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AI-DRIVEN METAL ADDITIVE MANUFACTURING: A CRITICAL REVIEW OF TECHNIQUES, CHALLENGES, AND EMERGING OPPORTUNITIES

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Abstract

Metal additive manufacturing (MAM) technology offers significant opportunities for the production of complex metal components, including greater design freedom and improved material utilization. However, issues such as process instability, defect formation, complex microstructure, and poor repeatability pose significant challenges to the realization of industrial applications of the MAM technology. In recent years, the implementation of AI and ML methods has been considered as one of the possible ways to address these problems. The goal of this paper is to provide a comprehensive overview of recent developments in metal additive manufacturing technology enabled by artificial intelligence methods, including process parameter optimization, defect detection, microstructure prediction, and material qualification. Developments in deep learning, Bayesian optimization, physics-guided machine learning, and related areas will be considered in detail, along with their potential contributions to advancing process-structure-property relationships. Also, the emergence of new trends in autonomous manufacturing systems, generative design, digital twins, and others will be discussed to demonstrate the transition from conventional trial-and-error approaches to AI-driven, autonomous manufacturing systems. Moreover, the issues with current methodologies will be addressed, including the need for reliable, explainable, and robust AI techniques for implementing MAM technology. Additionally, directions for addressing issues with the MAM technology will be provided.

Keywords. *Metal AM; AI-driven AM; PSP intelligence; Defect analytics; Physics-informed ML; Digital twins.*

1. Introduction

1.1. Metal Additive Manufacturing: Promises and Challenges

MAM builds components layer-by-layer using melted metal powders or wires, unlike subtractive manufacturing, as shown in Fig. 1. MAM uses a process of melting the metal powder or wire to create the component. In contrast, conventional machining relies on material removal from solid material. MAM technology has progressed from rapid prototyping to mass production in industries such as aerospace, medical devices, and automotive [1]. MAM offers high design freedom, enabling complex shapes, internal structures, and lattice designs without additional tooling. It enables topology optimization and reduces assembly requirements, as components can be produced in a single piece [2]. Another advantage of MAM technology is its ability to minimize material use, as most unused powders are reclaimable for reuse, reducing the Buy-to-Fly ratio, as shown in Table 1, even compared to traditional manufacturing techniques.

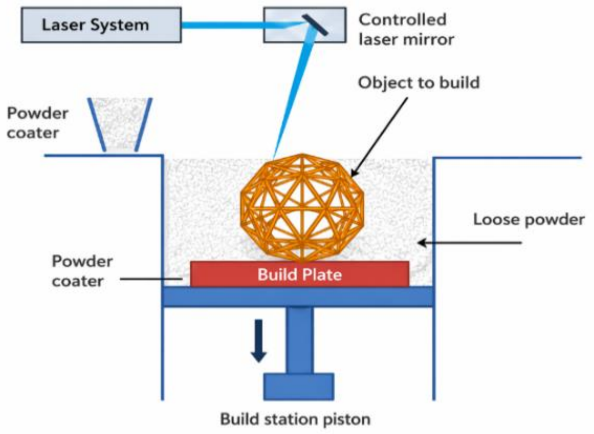

Fig. 1. Schematic representation of Laser Powder Bed Fusion (LPBF) process.

Additionally, digital CAD files allow for decentralized production. The metal AM process involves rapid heating and cooling, leading to high cooling rates and microstructures that are not in equilibrium. The metal parts

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thus produced exhibit anisotropic mechanical behavior. Warping and cracking occur because of thermal gradient-induced residual stress. Moreover, poor surface finish is another characteristic of a metal AM part. Post-processing, like annealing and machining, is thus necessary for the parts [3].

Table 1. Comparison between Conventional Manufacturing and Metal Additive Manufacturing

Aspect	Conventional Manufacturing	Metal Additive Manufacturing
Manufacturing Method	Material removal (machining, casting)	Layer-by-layer material addition
Design Complexity	High complexity increases cost	Complex geometries are achievable without a major cost increase
Material Utilization	High material waste (Buy-to-Fly up to 15:1)	Low waste (Buy-to-Fly ~1.5:1)
Microstructure	Cast or wrought structure	Rapid solidification, anisotropic structure
Surface Finish	Generally smooth	Requires post-processing
Assembly	Multiple parts and joining required	Part consolidation possible

1.2. The Emergence of AI as Enabling Technology

Conventional techniques for addressing issues in metal AM include trial-and-error approaches, DoE methods, and physics-based modeling, such as FEA and CFD. These conventional techniques prove useful but are extremely time-intensive and unable to traverse the high-dimensional parameter space associated with the AM process [4]. On the other hand, there is potential for artificial intelligence and machine learning (AI/ML) to enhance the metal AM process, given AI's capacity to handle nonlinearity and complex correlations between process parameters and product quality. AI can be used across the spectrum of metal AM, from process and material optimization to in-process monitoring and quality assurance [4,6]. CNNs work well for analyzing defects in melt-pool images and layer-by-layer information. RNN and LSTM techniques help in modeling thermal histories and evolutionary processes in AM. Moreover, Bayesian optimization efficiently explores the high-dimensional parameter space with limited data, whereas reinforcement learning techniques facilitate adaptive, autonomous process control.

1.3. Scope and Organization of This Review

Current investigations have examined the use of AI and ML in metal AM in several ways, including reinforcement learning, transfer learning, deep learning, DED technologies, HTM material characterization, and optimization of production rate and energy consumption [4].

Contributions of this review include:

1. A fair representation of AI techniques employed within selected metal AM processes, such as powder bed fusion, DED, and wire arc AM [5].
2. Categorizing machine learning approaches based on both their algorithms and application areas.
3. Discussion about challenges, e.g., data scarcity, lack of generalization, and physical insight incorporation.
4. Pointing out future research directions, especially autonomous and defect-free AM systems [6,7].

This paper is structured in the following way. The first section covers the basics of metal AM and AI/ML. Then, Sections 2–3 will deal with AI-assisted PSP model development and modeling of metal AM processes. Next, Sections 4 and 5 will discuss in-situ monitoring and process control. After that, we will talk about material development, challenges, future directions, and concluding remarks in Sections 6–9, respectively.

2. Core Principles of Metal Additive Manufacturing and AI

2.1 Metal AM Processes: Principles and Challenges

2.1.1. Major Metal AM Processes

The major metal-based Additive Manufacturing technologies discussed in this chapter are Laser Powder Bed Fusion, Electron Beam Melting, Directed Energy Deposition, and Wire Arc Additive Manufacturing.

2.1.2. Laser Powder Bed Fusion (L-PBF)

LPBF involves laying down a 20 to 100 microns-thick metal-powder layer on the build plate, followed by selective laser melting of the metal according to the CAD design. This is done by lowering the build plate and depositing a new metal powder layer [5].

LPBF enables the fabrication of complex parts but suffers from several drawbacks, such as keyhole porosity, incomplete fusion, and balling defects [4].

2.1.3. Electron Beam Melting (EBM)

In EBM, an electron beam is used as the energy source, and the process is carried out under vacuum at high temperatures. Although high-temperature melting reduces residual stress and distortion, it is still limited by its high vacuum requirements and compatibility issues [4].

2.1.4. Directed Energy Deposition (DED) and Wire Arc Additive Manufacturing (WAAM)

DED (Directed Energy Deposition) and WAAM (Wire Arc Additive Manufacturing) are metal AM processes based on deposition that use a concentrated energy source (such as a laser, electron beam, or arc). DED and WAAM technologies are ideal for manufacturing and repairing large parts due to their high material deposition rate and versatility. Nevertheless, these technologies may be subject to problems such as poor surface finish, poor dimensional accuracy, warping, and buildup of residual stresses [7-8].

2.1.6. Common Process Challenges

Several factors, including energy density, powder properties, environmental conditions, and geometry, influence the properties of metallic parts produced by additive manufacturing processes. The complexity of these parameters, due to nonlinearity and interactions, is a hindrance to optimization using trial-and-error methods [4,5]. The following problems are associated with the use of metallic additive manufacturing systems in industrial production: part size limitations, anisotropic behavior, overhangs, high system costs, low productivity, and dimensional accuracy issues. Common defects are warping, layer shifting, over- and under-extrusions, and the "elephant foot" phenomenon [9,10].

2.2 Key Technical Limitations

2.2.1. Void Formation

Interlayer voiding caused by inadequate layer bonding is an inherent challenge in additive manufacturing (AM). Although more common in extrusion-based printing methods such as fused deposition modeling (FDM), the problem can still occur in metal AM if the process is not properly managed. Optimal process control may alleviate interlayer voiding; studies show that rectangular nozzles produce better interlayer bonds than circular nozzles [9,11].

2.2.2. Stair-Stepping Effect

Because additive manufacturing builds parts layer by layer, a phenomenon called the stair-stepping effect occurs; however, it mostly affects the part's surface rather than its internal properties. To reduce surface roughness, additional operations such as machining, sanding, and sintering must be performed.

2.2.3. Anisotropy in Mechanical Properties and Microstructure

In the layer-by-layer additive manufacturing process, thermal gradients form, leading to directional solidification and anisotropic microstructure. This causes anisotropy in the material's properties, which are usually higher in the in-plane (layer) direction as compared to the build direction (Z direction) because of weak bonding between layers [12-14]. Anisotropy is also observed in metal powder bed fusion due to rapid solidification and directional grain growth.

2.2.4. Limited Build Volume

The majority of additive manufacturing devices have size limitations, resulting in large parts being manufactured in smaller segments that need to be bonded together later, either with adhesives or other fastening materials. This makes the manufacturing process slower and may affect structural strength [13]. To summarize, even though metal additive manufacturing is a breakthrough technology, several problems still need to be solved.

3. Artificial Intelligence and Machine Learning:

3.1 Key Concepts and Algorithms

Artificial Intelligence (AI) and Machine Learning (ML) encompass techniques that enable the acquisition of knowledge, the discovery of patterns, and the making of predictions or decisions with little to no human intervention. This segment will highlight the math concepts and the most prominent algorithms discussed in the context of metal additive manufacturing (AM) for newbies to AI.

i) The Mathematical Foundation of Learning

The fundamental goal of machine learning is to learn a function f that maps inputs X to outputs Y, i.e., $f: X \rightarrow Y$. The training process minimizes the loss function, which measures the distance between the actual and predicted outputs. Optimization algorithms help minimize the loss function to improve the model's accuracy. ML can be categorized into three types of learning:

ii) Supervised Learning

Supervised learning uses labeled datasets to train predictive models. A classic example is linear regression, where the relationship between predictors and response is expressed as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon \quad (1)$$

Where,

y	- dependent variable,
β_0	- intercept,
$\beta_1, \beta_2, \dots, \beta_n$	- regression coefficients,
$x_1, x_2, \dots, x_n$	- independent variables
ε	- the residual error [15].

iii) Unsupervised Learning

Unsupervised learning is a subset of ML that uses unlabeled data to discover patterns [15].

iv) Deep Learning

Deep learning is a subset of ML inspired by the human brain. It employs multi-layered artificial neural networks (ANNs) capable of modeling highly non-linear relationships in complex datasets. Key Algorithms in Metal Additive Manufacturing Research: A variety of AI/ML algorithms have been successfully applied in metal AM for process monitoring, defect detection, and property prediction.

3.2 Artificial Neural Networks (ANNs)

ANNs are computer models composed of interconnected neurons organized into layers: input, hidden, and output. During training, ANNs adjust their connection weights sequentially to minimize prediction error. Due to their ability to learn and approximate complex nonlinear functions, ANNs are commonly employed in metal AM to predict mechanical properties, map process-to-structure-to-property relationships, and optimize process parameters [5, 8].

3.3 Convolutional Neural Networks (CNNs)

CNNs are specific deep learning architectures designed to handle data with a grid or topological structure, especially images. By convolution, CNNs automatically learn features such as edges, textures, and geometric structures. In metal AM, CNNs are frequently employed for melt-pool observation, surface examination of individual layers, and radiographic defect identification [5, 16].

3.4 Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) Networks

RNNs and LSTMs are neural networks designed to handle sequences of data. Since they retain memory of previously seen data, they can learn temporal dependencies. Thus, they are useful for analyzing sensor signals, tracking temporal temperature changes, and understanding layer-to-layer interactions [5, 7].

3.5 Generative Adversarial Network (GAN)

GANs are composed of two opposing parts: a generator and a discriminator. GANs are powerful in generating realistic fake data. GANs are useful in the context of metal AM for generating additional data, generating defect shapes, and enhancing small experimental datasets [5, 16].

3.6 Gaussian Process Regression (GPR)

GPR is a type of probabilistic machine learning technique. GPR is powerful at providing predictions along with their levels of uncertainty. GPR is useful in the context of Bayesian optimization in metal AM for efficiently exploring a range of options for balancing exploration of new settings with known good settings [6, 8].

3.7 Random Forests (RF) and Gradient Boosting Machines (GBM)

Both RF and GBM are types of ensemble machine learning techniques. These are powerful in handling non-linear interactions between the parameters of the processes. Both models are useful for quality control in metal AM, providing clear measures of which features are important [4, 8].

3.8 Transformer Models

Transformer models use self-attention to handle sequences and various kinds of data. This is done efficiently by transformer models, unlike RNN-based models, for dealing with long-range relationships in the data. Research is ongoing in the field of metal additive manufacturing, including the application of transformers for melt-pool signal analysis, sensor fusion, and physics-informed models [5, 7]. Table 2 provides the comparative analysis of machine learning algorithms in metal-based AM.

4. AI for Process-Structure-Property Relationship Modeling

4.1 Predicting Multi-Physics Phenomena

In metal-based additive manufacturing, ML and AI techniques are employed to model PSP relationships and predict multi-physics processes involving thermal, fluid flow, and solidification aspects [17–20]. Thermal gradients and melt pool dynamics play a major role in microstructure development, residual stresses, defects, and, ultimately, mechanical properties such as yield strength and fatigue resistance [21,30,31].

Three ML techniques for multi-physics modeling may be considered: data-driven, physics-informed, and hybrid. Data-driven models provide correlations between input variables (process parameters) and outputs (PSP characteristics). These models require large amounts of training data and lack interpretability. Physics-informed models (PIML), such as physics-informed neural networks (PINNs), leverage governing laws to achieve accurate predictions with smaller datasets. Hybrid models use simulations together with ML models to perform multi-scale studies effectively.

Hierarchical frameworks encompassing macro-scale heat transfer, meso-scale microstructural development, and micro-scale mechanical responses are commonly used in ICME. Uncertainty quantification and variability continue to pose significant challenges in the field.

Table 2: Summary of Machine Learning Algorithms Used in Metal Additive Manufacturing

Algorithm Category	Representative Techniques	Common Applications	Key Strengths	References
Neural Networks	ANN, MLP, BPNN	Material property prediction; process parameter optimization	Strong capability to approximate complex nonlinear relationships	[4, 8]
Convolutional Neural Networks	CNN, DCNN, ResUNet, YOLO	Defect detection; melt pool analysis; image segmentation	Effective spatial feature extraction and translation invariance	[5, 16]
Recurrent Neural Networks	RNN, LSTM, GRU	Thermal history prediction; time-series monitoring	Efficient modeling of temporal dependencies in sequential data	[5]
Generative Models	GAN, cGAN, VAE	Synthetic data generation; defect simulation	Ability to generate realistic data and enhance dataset diversity	[5, 16]
Bayesian Methods	GPR, Bayesian Optimization	Parameter optimization; uncertainty quantification	Probabilistic prediction with efficient exploration of the search space	[6, 8]
Reinforcement Learning	DRL, DQN	Process control; adaptive optimization	Learns optimal strategies through sequential decision-making	[4]
Transformer-Based Models	ViViT, Physics-informed Transformers	Melt pool monitoring; physics-integrated modeling	Captures long-range dependencies and contextual relationships effectively	[5]

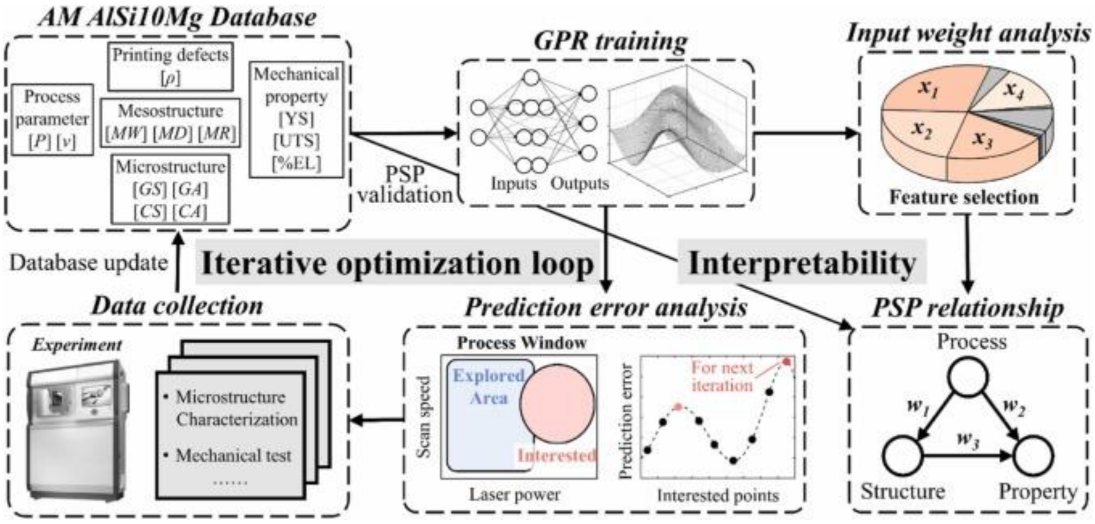

Fig. 2. Machine learning-based workflow for analyzing PSP relationships in additive manufacturing [85]. Reproduced under CC BY 4.0.

4.2 Microstructure and Mechanical Property Prediction

The advent of artificial intelligence, especially machine learning and deep learning, has greatly contributed to modeling PSP relations by capturing highly complex nonlinear interactions among process variables, microstructural characteristics, and mechanical properties [30,42,43]. DL techniques, in particular recurrent neural network architectures such as LSTM networks, are often applied to predict microstructure evolution under various mechanical, thermal, and transformation conditions as an efficient alternative to physics-based simulations, which are computationally expensive [45,46]. Data distribution learning through generative methods such as GANs and VAEs has further enabled microstructure generation and inverse materials design problems [49-52].

Figure 3 illustrates that AI-based algorithms, such as neural CA, can accurately simulate microstructure evolution during solidification, yielding results comparable to those of the classical CA model and experiments.

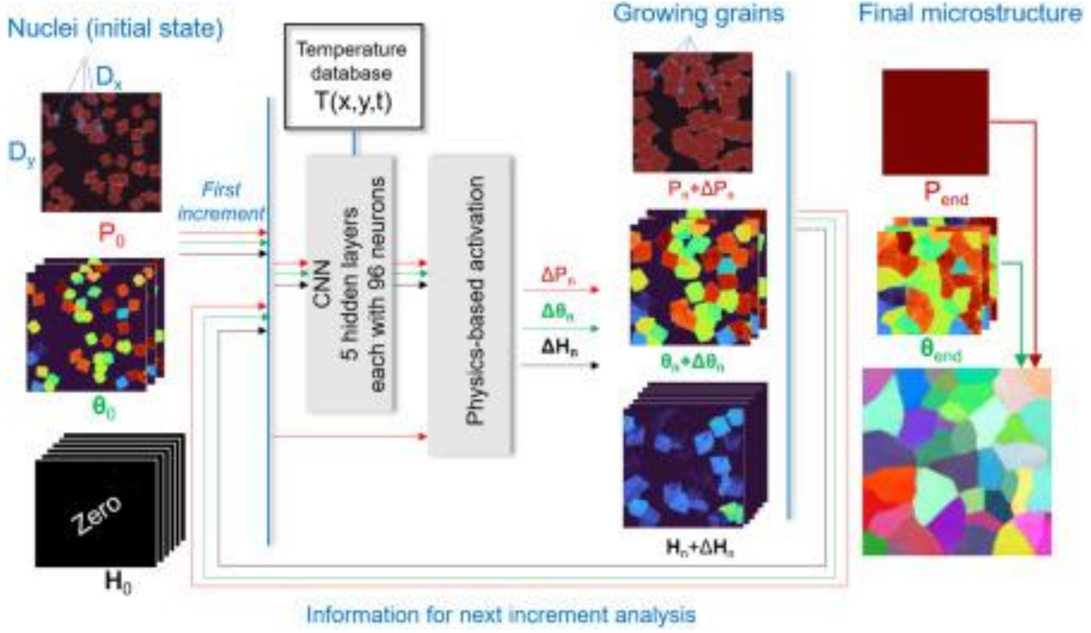

Fig. 3. Comparison of solidification microstructure evolution simulated using NCA and CA with experimental results (CC BY 4.0 license). [48]

AI also enables phase transformations and phase-fraction prediction, aiding alloy design through hierarchical modeling. Such models combine understanding of microstructure evolution with the prediction of mechanical properties, allowing the estimation of hardness, yield strength, ductility, and fracture toughness [54]. Feature engineering of material descriptors (composition, microstructure, and manufacturing history) with state-of-the-art ML/DL models is critical for achieving reliable PSP modeling [55,58].

In additive manufacturing processes, ML models have been extensively applied for optimizing process parameters (e.g., laser power, scan rate, and layer thickness) and for predicting the mechanical performance of fabricated parts (e.g., Inconel 718 alloys) [42,60]. Hierarchical modeling approaches, in conjunction with Multiphysics modeling, enable linking process parameters, microstructure evolution, and mechanical properties. Uncertainty quantification also improves the reliability of predictions [61–63].

There are still many challenges to address regarding reliability, generality, and interpretability. Proper validation of models and uncertainty quantification, along with incorporation of physical knowledge (thermodynamic and kinetic data from CALPHAD), will help improve the accuracy of predictive models. Microstructure evolution is an intrinsically complex problem that requires further work on multi-scale modeling techniques.

5. In-situ monitoring and defect detection

In-situ monitoring is crucial in additive manufacturing to maintain process stability and product quality, given its unique layered construction and heating cycles [66-68]. This issue is particularly relevant in industries such as aerospace and biomedical engineering, which require strict adherence to quality standards. Therefore, sophisticated sensor systems are utilized to monitor defects in the production process [67,68].

5.1. Sensor Technologies and Data Acquisition

Various sensors can be employed to monitor additive manufacturing in real time. This includes optical and thermal sensors that provide information on the melt pool, spatter generation, and surface morphology, as well as near-infrared sensing that delivers three-dimensional thermal data [71]. Surface deformation and strain can be measured using digital image correlation, and acoustic sensing is another technique that has proven effective for detecting surface and subsurface flaws at relatively low cost [66,68].

Non-destructive testing techniques such as ultrasound, eddy current, and X-ray testing are often employed alongside the above-mentioned techniques.

5.2. Deep Learning for Defect Detection and Quality Prediction

However, the massive data generated by in-situ inspection systems in AM requires sophisticated analysis tools. With the help of deep learning (DL), the scalability of defect detection and quality prediction is achieved irrespective of geometric features in LPBF processes [68].

The integration of DL with machine vision enables timely defect detection through novel approaches, such as attention mechanisms and multi-scale feature extraction. Furthermore, edge computing enables efficient real-time data detection and processing without requiring high-bandwidth connectivity [68,69].

Moreover, machine learning (ML) and deep learning algorithms aid in predictive defect detection, where process parameters, such as laser power, scan speed, etc., are correlated with material behavior. Optical, thermal, DIC, and acoustic sensors are deployed to detect melt pool behavior [70,71].

6. Process optimization and control

6.1. Parameter Optimization with Machine Learning

Metal AM process optimization is difficult due to the highly dimensional, non-linear nature of PSP [77]. The conventional methods of trial and error and simulation require considerable time and costs, but machine learning presents an alternative that is far more efficient [77-79].

i) Surrogate Modeling:

Metamodels represent complex simulations or experiments in a computationally efficient way by employing a model-building methodology based on empirical data. Surrogate modeling allows modeling of the PSP chain in metal additive manufacturing. Gaussian Process Regression (GPR) is the most common metamodeling method due to its predictive power and its ability to quantify uncertainties, which help optimize processes [65].

ii) Bayesian Optimization:

BO is a model-based technique that involves a sequential process aimed at optimizing expensive-to-evaluate functions. The use of a surrogate probabilistic model, primarily Gaussian process regression (GPR), alongside an acquisition function allows balancing exploration and exploitation, thereby minimizing the number of experiments required to find optimal process parameters efficiently. BO is particularly useful for optimizing complex alloys, such as AA2024, in PBF-LB/M [78]. Figure 4. Data flow of the active learning framework for single-track parameter optimization in Directed Energy Deposition (DED), incorporating a human-in-the-loop element to enhance decision-making and process accuracy.

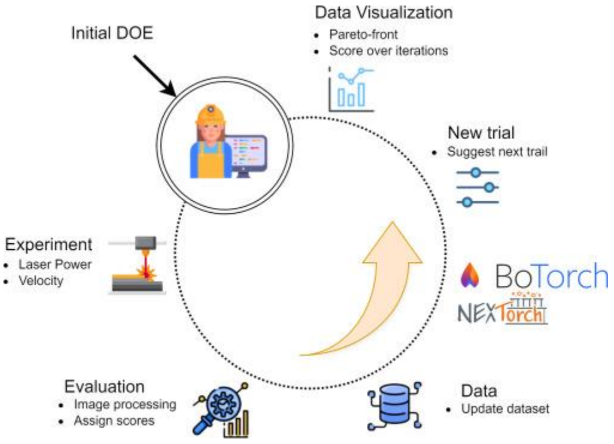

Fig. 4. Human-in-the-loop multi-objective Bayesian optimization framework for directed energy deposition with in-situ monitoring (CC BY 4.0 license) [84].

iii) Multi-objective Optimization (MOO):

Metal AM is associated with multiple objectives, such as maximizing strength and density and minimizing porosity and surface roughness [79]. In this regard, MOO can be implemented by determining Pareto-optimal solutions, in which any improvement in one objective does not result in a deterioration in the others. ML algorithms have gained popularity for solving MOO problems effectively [78,79].

iv) Constrained Optimization:

The application of optimization in metal AM requires considering constraints such as minimum density, low residual stress, and geometrical accuracy [78]. Constrained optimization techniques can facilitate such processes through penalty methods in Bayesian optimization.

6.2. Closed-Loop Control Systems in Metal Additive Manufacturing

Closed-loop control systems are crucial for metal additive manufacturing, enabling real-time parameter adjustment to improve quality and minimize defects, a capability not possible with fixed open-loop systems [82].

i) Feedback Control System Architectures

The feedback system monitors process changes and tunes parameters using PID, model predictive control (MPC), and adaptive control methods to ensure uniformity and desired microstructures [82].

ii) Melt Pool Control

Melt-pool control is fundamental to mechanical properties in LPBF and DED processes. In-situ monitoring with imaging and pyrometry stabilizes any disturbances, while machine learning models such as MeltpoolNet predict defects using in-situ measurements [83].

iii) Geometric Accuracy Control

In-situ metrology monitors layer-by-layer deviation to guarantee accuracy. Although in-situ correction is challenging, predictive modeling allows pre-processing distortion compensation [81].

iv) Temperature Control and Thermal Management

Temperature control regulates microstructure and defect formation. Thermocouples and thermal imaging sensors adjust process parameters, while surrogate and machine learning models enhance temperature prediction and control [80,82].

v) Tool Path and Scan Strategy Optimization

Tool path and scan strategies influence melt pool dynamics and residual stresses. Machine learning models (such as MeltpoolNet) aid defect prediction and real-time optimization, while interpretable machine learning improves PSP understanding and widens the range of LPBF processing [81–83].

7. AI for material development and qualification

AI in metal additive manufacturing is key to speeding up materials development and qualification/certification by effectively managing the interrelationships among processes, structures, and properties. This technology-based methodology reduces reliance on trial-and-error experiments and simulation models, resulting in more efficient parameter optimization [77].

7.1. Accelerated Alloy Development

Machine learning (ML) enables accelerated alloy discovery in metal AM by reducing the time and cost required for exploration of the parameter space. GPR models predict materials' structure and properties from process parameters, incorporating uncertainty to enable accurate PSP mapping. PIML improves predictions in situations where data are limited, while interpretable ML helps understand the links between process, structure, and properties in the LPBF process. BO enables rapid discovery of optimal process conditions with fewer iterations, which can help create difficult-to-manufacture alloys such as AA2024 [78,80].

7.2. Qualification and Certification

Qualification and certification of metal AM processes present several challenges owing to their variable nature. AI-based closed-loop control systems enable in-process monitoring and feedback, improving the reliability and quality of processes [80].

i) Process Feedback Control Systems

Through sensor-controller-actuator networks, the process feedback control system ensures that the process remains stable without defects and develops the appropriate microstructure [82].

ii) Melt Pool Control

Using real-time imaging and pyrometry, melt pool morphology is controlled with machine learning (ML) models to ensure consistent microstructure [83].

iii) Dimensional Control

Using in-process metrology and ML models, thermal stress-induced deformations are predicted and avoided through dimensional control (e.g., for Inconel 718).

iv) Control of Thermal Aspects

Thermal gradients are managed with infrared sensors and adaptive preheating, while AI-physically-guided ML models optimize thermal behavior and reduce defects.

Also, multi-objective optimization (MOO) techniques and Bayesian methods are used to identify Pareto-optimal solutions for conflicting goals, while constrained optimization helps select feasible and safe parameters for AM processes [84].

7.3. Case Study: Aerospace-Relevant Implementation

While it is difficult to provide specific details about the GKN Aerospace case study, AI approaches are effective in meeting the qualification and certification (Q&C) criteria of the aerospace industry. In-situ adaptive control based on machine learning can help detect and mitigate defects, which are necessary for components requiring higher reliability [82]. Control of the melt pool and thermal parameters ensures that standards for microstructure and mechanical properties are maintained. Furthermore, Bayesian optimization can help identify alloy parameters quickly for alloys such as AA2024, enabling a faster alloy qualification process [78,83].

8. Current challenges and limitations

Integration of AI into metal additive manufacturing is not without its challenges; problems include poor data quality, inability to generalize from models trained on available data, inadequate data transferability, non-interpretable algorithms, lack of trust in AI-generated results, and heavy computational demands.

8.1. Data Scarcity and Quality

Data availability and quality continue to pose significant hurdles when implementing AI technologies within metal AM processes. Collecting large volumes of data on essential variables, such as laser energy, scanning rate, layer thickness, and alloying elements, is both resource-intensive and time-consuming [77]. Furthermore, inconsistencies in sensor calibration, experimental conditions, and measurement procedures contribute to inaccuracies in the collected data and degrade the predictive capabilities of the models [83].

8.2. Model Generalization and Transferability

Generalizing models across various materials, equipment, and operating conditions is another significant challenge in metal AM [85]. Trained models on one system often yield inaccurate results on other systems due to variations in machine construction, materials, and environments, as well as the interrelationships among process–structure–property (PSP). The physics-guided ML model and Gaussian process model approaches help increase accuracy even when data are limited. At the same time, Bayesian optimization can be used to determine optimal parameters for specific conditions [40]. Still, there are challenges in developing universal generalizable models.

8.3. Interpretability and Trust

Interpreting and understanding are essential for utilizing AI technologies in the aerospace industry and biomedical engineering, where safety is the top priority. The majority of advanced machine learning algorithms can be characterized as black-box systems, which makes it difficult to conduct certification that requires a clear explanation of the mechanisms governing material performance and defect generation [86]. Currently, research aims to develop interpretable models that explain how material properties depend on parameters and process variables. Yet, constructing an interpretive model of the complex AM process remains problematic [82].

8.4. Computational and Infrastructure Requirements

The implementation of advanced artificial intelligence in metal AM systems is resource-intensive, requiring high-performance computing (HPC) and cloud computing environments to conduct deep learning. The ability of real-time adaptive control also relies on fast data acquisition and processing, made possible by advanced sensor and edge computing technologies [82]. The requirements become more severe when multi-objective optimization with constraints is involved, as it must explore the entire parameter space under multiple objectives. Therefore, it can impose a considerable cost on the development of the AI system [77].

9. Future research directions

The future research in metal additive manufacturing (AM) is increasingly structured around five interconnected domains: (1) autonomous AM systems, (2) physics-informed machine learning (PIML), (3) generative design and advanced process planning, (4) standardization and benchmarking, and (5) trustworthy artificial intelligence (AI) for certification [6, 87, 88].

9.1. Autonomous AM Systems

The use of artificial intelligence (AI) in additive manufacturing systems facilitates closed-loop, autonomous optimization of the process through the integration of in-process sensors (for instance, thermal cameras, photodiodes, acoustic emissions), along with edge-enabled AI, to manage critical variables like laser power, scan speed, and hatch distance [82]. Since additive manufacturing processes are stochastic and multi-physics, traditional rule-based optimization methods are inadequate, necessitating the implementation of sophisticated methodologies such as deep reinforcement learning to optimize toolpaths and thermal profiles in LPBF [89].

9.2. Physics-Informed Machine Learning (PIML)

The integration of physics into machine learning (also known as physics-informed ML) addresses important shortcomings of classical ML approaches by integrating laws of physics, such as those governing heat transfer, fluid dynamics, and solidification, into the models. This increases the model's generalization power, data efficiency, and interpretability, particularly important when working with limited data sets, such as in metal AM.

9.3. Generative Design and Advanced Process Planning

The combination of generative design and process planning improves additive manufacturing of metal parts by integrating topology optimization with process constraints to optimize geometry, build direction, and processing parameters [88]. The approach uses the advantages of additive manufacturing technology to create optimal designs with complex structures.

9.4. Standardization and Benchmarking

However, there are still considerable hurdles associated with standardization and benchmarking in the way of large-scale implementation of AM technologies [87,88]. Future research is needed to establish traceable metrology procedures, standardized defect assessment, and data sets with injected defects for testing the effectiveness of AI-based inspection systems [87].

9.5. Trustworthy AI for Certification

Trustworthy AI must be used to certify safety-critical components, requiring formal verification, transparent decision-making processes, and quantification of both epistemic and aleatoric uncertainties [87]. The use of digital twins, which combines sensor data with physics-based models and data, provides support throughout the entire lifecycle, including quality assurance and enhanced traceability and compliance [6,90].

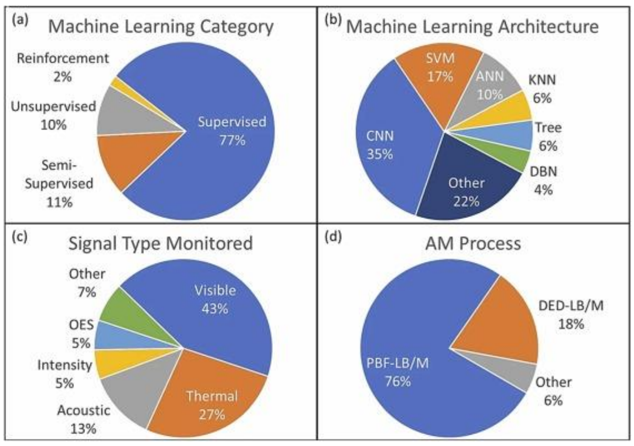

Fig. 5. Pie charts categorizing 50 studies on ML-based in-situ monitoring. Abbreviations: ANN, CNN, DBN, DED, KNN, LB/M, OES, PBF, SVM. [69]

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The image above depicts the concept of dynamic beam-shape sensing and control for an open-architecture metal AM system, which is fundamental for autonomous AM [82]. Such systems provide direct control over process conditions, which is useful for conducting fundamental research on AM and for developing advanced strategies to mitigate defects. The depiction of how the dynamic beam might be manipulated is illustrated in Figure 5.

10. Conclusion

This review emphasizes the significant opportunities AI and ML offer to improve the efficiency, reliability, and scalability of metal AM processes. Progress in deep learning, Bayesian optimization, and physics-based modeling has improved understanding of process-structure-property relationships. Nonetheless, several obstacles remain, including a lack of high-quality data, insufficient model generalization, and the absence of benchmarking standards. In safety-sensitive applications, AI and ML must be transparent, dependable, and account for uncertainty. Future developments will focus on autonomous manufacturing, physics-inspired learning, generative design, digital twins, and cooperation among academia, industry, and government institutions.

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