOF, and micro-level Monitoring Autonomy, which features advanced monitoring systems capable of overseeing the printing process and making real-time adjustments to ensure optimal print quality. Process autonomy spans the entire production spectrum, starting from the initial CAD model preparation, where designs are optimized for printing without manual intervention, to autonomous material handling systems that ensure materials are efficiently prepared and supplied. This approach aims to create a seamlessly integrated system that requires minimal human intervention, thus enhancing both the efficiency and scalability of manufacturing operations. By automating critical stages of the AM process, process autonomy supports the development of a fully autonomous production line, capable of autonomously adapting to varying demands and operating conditions.

The foundation of process autonomy is the accurate modeling of the PSP relationship, which enables effective recommendation and optimization throughout the entire AM process. These recommendations encompass crucial stages such as material selection, AM process selection, and parameter optimization. Traditionally, these stages have been addressed sequentially. However, a new approach involving concurrent design based on multidisciplinary design optimization is emerging. For example, Xiong *et al* [28] highlighted a concurrent design approach that includes key steps such as problem decomposition, discipline-specific analysis, strategy selection, and solution generation. By integrating these steps, the concurrent approach enhances the efficiency and effectiveness of the AM process, supporting the goal of achieving full process autonomy.

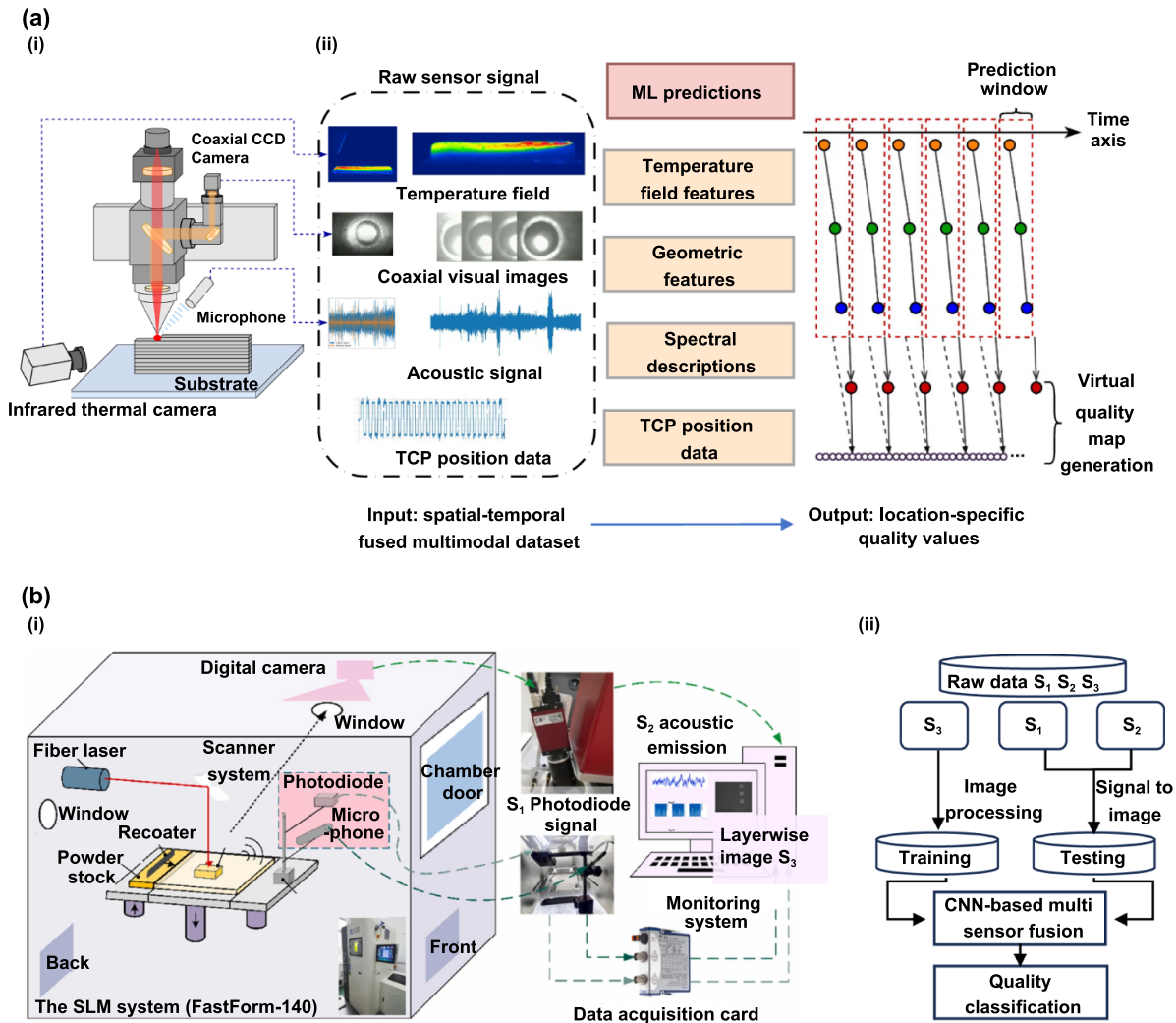


Figure 4. Examples of multi-sensor data fusion using ML techniques. (a) Multi-sensor fusion-based DT for localized quality prediction in robotic DED [125]. (i) A schematic diagram of the multi-sensor monitoring for the robotic-based DED system, incorporating a thermal infrared camera, a coaxial CCD camera, and a microphone sensor. (ii) An illustration of synchronization and registration between multi-sensor features and ML predictions. The ML model maps the spatiotemporally fused datasets to quality labels within the entire volumetric domain Reprinted from [125], © 2023 Elsevier Ltd. All rights reserved. (b) A CNN-based multi-sensor fusion approach for *in-situ* quality monitoring of the SLM process [146]. (i) A schematic representation of the *in-situ* multi-sensor monitoring system, developed with three off-axis sensors: a digital camera (layer-wise image S_3), a microphone (acoustic emission S_1), and a photodiode (photodiode signal S_2). (ii) The flowchart of the proposed approach, where a signal-to-image strategy converts the 1D acoustic emission and photodiode signals into 2D images. (b) (i), (ii) Reprinted from [146], © 2022 The Society of Manufacturing Engineers. Published by Elsevier Ltd. All rights reserved.

4.1. Model preparation

Model preparation is considered the first step in AM and traditionally requires significant human effort to draft and modify designs. While some research has focused on model management, which includes the reuse, matching, and modifications of the existing 3D digital models [150, 151], limitations become evident when new customized requirements are raised. Another domain is 3D reconstruction, which has proven to be helpful in repairing tasks for medical [152], manufacturing maintenance [153, 154], and construction [155]. With the development of AI technologies, especially the introduction of the generative AI ability, the design space of

AM has been enlarged, and more related progress can be transformed into practical applications in AM. Leveraging experience in large-scale 3D scene reconstruction, a single object can now be 3D modeled from 2D images captured from multiple views, particularly for complex-shaped objects. The NeRF [156] method can be used for handheld captures with a few input images. Recent trends related to 3D GS [157] are also credited for its high fidelity and rendering efficiency.

Furthermore, these methods are used for multi-view synthesis, which requires a substantial number of images from different views. Generative AI models, however, can generate these multi-view images with minimal text or

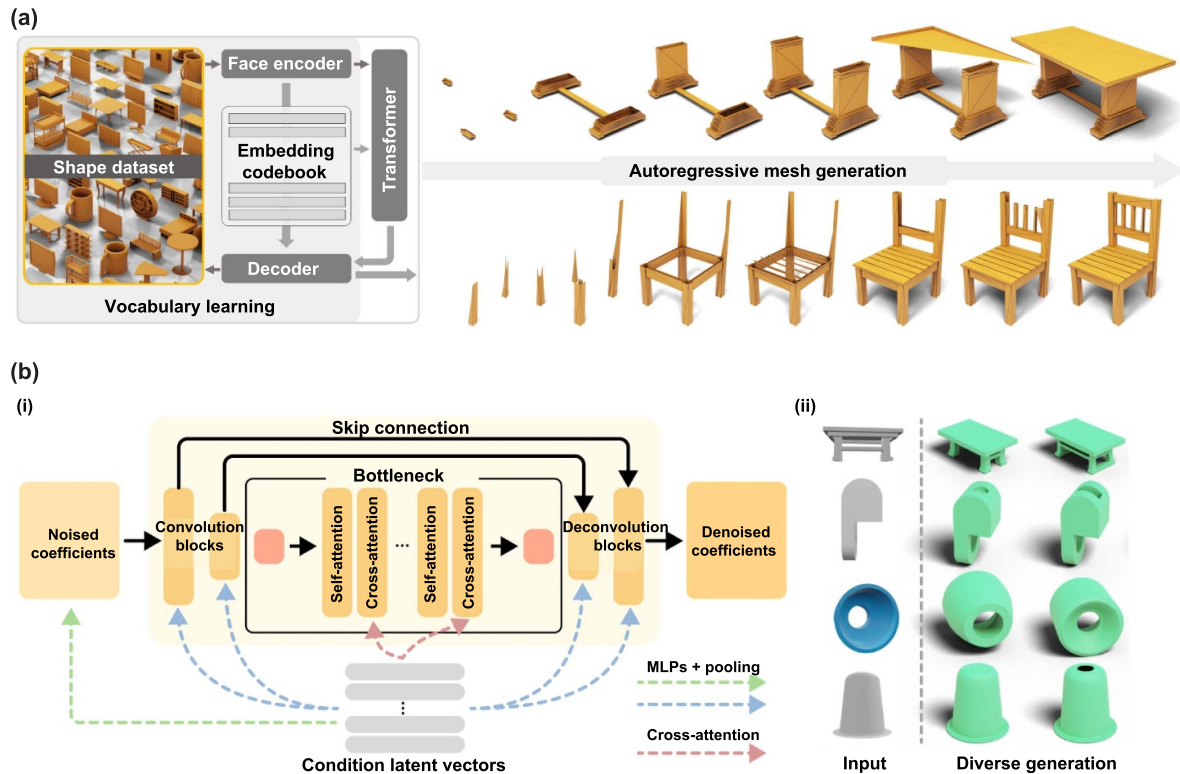


Figure 5. Potential of model preparation using Generative AI. (a) MeshGPT © (2024) IEEE. Reprinted, with permission, from [158]. This approach generates triangle meshes as sequences of triangles using a GPT-style transformer, trained on quantized geometric embeddings. (b) Make-a-Shape Reproduced from [164]. CC BY 4.0. This model generates 3D models from single-view, multi-view, point-cloud, and voxel inputs. (i) The generator network down samples input coefficients to a bottleneck feature volume, which is processed through attention layers and deconvolution to predict denoised coefficients. Condition latent vectors are integrated at three points in the architecture. (ii) The model demonstrates the ability to create diverse outputs from a single input image, accurately replicating visible parts while varying unseen areas.

image input, aiding the process from CAD to CAE to CAM. These methods utilize a pre-trained 2D text-to-image diffusion model as a prior and employ NeRF or 3D GS for optimizing a randomly initialized 3D model, ensuring 3D consistency. Nonetheless, these methods are primarily limited to generating simple, unobstructed three-dimensional objects and cannot represent the internal structure of the object, rendering the generation process complex and imperfect.

Further, these methods are used for multi-view synthesis, which requires a certain number of images under different views, while generative AI models can be used to generate the multi-view images with less text or image input, which helps with the process from CAD to CAE to CAM. These methods use a pre-trained 2D text-to-image diffusion model as a prior, and use NeRF or 3D GS for optimizing a randomly initialized 3D model and ensuring 3D consistency. However, these methods are mainly limited to generating simple, unobstructed three-dimensional objects, and cannot present the internal structure of the object, making the entire generation process complex and imperfect.

Recently, Siddiqui *et al* [158] introduced a Transformer-based network for mesh construction, which has the potential

to use text prompts for 3D model generation with high precision. More research is conducted inspired by the diffusion model, which aligns the textual, image, and 3D model feature, enabling text-to-3D [159–161], and image-to-3D [162, 163] model generation. Notably, Hui *et al* [164] introduced an innovative 3D generative model that encodes ten million publicly available shapes into a high-resolution TSDF. This TSDF is then broken down into multi-scale wavelet coefficients, which are subsequently used in a diffusion model for generation. The current trend of leveraging generative AI for model preparation is depicted in figure 5.

These advancements pave the way for 3D content creation, potentially bringing us closer to the realization of ‘What you think is what you get’ and significantly boosting the development of CAD design. However, there are still areas for improvement, particularly in achieving high-resolution and fine-grained details. The generated models often resemble the desired shapes but frequently omit intricate details. Another shortcoming is that these generated models have not undergone thorough post-evaluation, making them prone to defects when produced by AM. While resemblance is a basic requirement, the focus must shift towards ensuring the models’ properties meet the necessary standards.

4.2. AM process selection

Selecting the most appropriate AM process is essential once the target CAD model is prepared and materials are determined, as it directly affects the manufacturability of the part. The application area dictates the requirements for AM processes, including material applicability, performance requirements, part quality, and production cost. The primary criteria for selecting AM processes are technical viability, economic feasibility, and sustainability. This selection is essential for achieving process autonomy and influences future settings such as printing parameters [165].

Extensive research has been conducted to establish criteria for AM process selection. From a technical perspective, Gokuldoss *et al* [166] provided comprehensive guidelines that consider material types, technique limitations, post-processing requirements, and quality metrics. Additionally, the AHP has been utilized to select AM processes and machines based on their technical specifications [167]. For economic viability, Fera *et al* [168] enhanced previous AM cost models by incorporating additional factors such as preparation, machine usage, materials, energy, and post-processing costs. This improvement allows for a more accurate calculation of production costs across various AM processes.

Recently, sustainability criteria, including environmental impact, working conditions, and worker health, have been integrated into the AM process selection through comprehensive evaluations such as life cycle assessment, life cycle cost, and social life cycle assessment [169]. These evaluations have led to the development of methods that consider multiple criteria simultaneously, providing more holistic solutions for process selection. These methods range from knowledge-based systems to advanced multi-criteria decision-making approaches. For example, Zaman *et al* [170] combined Ashby's material selection charts with AHP, utilizing a database of 134 AM machines from 38 international vendors and a specialized AM materials database to identify optimal material-machine combinations for specific product designs. Similarly, Liu *et al* [171] proposed a process selection method applied early in the product design stage, which involves initial screening, technical evaluation, re-evaluation of feasible processes, and machine selection. This approach assesses the feasibility of AM from both technical and economic perspectives based on preliminary design specifications, iterating the design to align with AM techniques and selecting the most suitable machine.

In addition to AHP, other tools such as certainty pairwise comparison [172] and BNs [173] are also used in multi-criteria AM process selection. Despite these advancements, significant gaps persist, particularly in the limited application of ML. The challenges include: (i) the decision processes often lack generalization ability and robustness, functioning more like rule-based methods or search and pattern-matching engines, which can hinder adaptability to varied contexts requiring expert knowledge and long-term observation; (ii) current knowledge-based methods are less frequently used and lack efficient

mechanisms for knowledge extraction and update, which is a critical shortfall given the rapid advancements in the AM domain.

Addressing these gaps will significantly enhance the robustness and adaptability of AM process selection methods. By integrating more advanced and flexible approaches, these methods can be better equipped to keep pace with the dynamic nature of AM technological advancements, ultimately leading to more effective and autonomous manufacturing solutions.

4.3. PSP relationship modeling

DfAM encompasses model preparation, process selection, and design iteration and optimization of products and their manufacturing systems. The primary goal of DfAM is to enhance product quality and performance while minimizing development lead time and costs. Traditional DfAM methods often rely on surrogate models that require explicit relationships between variables. These relationships can be difficult to establish and may lack generalization, particularly in complex optimization tasks. To overcome these challenges, integrating ML into DfAM offers a promising alternative solution. ML can enhance the understanding of the interconnections between design and optimization variables, facilitating more effective forward and reverse design. One of the most critical issues in this context is the establishment of PSP relationships, which are essential for tasks such as geometry optimization and material development.

Several innovative ML-driven frameworks have been proposed to address the challenge of establishing PSP relationships. For instance, Jiang *et al* [174] proposed an innovative ML-driven framework to establish relationships between process, structure, and property, such as mapping from process parameters to structure and from structure to property. Similarly, Ackermann and Haase [175] presented a data-driven framework using physics-based simulation data to elucidate explainable process-microstructure linkages for metal AM. Saunders *et al* [176] introduced a GP-based workflow to connect process modeling to microstructure features, generalizing to unseen process parameter combinations. Additionally, PSP models need to incorporate physics knowledge with measurement and monitoring data to generate the required inputs. For instance, Ko *et al* [177] proposed a physics-guided ML framework that integrates a KG top-down approach with a data-driven bottom-up approach to construct and model new PSP knowledge. A detailed explanation of modeling the PSP relationships is depicted in figure 6.

4.4. Materials development

Material development in AM involves understanding the relationship between material properties and the AM process. This includes structural characterization, linking structure to properties, and designing and developing

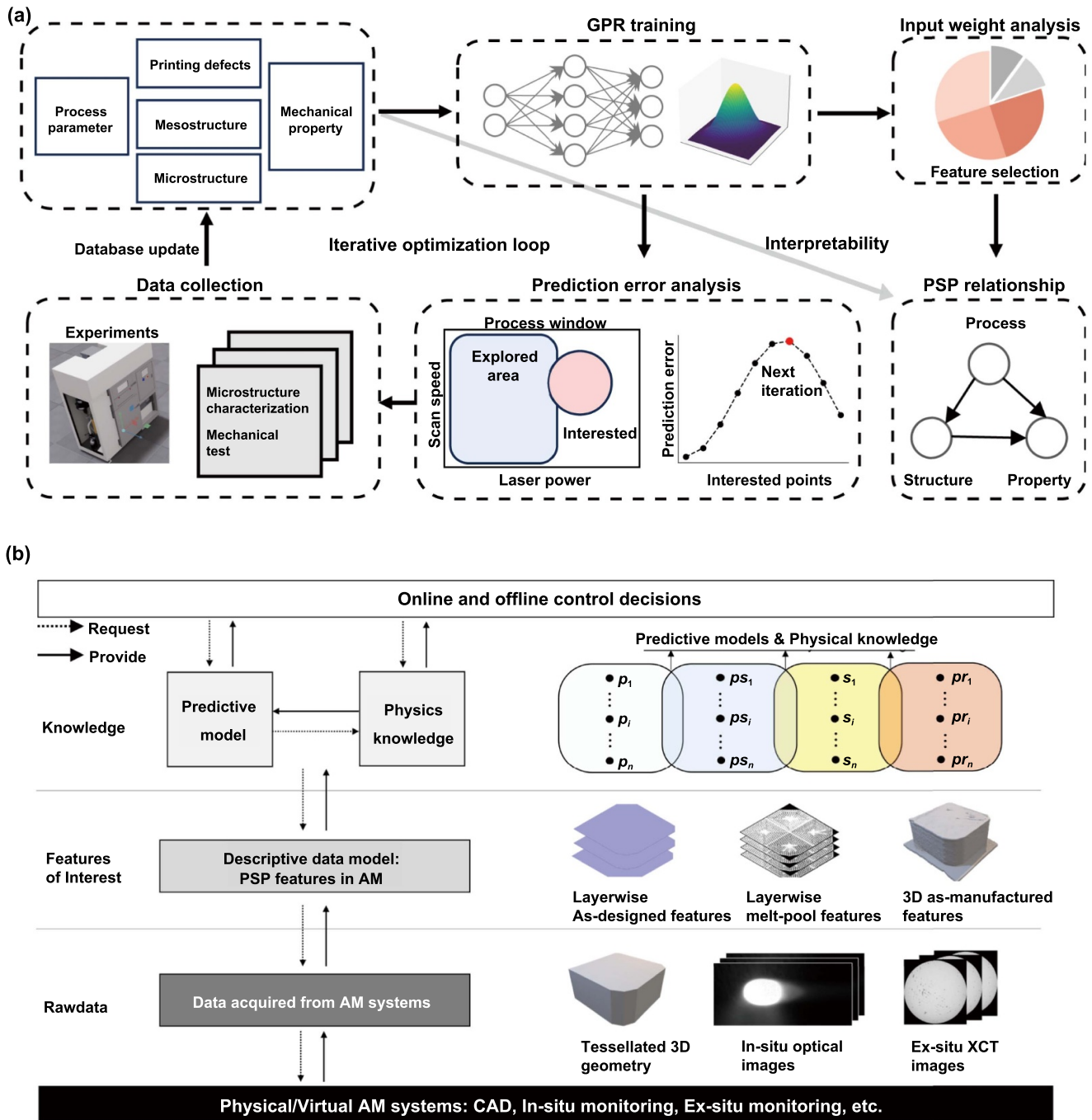


Figure 6. Examples of modeling the PSP relationship using ML techniques. (a) Overview of the PSP modeling framework and GPR prediction models for LPBF Reproduced from [178]. CC BY 4.0. A GPR model predicts the mechanical properties of LPBF-fabricated AlSi10Mg using previously unexplored process parameters and analyzes the prediction errors. Process parameters and physical/structural data serve as inputs, while mechanical properties are outputs. The predictive accuracy of single-output and multi-output GPR models is compared. (b) Example of modeling the PSP relationship in metals by integrating ML with physics knowledge. The proposed framework for physics-guided, ML-driven PSP analysis in metal AM. Process parameters, process signatures, structures, and properties are represented as $p_i, ps_i, s_i,$ and pr_i respectively. Reprinted from [177], © 2022 The Society of Manufacturing Engineers. Published by Elsevier Ltd. All rights reserved.

new materials [179]. Understanding material characteristics such as strength, toughness, hardness, and ductility is crucial for effectively mapping these properties to the AM process and ensuring the quality of the final product.

Material characterization is inherently complex and time-consuming. ML has demonstrated its utility in quickly predicting material properties and effectively identifying new materials based on existing knowledge. ML models can learn a low-dimensional latent space, where high-dimensional,

detailed designs can be projected. These models can then reconstruct the original design from any point in this latent space. Inverse schemes can exploit these generative capabilities to search the latent space rather than the high-dimensional space, potentially creating new materials with desired properties from optimal latent points. For example, Pilia *et al* [180] highlighted that ML could map a material's representation to its properties using historical or generated data. These representations can vary from basic chemo-structural descriptors to detailed electronic charge densities. Once this mapping is established, the properties of many new materials within the same subclass can be directly predicted, making the tasks of designing new materials and modeling the microstructure-to-property linkage complementary.

Despite these advances, AM faces a significant challenge due to the limited variety of materials, particularly in metal AM, where many metals and alloys suitable for conventional manufacturing are unsuitable for AM. Consequently, it is critical to discover new alloys or modify existing materials to possess good printability and the desired properties for AM. Johnson *et al* [181] suggested that ML could be employed for alloying titanium (Ti) with elements such as aluminum (Al), vanadium (V), zirconium (Zr), chromium (Cr), and hafnium (Hf) and then assessing the printability. They highlighted that while using a set of coarse-level selections to add alloying elements is feasible, explicitly creating all possible combinations of these elements is impractical. For instance, adding alloying elements in 1 wt% increments up to 15% of the total results in 15 503 alloy combinations, making practical experiments extremely time-consuming.

ML can significantly assist in material development by predicting microstructure and macroscopic properties. For example, Machaka *et al* [25] collected a dataset of 1 364 phase observations, including at least 36 predictive features specific to metallurgical conditions, correctly classifying HEA solid solution phases and predicting feasible phase transitions. ML can also help develop materials with desired properties. For instance, Yang *et al* [182] developed an ML-driven HEA design system for AM, producing an optimized sample with superior hardness, 24.8% higher than the highest hardness in the original dataset. Zou *et al* [183] used ML in collaboration with material science knowledge to improve the strength and ductility of Ti-based alloys. Rao *et al* [184] proposed a closed-loop system integrating ML with density-functional theory, thermodynamic calculations, and experiments. They achieved the automated discovery of HEAs with optimal thermal, magnetic, and electrical properties after processing and characterizing 17 new alloys out of millions of possible compositions.

ICME approaches further enhance ML's promise for extracting insights and developing comprehensive models of materials. Current ICME approaches have applications in linking various stages of the PSPP loop [185]. Wang and Xiong [186] reported a new method for AM materials development using a CALPHAD-based ICME framework, demonstrating that optimized compositions can increase the probability of successful AM builds by 44.7%.

In conclusion, effective ML tools can be invaluable for rapidly developing materials with desired properties and predicting properties for new materials. However, several concerns remain in material development: (i) many ML algorithms, especially those involving DL, lack interpretability and are often considered black boxes. Sometimes, understanding the reasons behind a decision is more important than the decision itself; (ii) there is a conflict between hand-crafted features and automatically extracted features. Hand-crafted features, which rely on expert knowledge, are more trustworthy and explainable. However, in ML model training, these features may reduce the model's adaptability; (iii) the feature selection problem is also linked to the size of the dataset. For small datasets, hand-crafted features may be more effective, which can be beneficial in developing new alloys.

4.5. Process parameter optimization

As AM increasingly undertakes the production of more sophisticated parts, the requirement for fine process control has heightened. Numerous factors contribute to the quality of AM products, necessitating dynamic optimization of a large number of interrelated parameters. For example, Chia *et al* [187] highlighted that even minute variations in parameters such as the laser power, scan speed, and layer thickness can affect the cooling rate, heat input, and thus impact the turn-out quality of the process and may induce defects in the microstructures and cause inconsistency in the mechanical property in the printed parts. Given the geometric diversity of printed parts, no one-size-fits-all approach effectively addresses optimal printing parameters for all scenarios. Furthermore, the scarcity of certain printing materials often necessitates zero-shot or few-shot optimization approaches instead of conventional trial-and-error methods.

In line with generic optimization frameworks, AM parameter optimization typically involves three core components: (i) decision variables, (ii) constraints, and (iii) objective function, which can be further divided into two categories: single objective and multi-objective for mesoscale level (i.e. porosity or relative density, melt pool geometries) and macroscale level (i.e. mechanical properties, energy, and material consumption) [165, 179]. Traditionally, this optimization problem is solved by systematic design of experiment or simulation methods, which are considered as search within sparse experimental data points such as using the Taguchi method [188]. While these methods can explore sparse experimental data points, they often require substantial trial-and-error efforts to identify the response behavior regions where performance improves. This makes it easy to arrive at suboptimal solutions, particularly since AM optimization is typically non-convex and NP-hard, meaning that it is computationally challenging to solve optimally.

To overcome the limitations posed by data scarcity and the vast optimization space, ML has emerged as a promising alternative. Leveraging ML makes it possible to predict printing properties and optimize process parameters more efficiently. These two elements are intricately linked, and

Table 4. Summary of ML models applied in process parameter optimization for AM process.

References	ML algorithm	AM process	Summary (\mathcal{I} is input, \mathcal{O} is objective)
Liu <i>et al</i> [189]	SVM	3D cementitious material printing	\mathcal{I} : flow parameters, print speed \mathcal{O} : predict printed filament deformation
Zou <i>et al</i> [190]	XGBoost, ANN, etc.	SLM	\mathcal{I} : laser speed, power, layer thickness, etc. \mathcal{O} : maximize relative density
Costa <i>et al</i> [191]	Genetic algorithms, ANN, etc.	SLM	\mathcal{I} : laser power, scan speed, hatch distance, etc. \mathcal{O} : maximize part density
Liu <i>et al</i> [192]	Physics-informed ML	LPBF	\mathcal{I} : laser parameters, scan strategy \mathcal{O} : predict porosity
Smoqi <i>et al</i> [193]	Physics-informed ML	LPBF	\mathcal{I} : melt pool temperature, spatter characteristics, etc. \mathcal{O} : monitor and control porosity
Sharma <i>et al</i> [195]	Decision tree	FDM	\mathcal{I} : infill density, wall thickness, layer thickness \mathcal{O} : predict dimensional variation
Tamir <i>et al</i> [201]	DNN, SVM, etc.	FDM	\mathcal{I} : layer height, print speed, filament extrusion speed \mathcal{O} : monitor and optimize print process
Barrionuevo <i>et al</i> [199]	SVM, MLP, etc.	SLM	\mathcal{I} : laser power, scan speed, powder size, etc. \mathcal{O} : maximize relative density
Park <i>et al</i> [202]	DNN	SLM	\mathcal{I} : laser power, scanning speed, hatch distance, etc. \mathcal{O} : achieve target density, minimize surface roughness
Pham <i>et al</i> [203]	Feedforward Neural network	DED	\mathcal{I} : temperature data, process simulation results \mathcal{O} : predict temperature and melt pool size
Lao <i>et al</i> [194]	ANN	3D concrete printing	\mathcal{I} : nozzle geometry \mathcal{O} : improve surface finish quality
Khorasani <i>et al</i> [196]	ANN	SLM	\mathcal{I} : laser power, scan speed, scanning method \mathcal{O} : optimize surface roughness
Shirmohammadi <i>et al</i> [197]	MLP	FDM	\mathcal{I} : nozzle temperature, print speed, layer thickness, etc. \mathcal{O} : minimize surface roughness
Qin <i>et al</i> [198]	DL-based PSO	SLS	\mathcal{I} : part fill, geometric ratio, height, etc. \mathcal{O} : minimize energy consumption
Shi <i>et al</i> [204]	DRL	DED	\mathcal{I} : laser power, scanning speed, scanning sequence \mathcal{O} : improve temperature uniformity, reduce hardness variability
Liao <i>et al</i> [205]	PINN	SLM	\mathcal{I} : infrared temperature data, process parameters \mathcal{O} : predict temperature and identify parameters
Kapusuzoglu <i>et al</i> [206]	Physics-informed ML	FDM	\mathcal{I} : extrusion temperature, part porosity \mathcal{O} : improve process control
Nagarajan <i>et al</i> [207]	KB-ANN	FDM	\mathcal{I} : nozzle temperature, print speed, wall thickness, etc. \mathcal{O} : improve model generalization
Liu <i>et al</i> [208]	Bayesian model, SVM, etc.	SLM	\mathcal{I} : printer settings, laser power, hatch spacing, etc. \mathcal{O} : accelerate new metal AM technology adoption

optimization can follow naturally if the outcomes of different parameter sets can be accurately predicted.

Recent studies have demonstrated the utility of various ML techniques for this purpose and are systematically summarized in table 4. For example, unsupervised methods such as SVM [189], and supervised techniques, including regression and classification approaches [179], have been used to establish relationships between process parameters and critical metrics such as density [190, 191], porosity [192, 193],

geometry [194, 195], surface quality [196, 197], and energy consumption [198]. These models allow for the identification of optimal parameter sets while reducing the need for costly physical experimentation. For example, Barrionuevo *et al* [199] investigated the optimal parameters of the SLM process to maximize the relative density of 316L stainless steel parts. They employed ML algorithms, including GBR, MLP, RFR, and KNN, to effectively learn the pattern with the large optimization space. Similarly, Nguyen *et al* [200]

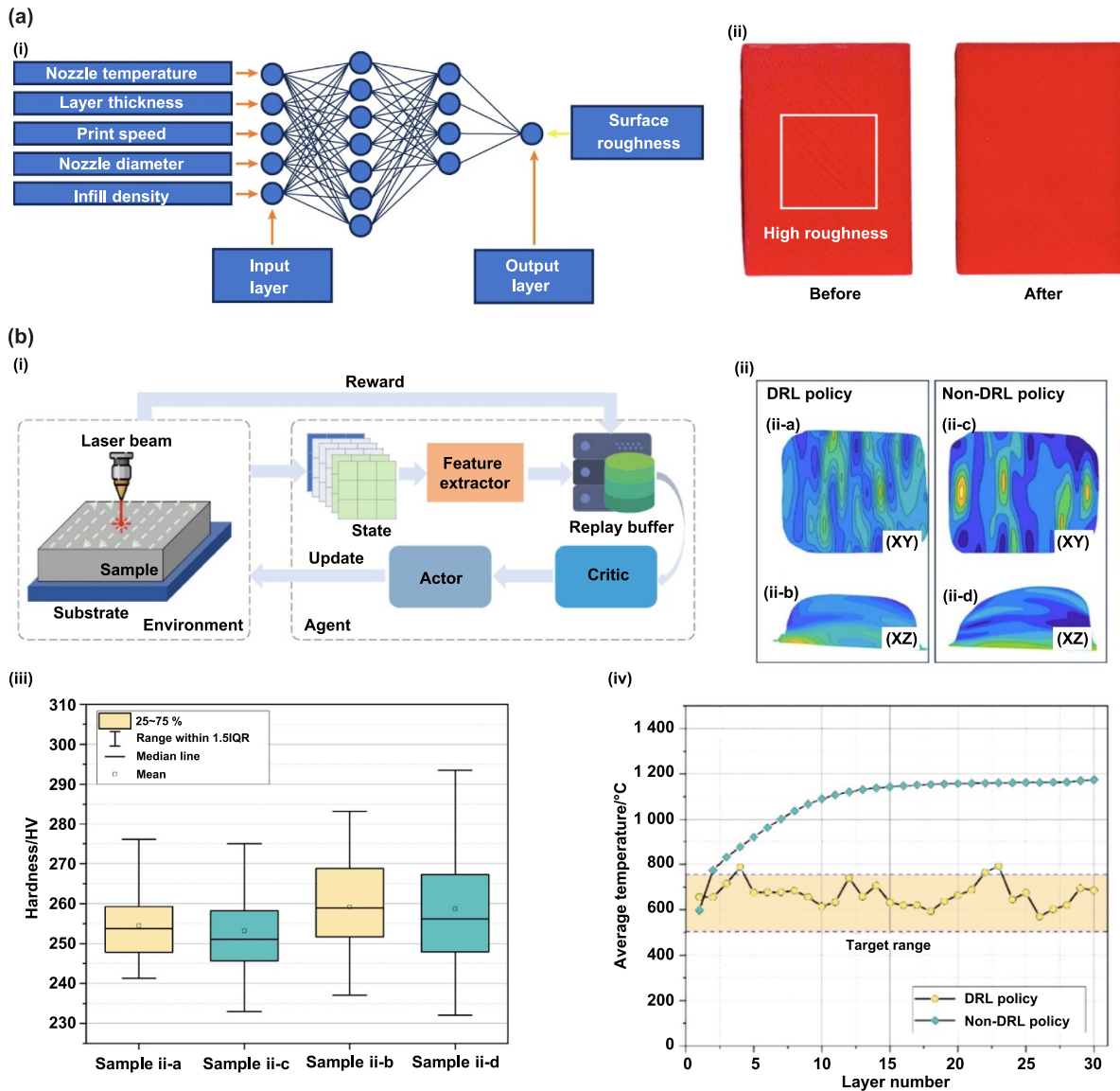


Figure 7. Examples of process parameter optimization using ML techniques. (a) Optimization of surface roughness in FDM 3D printing using a hybrid neural network and PSO approach (a) (i), (ii) Adapted from [197], with permission from Springer Nature. (i) Neural network trained on five process parameters (e.g. nozzle temperature) to predict surface roughness. (ii) Surface comparison of 3D-printed parts before (left) and after optimization (right), showing improved roughness. (b) Parameter optimization in DED of nickel alloys using DRL and a temperature simulation model. (i) DRL framework integrating a physical model for policy learning. (ii) Hardness contour plots comparing DRL (samples (ii-1) xy, (ii-2) xz directions) and non-DRL policies (samples (ii-3) xy, (ii-4) xz directions), with DRL producing more uniform hardness. (iii) DRL improved hardness consistency, with horizontal hardness variability increasing by 17.1% (interquartile range) and 31.8% (standard deviation) and vertical by 24.9% and 27.1%. (iv) DRL policies controlled average temperature effectively during the simulation phase. (b) (i)–(iv) Reprinted from [204], © 2024 The Society of Manufacturing Engineers. Published by Elsevier Ltd. All rights are reserved, including those for text and data mining, AI training, and similar technologies.

developed an ML platform to predict and optimize the AM process using MLP and CNN models. Typical examples of using ML techniques for process parameter optimization are shown in figure 7.

Recent research has increasingly focused on DL to create more robust models by adding layers to neural networks, thereby enhancing their ability to handle non-linear relationships inherent in AM processes. This addition is expected to gain a model that can grasp in-depth features, thus enhancing the ability to handle non-linear relationships, which aligns with the intricate nature of AM. For example, Park *et al*

[202] developed a supervised DNN to enhance the quality of Ti–6Al–4V parts fabricated using the SLM process. Their methodology optimizes key process parameters, including laser power, scanning speed, layer thickness, and hatch distance, to achieve targeted properties like density ratio and surface roughness. The model reliably produces parts with qualities nearly identical to predefined specifications, exhibiting maximum error rates between 0.9% and 4.4% in biomedical applications. However, it is important to note that DL is not suitable for all cases, as increasing the number of layers can complicate network convergence, which requires significantly

sufficient high-quality data. In AM, acquiring a huge amount of data is challenging due to the complexity of systematically producing low-quality samples and the high costs associated with reproducibility and experimentation, particularly in metal AM.

The AM process requires independent operations and seamless collaboration between different manufacturing components to produce products with consistent quality. Surrogate-based optimizations are commonly employed to optimize the entire AM process, although these techniques are often highly constrained to custom-designed tasks and do not generalize well to diverse settings. Conversely, RL, a technique that is capable of determining the optimal policy for sequential problems in a dynamic context, is effective in addressing variable manufacturing settings, even when encountering novel specifications. For instance, Venugopal and Anand [209] propose an RL-based TO strategy using the upper confidence bound method for structural and thermal generative design in AM. Using an exploration and exploitation scheme, the RL agent learns to generate optimized designs with scalability to real-world processes by maximizing rewards based on performance metrics like mass, compliance, and thermal distortion. Additionally, RL can facilitate online process parameter control. For example, Vagenas and Panoutsos [210] conducted case studies on potential instability factors of RL algorithms in AM scenarios, implementing a control policy to vary laser beam power to achieve desired melt depths following a predetermined scanning pattern. These successful applications highlight RL as an emerging technique in AM for automating process parameter optimization. The recent rise of RL in various applications is particularly driven by advancements in DL. DRL, which is based on DNNs that can model complex, non-linear relationships between states and actions, allows RL agents to approximate value functions or policies in high-dimensional state spaces. Leveraging large and high-quality datasets, DNNs can also handle large state and action spaces, making RL applicable to more complex environments and tasks. Furthermore, the data-driven nature of DL automates feature engineering, which is traditionally a time-consuming manual process. Consequently, DL and RL increasingly collaborate to solve complex sequential decision problems [211].

While ML significantly enhances the ability of parameter optimization in AM, it also comes with challenges. Data quality, quantity, and diversity can affect model performance. Additionally, the black-box nature of some ML models, like DNNs, can lead to issues in interpretability and trustworthiness among practitioners. Against this background, one notable aspect is the use of knowledge-based methods, which aim to enhance explainability by integrating physics-informed approaches and expert knowledge along with experimental data. Several examples of physical and knowledge-driven methods are presented in figure 8.

Physics-informed methods. Physics-informed methods represent a hybrid ML paradigm that incorporates physical

domain knowledge, such as thermo mechanical laws and constraints, into ML models [212, 213]. This approach effectively captures real-time system dynamics and the fundamental control physics of AM. The first step involves the accurate modeling of the physical features. For instance, Pham *et al* [203] developed a DL-based surrogate model to accurately predict temperature evolutions and melting pool sizes in metal bulk samples produced via the DED process. This model, trained on high-fidelity data from validated FEM, achieved a prediction accuracy of 99% for temperature evolutions and 98% for melting pool sizes compared to the FE model across unseen process settings.

Then, further integration can be applied for process parameter optimization based on the modeled physical features. For example, Baturynska *et al* [214] proposed a framework using FEM alongside ML techniques to assess and optimize process parameters in AM. The former approach relies on expertise, whereas the latter employs large datasets. Liao *et al* [205] created a hybrid framework that combines physics-based and data-driven methods to develop a model informed by physics for thermal analysis in AM. This model is capable of identifying unknown material and process parameters from partially observed temperature data. In a numerical example, the framework successfully estimated the values for laser absorptivity, heat capacity, and thermal conductivity, achieving an accuracy of less than 5% error using synthetic noisy infrared images. Traditional offline trial-and-error methods for setting parameters like scan sequence, laser power, and scanning speed are suboptimal and lack generalizability, often resulting in non-uniform physical distribution and inconsistent mechanical properties. Addressing these challenges, Shi *et al* [204] presented a novel approach that integrates DRL with a physics-informed method to optimize process parameters in DED. This method dynamically adjusts parameters to achieve optimal control and includes a cost-effective temperature simulation model. Experimental results show significant improvements in temperature uniformity and hardness variability in Inconel 718, with enhancements of 31.8% and 27.1% in horizontal and vertical building directions, respectively. Furthermore, the advent of physics-informed methodologies has catalyzed the exploration of advanced computational techniques like NO [215]. These operators, an evolution of traditional neural networks, are designed to learn mappings between functions across continuous domains. Their ability to generalize and extrapolate is exceptionally promising, demonstrating significant potential in accurately modeling complex, multiscale material properties.

In summary, integrating physical knowledge enhances prediction accuracy and ensures that results are physically meaningful. Additionally, this approach allows for accurate model predictions using minimal experimental data. Consequently, this method bridges the gap in physics knowledge within ML models and harnesses the capabilities of ML to uncover intricate relationships between process, material, and geometry in AM while also correcting approximations in physics-informed models [206].

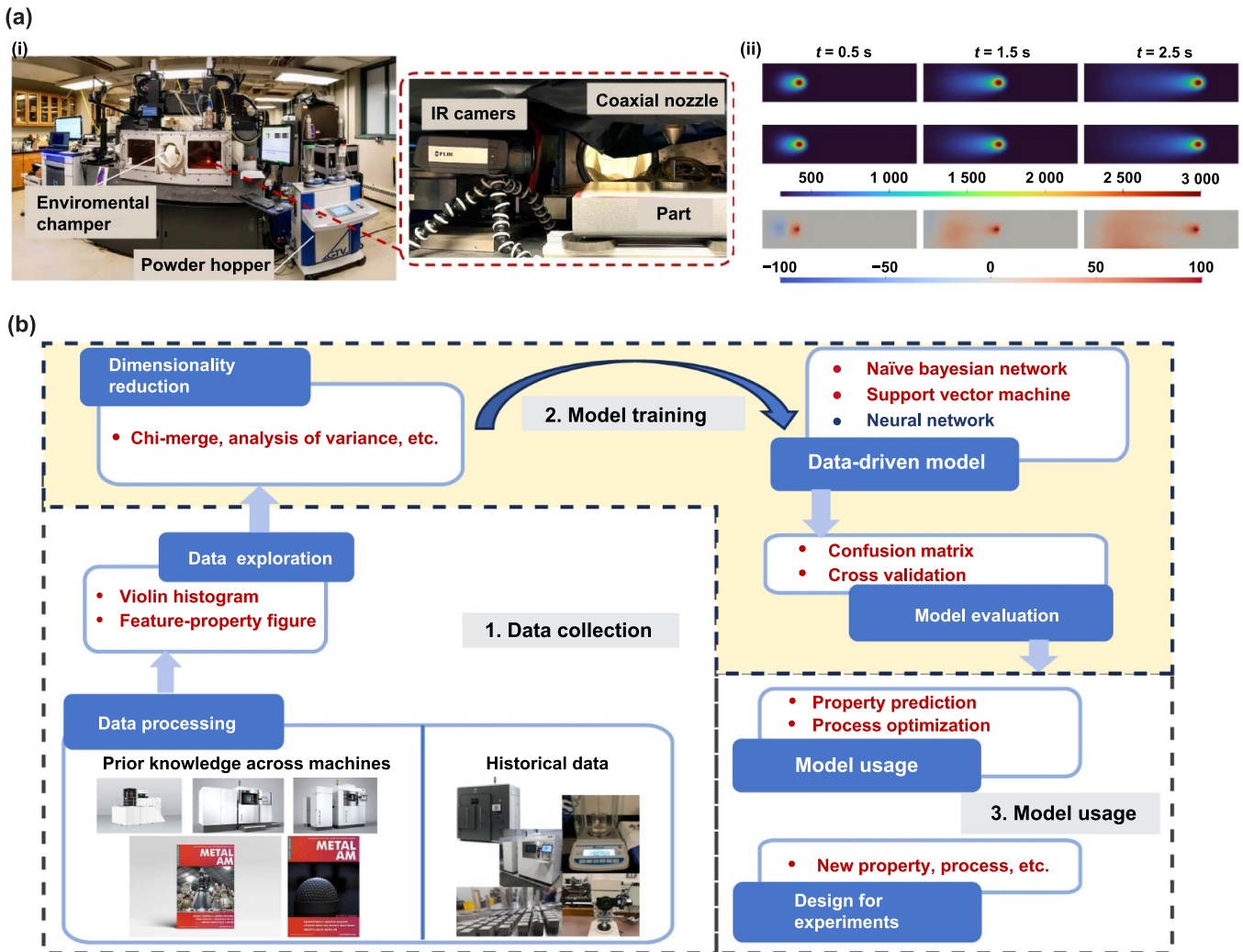


Figure 8. Examples of using physical-driven ML and knowledge-driven methods for optimizing process parameters. (a) Hybrid thermal modeling in AM processes with PINN (a) (i), (ii) Adapted from [205], with permission from Springer Nature. (i) Experimental setup, including an overview and temperature measurement arrangement. (ii) Temperature field comparison between benchmark FEM simulation (first row) and the trained PINN model (second row). (b) Learning framework for AM knowledge extraction and transfer. Reprinted from [208], © 2021 Elsevier B.V. All rights reserved.

Knowledge-informed methods. Leveraging expertise to support AM activities has become an emerging practice [216]. However, the knowledge system involved adds another layer of complexity. Beyond physical properties, representing knowledge in a structured format is challenging, leading to limited research on this topic. Liu *et al* [217] developed the NER framework of integrating the expert knowledge internalized in both academic materials and LLMs through RAG to automatically customize taxonomies for AM processes. Abdollahi *et al* [218] introduce a starting step with expert screening to select the parameter space, factors, and factor levels, before subsequent algorithms. Nagarajan *et al* [207] developed a KB-ANN that incorporates literature and expert insights on AM to define its structure. This KB-ANN model demonstrates superior generalization with fewer trained weights compared to traditional ANNs. Wang *et al* [219]

introduced a BNs-based knowledge management system to bridge the knowledge gap between designers and AM technologies, effectively modeling the AM domain under uncertainty. Liu *et al* [208] studied the feasibility of cross-machine knowledge transfer to accelerate the adoption of new metals AM printing technologies. These knowledge-informed methods offer several advantages: (i) pre-verification by experts introduces prior information, which can significantly reduce initial errors and improve the reliability of subsequent processes; (ii) similar to physics-informed methods, the integration of cross-disciplinary knowledge provides robust and explainable decision support, enhancing the interpretability of the models; (iii) a systematic knowledge system can streamline the search space for process parameter optimization, reducing computational costs and improving efficiency in developing AM processes.

4.6. Post-processing automation

Post-processing in AM is essential for removing support structures and unwanted edges or surfaces, ensuring the part's physical integrity and accuracy. This low-level operation ensures the part's physical integrity and accuracy. Furthermore, post-processing enhances the final product's overall performance, such as increasing fatigue life, which is a higher-level objective. Among various post-processing methods for AM parts, thermal techniques are particularly effective. These techniques alleviate residual stresses, reduce the likelihood of cracking, and homogenize the microstructure. Additionally, laser peening applies plastic compression perpendicular to the material's surface, causing lateral expansion. Laser polishing improves surface roughness, while machining and abrasive finishing enhance both form accuracy and surface finish [220].

Currently, the removal of support structures is performed manually. Automating this process, especially using industrial robots, would be beneficial for both small and large-scale productions. Industrial robots can be trained to generate trajectories, eliminating variations in surface quality and dimensional accuracy caused by human error [221]. Nelaturi *et al* [222] presented a related approach, considering collision-free automation for support removal in AM. They investigated a configuration space approach using a multi-axis machining instrument. The problem is modeled as a TSP, which is used to find collision-free paths through all accessible features, facilitating the removal of support structures using traditional machining to achieve the intended design.

In addition to robotic-based autonomy, ML techniques are increasingly utilized in post-processing. Vaidya and Anand [223] reported an image segmentation-assisted tool for pre- and post-processing operations in AM. This tool enables the fabrication of components directly from CAD geometry, reducing geometric dimensioning and tolerancing errors, such as flatness, cylindricity, and profile error. Another significant aspect is targeting the source of reduced post-processing, with the use of TO during the design process of the DfAM cycle, which can contribute to material waste reduction and minimize the need for support removal [224].

Moreover, Jannesari [225] highlighted that information from the post-processing phase can be used to optimize future builds. This presents an opportunity to trace quality factors such as defect density, surface roughness, dimensional accuracy, and reliability indicators like fatigue strength back to the initial design, material, or process conditions. Despite this potential, limited research exists on this topic. Ideally, most unwanted structures should be removed during the design and suitable AM process selection stages, and defects should be mitigated during monitoring and process parameter optimization stages. Therefore, focusing solely on post-processing may seem less meaningful. Nevertheless, post-processing autonomy remains under-investigated. It is essential for an end-to-end production solution, particularly for different methods of selection under various conditions. This process can be knowledge-driven, indicating that new

techniques related to knowledge management systems warrant further study.

5. End-to-end process integration & autonomy

The IAM system is often modeled as a cyber-physical system, where the cyber domain includes CAD design, STL file generation, G-code generation, simulation, and DT, while the physical domain encompasses material handling, AM machines (such as printers or robotics), *in-situ* sensors, and post-process inspection. However, the introduced control autonomy, monitoring autonomy, and process autonomy are currently implemented as separate modules within these two domains. This separation results in a lack of integration between different modules, hindering the development of a streamlined solution for the AAM system.

For example, even with mature commercial FDM processes, users must manually operate slicing software, transfer the generated G-code to the printer via USB, and then operate the printer to begin the printing process. This procedure can be particularly challenging for beginners. To realize an end-to-end solution, several aspects should be considered, such as schedule generation, HMI, experience extraction, etc. Under these considerations, each aspect will be discussed in detail below.

5.1. Nesting & scheduling

To increase production rates (yield or throughput) at the industrial level, particularly for mass customization, the AAM system should incorporate a closed-loop control system capable of planning, taking actions, reflecting, and adjusting as needed. An efficient scheduling system optimizes the sequence of operations by considering factors such as material availability, machine readiness, and expected completion times. Integrating predictive maintenance into the scheduling process can preemptively address potential machine failures, reducing downtime and improving overall efficiency.

Nesting involves packing multiple parts into a constrained build area or volume and determining their location and orientation within the build volume. It is also referred to as batch placement, bin-packing, knapsack, grouping parts, layout problem, layout planning, packing, and placement. Scheduling refers to assigning builds to AM machines for build cycles and includes terms like batch machine scheduling, dispatching, multi-task scheduling, part-to-printer assignment, production planning, sequencing, and task assignment. Taxonomically, nesting and scheduling are based on the physical system hierarchy of three levels: Part, Build, and AM Machine. This hierarchy results in six problem classes from the intersection or combinations of these levels [226, 227].

The introduction of AI aids in solving the NP-hard problem of nesting and scheduling. Yamashiro and Nonaka [228] utilized a LightGBM algorithm to predict processing time,

achieving optimal performance. Their optimization of parallel machine scheduling using estimated processing times resulted in an average reduction of approximately 30% in makespan. RL is also suitable for scheduling problems. For example, Ying and Lin [229] employed an iterated epsilon-greedy algorithm in a two-stage assembly AM scheduling problem to optimize job sequence and resource allocation, demonstrating improved effectiveness and efficiency in AM production planning. Alicastro *et al* [230] developed an RL-iterated local search meta-heuristic based on a Q-learning variable neighborhood search method. They framed the problem as a strip packing problem, aiming to minimize package height under specific physical constraints, thereby reducing total completion time and maximizing average profit per unit time.

Recent advancements in AI have led to the development of more sophisticated algorithms capable of real-time decision-making and adaptation, which have shown promise in dynamic and complex environments [231]. These models can adjust scheduling parameters in response to real-time data, enhancing efficiency and flexibility in production planning. Additionally, DT systems integrated with AI algorithms provide powerful tools for simulating and optimizing nesting and scheduling processes, enabling proactive adjustments and continuous improvement.

Meanwhile, nesting and scheduling are often associated with CMfg. For example, Wang *et al* [232] proposed a CV-based approach using morphological operations to efficiently nest irregular parts in the printing space, achieving higher productivity and lower costs in a cloud environment. Mashhadi and Salinas Monroy [233] developed a DL auction system that maximizes the utility of the AM Cloud by assigning production orders to manufacturers who can build objects at the lowest cost for customers willing to pay the highest price. These approaches highlight the potential of integrating AI-driven nesting and scheduling with cloud-based platforms to optimize resource allocation and production efficiency on a larger scale.

Research on nesting and scheduling is particularly beneficial to collaborative manufacturing, which involves the collaborative multi-site production problem in AM. In this scenario, orders must be batched and scheduled across several geographically dispersed manufacturing sites. Collaborative manufacturing is also closely related to CMfg, with the ultimate goal of achieving AMaaS [234]. By leveraging AI and integrating it with cloud-based systems, manufacturers can ensure more efficient resource allocation, reduced production times, and cost savings. Furthermore, advancements in AI-driven predictive analytics can enhance the coordination between sites, improving overall system resilience and responsiveness to market demands. As a result, AI-enabled collaborative manufacturing can lead to a more robust, scalable, and flexible production ecosystem.

5.2. HMI

In an end-to-end AAM system, HMI is pivotal in translating high-level user commands into precise machine actions. This

enables seamless communication between operators and complex manufacturing systems. The intricacy of AM processes, which often require real-time decision-making, poses challenges in designing HMI that are both user-friendly and capable of handling complex tasks. Moreover, the varied expertise levels of users, ranging from novices to experts, further complicate the design of effective interfaces. To address these issues, an HMI must strike a balance between simplicity and technical sophistication. This section explores the key challenges in developing practical HMI systems for AM, including balancing usability with system complexity, adapting to user skill levels, and facilitating real-time feedback. We also examine how emerging technologies offer promising solutions to these challenges.

Challenge 1: intuitive interfaces & usability. To address the challenge of balancing intuitiveness with complexity, various interface technologies have been explored. Traditional methods, such as touchscreens with streamlined controls or AR for step-by-step guidance, offer direct and user-friendly ways to interact with AM systems. Additionally, voice-activated systems can further enhance accessibility by reducing the need for manual inputs. Beyond these, advanced techniques like NLP algorithms can bridge the gap between human instructions and machine actions, making the interaction less dependent on specialized expertise. For instance, LLMs, pre-trained on vast datasets, can be fine-tuned to interpret user commands and adjust printing parameters autonomously, significantly improving accessibility and reducing the likelihood of user error. These technologies help streamline interactions, minimize cognitive load, and enhance the overall user experience.

While NLP techniques have been applied in AM, mainly in areas such as generative material design [235, 236], knowledge management [237, 238], and failure analysis [239], research specifically targeting HMI remains limited. A key factor in effective HMI for AM is understanding user intent. Traditional NLP techniques, such as Transformer-based models, have been employed for this purpose, but they often struggle with the intricate requirements of AM processes, where contextual awareness, adaptive learning, and task complexity are critical. The advent of LLMs provides a significant opportunity in this regard. These models, pre-trained on vast corpora, can be fine-tuned for domain-specific tasks, facilitating more natural communication and enabling seamless interaction between the user and the machine. Fan *et al* [240], for instance, proposed an LLM-driven framework that autonomously translates human instructions into machine-executable printing parameters, further advancing the potential of intuitive AM processes.

Challenge 2: adapting to user expertise. Another critical challenge is designing user interfaces that cater to users with varying levels of expertise. Novices may struggle with the complexity of AM systems, while expert users often require advanced features to maintain granular control. To accommodate these differences, it is essential to develop adaptive interfaces that scale in complexity according to user skill levels.

For inexperienced users, adaptive UIs play a crucial role in simplifying the complex workflows of AM. Technologies such as VR, AR, and MR have emerged as powerful tools to enhance these interfaces, particularly by offering step-by-step guidance and immersive learning environments. In the context of AM, VR has been widely applied in training scenarios to aid non-expert users in understanding fundamental concepts and processes. For example, Ostrander *et al* [241] demonstrated the effectiveness of VR in teaching introductory AM concepts, providing an engaging medium for novice users to interact with virtual models. Furthermore, VR supports DT data exchange, as demonstrated by Cai *et al* [242], where VR was used for toolpath planning and simulation in extrusion-based AM systems, offering novice users structured guidance on pre-determined layouts.

Similarly, AR has proven effective in enhancing AM training experiences. Fan *et al* [243] developed an AR-powered training system that integrates DT and VLMs, offering a hands-on immersive environment for metal AM. These immersive technologies not only simplify the learning process for novices but also provide intuitive visual feedback, reducing errors and build failures. Chheang *et al* [244] extended these benefits to expert collaboration, creating a VR-based platform for remote, collaborative inspection of AM-manufactured parts.

For more advanced users, MR presents unique opportunities to perform complex tasks by merging the virtual and physical environments. MR allows users to interact with both real and virtual objects simultaneously. As AM transforms digital CAD models into physical objects, MR enhances this process by overlaying additional data in real time, enabling users to interact more effectively with the physical environment. This integration enables the realization of more complex tasks like part design [245], simulation [246], and custom orthopedic model printing based on visual and tactile force feedback, as demonstrated by Malik *et al* [247]. These advanced functionalities cater to expert users who require precise control over complex AM processes.

Challenge 3: efficient feedback & system adaptation. Real-time feedback mechanisms are critical for ensuring the accuracy and efficiency of AM operations. In such systems, users must receive timely and relevant feedback to identify and correct errors during the manufacturing process. This becomes particularly challenging in high-stakes environments, such as aerospace or medical device manufacturing, where even minor delays or miscommunications can result in costly mistakes or compromised product quality. Therefore, systems must be designed to adapt dynamically to user inputs, ensuring smooth and error-free operation.

To address this challenge, continuous feedback loops—such as real-time error detection algorithms or adaptive prompts—allow the system to remain responsive to user actions. Multimodal feedback systems play a crucial role here: tactile feedback in AR environments can help prevent operational errors by providing physical cues, while visual or auditory signals keep users informed about system performance and

potential issues. Such systems not only improve user engagement but also enhance task accuracy by facilitating immediate error correction [244]. Furthermore, advanced learning-based feedback mechanisms can personalize system responses by analyzing user behavior over time. By adapting to past user interactions, the system can refine its recommendations and settings, leading to improved operational efficiency and user satisfaction [248].

Challenge 4: seamless human-machine co-creation.

Human-machine co-creation in AM represents an evolving paradigm where human creativity and problem-solving capabilities are combined with the computational power of AI-driven systems. In this collaboration, human operators excel at high-level decision-making, such as interpreting design requirements or troubleshooting unexpected issues, while AI systems are tasked with optimizing routine yet complex processes, such as predicting potential structural weaknesses or fine-tuning support structures. The core challenge lies in ensuring seamless communication between human operators and the machine, allowing them to exchange information fluidly and collaborate effectively.

A well-designed co-creation framework facilitates this interaction, enabling both humans and AI systems to learn from each other and refine processes over time. For example, AI can analyze large datasets to optimize printing parameters or suggest design improvements, which the human operator can then evaluate and implement [249]. This iterative process not only accelerates production cycles but also fosters innovation, particularly in creating lightweight, high-strength components for industries such as aerospace and automotive [250]. As Batra *et al* [250] emphasized, such co-creative processes can lead to groundbreaking innovations, enabling manufacturers to produce components with improved performance characteristics.

A key aspect of effective human-machine co-creation is the integration of multimodal information, which includes visual, auditory, and textual inputs. This approach mirrors the natural ways in which humans communicate, making interactions more intuitive and accessible, especially in complex AM environments. Multimodal communication allows operators to engage with machines more naturally, enhancing both the precision and efficiency of their tasks. Research has demonstrated the potential of these capabilities in various manufacturing applications, such as enabling more accurate scene interpretation [251], improving human-robot task planning [248], and enhancing anomaly detection [252].

In this context, the development of LMMs, such as the VLM, offers significant promise for advancing HMI in AM. These models combine visual and textual data to interpret user instructions more accurately, which is particularly valuable when transferring expert knowledge to less experienced users. By facilitating more natural, multimodal forms of instruction and feedback, LMMs can streamline complex processes and improve user understanding of the system's operations. This not only enhances communication between the operator and the machine but also enables more efficient task execution and

decision-making, particularly in scenarios where visual cues and natural language instructions are essential.

In conclusion, addressing the challenges of HMI in AM requires a multi-faceted approach that integrates intuitive design, adaptive interfaces, real-time feedback mechanisms, and co-creative frameworks. Technologies like NLP, AR, and multimodal systems hold significant potential to overcome these barriers, enhancing both user accessibility and system efficiency. Continued research and development in these areas will be crucial for advancing HMI in AM, particularly in complex, high-stakes manufacturing contexts.

5.3. Adoption & enhancement of AI agents

Integrating AI agents is pivotal to achieving a seamless end-to-end solution in autonomous systems. These self-refining agents function as controllers, coordinators, and continuous learners, making them essential for realizing the AAM system. However, a significant challenge in realizing the potential of AI agents is the scarcity and diversity of available data, which hampers their ability to learn effectively and adapt to various scenarios.

The autonomy of AI agents, driven by ML algorithms, heavily relies on the quantity and quality of data. Insufficient or non-representative data can lead to poorly trained models that struggle with a wide range of real-world scenarios, resulting in poor performance and a lack of adaptability. TL addresses this issue by allowing agents to inherit knowledge from previous experiences, adapt to new tasks, and support few-shot learning. Additionally, with adequate domain knowledge of AM processes, data augmentation techniques, such as generative models and simulations based on physical models, can create diverse synthetic datasets that mirror real-world scenarios. DT, which provides a virtual replica of the ISM environment, can also be employed to generate extensive and collaborative data sets that reflect real-world conditions [253]. These techniques help mitigate the effects of data scarcity and diversity, improving the robustness and adaptability of AI agents.

Another complexity in achieving fully autonomous processes arises from process variability and uncertainty, as manufacturing typically involves many steps to achieve desired outcomes. This makes it challenging for a single AI agent to identify the optimal policy for managing the entire AM process. Therefore, fostering collaboration between multiple agents by sharing knowledge and distributing expertise is crucial. FL is an effective solution that enhances overall model performance by leveraging distributed data without extensive new data collection, facilitating knowledge-sharing between AI agents. Additionally, MARL enables multiple autonomous agents to collaborate, with each specializing in different tasks within the AM process. This distribution of expertise boosts process control efficiency for complex AM scenarios. MARL allows each agent to focus on specific aspects of the process, integrating their expertise to adapt more effectively to dynamic and uncertain manufacturing environments. Consequently, MARL alleviates the burden on individual agents and reduces training costs. Through coordination and

shared insights, these specialized agents enhance overall process stability and efficiency, leading to more robust and reliable autonomous systems.

An illustration of methods to achieve full autonomy with AI agents in the AAM system is depicted in figure 9, where AI agents refine their expertise by interacting with both real-life manufacturing settings and virtual training environments. Specifically, DT generates synthetic data and conducts simulations based on physical entities, laying the foundation for diverse training scenarios. These agents can train under various schemes, such as TL, FL, and MARL, depending on the specific process requirements. These methods collectively empower autonomous agents to navigate uncertainties, leading to more efficient and precise manufacturing outcomes. Previous successful adoptions of these techniques are listed below.

TL. TL has significantly enhanced AI agents in AM applications, such as process control and quality assessment. Tang *et al* [254] provided a comprehensive review of TL applications in AM, emphasizing how domain knowledge transfer can reduce data requirements for optimizing new AM processes. This is evident in various applications. For instance, Cheng *et al* [255] introduced a TL-based technique to model shape deviations in AM, demonstrating the capability to achieve high-fidelity predictions despite limited and varied training data. Similarly, Pandiyan *et al* [256] showed that knowledge acquired by DL networks on one material, like stainless steel, in the LPBF process can be effectively transferred to another material, such as bronze. Their models, initially trained to classify LPBF process mechanisms like balling, lack of fusion pores, conduction mode, and keyhole pores, successfully transferred this knowledge to classify similar mechanisms in different materials. Furthermore, Huang *et al* [257] developed a TL-based melting pool modeling technique, leveraging pre-trained knowledge from low-fidelity data to fine-tune a multi-fidelity point-cloud neural network. This approach resulted in high-fidelity surrogate modeling for quality control in metal AM processes. In summary, TL has demonstrated significant potential in enhancing AM processes by effectively transferring prior knowledge across different materials and process parameters, reducing the need for extensive datasets, and accelerating model development.

Data augmentation. Data augmentation has been proven valuable in simulation and prediction by expanding the domain knowledge of AI agents thus reducing the necessity of physical trial-and-error experiments [258]. By using physical engines to simulate object behaviors under natural laws, it is possible to create near-infinite data sources and maintain operational safety during training through a process known as ‘sim-to-real’ transfer. In this context, DT serves as digital replicas of real-life manufacturing processes, allowing the simulation of various scenarios and conditions that may be impractical or impossible to replicate in the real world. This capability enables the generation of extensive and diverse datasets, thereby enhancing the robustness and adaptability of trained agents.

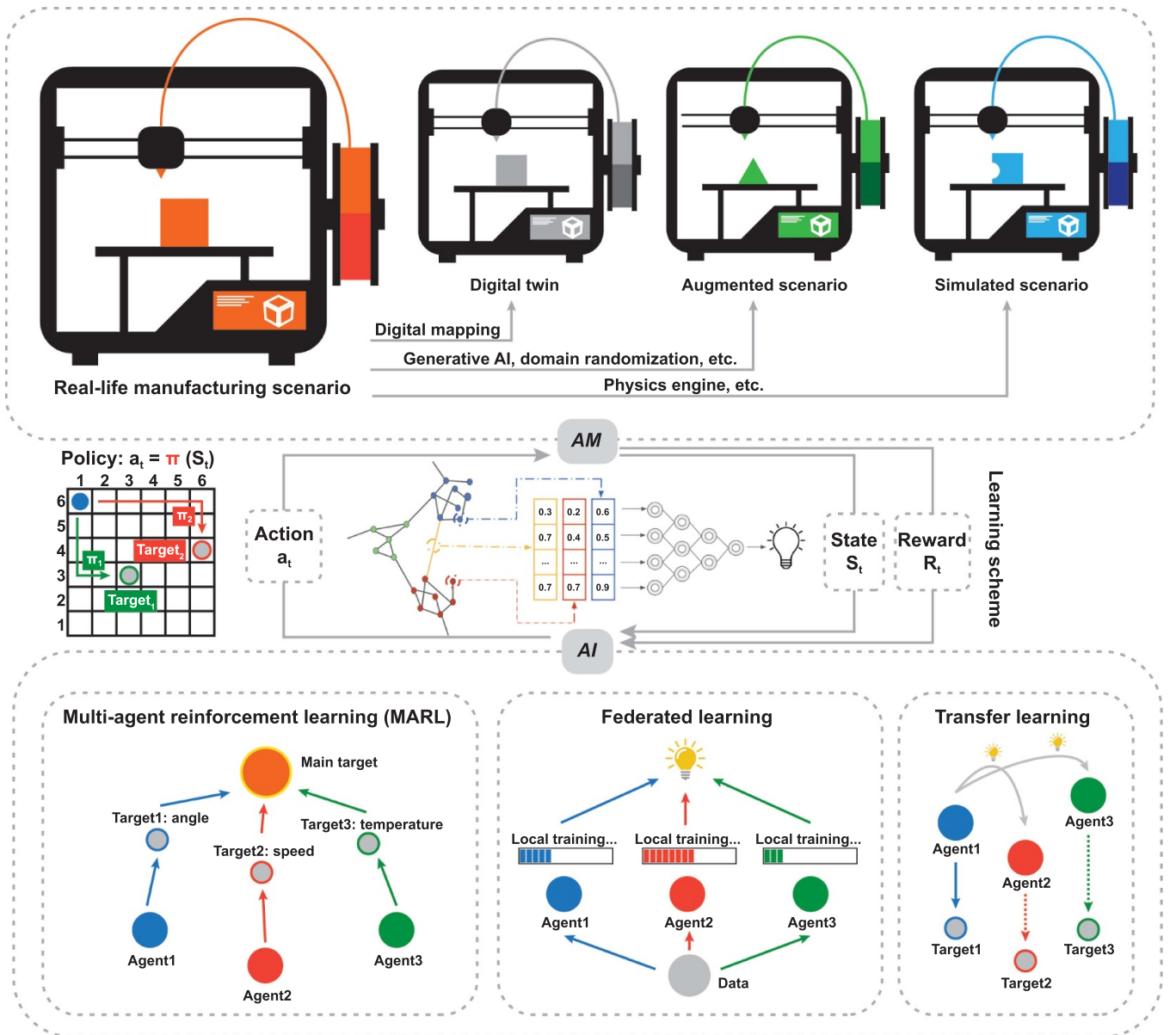


Figure 9. Adoption & enhancement of AI agents. This overview highlights techniques to improve AM process control through agent training and collaboration. The key focuses are effective training despite limited data and efficient collaboration for complex AM processes. DT, augmented scenarios, and simulations offer diverse training environments, helping agents adapt to real-life AM variations. Few-shot learning is enhanced through MARL and FL, where agents train locally on specific tasks and share knowledge. This combination of simulation and collaboration equips agents to handle real-world AM challenges.

Advanced techniques such as zero-shot transfer, system identification, domain randomization, domain adaptation, and learning with disturbances introduce greater variations than those found in real-life data, further strengthening the robustness of the trained agents [259]. The interaction between a DT and its physical counterpart creates a feedback loop where real-world data updates and refines the DT, which in turn generates new data to train the agents further. This continuous cycle leads to progressive improvements in the agents’ performance.

For instance, Ahmmed *et al* [260] proposed a data augmentation framework using the Mix up technique for pore detection in the LPBF process. Mix up interpolates training data to generate weakly labeled data, which helps regularize neural networks and prevent overfitting, thus improving generalization to unseen data. Their work significantly improved the agent’s ability to discern pores after training on the augmented dataset. Similarly, Conrad *et al* [261] proposed a workflow utilizing synthetic data to enhance AM part recognition algorithms. Their synthetic data was generated by

rendering AM parts in CAD software and Blender, adding noise textures to simulate real-life component irregularities, and using a physics engine to simulate parts being dropped from an elevated position, introducing more variations in image angles. This approach sufficiently trained the object recognition model and yielded promising results for AM part geometry recognition. Furthermore, Wong *et al* [262] refined a DL model to capture in-process information using a physics-based simulation dataset obtained from regression interpolation of pre- and post-process experimental data. The augmented data from a physics engine significantly improved the prediction performance of the trained DL model.

FL. The integration of data augmentation techniques in AM is widely recognized for improving the size and diversity of datasets. However, in real-world AM applications, these techniques often require significant manual effort, particularly for labeling high-quality data. FL offers a promising, yet still emerging, solution to these challenges by enabling AI models to learn collaboratively across distributed environments without the need to centralize raw data. Instead, only model updates are shared between participants, which not only preserves data privacy but also ensures communication efficiency.

In practical applications, FL has demonstrated considerable potential for enhancing defect detection in AM processes. For example, Mehta and Shao [263] applied FL to identify pixel-level defects in printed products. This study highlighted how FL could be used to develop high-precision semantic segmentation models for AM, even in scenarios where sharing data is restricted due to privacy concerns. By distributing the learning process across multiple AM devices, the researchers achieved defect detection accuracy comparable to centralized approaches while maintaining data security.

Similarly, Paramartha *et al* [264] explored the use of FL in a multi-site manufacturing environment by proposing a secure FL framework for fault detection in 3D printing processes. Their approach, known as 3DFed, enabled the distributed training of CNN-based models across various industrial sites, eliminating the need to share raw sensor data. The 3DFed framework demonstrated scalability and accuracy, achieving an average F1-score of 89% with minimal additional time costs, even when involving up to 100 clients. This study underscores the efficiency and security of FL in real-world AM settings, where decentralization is vital for protecting sensitive production data.

In addition, Shi and Kontar [265] addressed the issue of data heterogeneity across AM devices in distributed environments by developing a personalized FL model. This model incorporated domain adaptation techniques, allowing geographically dispersed 3D printers to collaboratively build a shared model while accommodating local variations. Tested on a prototype involving multiple connected AM devices, the PFL-DA model successfully managed both input space variability (covariate shift) and input-output relationship changes (concept shift). The results of this case study showed superior performance

and fairness across participating devices, further supporting the feasibility of FL in diverse AM environments.

In summary, while FL shows promise in addressing the challenges of data privacy, security, and heterogeneity in AM, it remains a relatively new trend, with only a few studies currently applying it to real-world AM scenarios. However, as FL continues to develop, it could complement data augmentation techniques by enabling more efficient data sharing and model improvement across decentralized AM environments.

MARL. As AM processes involve multiple domains and dynamic conditions, the complexity of these processes increases with spatial and temporal scale, making it impossible to predict all possible events or prepare for all scenarios. Real-time decision-making can only be effectively achieved through the collaboration of multiple agents. MARL can be applied to AM processes to achieve optimal results through real-time multi-agent collaboration, adapting to changes and uncertainties in real-life manufacturing environments [266]. MARL facilitates coordination between multiple AM sub-processes and allows for learning experiences without extensive prior knowledge. Both centralized and decentralized approaches are widely investigated for managing collaboration between agents. A centralized control scheme requires a central controller to manage all agent collaborations, while a decentralized scheme operates without one. Bahrpeyma and Reichelt [267] highlighted the potential of integrating MARL into the smart factory concept, involving multiple machines operating collaboratively, showing promise for MARL in AM processes.

To enhance fluent and immediate multi-agent collaboration in manufacturing scenarios, smart manufacturing agents should leverage both explicit and implicit knowledge, for instance, IKG, which captures empirical knowledge and recognized patterns in manufacturing processes. For instance, Zheng *et al* [268] proposed an IKG-driven MARL framework that adapts a knowledge transfer scheme from the domain knowledge base to enhance the system's self-configuration, self-optimization, and self-adjustment capabilities. Similarly, Alam *et al* [269] proposed an RL-based autonomous manufacturing system that leverages trained domain knowledge to iteratively refine interactions with the physical world. Their framework trains RL agents on tasks based on first principles, decomposing tasks to fundamental axioms before reasoning up to relevant questions and learning the probabilistic reward function for interacting with the physical world.

In conclusion, the adoption and enhancement of AI agents in autonomous manufacturing systems are essential to achieve precise, robust, and efficient autonomy. Despite challenges related to data scarcity and process variability, techniques such as TL, data augmentation, FL, and MARL provide robust solutions. These methods enable AI agents to learn effectively, adapt to new tasks, and collaborate efficiently, leading to improved process control and stability. By integrating real-life data with simulated environments and leveraging collaborative learning frameworks, AI agents can navigate the complexities of the manufacturing landscape, resulting in more resilient and reliable autonomous systems.

5.4. MMDF

In addition to multi-sensory fusion, where data from multiple sensors are merged to enhance *in-situ* monitoring, MMDF can further enhance AI agents' ability by providing a comprehensive understanding of AM processes. Unlike unimodal data, which captures only a single feature of an object, multi-modal data aggregates different modalities of data or knowledge with distinct characteristics from various sources, which provides a comprehensive view of the AM process and enhances AI agents' understanding of the process flow for better autonomy. This comprehensive approach has proven its value in applications such as monitoring and HMI, as discussed in sections 3.3 and 5.2, respectively. The most exciting adaptation of MMDF in AM is its promising advances in generating domain knowledge and expertise for AAM.

Domain knowledge & expertise. Recent trends in MMDF are increasingly integrating domain-specific knowledge, particularly through NLP technologies. In the manufacturing domain, this integration includes representing human knowledge in forms such as orders, receipts, and instructions. By aligning features from various sources of expertise and increasing the parameter size of models following a 'scaling law', researchers aim to achieve more sophisticated intelligence, as exemplified by models like GPT-4. This feature alignment enhances the capability of multi-modal fusion, allowing each modality to contribute effectively to the final objective. Developments in VLMs, such as LLaVA [270], have shown promise in understanding manufacturing environments and performing monitoring tasks [252]. These models can also assist in design tasks through their generative capabilities [271]. However, a significant challenge remains: current models struggle to fully comprehend the physical world. This limitation is particularly problematic in manufacturing processes where a deep understanding of physical interactions is crucial, and ML tools serve as supplementary aids rather than standalone solutions. Efforts are ongoing to address this challenge by developing models that offer a more grounded understanding of the physical world. For instance, Bardes *et al* [272] introduced V-JEPA, a model that uses a self-supervised learning approach on video streams within a joint embedding prediction architecture. This model serves as an early representation of the physical world, excelling in tasks requiring fine-grained motion understanding. Such advancements represent a step forward in bridging the gap between digital models and physical reality, enhancing the applicability of AI in AM. Azizzadenesheli *et al* [215] presented the NO framework for learning mappings between functions defined on continuous domains, especially the spatiotemporal processes, which could augment, or even replace, existing numerical simulators in AAM systems, such as CFD, predictive maintenance, and material modeling.

The broader potential applications for MMDF in AM are based on several current research trends. Although some of these trends have not yet been applied in AM, they hold significant potential for transformative impacts in areas such as product lifecycle management and

sustainability, and thus are promising to realize the AAM system.

Product lifecycle management. Recent advancements in MMDF have significantly enhanced the management of product lifecycle, particularly within AM processes. For example, Wan *et al* [273] tackled the issue of multi-source heterogeneous data perception fusion in intelligent manufacturing. They proposed a multimodal data cross-media perception fusion algorithm based on DT technology. This innovative approach improves intelligent processing in workshops and assembly lines, thereby facilitating the transition from digitalization to intelligence within enterprises. Furthermore, Liu *et al* [274] highlighted the critical role of extracting and fusing implicit knowledge from data to convert it into actionable intelligence, which is essential for the manufacturing industry's advancement. Their study, which focuses on predicting tool wear using MMDF in intelligent workshops, not only verifies the algorithm's effectiveness but also underscores its potential applicability in various production control scenarios. These advancements demonstrate that integrating MMDF techniques can lead to significant improvements in efficiency and intelligence in manufacturing processes, paving the way for more informed and proactive product lifecycle management.

Sustainability. Sustainability is another critical domain where MMDF shows significant promise. As manufacturing processes become increasingly complex, the integration of various data sources becomes essential. Wang *et al* [275] introduced a MAFN that integrates data from pixel-level, geometric-level, and processing-level sources. This approach addresses the complexities of part geometries and process parameters, aiming to improve energy-efficient design. By optimizing resource usage and reducing waste, this method exemplifies how MMDF can lead to more sustainable manufacturing practices from the energy-consumption aspect. Additionally, MMDF assists in lowering the cost of obtaining high-fidelity sensing results. While higher-quality sensing in AM allows for the detection of refined features, the associated costs have limited its widespread adoption. Biehler *et al* [276] proposed a soft sensing approach to reconstruct high-resolution 3D images from less expensive 2D sliced images and heterogeneous process inputs. Their model effectively reconstructs high-fidelity 3D representations at a lower cost, enhancing both economic sustainability and the generalizability of AM processes. Moreover, MMDF plays a vital role in predictive maintenance, particularly in reverse engineering for producing replacement parts. This technology enhances the sustainability of functional components in complex apparatuses, such as turbine blades. For instance, Bauer *et al* [277] developed a system utilizing optical scanning and CT scans with varying acceleration voltages to achieve precise geometric representations of gas turbines. In their study, a simplified test part produced via AM was scanned using two different CT scans and an optical surface scan. It was then reprinted and re-scanned to evaluate reconstruction errors. This system

employs the SLM process for rapid manufacturing, significantly reducing machine downtime during overhauls by swiftly providing spare parts. The fusion of optical and CT scan data yields detailed geometric and material compositions, which are crucial for effective maintenance and repair.

In summary, the integration of MMDF holds immense potential across various domains within AM. By leveraging advancements in technology and addressing current challenges, MMDF can drive significant improvements in defect prediction, predictive maintenance, process parameters optimization, data-driven process monitoring, and comprehensive KG generation, ultimately transforming the manufacturing landscape autonomously.

6. Future manufacturing: AAM system

The AAM system represents a paradigm shift in future manufacturing, aiming to maximize the autonomy of AM processes. This shift is driven by the enhanced integration of autonomy into control, monitoring, and process integration within AM systems. At its core, AAM relies on the dynamic interaction between AI agents and a hybrid human-machine intelligence model, pushing the system toward greater autonomy and efficiency.

This hybrid intelligence framework enables AM technologies to progress beyond simple task execution while becoming more integrated, service-oriented, and suitable for flexible environments. By leveraging AI technologies and the corresponding AI agents, the expecting system can anticipate needs and adapt to new information without human intervention. This marks a significant transformation in manufacturing approaches that improves efficiency and adaptability and paves the way for more adaptive, customized, robust, repeatable, and responsive AM solutions.

The proposed framework, illustrated in figure 10, utilizes the most challenging metal AM process as a use case. The framework is composed of four vital layers in a top-down manner: knowledge layer, generative solution layer, operational layer, and cognitive layer. Each layer plays an essential role in the overall functioning of the AAM system.

The knowledge layer forms the foundation by integrating sensory data, insights from physical models and simulations, and existing knowledge from libraries. This layer compiles and processes data to provide an accurate and comprehensive description of the current state of the AM process. Building upon this, the data processing is responsible for cleaning (profiling), enrichment (augmentation, integration, and feature engineering), and transformation (encoding, aggregation, and normalization), extracting features that the generative AI draws from when creating its outputs for the next layer. The generative solution layer utilizes AI techniques to fully understand the AM process by fusing the data from multi-sensors, building the PSP relationship, and then constructing the KG system from MMDF. The core of AI agents consists of LMMs and KGs, in which LMMs and KGs play equal roles and work in a mutually beneficial way to enhance both LMMs and KGs for bidirectional reasoning driven by both explicit and implicit

knowledge. The generative solution layer is critical and fundamental in driving towards AAM.

Moving to the operational layer, this stage starts with validation through two to three metallic alloys with hundreds of experimental data, which identifies output errors and provides corrective inputs back into the model—helping AI agents learn from their mistakes. Then the AI agent will be expanded to more than ten materials. After the improvements are confirmed, it is ready to expand to various aspects of the life cycle, including scheduling, design/testing, and process parameter optimization. By integrating predictive insights, the operational layer recommends optimal actions and adjustments to enhance efficiency and quality in the AM process. Finally, in the cognitive layer, AI agents autonomously plan, act, and reflect on results from current actions, orchestrating the aforementioned layers and incorporating feedback. This learning capability enables the cognitive layer to adapt and improve over time, becoming progressively smarter and more effective.

6.1. Knowledge layer

The knowledge layer encompasses the foundational infrastructure and data analytics essential for building an AAM system. This layer focuses on ‘how can we fully understand the problem’ using multiple sensors, simulations, and existing knowledge, integrating essential equipment such as hardware components and monitoring sensors alongside physical knowledge including heat treatment, fluid dynamics, and solid mechanics. These physical principles serve as the foundation for subsequent simulation methods like FEM and CFD. Additionally, this layer includes existing knowledge from textbooks, research papers, and industrial documentation, forming the backbone of the system’s physical and prior knowledge.

The process in the knowledge layer begins with comprehensive data collection from integrated sensors, typically including visible cameras, thermal imaging cameras, acoustic sensors, spectrometers, laser scanners, and x-ray imaging cameras. The purpose of the multi-sensor data acquisition is to collect data from different aspects to reflect the insights of the AM process. For instance, in LPBF, sensors track parameters such as laser power and scan speed to control the process accurately; *in-situ* monitoring data, including visible, thermal, x-ray images, and acoustic signals, are collected to ensure a detailed observation and analysis of the process is conducted.

To facilitate seamless transitions towards subsequent layers, the knowledge layer also undertakes essential tasks of data pre-processing and preliminary analysis. This involves cleaning, filtering, feature extraction, and structuring sensor data to reduce the data size, and ensure its usability for the next stages. The goal is to achieve real-time monitoring and control through advanced sensors and actuators, which continuously feed data into the system, enabling precise adjustments and timely responses to deviations.

Moreover, the knowledge layer incorporates existing knowledge from scientific literature, documentation, and physical-driven methods. This ensures that the AAM system benefits

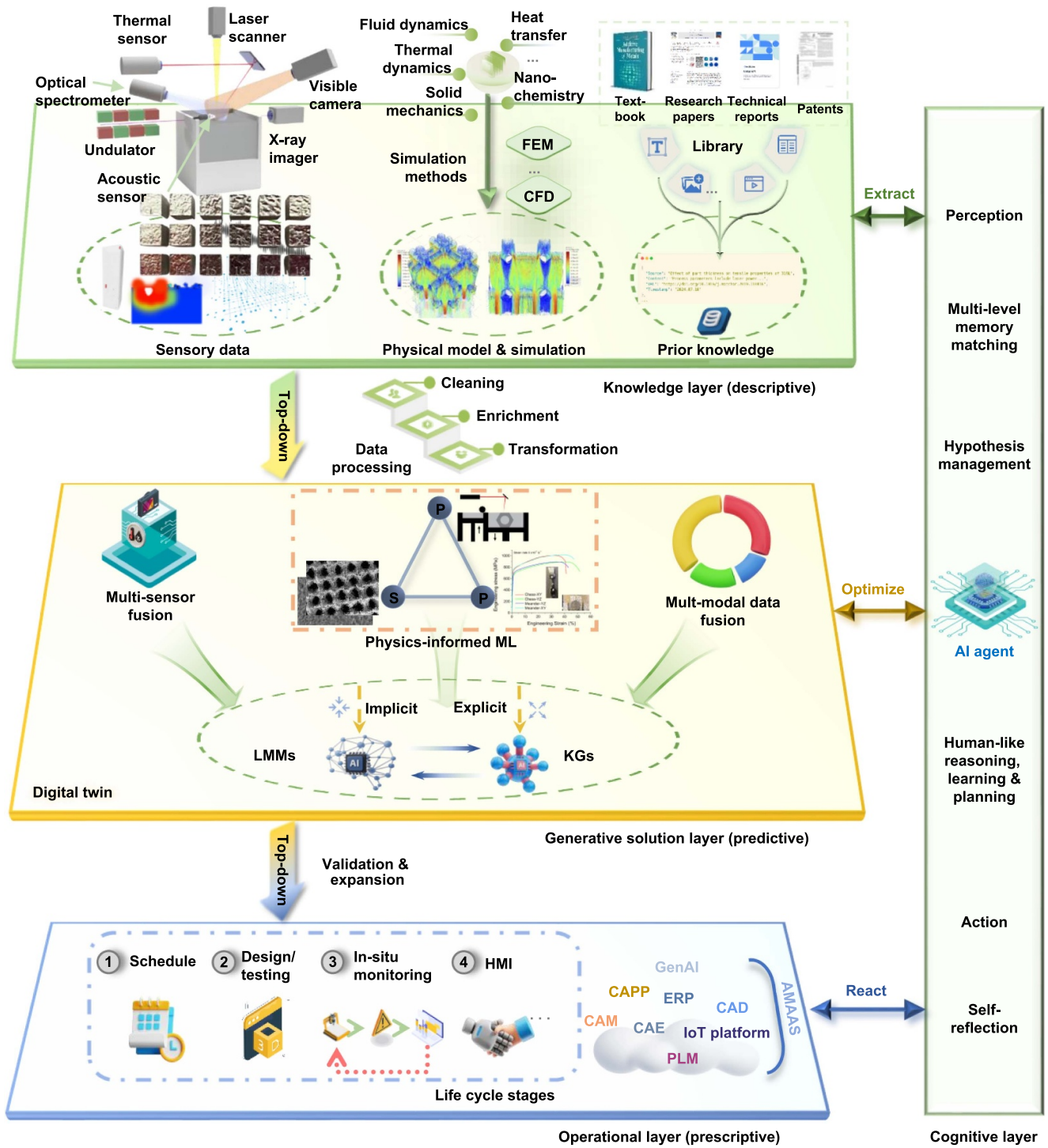


Figure 10. The proposed framework for the AAM system. It has four key layers: knowledge, generative solution, operational, and cognitive. The knowledge layer gathers insights from sensory data, models, simulations, and prior knowledge. The generative solution layer focuses on learning and reasoning about the metal AM process. The operational layer validates the AI agent and expands its application to various AM processes and life cycle stages. The cognitive layer serves as a high-level controller, enabling AI agents to perceive, reason, plan, act, and self-reflect. Together, these layers create an autonomous, end-to-end AAM system.

from both historical and contemporary research, enhancing its foundational understanding and operational efficiency.

In summary, the knowledge layer provides a robust and reliable foundation for the AAM system, ensuring its efficient and effective operation. The integration of advanced sensors, actuators, and existing knowledge sets the stage for higher-level functions, facilitating the transition to the generative solution.

6.2. Generative solution layer

Building upon the knowledge layer, the generative solution layer focuses on forecasting future outcomes based on processed data and initial insights. This layer leverages advanced data analytics, including multi-sensor fusion and ML techniques, to model the PSP relationships, supporting both monitoring and process parameters control.

A critical component of this layer is multi-sensor data fusion, as discussed in section 3.3. This technique combines data from various sensors to create a more comprehensive and accurate representation of the manufacturing process. By integrating data from different sources, combined with the physics model, the ML model is trained to form a DT of the AM process. The DT, continuously taking input data from the knowledge layer, simulates the dynamic AM processes. It enhances the reliability of predictions, reduces uncertainty, and improves decision-making accuracy. MMDF, highlighted in section 5.4, complements this approach by integrating diverse types of data (e.g. visual, textual, etc) from various sources to further enhance the quality of the predictive models. This holistic view enables better product life cycle management, predictive maintenance, and sustainability in AM processes.

Modeling PSP relationships is essential for predicting how variations in the manufacturing process influence the final properties of produced parts, as discussed in section 4.3. These models utilize a combination of physical-driven techniques and ML to simulate and predict material behavior under various conditions. Accurate PSP models allow for precise predictions and control over mechanical properties, thermal behavior, and micro-structural characteristics, thereby enhancing product quality and performance.

Within this generative solution layer, process monitoring tools in both *in-situ* and *ex-situ* manners are crucial, as highlighted in section 3. These tools use sensor data to ensure optimal parameters are applied in the manufacturing process. Advanced signal processing, anomaly detection algorithms, and predictive maintenance techniques are employed to detect deviations, predict potential issues, and recommend corrective actions. ML models identify patterns and trends, providing early warnings of possible defects or failures. This proactive approach maintains optimal production conditions and ensures high print quality.

Furthermore, knowledge transfer within this context is enhanced through the use of and interaction between LMMs and KGs. Unlike LLMs, LMMs incorporate multi-modal data, acting as internal memory systems and implicit knowledge repositories. These models provide valuable context and insights derived from extensive datasets. Conversely, KGs

serve as external memory systems and explicit knowledge repositories, offering structured data representations that aid in decision support for subsequent layers. The integration of LMMs and KGs allows the system to leverage existing knowledge more effectively, thereby enhancing both predictive capabilities and decision-making processes [278]. For instance, an LMM can suggest adjustments based on similar past scenarios, while a KG can elucidate complex relationships between different process parameters in AM processes. Importantly, there is a bidirectional relationship between LMMs and KGs. Techniques such as RAG [217, 279] can be employed to extract knowledge from external sources using textual queries, thereby enriching and expanding KGs. Conversely, a well-constructed KG can validate and enhance the knowledge stored within LMMs. To address the ‘hallucination’ issue, where LMMs generate inaccurate or misleading information, techniques like LoRA [280] can be utilized. LoRA facilitates efficient knowledge injection, enabling the system to adaptively store, verify, and update its knowledge base. This dynamic interplay between LMMs and KGs not only enhances knowledge representation but also improves decision support within AM processes.

In summary, the generative solution layer transforms raw data into actionable insights, offering a clear view of future outcomes based on current and historical data. This generative and predictive capability lays the groundwork for the optimization and autonomy efforts addressed in the operational layer, ultimately improving efficiency and product quality in the AM process.

6.3. Operational layer

The operational layer builds on insights from the generative solution layer, focusing on the question: ‘How can we make it happen?’ This layer is crucial for integrating various autonomous systems, optimizing the manufacturing process, and ensuring a streamlined, adaptive, and semantically aware AM process.

Firstly, the operational layer serves as the standardization framework for the life cycle stages within the AM process. It involves fine-tuning various aspects of the AM process to achieve automated flow and optimal performance. This includes optimizing efficiency, resource allocation, task scheduling, and controlling process parameters to enhance overall efficiency and quality. Advanced optimization algorithms and techniques are employed to balance competing objectives and constraints, ensuring the best possible outcomes. For instance, scheduling algorithms can allocate resources more effectively, while process optimization techniques adjust parameters to minimize defects and maximize throughput, as discussed in section 5.1.

Generative design tools are another essential component of this layer. These tools utilize ML techniques and advanced generative AI algorithms to create optimized designs that meet specific performance criteria automatically, as discussed in section 4.1. By exploring vast design spaces, these tools generate innovative solutions that traditional methods might overlook. Additionally, multi-objective optimization capabilities

balance conflicting requirements, resulting in highly efficient designs.

In addition to the optimization ability featured in the generative solution, HMI is a critical aspect of the operational layer, as highlighted in section 5.2. Incorporating intuitive UIs and AR tools enables operators to interact more effectively with the AM system. These interfaces provide real-time visualizations of the manufacturing process, allowing operators to monitor progress, diagnose issues, and make informed decisions. Voice recognition and NLP technologies further enhance interaction, enabling operators to communicate with the system using natural language commands. Moreover, semantic understanding capabilities allow the system to interpret and act upon data and commands with context-specific meanings. By integrating pre-built knowledge, the AM system understands and reasons about the relationships between different entities and processes, facilitating more intelligent and adaptive decision-making. This ensures that the manufacturing process aligns with desired specifications and constraints.

Furthermore, the concept of AMaaS encompasses essential tools ranging from design software like CAD, CAE, CAM to management systems such as ERP. By transforming predictive insights into actionable optimization strategies and integrating various subsystems and human-machine interfaces, the operational layer ensures the manufacturing process is continually improved and refined. This continuous improvement and refinement set the stage for the learning processes that occur in the cognitive layer.

6.4. Cognitive layer

The cognitive layer is pivotal in linking the knowledge, predictive, and operational layers through processes of interaction, learning, and adaptation. Within this layer, AI agents act as high-level controllers, assessing the skill pool in the operational layer to select appropriate skills for task execution based on the current state. These agents are responsible for planning and executing optimal actions, engaging in a lifelong learning process that enhances their expertise through continuous reflection and learning.

This approach is founded on the principles of the MDP, a robust framework for decision-making in AAM, which is comprised of several core components:

1. States (\mathcal{S}): these represent all possible conditions within the AAM system, such as the status of a print job, machine conditions, and material levels.
2. Actions (\mathcal{A}): these are the feasible operations that can be executed from a given state, such as adjusting printing parameters, changing material feeds, or altering environmental controls.
3. Transition Function (\mathcal{T}): defined by $\mathcal{T}(s' | s, a)$, this function dictates the probability of transitioning to a new state s' from the current state s upon taking action a . It encapsulates the inherent uncertainty in the manufacturing process due to factors like material behavior and machine performance.
4. Implicit policy (π): this is a strategy or rule specifying the action to be taken in each state, guiding the decision-making process with the goal of optimizing some aspect of the manufacturing operation, such as efficiency or quality.

These MDP components form a comprehensive framework for systematically analyzing and optimizing decisions in AAM systems. Through this framework, AI agents manage and execute manufacturing tasks effectively. They plan, observe, take actions, and reflect on outcomes, thereby enhancing their decision-making capabilities. By learning from the results of their actions, these agents continuously improve their strategies and adapt to new information.

For example, AI agents utilize the prior knowledge contained in the knowledge layer and predictive tools from the generative solution to access expert knowledge and external resources. They can leverage the modeled PSP relationship and query KGs to retrieve print parameter recommendations. These KGs can also be used for downstream applications, such as predicting printing parameters for new materials. For instance, an AI agent can use a KG to understand the relationship between different material properties and printing parameters, enabling more informed decisions.

Self-learning mechanisms are vital for the cognitive layer's ability to adapt and improve over time. By employing ML algorithms, the system analyzes historical data to identify patterns, optimize parameters, and predict outcomes. RL techniques dynamically adjust printing parameters to improve print quality and reduce defects. These algorithms continuously refine their models based on real-time process monitoring feedback, ensuring the AAM system evolves and enhances its performance within each manufacturing cycle.

In conclusion, the cognitive layer is crucial for decision-making within the AAM system. It leverages advanced AI and ML techniques to coordinate tools and achieve autonomy. This layer ensures the system evolves, continuously improving its efficiency and effectiveness in manufacturing tasks.

6.5. Discussion on the framework

The AAM framework presents a hierarchical approach to overcoming the critical technical issues inherent in AM. However, several potential challenges must be addressed to fully realize the framework's effectiveness, reliability, adaptability, and scalability. This discussion explores these challenges across 5 key areas: knowledge library grounding, scalability, non-linearity, robustness and trustworthiness, and reasoning prioritization, each essential for broadening the framework's effective application across various AM contexts.

Knowledge library grounding. The effectiveness of the AAM framework relies on a robust and continuously evolving knowledge library that integrates both historical and real-time sensory data within the knowledge layer. Maintaining this library poses challenges, as it must adapt to incorporate relevant, context-specific information for diverse AM processes. A significant risk stems from outdated or irrelevant data, which can lead to suboptimal decision-making, even when quality

controls are in place. To bolster the library's relevance, the framework could incorporate mechanisms for continuous data updates, real-time feedback, and periodic expert validation. Sustaining the knowledge library's adaptability amid advancing technologies and new materials also requires ongoing collaboration with domain experts. Such efforts are crucial for grounding the library in practical, actionable insights that align with current industry standards.

Scalability. For the AAM framework to remain relevant across various manufacturing scales, from customized small-batch production to large-scale industrial manufacturing, scalability is essential. Adapting the framework to these diverse scales introduces challenges in data handling, computational load, and processing efficiency, especially for high-volume applications where increased real-time data can strain processing capacity, potentially reducing speed and accuracy. Implementing hierarchical control systems and edge computing could help localize data processing closer to production sites, alleviating some of these issues. Nonetheless, scaling the AAM framework without compromising data accuracy, response times, or computational efficiency remains a complex challenge that requires further investigation.

Non-linearity. Addressing the non-linear relationships inherent in AM processes, especially within the generative solution layer, such as those between input parameters and final product properties, poses substantial challenges for the AAM framework's optimization capabilities. For instance, rapid temperature fluctuations or unexpected shifts in material behavior are particularly complex to manage in real time. While existing sensor and data fusion methods allow for some real-time adjustments, they fall short of fully capturing and modeling these non-linear dynamics. Enhancing real-time monitoring and multi-sensor data fusion could improve the framework's capacity to accurately model these intricate relationships. However, balancing responsiveness and reliability under non-linear conditions is resource-intensive, requiring substantial computational power and highlighting the need for efficient, real-time adaptability.

Robustness & trustworthiness against uncertainty. AM environments are inherently variable, with uncertainties arising from factors like material inconsistencies, machine-specific variations, and changing environmental conditions. Although the AAM framework employs advanced layers such as the generative solution layer and KGs to predict and manage these fluctuations, achieving consistent reliability across diverse AM scenarios is difficult. Enhancing robustness may require expanding the knowledge base with extensive historical data and integrating continuous learning capabilities. To effectively manage dynamic, previously unseen scenarios, the framework will also require rigorous testing, substantial data inputs, and a nuanced approach to intent recognition, each essential to creating a framework resilient to the inherent uncertainties of AM.

Priority of reasoning. In the operational layer, objectives like efficiency and quality often conflict, necessitating complex trade-offs in decision-making. Additionally, the adaptive parameter adjustments required in AM processes add further complexity. Striking a dynamic balance among these competing priorities is essential for AI-driven decision-making but remains challenging with static algorithms. Future iterations of the framework could incorporate adaptive prioritization mechanisms, possibly leveraging RL to dynamically adjust decision-making based on situational demands. Ensuring a stable and reliable balance between objectives in real-time is crucial, though achieving consistent and dependable results will require more sophisticated advancements.

While the AAM framework holds significant promise for advancing autonomy and adaptability in AM, several challenges remain. Addressing challenges in scalability, handling non-linearity, grounding knowledge, balancing priorities, and ensuring robustness and transparency will require ongoing refinement and thoughtful design. With sustained development, the framework can become an increasingly valuable tool in AM, but recognizing and tackling these challenges will be crucial for its broader applicability and sustained success.

7. Conclusion

In this work, we have comprehensively reviewed the current applications of AI in AM and highlighted the ongoing shift from IAM systems to AAM systems. We detailed the essential characteristics of AAM systems, including control autonomy, monitoring autonomy, process autonomy, and end-to-end process integration. Control autonomy involves robotic-assisted AM and automated toolpath design, while monitoring autonomy includes both *ex-situ* and *in-situ* monitoring with a growing trend toward multi-sensor data fusion. Process autonomy encompasses the entire AM process, including model preparation, process selection, PSP relationship modeling, and post-processing autonomy. Furthermore, we explored end-to-end process integration and autonomy, covering aspects such as nesting and scheduling, HMI, and the adoption of AI agents. Recognizing the power of ML, we also highlighted trends toward advanced technologies such as generative design and more robust HMI.

However, our review identifies several critical gaps in the current IAM systems compared to the ideal fully autonomous solution. Firstly, these systems often address different perspectives in isolation, resulting in a lack of integrated solutions for streamlined AM processes. Secondly, existing systems do not effectively apply prior knowledge from existing documentation or physically-driven knowledge. Lastly, the absence of a high-level controller hinders current systems from making global, long-sighted decisions based on partial observations, thereby lacking contextual understanding. These gaps underscore the growing need for a more integrated and adaptive system.

In response to these findings, we proposed an AAM system framework, which comprises four layers: knowledge, generative solution, operational, and cognitive. The cognitive layer, powered by AI agents, interacts with and controls the other layers seamlessly. These AI agents possess lifelong learning and optimization abilities, enhancing the performance of the other layers. Our proposed AAM system represents a paradigm shift in AM, aiming to enhance autonomy through the enhanced integration of AI, AI agents, and HMI. This hybrid intelligence framework allows AM technologies to progress beyond simple task execution, becoming more integrated, service-oriented, and adaptable to flexible and complex environments such as space. By leveraging AI agents, the system is capable of anticipating needs and adapting to new information without human intervention, marking a significant transformation in manufacturing approaches. The extracted knowledge can be reused and generalized to prepare for possible unseen or more complex environments in the future. This shift improves efficiency and adaptability, paving the way for more adaptive, customized, and responsive manufacturing solutions.

The knowledge layer provides the foundational infrastructure, integrating sensory data and prior knowledge to form a comprehensive understanding of the current state of the AM process. Building on this, the generative solution employs multi-sensor and multi-modal fusion alongside ML techniques to forecast PSP relationships, predict defects, and enable proactive adjustments. The operational layer then uses these predictive insights to optimize the entire life cycle of the AM process, which includes scheduling, design, and process parameter adjustments. Finally, the cognitive layer acts as a high-level controller that features autonomous planning, acting, and reflecting on outcomes. This drives the system towards continuous improvement.

In conclusion, the proposed AAM system framework promises to revolutionize AM by achieving unparalleled levels of autonomy, efficiency, and adaptability. By integrating AI-driven cognitive capabilities with robust predictive and operational analytics, the AAM system is poised to transform manufacturing processes, ensuring higher quality, cost reduction, and increased flexibility. This work lays the groundwork for future advancements in AM, highlighting the critical role of AI in shaping the next generation of manufacturing technology.

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ORCID iDs

Haolin Fan  <https://orcid.org/0000-0002-1808-2660>
 Chenshu Liu  <https://orcid.org/0009-0006-5037-3093>
 Shijie Bian  <https://orcid.org/0000-0003-2814-9854>
 Changyu Ma  <https://orcid.org/0000-0003-2321-8080>
 Junlin Huang  <https://orcid.org/0009-0001-4292-1786>
 Xuan Liu  <https://orcid.org/0000-0002-7922-9451>
 Thomas Lu  <https://orcid.org/0009-0002-6507-5954>
 Edward Chow  <https://orcid.org/0000-0003-2155-2464>
 Lianyi Chen  <https://orcid.org/0000-0003-3720-398X>
 Jerry Ying Hsi Fuh  <https://orcid.org/0000-0002-5225-7460>
 Wen Feng Lu  <https://orcid.org/0000-0003-4022-6912>
 Bingbing Li  <https://orcid.org/0000-0001-6140-4189>

References

- [1] Zhou L Y, Fu J Z and He Y 2020 A review of 3D printing technologies for soft polymer materials *Adv. Funct. Mater.* **30** 2000187
- [2] Jiang L, Walczyk D, McIntyre G, Bucinell R and Li B B 2019 Bioresin infused then cured mycelium-based sandwich-structure biocomposites: resin transfer molding (RTM) process, flexural properties, and simulation *J. Clean. Prod.* **207** 123–35
- [3] Fan Z Q, Tan Q Y, Kang C W and Huang H 2024 Advances and challenges in direct additive manufacturing of dense ceramic oxides *Int. J. Extrem. Manuf.* **6** 052004
- [4] Yan Y F, Kou S Q, Yang H Y, Shu S L, Qiu F, Jiang Q C and Zhang L C 2023 Ceramic particles reinforced copper matrix composites manufactured by advanced powder metallurgy: preparation, performance, and mechanisms *Int. J. Extrem. Manuf.* **5** 032006
- [5] de Barros N R *et al* 2023 Gelatin methacryloyl and Laponite bioink for 3D bioprinted organotypic tumor modeling *Biofabrication* **15** 045005
- [6] Rashad A, Gomez A, Gangrade A, Zehtabi F, Mandal K, Maity S, Ma C Y, Li B B, Khademhosseini A and De Barros N R 2024 Effect of viscosity of gelatin methacryloyl-based bioinks on bone cells *Biofabrication* **16** 045036
- [7] Gilmer D B, Han L, Lehmann M L, Siddel D H, Yang G, Chowdhury A U, Doughty B, Elliott A M and Saito T 2021 Additive manufacturing of strong silica sand structures enabled by polyethyleneimine binder *Nat. Commun.* **12** 5144
- [8] Chen L Y, Qin P, Zhang L N and Zhang L C 2024 An overview of additively manufactured metal matrix composites: preparation, performance, and challenge *Int. J. Extrem. Manuf.* **6** 052006
- [9] Ma H Y, Wang J C, Qin P, Liu Y J, Chen L Y, Wang L Q and Zhang L C 2024 Advances in additively manufactured titanium alloys by powder bed fusion and directed energy deposition: microstructure, defects, and mechanical behavior *J. Mater. Sci. Technol.* **183** 32–62
- [10] Jian B C, Li H G, He X N, Wang R, Yang H Y and Ge Q 2024 Two-photon polymerization-based 4D printing and its applications *Int. J. Extrem. Manuf.* **6** 012001
- [11] Lee S J, Jeong W and Atala A 2024 3D Bioprinting for engineered tissue constructs and patient-specific models: current progress and prospects in clinical applications *Adv. Mater.* **36** e2408032
- [12] Duan Y Q, Xie W S, Yin Z P and Huang Y A 2024 Multi-material 3D nanoprinting for structures to

- functional micro/nanosystems *Int. J. Extrem. Manuf.* **6** 063001
- [13] Chen Z J, Zhang C and Zheng Z J 2024 Advancements in transfer printing techniques for flexible electronics: adjusting interfaces and promoting versatility *Int. J. Extrem. Manuf.* **6** 052005
- [14] Davoodi E *et al* 2022 Additively manufactured metallic biomaterials *Bioact. Mater.* **15** 214–49
- [15] Costabeber G *et al* 2024 Additive manufacturing of polylactic acid scaffolds dip-coated with polycaprolactone for bone tissue engineering *Mater. Today Commun.* **40** 109646
- [16] Li B B, Hesar B D, Zhao Y W and Ding L 2023 Design and additive manufacturing of porous titanium scaffolds for optimum cell viability in bone tissue engineering *Proc. Inst. Mech. Eng. B* **237** 2015–24
- [17] Ma C Y, Grandhi M, Mallory P, Liu Z C, Li B B and Kang B 2024 Directed energy deposited SS316L with nano-Y₂O₃ additions: powder processing, microstructure, and mechanical properties *Prog. Addit. Manuf.* pp 1–16
- [18] Wei S S, Zhang J L, Zhang L, Zhang Y J, Song B, Wang X B, Fan J X, Liu Q and Shi Y S 2023 Laser powder bed fusion additive manufacturing of NiTi shape memory alloys: a review *Int. J. Extrem. Manuf.* **5** 032001
- [19] Zhang L C and Wang J C 2024 Stabilizing 3D-printed metal alloys *Science* **383** 586–7
- [20] Hai Alami A, Ghani Olabi A, Khuri S, Aljaghoub H, Alasad S, Ramadan M and Ali Abdelkareem M 2024 3D printing in the food industry: recent progress and role in achieving sustainable development goals *Ain Shams Eng. J.* **15** 102386
- [21] Son J H, Kim H, Choi Y and Lee H 2024 3D printed energy devices: generation, conversion, and storage *Microsyst. Nanoeng.* **10** 93
- [22] Ma G W, Buswell R, Leal da Silva W R, Wang L, Xu J and Jones S Z 2022 Technology readiness: a global snapshot of 3D concrete printing and the frontiers for development *Cem. Concr. Res.* **156** 106774
- [23] Ye J H, El Desouky A and Elwany A 2024 On the applications of additive manufacturing in semiconductor manufacturing equipment *J. Manuf. Process.* **124** 1065–79
- [24] Haghnegahdar L, Joshi S S and Dahotre N B 2022 From IoT-based cloud manufacturing approach to intelligent additive manufacturing: industrial Internet of Things—an overview *Int. J. Adv. Manuf. Technol.* **119** 1461–78
- [25] Machaka R, Motsi G T, Raganya L M, Radingoana P M and Chikosha S 2021 Machine learning-based prediction of phases in high-entropy alloys: a data article *Data Brief* **38** 107346
- [26] Zheng Z W, Yue X Z, Wang J C and Hou J 2024 A framework for general-purpose microscopic image analysis via self-supervised learning *Mater. Charact.* **213** 114003
- [27] Wang H *et al* 2024 Recent advances in machine learning-assisted fatigue life prediction of additive manufactured metallic materials: a review *J. Mater. Sci. Technol.* **198** 111–36
- [28] Xiong Y, Tang Y L, Zhou Q, Ma Y S and Rosen D W 2022 Intelligent additive manufacturing and design: state of the art and future perspectives *Addit. Manuf.* **59** 103139
- [29] Ko H, Witherell P, Lu Y, Kim S and Rosen D W 2021 Machine learning and knowledge graph based design rule construction for additive manufacturing *Addit. Manuf.* **37** 101620
- [30] Lu L, Hou J, Yuan S Q, Yao X L, Li Y M and Zhu J H 2023 Deep learning-assisted real-time defect detection and closed-loop adjustment for additive manufacturing of continuous fiber-reinforced polymer composites *Rob. Comput. Integr. Manuf.* **79** 102431
- [31] Phua A, Davies C H J and Delaney G W 2022 A digital twin hierarchy for metal additive manufacturing *Comput. Ind.* **140** 103667
- [32] Mu H C, He F Y, Yuan L, Commins P, Wang H M and Pan Z X 2023 Toward a smart wire arc additive manufacturing system: a review on current developments and a framework of digital twin *J. Manuf. Syst.* **67** 174–89
- [33] Zhang Y, Safdar M, Xie J R, Li J H, Sage M and Zhao Y F 2023 A systematic review on data of additive manufacturing for machine learning applications: the data quality, type, preprocessing, and management *J. Intell. Manuf.* **34** 3305–40
- [34] 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** 309–26
- [35] An J and Leong K F 2023 Multi-material and multi-dimensional 3D printing for biomedical materials and devices *Biomed. Mater. Devices* **1** 38–48
- [36] Shaukat U, Rossegger E and Schlögl S 2022 A review of multi-material 3D printing of functional materials via vat photopolymerization *Polymers* **14** 2449
- [37] 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
- [38] Rafiee M, Farahani R D and Therriault D 2020 Multi-material 3D and 4D printing: a survey *Adv. Sci.* **7** 1902307
- [39] Bhatt P M, Malhan R K, Shembekar A V, Yoon Y J and Gupta S K 2020 Expanding capabilities of additive manufacturing through use of robotics technologies: a survey *Addit. Manuf.* **31** 100933
- [40] Pires J N, Azar A S, Nogueira F, Zhu C Y, Branco R and Tankova T 2022 The role of robotics in additive manufacturing: review of the AM processes and introduction of an intelligent system *Ind. Robot.* **49** 311–31
- [41] Kaji F, Jinoop A N, Zardoshtian A, Hallen P, Frikel G, Tang T Y, Zimny M and Toyserkani E 2023 Robotic laser directed energy deposition-based additive manufacturing of tubular components with variable overhang angles: adaptive trajectory planning and characterization *Addit. Manuf.* **61** 103366
- [42] Wu C M, Dai C K, Fang G X, Liu Y J and Wang C C L 2017 RoboFDM: a robotic system for support-free fabrication using FDM *IEEE Int. Conf. on Robotics and Automation (ICRA 2017) (Singapore, 29 May–03 June)* (IEEE) pp 1175–80
- [43] Bhatt P M, Malhan R K, Rajendran P and Gupta S K 2020 Building free-form thin shell parts using supportless extrusion-based additive manufacturing *Addit. Manuf.* **32** 101003
- [44] Badarinath R and Prabhu V 2021 Integration and evaluation of robotic fused filament fabrication system *Addit. Manuf.* **41** 101951
- [45] Reisch R, Hauser T, Kamps T and Knoll A 2020 Robot based wire arc additive manufacturing system with context-sensitive multivariate monitoring framework *Procedia Manuf.* **51** 732–9
- [46] Zapata A, Benda A, Spreitler M, Zhao X F, Bernauer C, Yoshioka H and Zaeh M F 2023 A model-based approach to reduce kinematics-related overfill in robot-guided laser directed energy deposition *CIRP J. Manuf. Sci. Technol.* **45** 200–9
- [47] Tiryaki M E, Zhang X and Pham Q C 2019 Printing-while-moving: a new paradigm for large-scale

- robotic 3D Printing *Proc. IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS 2019) (Macau, China, 3–8 November)* (IEEE) pp 2286–91
- [48] Lachmayer L, Recker T and Raatz A 2022 Contour tracking control for mobile robots applicable to large-scale assembly and additive manufacturing in construction *Procedia CIRP* **106** 108–13
- [49] Sustarevas J, Kanoulas D and Julier S 2022. Autonomous mobile 3D printing of large-scale trajectories *Proc. IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS 2022) (Kyoto, Japan, 23–27 October)* (IEEE) pp 6561–8
- [50] Zhang K *et al* 2022 Aerial additive manufacturing with multiple autonomous robots *Nature* **609** 709–17
- [51] Sustarevas J, Kanoulas D and Julier S 2021 Task-consistent path planning for mobile 3D printing *Proc. IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS 2021) (Prague, Czech Republic, September 27–1 October)* (IEEE) pp 2143–50
- [52] Alhijaily A, Kilic Z M and Bartolo A N P 2023 Teams of robots in additive manufacturing: a review *Virtual Phys. Prototyp.* **18** e2162929
- [53] Jiang J C and Ma Y S 2020 Path planning strategies to optimize accuracy, quality, build time and material use in additive manufacturing: a review *Micromachines* **11** 633
- [54] Tian C X, Li T J, Bustillos J, Bhattacharya S, Turnham T, Yeo J and Moridi A 2021 Data-driven approaches toward smarter additive manufacturing *Adv. Intell. Syst.* **3** 2100014
- [55] Volpato N, Galvão L C, Nunes L F, Souza R I and Oguido K 2020 Combining heuristics for tool-path optimisation in material extrusion additive manufacturing *J. Oper. Res. Soc.* **71** 867–77
- [56] Gharehpapagh B, Dilberoglu U M, Yaman U and Dolen M 2023 Adaptive toolpath generation for material extrusion additive manufacturing using a nozzle with rectangular orifice *Addit. Manuf.* **78** 103873
- [57] Gopsill J A, Shindler J and Hicks B J 2018 Using finite element analysis to influence the infill design of fused deposition modelled parts *Prog. Addit. Manuf.* **3** 145–63
- [58] Lachmayer L, Ekanayaka V, Hürkamp A and Raatz A 2021 Approach to an optimized printing path for additive manufacturing in construction utilizing FEM modeling *Procedia CIRP* **104** 600–5
- [59] Sales E, Kwok T H and Chen Y 2021 Function-aware slicing using principal stress line for toolpath planning in additive manufacturing *J. Manuf. Process.* **64** 1420–33
- [60] Ren H L, Wang D, Liu G, Rosen D W and Xiong Y 2024 Concurrent optimization of structural topology and toolpath for additive manufacturing of continuous fiber-reinforced polymer composites *Comput. Methods Appl. Mech. Eng.* **430** 117227
- [61] Stathatos E and Vosniakos G C 2019 Real-time simulation for long paths in laser-based additive manufacturing: a machine learning approach *Int. J. Adv. Manuf. Technol.* **104** 1967–84
- [62] Yanamandra K, Chen G L, Xu X B, Mac G and Gupta N 2020 Reverse engineering of additive manufactured composite part by toolpath reconstruction using imaging and machine learning *Compos. Sci. Technol.* **198** 108318
- [63] Qin M, Ding J H, Qu S, Song X, Wang C C L and Liao W H 2024 Deep reinforcement learning based toolpath generation for thermal uniformity in laser powder bed fusion process *Addit. Manuf.* **79** 103937
- [64] Kim D H and Zohdi T I 2022 Tool path optimization of selective laser sintering processes using deep learning *Comput. Mech.* **69** 383–401
- [65] Zhou Z Y, Shen H Y, Lin J H, Liu B and Sheng X J 2022 Continuous tool-path planning for optimizing thermo-mechanical properties in wire-arc additive manufacturing: an evolutionary method *J. Manuf. Process.* **83** 354–73
- [66] Li L, McGuan R, Isaac R, Kavehpour P and Candler R 2021 Improving precision of material extrusion 3D printing by *in-situ* monitoring & predicting 3D geometric deviation using conditional adversarial networks *Addit. Manuf.* **38** 101695
- [67] Zhou B and Tian T T 2021 A path planning method of lattice structural components for additive manufacturing *Int. J. Adv. Manuf. Technol.* **116** 1467–90
- [68] Dong Y W and Hu B 2023 Optimized control method for fused deposition 3D printing slice contour path based on improved hopfield neural network *Appl. Artif. Intell.* **37** 2219946
- [69] Nguyen L, Buhl J and Bambach M 2020 Continuous Eulerian tool path strategies for wire-arc additive manufacturing of rib-web structures with machine-learning-based adaptive void filling *Addit. Manuf.* **35** 101265
- [70] Kunchala B K R, Gamini S and Anilkumar T C 2023 Inclusion of IoT technology in additive manufacturing: machine learning-based adaptive bead modeling and path planning for sustainable wire arc additive manufacturing and process optimization *Proc. Inst. Mech. Eng. C* **237** 120–32
- [71] Petrik J and Bambach M 2023 Reinforcement learning and optimization based path planning for thin-walled structures in wire arc additive manufacturing *J. Manuf. Process.* **93** 75–89
- [72] Sideris I, Duncan S, Fabbri M, Crivelli F, Afrasiabi M and Bambach M 2024 End-to-end path planning for homogeneous temperature fields in additive manufacturing *J. Mater. Process. Technol.* **327** 118364
- [73] Ren K, Chew Y, Liu N, Zhang Y F, Fuh J Y H and Bi G J 2021 Integrated numerical modelling and deep learning for multi-layer cube deposition planning in laser aided additive manufacturing *Virtual Phys. Prototyp.* **16** 318–32
- [74] Qin M, Qu S, Ding J H, Song X, Gao S M, Wang C C L and Liao W H 2023 Adaptive toolpath generation for distortion reduction in laser powder bed fusion process *Addit. Manuf.* **64** 103432
- [75] Ikeuchi D, Vargas-Uscategui A, Wu X F and King P C 2021 Data-efficient neural network for track profile modelling in cold spray additive manufacturing *Appl. Sci.* **11** 1654
- [76] Ikeuchi D, Vargas-Uscategui A, Wu X F and King P C 2024 Data-driven overlapping-track profile modeling in cold spray additive manufacturing *J. Therm. Spray Technol.* **33** 530–9
- [77] Mozaffar M, Ebrahimi A and Cao J 2020 Toolpath design for additive manufacturing using deep reinforcement learning (arXiv: 2009.14365)
- [78] Segovia Ramírez I, García Márquez F P and Papaelias M 2023 Review on additive manufacturing and non-destructive testing *J. Manuf. Syst.* **66** 260–86
- [79] du Plessis A, Yadroitsava I and Yadroitsev I 2020 Effects of defects on mechanical properties in metal additive manufacturing: a review focusing on x-ray tomography insights *Mater. Des.* **187** 108385
- [80] Du Plessis A, MacDonald E, Waller J M and Berto F 2021 Non-destructive testing of parts produced by laser powder bed fusion *Fundamentals of Laser Powder Bed Fusion of Metals (Additive Manufacturing Materials and Technologies)* ed I Yadroitsev, I Yadroitsava, A du Plessis and E MacDonald (Elsevier) pp 277–300

- [81] Wong V W H, Ferguson M, Law K, Lee Y T and Witherell P 2022 Segmentation of additive manufacturing defects using U-Net *J. Comput. Inf. Sci. Eng.* **22** 031005
- [82] Ronneberger O, Fischer P and Brox T 2015. U-Net: convolutional networks for biomedical image segmentation *Proc. 18th Int. Conf. on Medical Image Computing and Computer-Assisted Intervention (MICCAI 2015) (Munich, Germany, 5–9October)* (Springer) pp 234–41
- [83] Çiçek Ö, Abdulkadir A, Lienkamp S S, Brox T and Ronneberger O 2016 3D U-Net: learning dense volumetric segmentation from sparse annotation *Proc. 19th Int. Conf. on Medical Image Computing and Computer-Assisted Intervention (MICCAI 2016) (Athens, Greece, 17–21October)* (Springer) pp 424–32
- [84] Zamiela C, Jiang Z P, Stokes R, Tian Z H, Netchaev A, Dickerson C, Tian W M and Bian L K 2023 Deep multi-modal U-Net fusion methodology of thermal and ultrasonic images for porosity detection in additive manufacturing *J. Manuf. Sci. Eng.* **145** 061009
- [85] Aydogan B and Chou K 2024 Review of *in situ* detection and ex situ characterization of porosity in laser powder bed fusion metal additive manufacturing *Metals* **14** 669
- [86] Abouelnour Y and Gupta N 2024 Comparison of *in-situ* nondestructive testing and ex-situ methods in additive manufactured specimens for internal feature detection *Res. Nondestr. Eval.* **35** 20–31
- [87] Petsiuk A L and Pearce J M 2020 Open source computer vision-based layer-wise 3D printing analysis *Addit. Manuf.* **36** 101473
- [88] Cannizzaro D, Varrella A G, Paradiso S, Sampieri R, Chen Y K, Macii A, Patti E and Cataldo S D 2022 *In-situ* defect detection of metal additive manufacturing: an integrated framework *IEEE Trans. Emerg. Top. Comput.* **10** 74–86
- [89] Brion D A J and Pattinson S W 2022 Generalisable 3D printing error detection and correction via multi-head neural networks *Nat. Commun.* **13** 4654
- [90] Drissi-Daoudi R, Pandiyan V, Logé R, Shevchik S, Masinelli G, Ghasemi-Tabasi H, Parrilli A and Wasmer K 2022 Differentiation of materials and laser powder bed fusion processing regimes from airborne acoustic emission combined with machine learning *Virtual Phys. Prototyp.* **17** 181–204
- [91] Ye Z H, Liu C N, Tian W M and Kan C 2021 *In-situ* point cloud fusion for layer-wise monitoring of additive manufacturing *J. Manuf. Syst.* **61** 210–22
- [92] Lin W Y, Shen H Y, Fu J Z and Wu S Y 2019 Online quality monitoring in material extrusion additive manufacturing processes based on laser scanning technology *Precis. Eng.* **60** 76–84
- [93] Chen H, Yaseer A and Zhang Y M 2022 Top surface roughness modeling for robotic wire arc additive manufacturing *J. Manuf. Mater. Process.* **6** 39
- [94] Charalampous P, Kostavelis I, Kopsacheilis C and Tzovaras D 2021 Vision-based real-time monitoring of extrusion additive manufacturing processes for automatic manufacturing error detection *Int. J. Adv. Manuf. Technol.* **115** 3859–72
- [95] Dong W, Lian J, Yan C P, Zhong Y R, Karnati S, Guo Q L, Chen L Y and Morgan D 2024 Deep-learning-based segmentation of keyhole in *in-situ* x-ray imaging of laser powder bed fusion *Materials* **17** 510
- [96] Cunningham R, Zhao C, Parab N, Kantzos C, Pauza J, Fezzaa K, Sun T and Rollett A D 2019 Keyhole threshold and morphology in laser melting revealed by ultrahigh-speed x-ray imaging *Science* **363** 849–52
- [97] Shevchik S A, Masinelli G, Kenel C, Leinenbach C and Wasmer K 2019 Deep learning for *in situ* and real-time quality monitoring in additive manufacturing using acoustic emission *IEEE Trans. Ind. Inform.* **15** 5194–203
- [98] Waller J M, Parker B H, Hodges K L, Burke E R and Walker J L 2014 *Nondestructive Evaluation of Additive Manufacturing State-of-the-Discipline Report* (NASA WSTF) (<https://doi.org/10.1016/j.jaac.2014.05.004>)
- [99] 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
- [100] 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** 666–72
- [101] Shevchik S A, Kenel C, Leinenbach C and Wasmer K 2018 Acoustic emission for *in situ* quality monitoring in additive manufacturing using spectral convolutional neural networks *Addit. Manuf.* **21** 598–604
- [102] Mukhtadir M A, Hasan M N and Alam M 2022 Additive manufacturing and acoustic Emission: a brief review *J. Addit. Manuf. Technol.* **2** 632
- [103] Segovia Ramírez I, Das B and García Márquez F P 2022 Fault detection and diagnosis in photovoltaic panels by radiometric sensors embedded in unmanned aerial vehicles *Prog. Photovolt., Res. Appl.* **30** 240–56
- [104] Kononenko D Y, Nikonova V, Seleznev M, van den Brink J and Chernyavsky D 2023 An *in situ* crack detection approach in additive manufacturing based on acoustic emission and machine learning *Addit. Manuf. Lett.* **5** 100130
- [105] Mohammadi M G and Elbestawi M 2020 Real time monitoring in L-PBF using a machine learning approach *Procedia Manuf.* **51** 725–31
- [106] Becker P, Roth C, Roennau A and Dillmann R 2020 Acoustic anomaly detection in additive manufacturing with long short-term memory neural networks *Proc. IEEE 7th Int. Conf. on Industrial Engineering and Applications (ICIEA 2020) (Bangkok, Thailand, 16–21April)* (IEEE) pp 921–6
- [107] Wang S Y, Wang Y C, Liu C S and Mazumder J 2020 *In-situ* monitoring on micro-hardness of laser molten zone on AISI4140 steel by spectral analysis *Sci. Rep.* **10** 4241
- [108] 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** 336–41
- [109] Sun W B, Zhang Z H, Ren W J, Mazumder J and Jin J H 2022 *In situ* monitoring of optical emission spectra for microscopic pores in metal additive manufacturing *J. Manuf. Sci. Eng.* **144** 011006
- [110] Choi J, Wooldridge M and Mazumder J 2023 Spectroscopy-based smart optical monitoring system in the applications of laser additive manufacturing *J. Laser Appl.* **35** 012030
- [111] Ren W J, Zhang Z F, Lu Y, Wen G R and Mazumder J 2021 *In-situ* monitoring of laser additive manufacturing for Al7075 alloy using emission spectroscopy and plume imaging *IEEE Access* **9** 61671–9
- [112] Montazeri M, Nassar A R, Dunbar A J and Rao P 2019 In-process monitoring of porosity in additive manufacturing using optical emission spectroscopy *IIEE Trans.* **52** 500–15
- [113] Bian S J, Li C, Fu Y W, Ren Y T, Wu T Z, Li G P and Li B B 2021 Machine learning-based real-time monitoring system for smart connected worker to improve energy efficiency *J. Manuf. Syst.* **61** 66–76

- [114] Li C, Bian S J, Wu T Z, Donovan R P and Li B B 2022 Affordable artificial intelligence-assisted machine supervision system for the small and medium-sized manufacturers *Sensors* **22** 6246
- [115] Bian S J, Lin T C, Li C, Fu Y W, Jiang M R, Wu T Z, Hang X Y and Li B B 2021 Real-time object detection for smart connected worker in 3D printing *Proc. 21st Int. Conf. on Computational Science (ICCS 2021) (Krakow, Poland, 16–18 June)* (Springer) pp 554–67
- [116] Manivannan S 2023 Automatic quality inspection in additive manufacturing using semi-supervised deep learning *J. Intell. Manuf.* **34** 3091–108
- [117] Song H, Li C X, Fu Y H, Li R S, Zhang H Q and Wang G L 2023 A two-stage unsupervised approach for surface anomaly detection in wire and arc additive manufacturing *Comput. Ind.* **151** 103994
- [118] Chen A, Kopsaftopoulos F and Mishra S 2024 An unsupervised online anomaly detection method for metal additive manufacturing processes via a statistical time-frequency domain algorithm *Struct. Health Monit.* **23** 1926–48
- [119] Lui C F, Maged A and Xie M 2024 A novel image feature based self-supervised learning model for effective quality inspection in additive manufacturing *J. Intell. Manuf.* **35** 3543–58
- [120] Mattera G, Polden J, Caggiano A, Nele L, Pan Z X and Norrish J 2024 Semi-supervised learning for real-time anomaly detection in pulsed transfer wire arc additive manufacturing *J. Manuf. Process.* **128** 84–97
- [121] 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
- [122] Oleff A, Küster B and Overmeyer L 2024 Determination of quality classes for material extrusion additive manufacturing using image processing *Int. J. Adv. Manuf. Technol.* **132** 1585–98
- [123] Akhavan J, Lyu J and Manoochehri S 2024 A deep learning solution for real-time quality assessment and control in additive manufacturing using point cloud data *J. Intell. Manuf.* **35** 1389–406
- [124] Chen L Q, Yao X L, Xu P, Moon S K and Bi G J 2021 Rapid surface defect identification for additive manufacturing with *in-situ* point cloud processing and machine learning *Virtual Phys. Prototyp.* **16** 50–67
- [125] 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 *Rob. Comput. Integr. Manuf.* **84** 102581
- [126] Lee E T, Fan Z Y and Sencer B 2023 A new approach to detect surface defects from 3D point cloud data with surface normal Gabor filter (SNGF) *J. Manuf. Process.* **92** 196–205
- [127] Chew S Y, Asadi E, Vargas-Uscategui A, King P, Gautam S, Bab-Hadiashar A and Cole I 2024 In-process 4D reconstruction in robotic additive manufacturing *Rob. Comput. Integr. Manuf.* **89** 102784
- [128] Zhao C, Fezzaa K, Cunningham R W, Wen H D, De Carlo F, Chen L, Rollett A D and Sun T 2017 Real-time monitoring of laser powder bed fusion process using high-speed x-ray imaging and diffraction *Sci. Rep.* **7** 3602
- [129] Guo Q L, Zhao C, Escano L I, Young Z, Xiong L H, Fezzaa K, Everhart W, Brown B, Sun T and Chen L Y 2018 Transient dynamics of powder spattering in laser powder bed fusion additive manufacturing process revealed by *in-situ* high-speed high-energy x-ray imaging *Acta Mater.* **151** 169–80
- [130] Leung C L A, Marussi S, Atwood R C, Towrie M, Withers P J and Lee P D 2018 *In situ* x-ray imaging of defect and molten pool dynamics in laser additive manufacturing *Nat. Commun.* **9** 1355
- [131] Qin X B, Fan D P, Huang C Y, Diagne C, Zhang Z C, Sant'Anna A C, Suárez A, Jagersand M and Shao L 2021 Boundary-aware segmentation network for mobile and web applications (arXiv: 2101.04704)
- [132] Fernandez-Zelaia P, Dryepondt S N, Ziabari A K and Kirka M M 2024 Self-supervised learning of spatiotemporal thermal signatures in additive manufacturing using reduced order physics models and transformers *Comput. Mater. Sci.* **232** 112603
- [133] Li W, Lambert-Garcia R, Getley A C M, Kim K, Bhagavath S, Majkut M, Rack A, Lee P D and Leung C L A 2024 AM-SegNet for additive manufacturing *in situ* x-ray image segmentation and feature quantification *Virtual Phys. Prototyp.* **19** e2325572
- [134] Shin S J, Lee J H, Jadhav S and Kim D B 2024 Material-adaptive anomaly detection using property-concatenated transfer learning in wire arc additive manufacturing *Int. J. Precis. Eng. Manuf.* **25** 383–408
- [135] Hossain M S and Taheri H 2020 *In situ* process monitoring for additive manufacturing through acoustic techniques *J. Mater. Eng. Perform.* **29** 6249–62
- [136] 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** 2277–92
- [137] Mathieu M, Henaff M and LeCun Y 2014 Fast training of convolutional networks through FFTs *Proc. 2nd Int. Conf. on Learning Representations (ICLR 2014) (Banff, Canada, 14–16 April)* (ICLR) (<https://doi.org/10.48550/arXiv.1312.5851>)
- [138] 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
- [139] Pandiyan V, Wróbel R, Richter R A, Leparoux M, Leinenbach C and Shevchik S 2024 Monitoring of Laser Powder Bed Fusion process by bridging dissimilar process maps using deep learning-based domain adaptation on acoustic emissions *Addit. Manuf.* **80** 103974
- [140] Song J Y, Dass A, Moridi A and McLaskey G C 2024 Detection of defects during laser-powder interaction by acoustic emission sensors and signal characteristics *Addit. Manuf.* **82** 104035
- [141] 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** 1339–46
- [142] Liu H L, Gobert C, Ferguson K, Abranovic B, Chen H R, Beuth J L, Rollett A D and Kara L B 2024 Inference of highly time-resolved melt pool visual characteristics and spatially-dependent lack-of-fusion defects in laser powder bed fusion using acoustic and thermal emission data *Addit. Manuf.* **83** 104057
- [143] Petrich J, Snow Z, Corbin D and Reutzel E W 2021 Multi-modal sensor fusion with machine learning for data-driven process monitoring for additive manufacturing *Addit. Manuf.* **48** 102364
- [144] Chen L Q, Yao X L, Feng W H, Chew Y and Moon S K 2023 Multimodal sensor fusion for real-time location-dependent defect detection in laser-directed energy deposition *Proc.*

- ASME 2023 Int. Design Engineering Technical Conf. and Computers and Information in Engineering Conf. (Boston, Massachusetts, USA, 20–23 August) (American Society of Mechanical Engineers) pp [DETC2023-110284](#)
- [145] Vandone A, Baraldo S and Valente A 2018 Multisensor data fusion for additive manufacturing process control *IEEE Rob. Autom. Lett.* **3** 3279–84
- [146] Li J C, Zhou Q, Cao L C, Wang Y Z and Hu J X 2022 A convolutional neural network-based multi-sensor fusion approach for *in-situ* quality monitoring of selective laser melting *J. Manuf. Syst.* **64** 429–42
- [147] Grasso M, Gallina F and Colosimo B M 2018 Data fusion methods for statistical process monitoring and quality characterization in metal additive manufacturing *Procedia CIRP* **75** 103–7
- [148] Moretti M, Bianchi F and Senin N 2020 Towards the development of a smart fused filament fabrication system using multi-sensor data fusion for in-process monitoring *Rapid Prototyp. J.* **26** 1249–61
- [149] Li J C, Zhang X G, Zhou Q, Chan F T S and Hu Z 2022 A feature-level multi-sensor fusion approach for *in-situ* quality monitoring of selective laser melting *J. Manuf. Process.* **84** 913–26
- [150] Li W J, Mac G, Tsoutsos N G, Gupta N and Karri R 2020 Computer aided design (CAD) model search and retrieval using frequency domain file conversion *Addit. Manuf.* **36** 101554
- [151] Hou J H, Luo C Q, Qin F W, Shao Y L and Chen X X 2023 FuS-GCN: efficient B-rep based graph convolutional networks for 3D-CAD model classification and retrieval *Adv. Eng. Inform.* **56** 102008
- [152] Nyberg E L, Farris A L, Hung B P, Dias M, Garcia J R, Dorafshar A H and Grayson W L 2017 3D-Printing Technologies for Craniofacial Rehabilitation, Reconstruction, and Regeneration *Ann. Biomed. Eng.* **45** 45–57
- [153] Zheng Y F, Qureshi A J and Ahmad R 2018 Algorithm for remanufacturing of damaged parts with hybrid 3D printing and machining process *Manuf. Lett.* **15** 38–41
- [154] Kim H, Cha M, Kim B C, Lee I and Mun D 2019 Maintenance framework for repairing partially damaged parts using 3D printing *Int. J. Precis. Eng. Manuf.* **20** 1451–64
- [155] Yeon J, Kang J L and Yan W 2018 Spall damage repair using 3D printing technology *Autom. Constr.* **89** 266–74
- [156] Mildenhall B, Srinivasan P P, Tancik M, Barron J T, Ramamoorthi R and Ng R 2021 NeRF: representing scenes as neural radiance fields for view synthesis *Commun. ACM* **65** 99–106
- [157] Kerbl B, Kopanas G, Leimkuehler T and Drettakis G 2023 3D Gaussian splatting for real-time radiance field rendering *ACM Trans. Graph.* **42** 139
- [158] Siddiqui Y, Alliegro A, Artemov A, Tommasi T, Sirigatti D, Rosov V, Dai A and NieBner M 2024 MeshGPT: generating triangle meshes with decoder-only transformers *Proc. 2024 IEEE CVPR (Seattle, WA, USA, 17–21 June)* (IEEE) pp [19615–25](#)
- [159] Lin C H, Gao J, Tang L M, Takikawa T, Zeng X H, Huang X, Kreis K, Fidler S, Liu M Y and Lin T Y 2023 Magic3D: high-resolution text-to-3D content creation *Proc. 2023 IEEE CVPR (Vancouver, BC, Canada, 17–24 June)* (IEEE) pp [300–9](#)
- [160] Xu J L, Wang X T, Cheng W H, Cao Y P, Shan Y P, Qie X H and Gao S H 2023 Dream3D: zero-shot text-to-3D synthesis using 3D shape prior and text-to-image diffusion models *Proc. 2023 IEEE/CVF Conf. on Computer Vision and Pattern Recognition* (IEEE) pp [20908–18](#)
- [161] Yi H, Zheng Z D, Xu X Y and Chua T S 2023 Progressive text-to-3D generation for automatic 3D prototyping (arXiv: [2309.14600](#))
- [162] Long X X *et al* 2024 Wonder3D: single image to 3D using cross-domain diffusion *Proc. IEEE/CVF Conf. on Computer Vision and Pattern Recognition (CVPR 2024) (Seattle, WA, USA, 16–22 June)* (IEEE) pp [9970–80](#)
- [163] Liu M H, Xu C, Jin H A, Chen L H, Varma T M, Xu Z X and Su H 2023 One-2-3-45: any single image to 3D mesh in 45 seconds without per-shape optimization *Proc. 37th Int. Conf. on Neural Information Processing Systems (NIPS '23) (New Orleans, LA, USA, 10–16 December)* vol 976 (Curran Associates Inc.) pp [22226–46](#)
- [164] Hui K H, Sanghi A, Rampini A, Rahimi Malekshan K, Liu Z Z, Shayani H and Fu C W 2024 Make-A-Shape: a ten-million-scale 3D shape model *Proc. 41st Int. Conf. on Machine Learning (Vienna, Austria, 21–27 July)* vol 235 (PMLR) pp 20660–81 (available at: <https://proceedings.mlr.press/v235/hui24a.html>)
- [165] Liu C N, Tian W M and Kan C 2022 When AI meets additive manufacturing: challenges and emerging opportunities for human-centered products development *J. Manuf. Syst.* **64** 648–56
- [166] Gokuldoss P K, Kolla S and Eckert J 2017 Additive manufacturing processes: selective laser melting, electron beam melting and binder jetting-selection guidelines *Materials* **10** 672
- [167] Mançanares C G, de S. Zancul E, Cavalcante da Silva J and Cauchick Miguel P A 2015 Additive manufacturing process selection based on parts' selection criteria *Int. J. Adv. Manuf. Technol.* **80** 1007–14
- [168] Fera M, Fruggiero F, Costabile G, Lambiase A and Pham D T 2017 A new mixed production cost allocation model for additive manufacturing (MiProCAMAM) *Int. J. Adv. Manuf. Technol.* **92** 4275–91
- [169] Ribeiro I, Matos F, Jacinto C, Salman H, Cardeal G, Carvalho H, Godina R and Peças P 2020 Framework for life cycle sustainability assessment of additive manufacturing *Sustainability* **12** 929
- [170] Zaman U K U, Rivette M, Siadat A and Mousavi S M 2018 Integrated product-process design: material and manufacturing process selection for additive manufacturing using multi-criteria decision making *Rob. Comput. Integr. Manuf.* **51** 169–80
- [171] Liu W, Zhu Z C and Ye S H 2020 A decision-making methodology integrated in product design for additive manufacturing process selection *Rapid Prototyp. J.* **26** 895–909
- [172] Ren D Q, Choi J K and Schneider K 2022 A multicriteria decision-making method for additive manufacturing process selection *Rapid Prototyp. J.* **28** 77–91
- [173] Ghuge S and Akarte M 2024 Additive manufacturing process root selection using bayesian network *Procedia Comput. Sci.* **232** 698–707
- [174] Jiang J C, Xiong Y, Zhang Z Y and Rosen D W 2022 Machine learning integrated design for additive manufacturing *J. Intell. Manuf.* **33** 1073–86
- [175] Ackermann M and Haase C 2023 Machine learning-based identification of interpretable process-structure linkages in metal additive manufacturing *Addit. Manuf.* **71** 103585
- [176] Saunders R N, Teferra K, Elwany A, Michopoulos J G and Lagoudas D 2023 Metal AM process-structure-property relational linkages using Gaussian process surrogates *Addit. Manuf.* **62** 103398
- [177] Ko H, Lu Y, Yang Z, Ndiaye N Y and Witherell P 2023 A framework driven by physics-guided machine learning for process-structure-property causal analytics in additive manufacturing *J. Manuf. Syst.* **67** 213–28

- [178] Liu Q, Chen W L, Yakubov V, Kruzic J J, Wang C H and Li X P 2024 Interpretable machine learning approach for exploring process-structure-property relationships in metal additive manufacturing *Addit. Manuf.* **85** 104187
- [179] Wang C, Tan X P, Tor S B and Lim C S 2020 Machine learning in additive manufacturing: state-of-the-art and perspectives *Addit. Manuf.* **36** 101538
- [180] Pilania G, Wang C C, Jiang X, Rajasekaran S and Ramprasad R 2013 Accelerating materials property predictions using machine learning *Sci. Rep.* **3** 2810
- [181] Johnson N S, Vulimiri P S, To A C, Zhang X, Brice C A, Kappes B B and Stebner A P 2020 Invited review: machine learning for materials developments in metals additive manufacturing *Addit. Manuf.* **36** 101641
- [182] Yang C, Ren C, Jia Y F, Wang G, Li M J and Lu W C 2022 A machine learning-based alloy design system to facilitate the rational design of high entropy alloys with enhanced hardness *Acta Mater.* **222** 117431
- [183] Zou C X *et al* 2021 Integrating data mining and machine learning to discover high-strength ductile titanium alloys *Acta Mater.* **202** 211–21
- [184] Rao Z Y *et al* 2022 Machine learning-enabled high-entropy alloy discovery *Science* **378** 78–85
- [185] Motaman S A H, Kies F, Köhnen P, Létang M, Lin M X, Molotnikov A and Haase C 2020 Optimal design for metal additive manufacturing: an integrated computational materials engineering (ICME) approach *JOM* **72** 1092–104
- [186] Wang X and Xiong W 2020 Uncertainty quantification and composition optimization for alloy additive manufacturing through a CALPHAD-based ICME framework *npj Comput. Mater.* **6** 188
- [187] Chia H Y, Wu J Z, Wang X Z and Yan W T 2022 Process parameter optimization of metal additive manufacturing: a review and outlook *J. Mater. Inform.* **2** 16
- [188] Liu Y, Liu C, Liu W S, Ma Y Z, Tang S W, Liang C P, Cai Q S and Zhang C 2019 Optimization of parameters in laser powder deposition AlSi10Mg alloy using Taguchi method *Opt. Laser Technol.* **111** 470–80
- [189] Liu Z X, Li M Y, Weng Y W, Qian Y, Wong T N and Tan M J 2020 Modelling and parameter optimization for filament deformation in 3D cementitious material printing using support vector machine *Composites B* **193** 108018
- [190] Zou M, Jiang W G, Qin Q H, Liu Y C and Li M L 2022 Optimized XGBoost model with small dataset for predicting relative density of Ti-6Al-4V parts manufactured by selective laser melting *Materials* **15** 5298
- [191] Costa A, Buffa G, Palmeri D, Pollara G and Fratini L 2022 Hybrid prediction-optimization approaches for maximizing parts density in SLM of Ti6Al4V titanium alloy *J. Intell. Manuf.* **33** 1967–89
- [192] Liu R, Liu S and Zhang X L 2021 A physics-informed machine learning model for porosity analysis in laser powder bed fusion additive manufacturing *Int. J. Adv. Manuf. Technol.* **113** 1943–58
- [193] Smoqi Z, Gaikwad A, Bevans B, Kobir M H, Craig J, Abul-Haj A, Peralta A and Rao P 2022 Monitoring and prediction of porosity in laser powder bed fusion using physics-informed melt pool signatures and machine learning *J. Mater. Process. Technol.* **304** 117550
- [194] Lao W X, Li M Y, Wong T N, Tan M J and Tjahjowidodo T 2020 Improving surface finish quality in extrusion-based 3D concrete printing using machine learning-based extrudate geometry control *Virtual Phys. Prototyp.* **15** 178–93
- [195] Sharma P, Vaid H, Vajpeyi R, Shubham P, Agarwal K M and Bhatia D 2022 Predicting the dimensional variation of geometries produced through FDM 3D printing employing supervised machine learning *Sens. Int.* **3** 100194
- [196] Khorasani A M, Gibson I, Ghasemi A and Ghaderi A 2020 Modelling of laser powder bed fusion process and analysing the effective parameters on surface characteristics of Ti-6Al-4V *Int. J. Mech. Sci.* **168** 105299
- [197] Shirmohammadi M, Goushchi S J and Keshtiban P M 2021 Optimization of 3D printing process parameters to minimize surface roughness with hybrid artificial neural network model and particle swarm algorithm *Prog. Addit. Manuf.* **6** 199–215
- [198] Qin J, Liu Y, Grosvenor R, Lacan F and Jiang Z G 2020 Deep learning-driven particle swarm optimisation for additive manufacturing energy optimisation *J. Clean. Prod.* **245** 118702
- [199] Barrionuevo G O, Ramos-Grez J A, Walczak M and Betancourt C A 2021 Comparative evaluation of supervised machine learning algorithms in the prediction of the relative density of 316L stainless steel fabricated by selective laser melting *Int. J. Adv. Manuf. Technol.* **113** 419–33
- [200] Nguyen P D, Nguyen T Q, Tao Q B, Vogel F and Nguyen-Xuan H 2022 A data-driven machine learning approach for the 3D printing process optimisation *Virtual Phys. Prototyp.* **17** 768–86
- [201] Tamir T S, Xiong G, Fang Q H, Yang Y, Shen Z, Zhou M C and Jiang J C 2023 Machine-learning-based monitoring and optimization of processing parameters in 3D printing *Int. J. Comput. Integr. Manuf.* **36** 1362–78
- [202] Park H S, Nguyen D S, Le-Hong T and Van Tran X 2022 Machine learning-based optimization of process parameters in selective laser melting for biomedical applications *J. Intell. Manuf.* **33** 1843–58
- [203] Pham T Q D, Hoang T V, Van Tran X, Pham Q T, Fetni S, Duchêne L, Tran H S and Habraken A M 2023 Fast and accurate prediction of temperature evolutions in additive manufacturing process using deep learning *J. Intell. Manuf.* **34** 1701–19
- [204] Shi S, Liu X W, Wang Z, Chang H, Wu Y N, Yang R and Zhai Z R 2024 An intelligent process parameters optimization approach for directed energy deposition of nickel-based alloys using deep reinforcement learning *J. Manuf. Process.* **120** 1130–40
- [205] Liao S H, Xue T J, Jeong J, Webster S, Ehmann K and Cao J 2023 Hybrid thermal modeling of additive manufacturing processes using physics-informed neural networks for temperature prediction and parameter identification *Comput. Mech.* **72** 499–512
- [206] Kapusuzoglu B and Mahadevan S 2020 Physics-informed and hybrid machine learning in additive manufacturing: application to fused filament fabrication *JOM* **72** 4695–705
- [207] Nagarajan H P N, Mokhtarian H, Jafarian H, Dimassi S, Bakrani-Balani S, Hamedi A, Coatanéa E, Gary Wang G and Haapala K R 2019 Knowledge-based design of artificial neural network topology for additive manufacturing process modeling: a new approach and case study for fused deposition modeling *J. Mech. Des.* **141** 021705
- [208] Liu S, Stebner A P, Kappes B B and Zhang X L 2021 Machine learning for knowledge transfer across multiple metals additive manufacturing printers *Addit. Manuf.* **39** 101877
- [209] Venugopal V and Anand S 2023 Structural and thermal generative design using reinforcement learning-based search strategy for additive manufacturing *Manuf. Lett.* **35** 564–75
- [210] Vagenas S and Panoutsos G 2023 Stability in reinforcement learning process control for additive manufacturing *IFAC-PapersOnLine* **56** 4719–24

- [211] Del Real Torres A, Andreiana D S, Ojeda Roldán Á, Hernández Bustos A and Acevedo Galicia L E 2022 A review of deep reinforcement learning approaches for smart manufacturing in industry 4.0 and 5.0 framework *Appl. Sci.* **12** 12377
- [212] Gunasegaram D R, Murphy A B, Barnard A, DebRoy T, Matthews M J, Ladani L and Gu D 2021 Towards developing multiscale-multiphysics models and their surrogates for digital twins of metal additive manufacturing *Addit. Manuf.* **46** 102089
- [213] Guo S H, Agarwal M, Cooper C, Tian Q, Gao R X, Guo W H and Guo Y B 2022 Machine learning for metal additive manufacturing: towards a physics-informed data-driven paradigm *J. Manuf. Syst.* **62** 145–63
- [214] Baturynska I, Semeniuta O and Martinsen K 2018 Optimization of process parameters for powder bed fusion additive manufacturing by combination of machine learning and finite element method: a conceptual framework *Procedia CIRP* **67** 227–32
- [215] Azizzadenesheli K, Kovachki N, Li Z Y, Liu-Schiaffini M, Kossaiji J and Anandkumar A 2024 Neural operators for accelerating scientific simulations and design *Nat. Rev. Phys.* **6** 320–8
- [216] Mbow M M, Grandvallet C, Vignat F, Marin P R, Perry N and Pourroy F 2022 Mathematization of experts knowledge: example of part orientation in additive manufacturing *J. Intell. Manuf.* **33** 1209–27
- [217] Liu X, Erkoyuncu J A, Fuh J Y H, Lu W F and Li B B 2025 Knowledge extraction for additive manufacturing process via named entity recognition with LLMs *Rob. Comput. Integr. Manuf.* **93** 102900
- [218] Abdollahi S, Davis A, Miller J H and Feinberg A W 2018 Expert-guided optimization for 3D printing of soft and liquid materials *PLoS One* **13** e0194890
- [219] Wang Y B, Blache R, Zheng P and Xu X 2018 A knowledge management system to support design for additive manufacturing using Bayesian networks *J. Mech. Des.* **140** 051701
- [220] Peng X, Kong L B, Fuh J Y H and Wang H 2021 A review of post-processing technologies in additive manufacturing *J. Manuf. Mater. Process.* **5** 38
- [221] George A, Ali M and Papakostas N 2021 Utilising robotic process automation technologies for streamlining the additive manufacturing design workflow *CIRP Ann.* **70** 119–22
- [222] Nelaturi S, Behandish M, Mirzendehtel A M and de Kleer J 2019 Automatic support removal for additive manufacturing post processing *Comput.-Aided Des.* **115** 135–46
- [223] Vaidya R and Anand S 2016 Image processing assisted tools for pre- and post-processing operations in additive manufacturing *Procedia Manuf.* **5** 958–73
- [224] Chen H, Joglekar A, Whitefoot K S and Burak Kara L 2023 Concurrent build direction, part segmentation, and topology optimization for additive manufacturing using neural networks *J. Mech. Des.* **145** 091702
- [225] Jannesari Ladani L 2021 Applications of artificial intelligence and machine learning in metal additive manufacturing *J. Phys. Mater.* **4** 042009
- [226] Oh Y, Witherell P, Lu Y and Sprock T 2020 Nesting and scheduling problems for additive manufacturing: a taxonomy and review *Addit. Manuf.* **36** 101492
- [227] Pinto M, Silva C, Thürer M and Moniz S 2024 Nesting and scheduling optimization of additive manufacturing systems: mapping the territory *Comput. Oper. Res.* **165** 106592
- [228] Yamashiro H and Nonaka H 2021 Estimation of processing time using machine learning and real factory data for optimization of parallel machine scheduling problem *Oper. Res. Perspect.* **8** 100196
- [229] Ying K C and Lin S W 2023 Minimizing makespan in two-stage assembly additive manufacturing: a reinforcement learning iterated greedy algorithm *Appl. Soft Comput.* **138** 110190
- [230] Alicastrro M, Ferone D, Festa P, Fugaro S and Pastore T 2021 A reinforcement learning iterated local search for makespan minimization in additive manufacturing machine scheduling problems *Comput. Oper. Res.* **131** 105272
- [231] Morariu C, Morariu O, Răileanu S and Borangiu T 2020 Machine learning for predictive scheduling and resource allocation in large scale manufacturing systems *Comput. Ind.* **120** 103244
- [232] Wang Y B, Zheng P, Xu X, Yang H Y and Zou J 2019 Production planning for cloud-based additive manufacturing—a computer vision-based approach *Rob. Comput. Integr. Manuf.* **58** 145–57
- [233] Mashhadi F and Salinas Monroy S A 2020 Deep learning for optimal resource allocation in IoT-enabled additive manufacturing *Proc. 2020 IEEE 6th WF-IoT (New Orleans, Louisiana, USA, 6–9 April)* (IEEE) pp 1–6
- [234] Zehetner D and Gansterer M 2022 The collaborative batching problem in multi-site additive manufacturing *Int. J. Prod. Econ.* **248** 108432
- [235] Hsu Y C, Yang Z Z and Buehler M J 2022 Generative design, manufacturing, and molecular modeling of 3D architected materials based on natural language input *APL Mater.* **10** 041107
- [236] Yang Z Z and Buehler M J 2021 Words to matter: de novo architected materials design using transformer neural networks *Front. Mater.* **8** 740754
- [237] Kumar A and Starly B 2022 “FabNER”: information extraction from manufacturing process science domain literature using named entity recognition *J. Intell. Manuf.* **33** 2393–407
- [238] Fan H L, Fuh J, Lu W F, Kumar A S and Li B B 2024 Unleashing the potential of large language models for knowledge augmentation: a practical experiment on incremental sheet forming *Procedia Comput. Sci.* **232** 1269–78
- [239] Caglar T R, Andrushchenko E, Mayer J and Jochem R 2023 Estimation of fused deposition modelling failure from open community data with natural language process *Procedia CIRP* **120** 1226–31
- [240] Fan H L, Liu X, Fuh J Y H, Lu W F and Li B B 2024 Embodied intelligence in manufacturing: leveraging large language models for autonomous industrial robotics *J. Intell. Manuf.* 1–17
- [241] Ostrander J K, Tucker C S, Simpson T W and Meisel N A 2020 Evaluating the use of virtual reality to teach introductory concepts of additive manufacturing *J. Mech. Des.* **142** 051702
- [242] Cai Y, Wang Y and Burnett M 2020 Using augmented reality to build digital twin for reconfigurable additive manufacturing system *J. Manuf. Syst.* **56** 598–604
- [243] Fan H L, Zhang H J, Ma C Y, Wu T Z, Fuh J Y H and Li B B 2024 Enhancing metal additive manufacturing training with the advanced vision language model: a pathway to immersive augmented reality training for non-experts *J. Manuf. Syst.* **75** 257–69
- [244] Chheang V, Weston B T, Cerda R W, Au B, Giera B, Bremer P T and Miao H C 2024 A virtual environment for collaborative inspection in additive manufacturing *Proc. 2017 CHI Conf. Extended Abstracts on Human Factors in*

- Computing Systems (Honolulu, HI, USA, 11–16 May)* vol 26 (Association for Computing Machinery) pp 1–7
- [245] Mourtzis D, Angelopoulos J and Panopoulos N 2021 Collaborative manufacturing design: a mixed reality and cloud-based framework for part design *Procedia CIRP* **100** 97–102
- [246] Mourtzis D, Angelopoulos J and Panopoulos N 2022 Integration of mixed reality to CFD in industry 4.0: a manufacturing design paradigm *Procedia CIRP* **107** 1144–9
- [247] Malik A, Lhachemi H and Shorten R 2020 I-nteract: a cyber-physical system for real-time interaction with physical and virtual objects using mixed reality technologies for additive manufacturing *IEEE Access* **8** 98761–74
- [248] Zheng P, Li C X, Fan J M and Wang L H 2024 A vision-language-guided and deep reinforcement learning-enabled approach for unstructured human-robot collaborative manufacturing task fulfilment *CIRP Ann.* **73** 341–4
- [249] Xiong Y, Tang Y L, Kim S and Rosen D W 2023 Human-machine collaborative additive manufacturing *J. Manuf. Syst.* **66** 82–91
- [250] Batra R, Song L and Ramprasad R 2020 Emerging materials intelligence ecosystems propelled by machine learning *Nat. Rev. Mater.* **6** 655–78
- [251] Xia K S, Saïdy C, Kirkpatrick M, Anumba N, Sheth A and Harik R 2021 Towards semantic integration of machine vision systems to aid manufacturing event understanding *Sensors* **21** 4276
- [252] Gao H H, Jiang W Y, Ran Q H Z and Wang Y 2024 Vision-language interaction via contrastive learning for surface anomaly detection in consumer electronics manufacturing *IEEE Trans. Consum. Electron.* **70** 6119–30
- [253] Chow E *et al* 2024 Collaborative moonwalkers *Proc. 2024 IEEE Aerospace Conf. (Big Sky, Montana, USA, 2–9 March)* (IEEE) pp 1–15
- [254] Tang Y F, Rahmani Dehaghani M and Wang G G 2023 Review of transfer learning in modeling additive manufacturing processes *Addit. Manuf.* **61** 103357
- [255] Cheng L W, Tsung F and Wang A D 2017 A statistical transfer learning perspective for modeling shape deviations in additive manufacturing *IEEE Rob. Autom. Lett.* **2** 1988–93
- [256] Pandiyan V, Drissi-Daoudi R, Shevchik S, Masinelli G, Le-Quang T, Logé R and Wasmer K 2022 Deep transfer learning of additive manufacturing mechanisms across materials in metal-based laser powder bed fusion process *J. Mater. Process. Technol.* **303** 117531
- [257] Huang X F, Xie T L, Wang Z, Chen L, Zhou Q and Hu Z 2022 A transfer learning-based multi-fidelity point-cloud neural network approach for melt pool modeling in additive manufacturing *ASCE-ASME J. Risk Uncertain. Eng. Syst. B* **8** 011104
- [258] Caiazza F and Alfieri V 2019 Simulation of laser-assisted directed energy deposition of aluminum powder: prediction of geometry and temperature evolution *Materials* **12** 2100
- [259] Zhao W S, Queralt J P and Westerlund T 2020 Sim-to-real transfer in deep reinforcement learning for robotics: a survey *Proc. 2020 IEEE Symp. Series on Computational Intelligence (Canberra, Australia, 1–4 December)* (IEEE) pp 737–44
- [260] Ahmmed B *et al* 2024 Deep learning with mixup augmentation for improved pore detection during additive manufacturing *Sci. Rep.* **14** 13365
- [261] Conrad J, Rodriguez S, Omidvarkarjan D, Ferchow J and Meboldt M 2023 Recognition of additive manufacturing parts based on neural networks and synthetic training data: a generalized end-to-end workflow *Appl. Sci.* **13** 12316
- [262] Liang Wong S J, Chen C X, Tan E Z E and Li H 2024 Integration of physics-based data in deep learning model training for predicting the effect of sulfur content in the directed energy deposition process *Int. J. AI Mater. Des.* **1** 44
- [263] Mehta M and Shao C H 2022 Federated learning-based semantic segmentation for pixel-wise defect detection in additive manufacturing *J. Manuf. Syst.* **64** 197–210
- [264] Paramartha Putra M A, Verana M, Sampedro G A, Kim D S and Lee J M 2022 3DFed: a secure federated learning-based system for fault detection in 3D printer industry *Proc. 2022 13th Int. Conf. on Information and Communication Technology Convergence (ICTC) (Jeju Island, Republic of Korea, 19–21 October)* (IEEE) pp 1459–62
- [265] Shi N C and Kontar R A 2023 Personalized federated learning via domain adaptation with an application to distributed 3D printing *Technometrics* **65** 328–39
- [266] Zhang K Q, Yang Z R and Başar T 2021 Multi-agent reinforcement learning: a selective overview of theories and algorithms *Handbook of Reinforcement Learning and Control (Studies in Systems, Decision and Control)* vol 325, ed K G Vamvoudakis, Y Wan, F L Lewis and D Cansever (Springer) pp 321–84
- [267] Bahrpeyma F and Reichelt D 2022 A review of the applications of multi-agent reinforcement learning in smart factories *Front. Robot. AI* **9** 1027340
- [268] Zheng P, Xia L Q, Li C X, Li X Y and Liu B F 2021 Towards Self-X cognitive manufacturing network: an industrial knowledge graph-based multi-agent reinforcement learning approach *J. Manuf. Syst.* **61** 16–26
- [269] Alam M F, Shtein M, Barton K and Hoelzle D 2023 Reinforcement learning enabled autonomous manufacturing using transfer learning and probabilistic reward modeling *IEEE Control Syst. Lett.* **7** 508–13
- [270] Liu H T, Li C Y, Wu Q Y and Lee Y J 2023 Visual instruction tuning *Proc. Advances in Neural Information Proc. Systems (NeurIPS 2023) (New Orleans, Louisiana, USA, 10–16 December)* vol 36 (Curran Associates Inc.) p 1516 (available at: https://proceedings.neurips.cc/paper_files/paper/2023/file/6dcf277ea32ce3288914faf369fe6de0-Paper-Conference.pdf)
- [271] Picard C, Edwards K M, Doris A C, Man B, Giannone G, Alam M F and Ahmed F 2023 From concept to manufacturing: evaluating vision-language models for engineering design (arXiv:2311.12668)
- [272] Bardes A, Garrido Q, Ponce J, Chen X L, Rabbat M, LeCun Y, Assran M and Ballas N 2024 Revisiting feature prediction for learning visual representations from video (arXiv:2404.08471)
- [273] Wan X, Liu L L, Feng B W, Chen C and Wang Y 2021 Research on multi-modal data cross-media perception fusion algorithm based on digital twin *Advanced Manufacturing and Automation X* vol 737, ed X Y Des Wang, K Martinsen, T Yu and K S Wang (Springer) pp 221–9
- [274] Liu L L, Wan X, Gao Z G and Zhang X Y 2023 An improved MPGA-ACO-BP algorithm and comprehensive evaluation system for intelligence workshop multi-modal data fusion *Adv. Eng. Inform.* **56** 101980
- [275] Wang K, Song Y Y, Sheng H S, Xu J H, Zhang S Y and Qin J 2022 Energy efficiency design for eco-friendly additive

- manufacturing based on multimodal attention fusion *J. Manuf. Process.* **79** 720–30
- [276] Biehler M, Li J and Shi J J 2024 FUSION3D: multimodal data fusion for 3D shape reconstruction: a soft-sensing approach *IISE Transactions* pp 1–15
- [277] Bauer F, Schrapp M and Szijarto J 2019 Accuracy analysis of a piece-to-piece reverse engineering workflow for a turbine foil based on multi-modal computed tomography and additive manufacturing *Precis. Eng.* **60** 63–75
- [278] Pan S R, Luo L H, Wang Y F, Chen C, Wang J P and Wu X D 2024 Unifying large language models and knowledge graphs: a roadmap *IEEE Trans. Knowl. Data Eng.* **36** 3580–99
- [279] Lewis P *et al* 2020 Retrieval-augmented generation for knowledge-intensive NLP tasks *Proc. 34th Int. Conf. on Neural Information Processing Systems (Vancouver, BC, Canada, 6–12December)* (Curran Associates Inc.) pp 9459–74
- [280] Hu E J, Shen Y L, Wallis P, Allen-Zhu Z, Li Y Z, Wang S A, Wang L and Chen W Z 2022 LoRA: low-rank adaptation of large language models *Proc. 10th Int. Conf. on Learning Representations (ICLR)* (<https://doi.org/10.1523/JNEUROSCI.2255-21.2022>)