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SURVEY

Artificial Intelligence for Control in Laser-Based Additive Manufacturing: A Systematic Review

JOÃO SOUSA[1,2,3,4,5], BENEDIKT BRANDAU[6,7], ROYA DARABI[1,5], ARMANDO SOUSA[1,8], FRANK BRUECKNER[3,6], ANA REIS[1,5], AND LUÍS PAULO REIS[1,2], (Senior Member, IEEE)

[1]Faculty of Engineering, University of Porto (FEUP), 4200-465 Porto, Portugal
[2]Artificial Intelligence and Computer Science Laboratory (LIACC), Faculty of Engineering, University of Porto (FEUP), 4200-465 Porto, Portugal
[3]Additive Manufacturing and Surface Technology Center, Fraunhofer IWS, 01277 Dresden, Germany
[4]Unity of Advanced Manufacturing, Institute of Science and Innovation in Mechanical and Industrial Engineering (INEGI), 4200-465 Porto, Portugal
[5]Associate Laboratory for Energy, Transports and Aerospace (LAETA), Faculty of Engineering, University of Porto (FEUP), 4200-465 Porto, Portugal
[6]Department of Engineering Sciences and Mathematics, Luleå University of Technology, 971 87 Luleå, Sweden
[7]Research and Development Laser Processing Center, JENOPTIK Automatisierungstechnik GmbH, 07745 Jena, Germany
[8]Center for Robotics in Industry and Intelligent Systems (CRIIS), INESC Technology and Science (INESC TEC), 4200-465 Porto, Portugal

Corresponding author: João Sousa (jpsousa@inegi.up.pt)

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ABSTRACT Laser-based additive manufacturing (LAM) offers the ability to produce near-net-shape metal parts with unparalleled energy efficiency and flexibility in both geometry and material selection. Despite advantages, these processes are inherently, as they are characterized by multiphysics interactions, multiscale phenomena, and highly dynamic behaviors, making their modeling and optimization particularly challenging. Artificial intelligence (AI) has emerged as a promising tool for enhancing the monitoring and control of additive manufacturing. This paper presents a systematic review of AI applications for real-time control of laser-based manufacturing processes, analyzing 16 relevant articles sourced from Scopus, IEEE Xplore, and Web of Science databases. The primary objective of this work is to contribute to the advancement of autonomous manufacturing systems capable of self-monitoring and self-correction, ensuring optimal part quality, enhanced efficiency, and reduced human intervention. Our findings indicate that 62.5 % of the 16 analyzed studies have deployed AI-driven controllers in real-world scenarios, with over 56 % using AI for control strategies, such as Reinforcement Learning. Furthermore, 62.5 % of the studies employed AI for process modeling or monitoring, which was integral to the development or data pipelines of the controllers. By defining a groundwork for future developments, this review not only highlights current advancements but also hints future innovations that will likely include AI-based controllers.

INDEX TERMS Additive manufacturing, artificial intelligence, close-loop control, machine learning, reinforcement learning.

I. INTRODUCTION

LAM, a subset of Additive Manufacturing (AM), is reshaping production systems by enabling the production of metal parts layer by layer, offering flexibility in both part geometry and material [1]. These processes are transforming production systems, offering significant economic potential despite their nascent stage compared with traditional manufacturing methods [2]. Key challenges, such as material limitations and the need for optimized process control, remain critical areas of development due to the evolving process environment, where temperature accumulation and changes in the cooling rate affect process stability as well as the metallurgical and mechanical properties of the produced parts [3], [4], [5]. Despite these challenges, LAM offers unprecedented advantages due to its layer-by-layer material

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addition methodology. These include exceptional design flexibility [6], [7], improved mechanical properties [8], enhanced energy efficiency [9], and the ability to produce complex 3D parts in a single cycle using various materials, which reduces manufacturing time and waste [10], [11], [12]. LAM also enables the creation and repair of complex, lightweight, and multifunctional components [13], [14], [15], as well as parts with functionally graded materials, supporting the production of intricate geometries and small lot sizes. This aligns with the future of manufacturing, Industry 5.0, and sustainability goals [16], [17].

According to the Standard Terminology for Additive Manufacturing Technologies (ASTM F2792-12) [18], LAM encompasses into two main processes: (i) Powder Bed Fusion (PBF), also known as Selective Laser Melting (SLM); and (ii) Directed Energy Deposition (DED), also known as Laser Metal Deposition (LMD) or Laser Cladding. They are different processes, with the main difference being how the material is added. In PBF, a thin layer of metal powder is spread, and the laser(s) fuse the powder, creating a melt pool (MP) where the material solidifies to form the desired part layer by layer [19]. In contrast, in DED, the powder is continuously fed through a nozzle system while the laser simultaneously melts it, creating the MP, which solidifies to form the part. An alternative version uses a wire (W-DED) instead of powder [20], [21] - Figure 1.

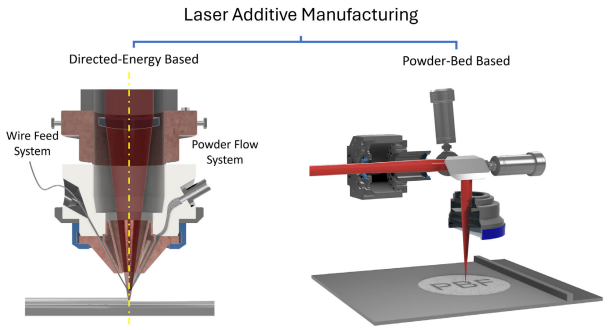


FIGURE 1. Diagram illustrating the processes of directed energy deposition (DED) and powder bed fusion (PBF). It highlights the main difference in how the material is added during the manufacturing process.

PBF and DED (Figure 1) differ significantly in process dynamics. Current PBF sytems operates at lower laser power and high scanning speeds - typically under 1 kW and 2000 mm s^{-1}, and is suited for high-precision, small-scale parts, while DED can use laser power up to 40 kW, enabling larger-scale structures and higher deposition rates. These differences affect MP characteristics, thermal gradients, and solidification rates, leading to distinct microstructural features and defect profiles [22]. These differences require specialized in-situ monitoring strategies: PBF requires high-frequency monitoring due to rapid solidification [23], while DED is characterized by noisier and high temperature environments [24]. Ultimately, monitoring solutions must be tailored to the specific characteristics of each process.

Artificial Intelligence (AI) is a data-driven approach increasingly used to handle complex problems as computing power increases and new techniques appear [25]. From weather and climate forecasts [26], turbulence models [27], heat transfer problems [28], and others, the use of AI is helping researchers to better understand and interact with our world. In recent years, machine learning technologies, and in particular deep learning, have led to impressive advances in processing diverse types of data such as images [29], language [30] and time-series data [31]. Bringing these significant advancements to real-world applications is a formidable challenge, especially within dynamic systems where time sensitivity is crucial. Nonetheless, fields such as autonomous vehicles [32], [33], robotics [34], [35], game playing [36], [37], and nuclear fusion [38] are poised to gain substantial advantages from advancements in technologies such as AI.

The use of AI to control dynamical systems offers several advantages: (i) AI algorithms can adapt to complex and nonlinear system dynamics, making them suitable for a wide range of applications [39]; (ii) AI-based controllers can learn from experience, continuously improving their performance over time [40], [41]; and (iii) AI control systems can manage unknown or unmodeled dynamics and uncertainties, common challenges in traditional control approaches [42].

Given that LAM is a relatively recent and digitally integrated manufacturing process, many AI models and techniques may be used to address problems with choosing process parameters, optimizing processes, monitoring, controlling, designing materials, and designing parts [25], [43], [44]. Consequently, the scientific community is conducting a significant amount of research on AI applications to address AM difficulties. Additionally, due to the flexibility and strength of AI methods in automatically and efficiently extracting information from data, these can be applied to implement innovative and scalable monitoring or control strategies to prevent defects and optimize the technology process [45]. By gathering information from in-situ sensors, it is expected that AI systems can improve monitoring systems and control the process, enabling the production of high-quality, complex parts with greater precision and reliability [43], [46].

In our research, we observed a notable surge in the application of AI for monitoring and control in LAM. This trend is evidenced by the exponential growth in the number of published papers, as illustrated in Figure 2. Monitoring applications currently represent the most prevalent use of AI in LAM. However, this review highlights the potential of AI models not just for observing and analyzing processes but also for actively intervening and optimizing control mechanisms. The emphasis on monitoring applications underscores the critical role of real-time data acquisition and analysis at the melt pool scale. While monitoring remains essential, leveraging AI for control can potentially offer a transformative opportunity to close the loop in process automation.

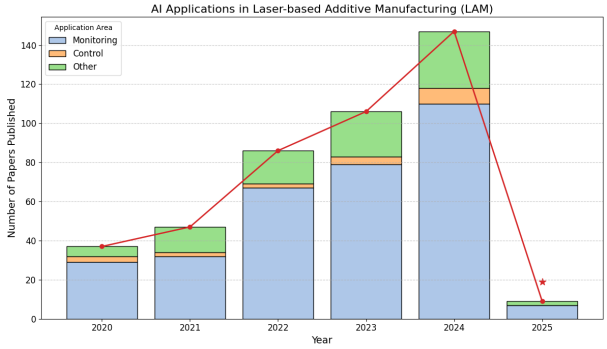


FIGURE 2. A diagram illustrating the growth in the number of papers and the primary applications of AI in LAM over recent years, as identified in this review based on the Scopus, IEEE Xplore, and Web of Science databases.

Manufacturing processes and robotics share challenges in modeling and control due to their highly dynamic nature and the limited availability of datasets [47], [48]. Despite manufacturing processes being extremely demanding, LAM involves a time-dependent and harsh environment due to high power laser, making monitoring difficult [49], [50]. AI is already being used to monitor these processes based on in-situ data for various objectives, primarily for quality assessment or defect prediction [51], [52]. As shown in Figure 2, monitoring solutions are already widely reported compared to process control. The subsequent step beyond monitoring is to control the LAM process, which could lead to significant benefits such as producing defect-free parts, achieving more consistent mechanical properties, and manufacturing parts closer to the desired final shape [53], [54]. Progress in this direction would move us toward a fully autonomous process, but despite these potential advantages, this area remains under active research with relatively few studies published so far.

This work provides a systematic review of the use of AI for real-time control of process parameters, focusing the practical application of AI models to influence real-world processes. In Section II, we provide an overview of the main steps to develop an AI-based controller. Section III covers the methods employed, while Section IV presents the results. In Section V, we discuss the findings, highlight unresolved challenges, and suggest directions for future research. Finally, Section VI provides the conclusion.

II. DEVELOPING AN AI-BASED CONTROLLER

In this section, we outline the key steps and methods for developing an AI-based controller. This overview provides the necessary context for the detailed discussions in the following sections.

As a dynamic system operating in discrete time, LAM can be described with control actions as follows:

$$\mathbf{x}[k+1] = f(\mathbf{x}[k], u[k], w_d[k]) \tag{1}$$

where $\mathbf{x}[k]$ represents the state of the system at discrete time step k, $u[k]$ is the control action, and f is a vector field that may depend on the current state $\mathbf{x}[k]$, the control action $u[k]$, and $w_d[k]$, which represents external disturbances [55].

The sensor signals $\mathbf{y}[k]$ can be described as:

$$\mathbf{y}[k] = g(\mathbf{x}[k], u[k], w_n[k]) \tag{2}$$

where $w_n[k]$ represents measurement noise and uncertainty.

In general, a closed-loop controller can be understood as an optimization procedure that seeks to minimize a cost function J, which represents the desired performance of the system:

$$u[k]^* = \arg\min_{u[k]} J(\mathbf{x}[k], u[k], d_s[k]) \tag{3}$$

where $u[k]^*$ is the optimal control action that minimizes J, given the actual or predicted state $\mathbf{x}[k]$, the control action $u[k]$, and the desired setpoint $d_s[k]$. Figure 3 shows a representative diagram of a standard control framework.

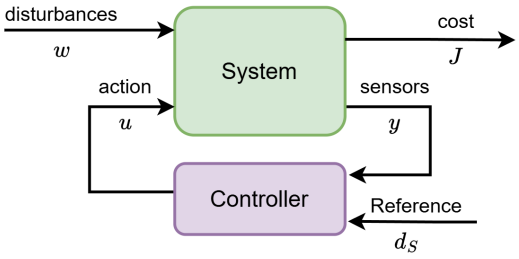


FIGURE 3. In feedback control systems, measurements y are sent to a controller, which then generates the actuation signal u to control the system. The goal of the control law is to adjust the system dynamics to ensure optimal performance, as indicated by the cost function J, while compensating for external disturbances and noise w. Additionally, the external input w may include a desired setpoint d_s that the system aims to achive [55].

With this understanding of the controller as an optimization problem, we can now outline the specific steps involved in developing a controller where AI can play a crucial role - Figure 4. The following steps detail the development process of a controller where AI can contribute:

1) **Intelligent Sampling** the process dynamics: Collect data to capture the dynamic behavior of the process over time.
2) **Monitoring**: Processing or modeling the raw data by cleaning, preprocessing, and/or creating a model based on the collected data to prepare it for control decisions.
3) **Modeling** the process dynamics: Develop a mathematical or computational model that represents the process dynamics based on the processed data.
4) **Planning** and training the control model: Design and train an AI-based control model that can utilize model predictions to manage and optimize the process effectively.
5) **Evaluate** uncertainty, robustness, and explainability: Assess the control model for its performance under uncertainty, its robustness in various conditions, and its ability to provide understandable and transparent results.

Depending on the extent of AI integration at various stages, different flavors of AI-based control systems can be implemented in LAM. When a simulation environment is available to model the process dynamics, sim-to-real approaches are likely to be useful.

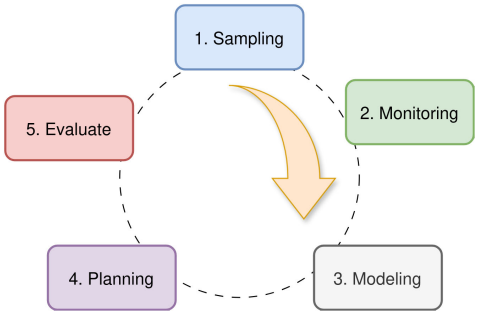


FIGURE 4. Schematic representation of the controller development process, highlighting the key steps: Sampling, Monitoring, Modeling (dynamics), Planning (optimal control action), and Evaluation. The diagram illustrates that while each step is important, they are not mandatory and can be iteratively adjusted. AI techniques can be integrated at any stage, either individually or in combination, to enhance the system performance.

A. INTELLIGENT SAMPLING

LAM is a complex dynamic system involving non-linear mass and heat transfer coupled with material solidification [56], [57]. Due to high evaluation costs, efficient sampling is critical to maximizing information from minimal trials [58]. Sampling methods in Design of Experiments (DoE) can be categorized as either classical or adaptive. Classical DoE methods, such as factorial designs, set the sampling pattern in advance and do not adapt during the experiment. In contrast, adaptive DoE methods, including Bayesian Optimization (BO), adjust sampling based on exploration and exploitation criteria, focusing on areas where rapid changes or non-linear behavior are observed [59], [60].

BO, a model-based global optimization method, guides experiments toward global optima by considering the optimum of the modeled objective [61]. It is particularly effective for complex, non-linear, and costly systems. BO has shown success in various fields, including hyperparameter tuning in computer science [62], robotics [63], recommendation systems [64], and manufacturing. For instance, in additive manufacturing systems, BO has optimized material geometry in extrusion machines with fewer experiments compared to factorial designs [65]. Additionally, a Multi-objective Bayesian Optimization approach improved mechanical properties like hardness and part density in the PBF process by adjusting parameters such as laser power and scanning speed [66].

B. AI-BASED PROCESS MONITORING

Before monitoring the process, it is essential to first integrate sensors into the system. Sensing the LAM process involves several key factors:

1) **Mounting Position**: Sensors can be positioned either on-axis, where they are aligned with the optical path of the laser, or off-axis, where they are mounted externally [67].
2) **Measurement Targets**: The primary targets for measurement include thermal signals, visual signals, acoustic signals, and spectral signals [67].
3) **Measurement Timing**: Real-time sensing focuses on the MP, which is crucial for monitoring. Key attributes include geometric and temperature features of the MP, which correlate with process stability (or quality), mechanical properties and potential defects [52], [68]. When direct monitoring of the MP is challenging due to sensor placement constraints or high-speed data processing demands, some researchers employ layer-wise evaluation methods [69], [70] - meaning that the process is evaluated only between layers.

Given the importance of the MP for process monitoring, thermal and visual signals are commonly used, making image-based data a popular choice. Consequently, AI models such as Convolutional Neural Networks (CNNs) are frequently employed to process these data [71], [72], [73], [74]. For processed data, Artificial Neural Networks (ANNs) are often employed. For instance, Chen et al. [73] explored various approaches for defect prediction using multiple sensors, including on-axis visual cameras, off-axis thermal cameras, and audio signals. Among these, the ANN model achieved the highest accuracy [73].

The main challenge in applying AI for monitoring of LAM is effectively labeling the data. Various approaches have been proposed, focusing on the final geometry of printed tracks, mechanical properties, or metallurgical analysis. These evaluations can be expensive, so for control purposes, targets are often based on AI monitoring models or simplified melt pool signatures, such as temperature and dimensions [52], [67], [68].

C. MODELING SYSTEM DYNAMICS

Modeling system dynamics involves creating mathematical or computational representations to understand and predict the behavior of complex systems over time. This is essential in fields such as engineering, economics, and biology, where surrogate models are required for effective analysis and control. Most industrial applications rely on empirical models, including linear system dentification [75], ANN [76], and autoregressive models (e.g., ARX, ARMA, NARX, and NARMAX) [77], [78]. These surrogate models simplify the system dynamics for practical use but may not fully capture complex behaviors. As a supervised learning problem, ANN are widely used for capturing intricate nonlinear relationships in dynamic systems [76], [79]. Variants such as Recurrent Neural Networks (RNNs) [80] and Long Short-Term Memory networks (LSTMs) [81] are particularly effective for handling time-series data and modeling temporal dependencies.

Relevant data-driven methods to model system dynamics include Dynamic Mode Decomposition (DMD) and Sparse Identification of Nonlinear Dynamics (SINDy), which are advanced techniques for modeling complex dynamic systems [55]. DMD is a data-driven method that decomposes time series data into modes representing the system's dominant dynamic patterns, making it useful for revealing underlying structures [82]. SINDy complements this by identifying sparse, interpretable models that describe nonlinear dynamics using a small set of governing equations [83].

D. CONTROL SYSTEM

AI, and more specifically machine learning, is rapidly advancing, enabling us to model complex systems directly from observational data rather than relying on first-principles modeling. [84], [85]. This approach is increasingly being applied to control systems, where machine learning techniques such as adaptive neural networks [86], genetic algorithms [87], and reinforcement learning [88], are used to map sensor data to actions. These methods are particularly well-suited for managing high-dimensional, nonlinear systems that are difficult to model using conventional analytical approaches. Although challenging due to the complexity and scale of the problems, current efforts are focused on using machine learning to enhance the ability to analyze and control these dynamic systems, potentially transforming their performance and enabling more efficient and adaptive systems [55].

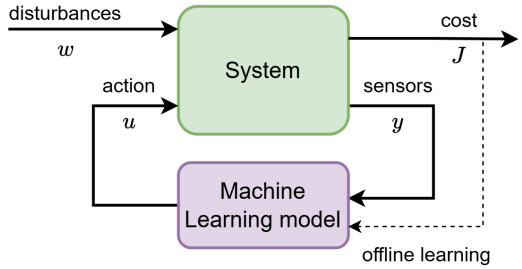


FIGURE 5. In the depicted setup, a machine learning model is employed to control the process through offline training. The model is trained on historical data to generate the actuation signal $u(t)$ based on measurements $y(t)$. The objective is to optimize system performance based on a predefined cost function J, while adapting to external disturbances and noise w. Additionally, the system aims to track a reference trajectory d_s, which is included in the external input w [55].

The Proportional-Integral-Derivative (PID) controller is one of the most widely used and extensively studied control strategies in both industry and academia [89]. Despite its popularity, tuning a PID controller can be challenging in practice. Over the past few decades, researchers have sought to automate this tuning process by employing various AI techniques, including heuristics and metaheuristics such as Simulated Annealing (SA), Particle Swarm Optimization (PSO), and Genetic Algorithms (GA), among others [90]. Additionally, other approaches like Fuzzy PID [91], Adaptive PID [92], and the use of Artificial Neural Networks (ANN) to adjust PID parameters [93] have been explored in hope of optimizing certain performance indices.

The standard formulation of a PID controller is given by:

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau)\, d\tau + K_d \frac{de(t)}{dt} \tag{4}$$

where $u(t)$ is the control signal, $e(t)$ is the error signal (defined as the difference between the setpoint and the process variable), K_p is the proportional gain, K_i is the integral gain, and K_d is the derivative gain. The proportional term provides an output proportional to the current error, the integral term accounts for the accumulation of past errors, and the derivative term predicts future errors based on the current rate of change. By adjusting the values of K_p, K_i, and K_d, the controller can be tuned to achieve desired performance characteristics, such as minimal overshoot, reduced settling time, and reduced steady-state error [94].

Model Predictive Control (MPC) [95] uses a surrogate model of the system dynamics to run an optimization directly inside the control loop. MPC is particularly effective for managing highly nonlinear systems that involve constraints, time delays, non-minimum-phase behaviors, and potential instabilities [96], [97]. In most industrial settings, the implementation of MPC typically involves utilizing a model that was discussed previously in the section on *Modeling System Dynamics*.

End-to-end AI approaches, in which a single AI model is employed to map input data directly to control actions, such as those used in autonomous vehicles [98], [99], liquid neural networks [100], and Reinforcement Learning (RL) [101], [102] can bypass the need for explicit surrogate models by directly integrating perception, decision-making, and control within a single, unified framework. These systems leverage deep learning architectures to process complex sensor inputs, make real-time decisions, and generate control commands, allowing them to adapt to highly dynamic environments. However, while end-to-end AI offers significant flexibility and adaptability, it can also be challenging to track and interpret the decision-making process, making it difficult to diagnose issues or ensure transparency in critical applications [103].

Reinforcement Learning (RL) is a type of machine learning where an agent learns to make decisions by interacting with an environment to maximize cumulative rewards - Figure 6. RL methods generally fall into three main categories: (i) **Value-Based Methods** [104] focus on learning a value function $Q(s, a)$ that estimates the expected cumulative reward for taking an action a in a state s and following the optimal policy afterward. Actions are selected based on maximizing this value function, as seen in algorithms like Q-learning [105]; (ii) **Policy-Based Methods** [106] directly optimize the policy $\pi(a|s)$, which maps states to actions to maximize expected cumulative rewards. This approach is particularly useful in environments with continuous action spaces or where the optimal policy is not deterministic; and (iii) **Actor-Critic Methods** [107] combine both approaches:

the "actor" updates the policy $\pi(a|s)$ based on feedback from the "critic", which estimates the value function $V(s)$ or the advantage function $A(s, a)$. This hybrid approach leverages the strengths of both value-based and policy-based methods, leading to more stable and efficient learning.

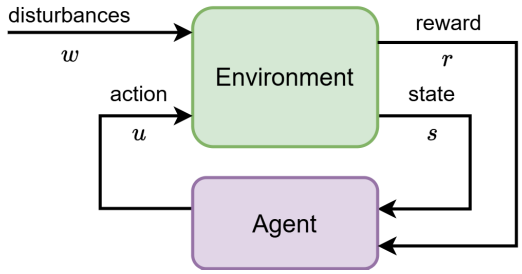


FIGURE 6. In the reinforcement learning framework depicted, the process is controlled by an RL agent that interacts with the environment. The agent receives observations from the state s and takes actions a to influence the system. The goal is to maximize the cumulative reward R, which guides the agent to optimize its policy. The reward function provides feedback on the quality of the actions taken, helping the agent adjust its strategy to improve overall system performance.

Although RL can automate decision-making, it often requires extensive data and many iterations to achieve good performance, making it sample-inefficient and computationally expensive [108]. To mitigate this, RL is frequently trained in simulated environments, where the model dynamics are known, before being transferred to the real world. Recently, model-based reinforcement learning has led to impressive results by being more data efficient [109], [110]. However, deep learning relies on substantial data resources to generalize effectively, and its lack of interpretability presents significant challenges.

Other approaches include Imitation Learning (IL) [111] and Inverse Optimal Control (IOC) [112], [113]. IL trains models to directly mimic expert behavior from demonstrations, while IOC infers the underlying cost function that the expert is optimizing. Both methods are related to reinforcement learning but focus on replicating expert behavior without the need for trial-and-error exploration by also training offline (offline RL) [114].

E. EVALUATION

In developing AI-driven control systems, ensuring the desired performance requires addressing three key aspects: explainability, uncertainty, and robustness [115], [116], [117]. Explainability involves understanding the decision-making process of the AI model, often quantified through metrics such as feature importance and sensitivity analysis [103]. Uncertainty, represented by the variance, σ^2, in the model's predictions or by probabilistic estimates $P(y \mid x)$, must be managed to ensure reliable system behavior under varying conditions [118]. Model uncertainty is primarily induced by the model architecture, the training process, and insufficient representation of certain regions in the training data [118]. Robustness is assessed by evaluating the stability of the system $\|\Delta x(t)\| \leq \epsilon$, where $\Delta x(t)$ denotes deviations from the expected state and ϵ is a tolerance threshold. Together, these aspects ensure that the AI system performs consistently, adapts to unforeseen disturbances, and provides transparent results [119].

Explainability is addressed through methods such as SHapley values [120] and LIME [121], which provide insights into how input features influence model predictions. Uncertainty is managed using probabilistic models such as Bayesian networks and Gaussian processes [122], along with techniques like Monte Carlo Dropout and ensemble methods to estimate prediction confidence [123]. Robustness is strengthened through robust optimization methods, adversarial training, and regularization techniques, ensuring the system maintains performance and stability despite variations and disturbances [124], [125].

III. METHODS

In this section, we describe the methodology implemented for conducting the systematic review and analysis. The approach ensures reproducibility and reliability, covering the study design, search strategies, inclusion criteria, and data extraction process.

A. STUDY DESIGN

This systematic review and analysis were conducted in accordance with the PRISMA 2020 guidelines [126] for the development and reporting of systematic reviews.

B. SEARCH STRATEGIES

A systematic literature search was conducted to identify studies that applied AI-based methods to in-situ data. The Scopus, IEEE Xplore and Web of Science meta-databases were used as sources of high-quality samples as of December 27, 2024, as shown in Table 1.

C. ELIGIBILITY CRITERIA AND STUDY SELECTION

Original studies that applied AI in any step of the development of a controller were included and divided into two different categories: (i) data-driven, or (ii) model-driven including FEM simulation. There was no restriction on the type of models or algorithms used. Studies were excluded when one of the following conditions was fulfilled: (i) non-original publications (reviews, surveys, roadmaps, and book chapters); (ii) grey literature (conference abstracts, notes, letters to the editor); (iii) manuscripts written in languages other than English; (iv) AI focused only for monitoring or event detection; (v) AI is focused on only modeling the process; (vi) studies dealing with other technological processes or areas such as part design, path planning or robotics are considered out of scope; and (vi) if AI is not applied.

After removing duplicates every study was individually assessed using the inclusion and exclusion criteria to determine eligibility for inclusion in the systematic review.

TABLE 1. Research query applied in two databases: Scopus and IEEE Xplorer.

Context	Link	Key Terms
Objective		"control" OR "adaptive control" OR "feedback control" OR "close loop" OR "close-loop" OR "optimization" OR "optimisation"
Means	AND	"artificial intelligence" OR "machine learning" OR "deep learning" OR "reinforcement learning" OR "neural networks" OR "Large Language Model" OR "Transformer" OR "Convolutional Neural Network"
Constrain	AND	"real-time" OR "online" OR "in-situ"
Application	AND	("laser metal deposition" OR "3D metal printing" OR "additive manufacturing" OR "metal additive manufacturing" OR "direct energy deposition" OR "directed energy deposition" OR "laser cladding" OR "laser additive manufacturing" OR "laser metal fusion" OR "laser powder bed fusion" OR "laser-based additive manufacturing" OR "laser direct metal deposition" OR "DED" OR "P-DED" OR "W-DED" OR "LMD" OR"SLM" OR "PBF" OR "PBF" OR "LAM" OR "WLAM"
Exclusion	AND NOT	polymer

Publications were initially screened based on titles and abstracts, followed by a full-text examination. Then, data extraction was performed to evaluate the clarity and quality of the described methods and findings.

D. DATA EXTRACTION, MANAGEMENT, AND SYNTHESIS

The extracted data from the included studies were compiled in a Microsoft Excel spreadsheet, including the following information: (i) author, (ii) year of publication, (iii) data (input data, and output data), and (iv) model or algorithm used, (v) main objective, (vi) methods and (vii) study findings.

IV. RESULTS

A. SEARCH RESULTS

Following the PRISMA guidelines and procedures outlined in Section III, a total of **681** studies were found. After the automatic removal of **126** duplicates, **555** publications were screened based on titles and abstracts and **17** were chosen for further evaluation based on the described eligibility criteria and study selection, resulting in **16** selected for this review. The summary of the screening process is described in Figure 7.

B. OVERVIEW OF STUDIES

The Table 2 offers a comprehensive summary of the studies included in the review, with the oldest published in 2021. It outlines the different methodologies, objectives, effectiveness, and limitations across various LAM processes.

These studies aim to address key challenges, reducing defects such as porosity [128] and surface roughness [142],

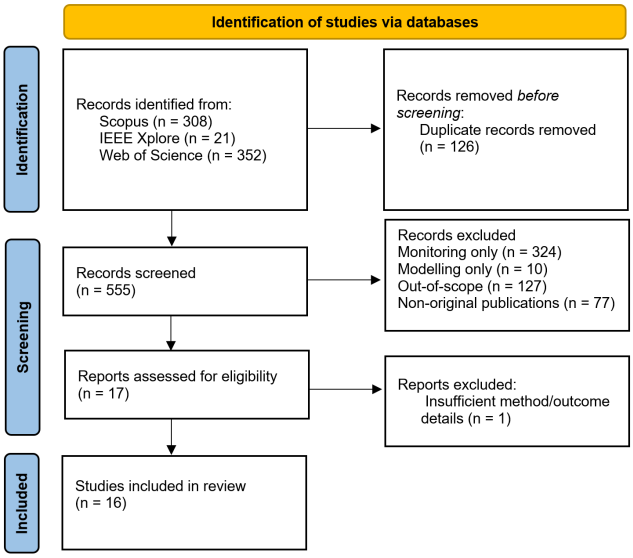


FIGURE 7. PRISMA flow diagram with the different stages of the study selection process [126].

optimizing process stability [127], [129], [133], [134], [137], [141], and enhancing material properties [131]. More than 68 % of the 16 studies focus on overcoming instability issues caused by underheating or overheating (thermal accumulation). All studies reported significant positive findings when evaluated in simulated and real-world settings. The majority of studies (62.5 %) include an experimental evaluation.

C. AI ROLE IN CONTROL

The Table 3 categorizes LAM studies based on sampling methods, monitoring techniques, modeling approaches, control models and algorithms, planning methodologies, and real-time performance. It highlights trends such as the shift from model-free to model-based approaches and differences in real-time evaluations, such as control frequency or layer-wise strategies, thereby aiding in the assessment of LAM strategies and technologies.

Based on Section II and Table 3, the results reveal several key findings: (i) Despite the high cost of evaluating LAM, classical DoE sampling approaches remain the most widely used, demonstrating their continued relevance in the field; (ii) For process monitoring, traditional data processing methods are more commonly employed than AI/ML techniques, indicating a preference for established approaches over newer, potentially more complex methods; (iii) Both FEM and machine learning approaches are frequently used to model processes, which plays a crucial role in planning and optimizing control actions, as well as in controller development; (iv) Although classical PID controllers with manual or traditional tuning methods are still prevalent, more advanced approaches like MPC and RL are also being utilized. Notably, [134] found that MPC outperforms PID, particularly when the model incorporates uncertainty; (v) In line with modeling efforts, model-based planning is more commonly reported than

TABLE 2. Overview of the studies included in the review, along with the methodologies, objective, key findings, effectiveness, and limitations.

Ref.	Year	Process	Methodologies	Objective	Key Findings	Eff.	Limitations
[127]	2024	W-DED	Modelling + Experimental	Uniform width tracks	Linked process parameters to final qualities using process signatures	-	Only single-tracks; Handcrafted features
[128]	2023	DED	Experimental	Reduce porosity with MP width control	Achieved 81% porosity reduction, by using ANN to estimate MP depth	Yes	Manually tuned PID; Handcrafted features
[129]	2024	PBF	Simulation + Experimental	Homogenized MP measurements	RL control strategy that can anticipate geometric effects while responding to in-situ measurements	-	Discrete action and observation spaces
[130]	2024	PBF	Simulation	Reduce lack of fusion defect	Integration of an RNN for predictions and RL for parameter feedback	-	Requires experimental validation; Highly simplified simulation
[131]	2024	DED	Simulation + Modeling	Maximizing part precipitation hardening time	Integrated real-time monitoring, modeling, and control into a framework, with a surrogate model for temperature prediction and uncertainty	-	Requires experimental validation
[132]	2024	DED	Simulation	Mitigate abnormal molten pool depth increase during deposition	PPO with CNN agent achieved better results with temperature map input (image)	-	Requires experimental validation
[133]	2023	DED	Simulation + Experimental	Depth homogeneity in three overlapped single-tracks	Optimized FEM dilution rates and highlighted the impact of heat accumulation on multi-pass cladding	Yes	Implemented on only 3 tracks
[134]	2022	PBF	Simulation + Modeling	Minimize process disturbances compromising part quality	MPC outperformed PID in controlling process uncertainty, but underperformed without sufficient data	-	Requires experimental validation
[135]	2020	PBF	Simulation	Achieve homogeneous melt pool	Standard deviation of powder bed temperature along the scan path reduced by 48% in simulated test cases	-	Requires experimental validation; Highly simplified simulation
[136]	2023	DED	Experimental	Mitigate intra-layer instabilities	Achieved temperature tracking, improving specimen quality	Yes	Assumes correct temperature measurement
[137]	2024	PBF	Experimental	Homogeneous internal surface and stability	Mitigated defects in subsequent layers, preventing propagation, minimizing frequent laser power adjustments	Yes	Mitigation not fully resolved
[138]	2024	PBF	Experimental	Improve surface quality and reduce failure risks	Achieved 98% accuracy predicting surface quality, enabling testing of several control approaches	Yes	Discrete quality prediction (3 states)
[139]	2024	DED	Simulation + Experimental	Address nonuniform temperature distribution to improve mechanical properties	Developed simulation model to train RL algorithm and improve temperature uniformity and hardness variability	Yes	Reward function based on mean temperature
[140]	2023	PBF	Simulation	Avoid thermally induced abnormalities causing defects	Optimized printing sequence for uniform temperature distribution, identified key relationships between process parameters and thermal distribution	-	Requires experimental validation
[141]	2021	PBF	Experimental	Reduce inconsistent part quality caused by heat accumulation	Used wavelet analysis for tracking sintering trends, enabling continuous laser power adjustment	Yes	More validation needed
[142]	2021	PBF	Modelling + Experimental	Lower costs, enhance environmental impact, and improve print quality	Achieved optimal surface roughness faster than Q-Learning	Yes	Discrete observation space (5 classes)

Legend: MP = Melt pool, DED = Directed Energy Deposition, PBF = Powder Bed Fusion, ANN = Artificial Neural Network, PID = Proportional-Integral-Derivative controller, RL = Reinforcement Learning, FEM = Finite Element Method, MPC = Model Predictive Control, CNN = Convolutional Neural Network, RNN = Recurrent Neural Network.

model-free approaches. Specifically, [142] highlighted that in RL, a model-based RL (MBRL) approach achieved optimal process parameters, leading to higher rewards and lower surface roughness more quickly than the Q-Learning (model-free) reference implementation; (vi) Real-time applications are less frequently reported, with a preference for layer-wise planning approaches; (vii) Although AI methods are often regarded as black-boxes, there is a noticeable absence in the implementation and reporting of evaluation metrics such as explainability, uncertainty, and robustness. These results

TABLE 3. Summary of methodologies, real-time capabilities, and evaluation criteria included in the review, highlighting the sampling, monitoring, modeling, controller types, planning strategies, and the real-time performance (Hz) of the various approaches.

Ref	Sampling	Monitoring	Modeling	Controller	Planning	Real-time (Hz)	Evaluation
[127]	DOE	-	ANN	PID	Model-based	13	-
[128]	DOE	ANN	-	PID	Model-free	80	-
[129]	RL	-	Autoregressive model	Tabular Q-learning	Model-based	2000	-
[130]	DOE	RNN	-	PPO	Model-free	-	-
[131]	DOE + Bayesian Sampling	-	Bayesian LSTM	MPC	Model-based	-	Monte Carlo dropout; Gaussian Process
[132]	RL	CNN+ANN	-	PPO	Model-free	-	-
[133]	-	-	Simulation	CNN + FEM	Model-based	-	-
[134]	DOE	-	Gaussian Regression Model	MPC; PID	Model-based	-	-
[135]	-	-	-	ANN	Model-free	-	-
[136]	-	-	-	ILC	Model-free	60	-
[137]	DOE	U-Net	-	P-Controller	Model-free	Layer-wise	-
[138]	DOE	CNN	-	Fuzzy controller	Model-free	Layer-wise	-
[139]	RL	-	Simulation	PPO	Model-based	Layer-wise	-
[140]	-	-	Simulation	GA	Model-based	Layer-wise	-
[141]	DOE	-	ANN	PID	Model-free	Layer-wise	-
[142]	-	CNN + SVM	Random Forest	Model-based RL	Model-based	Layer-wise	-

Legend: DOE = Design of Experiment (classical); **RL** = Reinforcement Learning; **ANN** = Artificial Neural Network; **FEM** = Finite Element Model; **PID** = Proportional-Integral-Derivative controller; **MPC** = Model Predictive Control; **CNN** = Convolution Neural Network; **GA** = Genetic Algorithm; **ILC** = Iterative Learning Control;

underscore the ongoing reliance on traditional methods while highlighting the emerging adoption of more advanced techniques in specific areas.

Based on the comprehensive review of the studies included in Table 2 and Table 3, we present the findings organized into sub-sections based on key AI methodologies employed in LAM.

D. MACHINE LEARNING AND DEEP LEARNING TECHNIQUES IN LAM

Machine learning (ML) techniques are widely used in LAM for process monitoring, defect detection, and quality prediction. Artificial Neural Networks (ANNs) predict defects like porosity and surface roughness by modeling complex relationships between process parameters and part quality, as demonstrated in [128]. Support Vector Machines (SVMs) are effective for defect detection and quality monitoring, particularly in high-dimensional spaces [134]. Gaussian Regression Models are used for process prediction and optimization, such as predicting disturbances affecting part quality [128].

Despite the adoption of machine learning (ML) techniques in LAM, challenges persist, including the need for handcrafted data preprocessing and the difficulty of generalizing models to new, unseen conditions.

Deep learning (DL) methods, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), are widely used in LAM for process monitoring, defect detection, and optimization. CNNs are effective for image-based monitoring, assessing defects like surface roughness or process quality [136]. RNNs are suited for tasks involving temporal data, such as predicting changes in process variables over time [130].

Despite their ability to handle complex, non-linear relationships, deep learning methods require significant computational resources and experimental validation, which limits their widespread adoption in practical applications.

E. MODEL-BASED METHODS IN LAM

Model-based approaches, such as Model Predictive Control (MPC) and Finite Element Method (FEM), are widely applied in LAM for process simulation and optimization. MPC models system dynamics based on data, enabling real-time predictions of future process states and parameter adjustments to optimize part quality, enhancing robustness and stability [131], [134]. In contrast, FEM uses physics-based modeling to simulate the thermal and mechanical behavior of materials, providing insights into heat distribution, residual stress, and deformation for improved process planning [133].

Although model-based methods provide accurate predictions and greater control over the process, they are computationally intensive and require precise models and calibration, which can be challenging in real-world LAM applications.

F. REINFORCEMENT LEARNING IN LAM

RL has gained attention for real-time control and decision-making in LAM. Studies reviewed in this paper demonstrate that the use of classical control systems such as adaptive iterative learning controller (ILC) [136] is not enough to control the process as the process is highly non-linear. The use of RL for adaptive process optimization and control can be the solution. Proximal Policy Optimization (PPO) [132] and Q-learning [129] are applied to adapt process parameters such as laser power and speed in response to real-time feedback. These methods excel in dynamic environments where continuous learning and adaptation are required.

RL has significant potential as a powerful tool for controlling complex, multivariable systems and optimizing processes. However, its implementation in real-world scenarios faces significant challenges, including computational intensity, the requirement for large datasets, numerous training episodes, and precise real-time data collection and decision-making [139]. To overcome these limitations, alternative planning approaches have been explored, including heuristics and meta-heuristics. For example, Malekipour et al. [140] employed a Genetic Algorithm (GA) for planning purposes, although their methodology was tested exclusively in a simulated environment.

Recent studies combine multiple AI techniques to leverage their complementary strengths. For instance, reinforcement learning (RL) is integrated with deep learning models like CNNs for process monitoring and ANNs for defect prediction, offering real-time adaptability and high accuracy [132]. Similarly, hybrid models combining FEM for process simulation with RL for optimization balance the precision of physics-based models with the adaptability of RL, improving process efficiency and quality [133].

G. CHALLENGES AND LIMITATIONS

Despite the promising potential of AI methods in LAM, several challenges and limitations persist that hinder their widespread adoption and effectiveness:

- Data requirements: AI models often require large, high-quality datasets to function effectively. However, obtaining such datasets in LAM environments can be challenging due to limited data availability or quality constraints.
- Computational Complexity: Advanced AI techniques, including deep learning, reinforcement learning (RL), and finite element methods (FEM), are computationally intensive. These methods demand significant hardware resources, specialized expertise, and extended training times, limiting their practical use.
- Real-World validation: Many AI-based solutions are validated primarily through simulations or limited experimental setups. Real-world testing is essential to confirm their reliability and applicability to actual LAM systems.
- Explainability and interpretability: The "black-box" nature of many AI models poses a significant challenge. Greater transparency in decision-making processes is needed to build trust and facilitate adoption in industrial applications.
- Evaluation metrics: The current research often overlooks critical evaluation metrics such as explainability, robustness, and scalability. This gap makes it difficult to assess the true potential and readiness of AI-based approaches for deployment.

Addressing these challenges is crucial to advancing the field. Enhancements in data accessibility, computational efficiency, real-world testing, model interpretability, and comprehensive evaluation could significantly improve the adoption and impact of AI methodologies in LAM.

V. DISCUSSION

Control and planning are inherently challenging tasks in LAM. AI research in control continues to face significant challenges such as: (i) understanding how machines can observe the world to learn, make predictions, and take actions; (ii) developing ways for machines to plan and reason effectively while addressing uncertainty; and (iii) enabling machines to represent input data and actions in a hierarchical structure, with a strong emphasis on explainability [143], [144], [145].

The potential of using AI for process control has been demonstrated in various applications. However, some studies still rely on classic controllers, such as PID, that are manually tuned or use hand-crafted model inputs. Such reliance on human bias in designing and tuning the controllers introduces inefficiencies that affect the precision and responsiveness of the controller, limiting the system in fully utilizing the collected data. Another critical limitation is the need for real-time capabilities, not only to take action layer-wise but continuously, particularly in PBF processes, where the dynamics are very fast. Furthermore, the evaluation metrics and objectives across studies differ, which makes comparisons difficult. Standardization of evaluation metrics is necessary to facilitate meaningful comparisons and accelerate controller development. For example, CT-scans for defect detection, such as porosity, part deformation, and surface roughness, could be critical metrics to consider.

Another limitation is the data labeling practices. While the process is continuous, some studies rely on discrete values to quantify the process, such as state/quality. This reliance on discrete data highlights the limitations in how we approach data collection and labeling in these processes. The continuous nature of the process requires real-time

data labeling to accurately monitor and control the system. Therefore, there is a need to develop methods for labeling real-time data, which is crucial for effectively applying AI techniques in process monitoring and control. Without proper real-time labeling, AI-driven systems may struggle to adapt and respond quickly to dynamic changes in the manufacturing process.

The development of AI-based controllers for LAM processes presents both opportunities and challenges. While the systematic review highlights the potential of AI to enhance process control, it is limited by the small sample size, which may bias the conclusions. This section outlines the critical steps involved in developing an AI-based controller—spanning from data sampling to the evaluation of the control model—and suggests future research directions to address current limitations and enhance the applicability of AI in LAM:

- A key first step in developing a robust AI-based controller is **sampling the process dynamics**. Accurate and comprehensive data collection is crucial for capturing the complex behavior of LAM processes over time. Current research underscores the importance of this phase, but there is a need for more sophisticated sampling techniques that not only capture the inherent variability and nonlinearity of LAM but also do so in a sample-efficient manner, given the high costs associated with the process. Further efforts should prioritize the development and deployment of adaptive sampling methods such as Bayesian Optimization [59], [146] that dynamically adjust to process changes, ensuring that the collected data is both representative and minimal. This approach will optimize the use of resources while still providing the necessary data quality for the subsequent steps.
- Once data is collected, effective **monitoring and preprocessing** becomes crucial. Raw data must be cleaned, preprocessed, and possibly modeled to prepare it for control decisions. While traditional data processing techniques remain prevalent in this review, there is growing interest in AI-driven methods that can automate and enhance these tasks [43], [46], [52], [147]. Additional studies should aim to explore the use of AI monitoring solutions in this step, as it is essential for creating accurate and robust process models. Other directions include novel approaches to monitor the process such using multimodal data from different sensors [147] and self-supervised learning [74].
- The next step involves **modeling the process dynamics**, where the goal is to create a mathematical or computational model that accurately reflects the LAM process based on data. The reviewed studies highlight the use finite element methods (FEM) but these models often require significant computational resources, specialized expertise, and experimental data for correct calibration [148]. Additional research should focus on creating more efficient and accessible modeling frameworks, possibly through hybrid approaches that combine the strengths of FEM and AI such as world models [149], [150], enabling more accurate and versatile process representations.
- **Planning and training the control model** is the critical phase where the AI-based controller is designed and trained to utilize model predictions effectively. Advanced techniques like RL and MPC have shown promise, yet their adoption remains limited in an industrial setting. Given the limited availability of high-quality datasets, MPC and RL rely on system models for exploration and training. Ongoing research should emphasize improving these training processes, particularly in handling the uncertainties and dynamic nature of LAM processes. Moreover, developing and testing training algorithms that balance performance optimization with computational efficiency - such as model-based RL [109], is essential for developing AI-based controllers viable for real-time applications.
- Finally, the **evaluation** of the control model uncertainty, robustness, and explainability is essential for its successful deployment in industrial settings. Future research should prioritize developing evaluation frameworks that incorporate these critical metrics, ensuring that AI models are not only effective but also transparent and resilient under various operating conditions. Improving the explainability of AI decisions is particularly important for gaining operator trust and facilitating the integration of AI into existing manufacturing workflows.

VI. CONCLUSION

AI is a transformative technology with the potential to address current challenges in LAM. Despite the limited number of studies reviewed, we have outlined the key steps where AI can significantly contribute to the development of AI-based controllers. Adopting AI across these steps should be more widespread and accompanied by rigorous evaluation metrics. Advancing the development of adaptive sampling methods and advanced modeling techniques to quantify processes in real time is critical for applying state-of-the-art control methods, given the limited availability of datasets. By focusing on these areas, future research can accelerate the development and adoption of AI-based controllers in LAM, leading to more efficient, reliable, and autonomous manufacturing processes.

In conclusion, this review establishes a foundational basis that highlights current advancements and research gaps. It highlights the considerable potential for AI to significantly impact LAM processes by enhancing process optimization and real-time decision-making. Future research in AI-driven methodologies is poised to drive substantial innovation and efficiency, marking it as a crucial area for continued exploration.

REFERENCES

[1] M. Armstrong, H. Mehrabi, and N. Naveed, "An overview of modern metal additive manufacturing technology," *J. Manuf. Processes*, vol. 84, pp. 1001–1029, Dec. 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1526612522007459

[2] R. E. Laureijs, J. B. Roca, S. P. Narra, C. Montgomery, J. L. Beuth, and E. R. H. Fuchs, "Metal additive manufacturing: Cost competitive beyond low volumes," *J. Manuf. Sci. Eng.*, vol. 139, no. 8, Aug. 2017, Art. no. 81010, doi: 10.1115/1.4035420.

[3] B. M. Colosimo, S. Cavalli, and M. Grasso, "A cost model for the economic evaluation of in-situ monitoring tools in metal additive manufacturing," *Int. J. Prod. Econ.*, vol. 223, May 2020, Art. no. 107532. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0925527319303597

[4] B. Sheng, J. Kanfoud, and T.-H. Gan, "Quality control of metal additive manufacturing," in *Advanced Additive Manufacturing*. London, U.K.: IntechOpen, 2022. [Online]. Available: https://www.intechopen.com/chapters/81187

[5] M. Qu, Q. Guo, L. I. Escano, A. Nabaa, S. M. H. Hojjatzadeh, Z. A. Young, and L. Chen, "Controlling process instability for defect lean metal additive manufacturing," *Nature Commun.*, vol. 13, no. 1, p. 1079, Feb. 2022. [Online]. Available: https://www.nature.com/articles/s41467-022-28649-2

[6] J. Jiang, Y. Xiong, Z. Zhang, and D. W. Rosen, "Machine learning integrated design for additive manufacturing," *J. Intell. Manuf.*, vol. 33, no. 4, pp. 1073–1086, Apr. 2022, doi: 10.1007/s10845-020-01715-6.

[7] T. Vaneker, A. Bernard, G. Moroni, I. Gibson, and Y. Zhang, "Design for additive manufacturing: Framework and methodology," *CIRP Ann.*, vol. 69, no. 2, pp. 578–599, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0007850620301396

[8] F. Weng, Y. Chew, Z. Zhu, X. Yao, L. Wang, F. L. Ng, S. Liu, and G. Bi, "Excellent combination of strength and ductility of CoCrNi medium entropy alloy fabricated by laser aided additive manufacturing," *Additive Manuf.*, vol. 34, Aug. 2020, Art. no. 101202. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2214860420305741

[9] M. K. Niaki, S. A. Torabi, and F. Nonino, "Why manufacturers adopt additive manufacturing technologies: The role of sustainability," *J. Cleaner Prod.*, vol. 222, pp. 381–392, Jun. 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0959652619307024

[10] B. Blakey-Milner, P. Gradl, G. Snedden, M. Brooks, J. Pitot, E. Lopez, M. Leary, F. Berto, and A. du Plessis, "Metal additive manufacturing in aerospace: A review," *Mater. Des.*, vol. 209, Nov. 2021, Art. no. 110008. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0264127521005633

[11] B. Hao and G. Lin, "Additive manufacturing technology and its application in die manufacturing," *IOP Conf. Ser., Earth Environ. Sci.*, vol. 632, no. 2, Jan. 2021, Art. no. 022077, doi: 10.1088/1755-1315/632/2/022077.

[12] M. Delic and D. R. Eyers, "The effect of additive manufacturing adoption on supply chain flexibility and performance: An empirical analysis from the automotive industry," *Int. J. Prod. Econ.*, vol. 228, Oct. 2020, Art. no. 107689.

[13] A. A. Martin, J. A. Hammons, H. B. Henderson, N. P. Calta, M. H. Nielsen, C. C. Cook, J. Ye, A. A. Maich, N. E. Teslich, T. T. Li, M. J. Thompson, M. F. Besser, M. J. Matthews, R. T. Ott, O. Rios, S. K. McCall, T. M. Willey, and J. R. I. Lee, "Enhanced mechanical performance via laser induced nanostructure formation in an additively manufactured lightweight aluminum alloy," *Appl. Mater. Today*, vol. 22, Mar. 2021, Art. no. 100972.

[14] A. Boschetto, L. Bottini, L. Macera, and S. Vatanparast, "Additive manufacturing for lightweighting satellite platform," *Appl. Sci.*, vol. 13, no. 5, p. 2809, Feb. 2023.

[15] C. Wei and L. Li, "Recent progress and scientific challenges in multi-material additive manufacturing via laser-based powder bed fusion," *Virtual Phys. Prototyping*, vol. 16, no. 3, pp. 347–371, May 2021.

[16] A. Jamwal, R. Agrawal, M. Sharma, and A. Giallanza, "Industry 4.0 technologies for manufacturing sustainability: A systematic review and future research directions," *Appl. Sci.*, vol. 11, no. 12, p. 5725, Jun. 2021. [Online]. Available: https://www.mdpi.com/2076-3417/11/12/5725

[17] N. Jyeniskhan, A. Keutayeva, G. Kazbek, M. H. Ali, and E. Shehab, "Integrating machine learning model and digital twin system for additive manufacturing," *IEEE Access*, vol. 11, pp. 71113–71126, 2023.

[18] *Standard Terminology for Additive Manufacturing Technologies*, Standard F2792-12, 2012. [Online]. Available: https://www.astm.org/f2792-12.html

[19] X. Zhao and T. Wang, "Laser powder bed fusion of powder material: A review," *3D Printing Additive Manuf.*, vol. 10, no. 6, pp. 1439–1454, Dec. 2023.

[20] D. Svetlizky, M. Das, B. Zheng, A. L. Vyatskikh, S. Bose, A. Bandyopadhyay, J. M. Schoenung, E. J. Lavernia, and N. Eliaz, "Directed energy deposition (DED) additive manufacturing: Physical characteristics, defects, challenges and applications," *Mater. Today*, vol. 49, pp. 271–295, Oct. 2021.

[21] A. Bandyopadhyay, K. D. Traxel, M. Lang, M. Juhasz, N. Eliaz, and S. Bose, "Alloy design via additive manufacturing: Advantages, challenges, applications and perspectives," *Mater. Today*, vol. 52, pp. 207–224, Jan. 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1369702121004314

[22] D. Gu, X. Shi, R. Poprawe, D. L. Bourell, R. Setchi, and J. Zhu, "Material-structure-performance integrated laser-metal additive manufacturing," *Science*, vol. 372, no. 6545, May 2021, Art. no. eabg1487, doi: 10.1126/science.abg1487.

[23] Y. Cao, H. L. Wei, T. Yang, T. T. Liu, and W. H. Liao, "Printability assessment with porosity and solidification cracking susceptibilities for a high strength aluminum alloy during laser powder bed fusion," *Additive Manuf.*, vol. 46, Oct. 2021, Art. no. 102103.

[24] Z.-J. Tang, W.-W. Liu, L.-N. Zhu, Z.-C. Liu, Z.-R. Yan, D. Lin, Z. Zhang, and H.-C. Zhang, "Investigation on coaxial visual characteristics of molten pool in laser-based directed energy deposition of AISI 316L steel," *J. Mater. Process. Technol.*, vol. 290, Apr. 2021, Art. no. 116996.

[25] M. D. Xames, F. K. Torsha, and F. Sarwar, "A systematic literature review on recent trends of machine learning applications in additive manufacturing," *J. Intell. Manuf.*, vol. 34, no. 6, pp. 2529–2555, 2022.

[26] K. Kashinath et al., "Physics-informed machine learning: Case studies for weather and climate modelling," *Phil. Trans. Roy. Soc. A: Math., Phys. Eng. Sci.*, vol. 379, no. 2194, Apr. 2021, Art. no. 20200093.

[27] J.-L. Wu, H. Xiao, and E. Paterson, "Physics-informed machine learning approach for augmenting turbulence models: A comprehensive framework," *Phys. Rev. Fluids*, vol. 3, no. 7, Jul. 2018, Art. no. 074602.

[28] N. Zobeiry and K. D. Humfeld, "A physics-informed machine learning approach for solving heat transfer equation in advanced manufacturing and engineering applications," *Eng. Appl. Artif. Intell.*, vol. 101, May 2021, Art. no. 104232.

[29] B. Jena, S. Saxena, G. K. Nayak, L. Saba, N. Sharma, and J. S. Suri, "Artificial intelligence-based hybrid deep learning models for image classification: The first narrative review," *Comput. Biol. Med.*, vol. 137, Oct. 2021, Art. no. 104803.

[30] M. Banane and A. Erraissi, "A comprehensive study of natural language processing techniques based on big data," in *Proc. Int. Conf. Decis. Aid Sci. Appl. (DASA)*, Mar. 2022, pp. 1492–1497.

[31] A. Iqbal and R. Amin, "Time series forecasting and anomaly detection using deep learning," *Comput. Chem. Eng.*, vol. 182, Mar. 2024, Art. no. 108560. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0098135423004301

[32] D. Kalathil, V. K. Mandal, A. Gune, K. Talele, P. Chimurkar, and M. Bansode, "Self driving car using neural networks," in *Proc. Int. Conf. Appl. Artif. Intell. Comput. (ICAAIC)*, May 2022, pp. 213–217.

[33] F. Gao, Y. Cheng, M. Gao, C. Ma, H. Liu, Q. Ren, and Z. Zhao, "Design and implementation of an autonomous driving delivery robot," in *Proc. 41st Chin. Control Conf. (CCC)*, Jul. 2022, pp. 3832–3837.

[34] Z. Wang, H. Yan, Y. Wang, Z. Xu, Z. Wang, and Z. Wu, "Research on autonomous robots navigation based on reinforcement learning," 2024, *arXiv:2407.02539*.

[35] M. Hossain, "Autonomous delivery robots: A literature review," *IEEE Eng. Manag. Rev.*, vol. 51, no. 4, pp. 77–89, Dec. 2023.

[36] C. Hu, Y. Zhao, Z. Wang, H. Du, and J. Liu, "Games for artificial intelligence research: A review and perspectives," 2023, *arXiv:2304.13269*.

[37] B. Xia, X. Ye, and A. O. M. Abuassba, "Recent research on AI in games," in *Proc. Int. Wireless Commun. Mobile Comput. (IWCMC)*, Jun. 2020, pp. 505–510.

[38] J. Degrave et al., "Magnetic control of tokamak plasmas through deep reinforcement learning," *Nature*, vol. 602, no. 7897, pp. 414–419, Feb. 2022, doi: 10.1038/s41586-021-04301-9.

[39] H. Robinson, S. Pawar, A. Rasheed, and O. San, "Physics guided neural networks for modelling of non-linear dynamics," *Neural Netw.*, vol. 154, pp. 333–345, Oct. 2022.

[40] F. Piqué, H. T. Kalidindi, L. Fruzzetti, C. Laschi, A. Menciassi, and E. Falotico, "Controlling soft robotic arms using continual learning," *IEEE Robot. Autom. Lett.*, vol. 7, no. 2, pp. 5469–5476, Apr. 2022.

[41] A. Banerjee, S. S. Mwanje, and G. Carle, "Toward control and coordination in cognitive autonomous networks," *IEEE Trans. Netw. Service Manage.*, vol. 19, no. 1, pp. 49–60, Mar. 2022.

[42] Y. Lv, J. Na, Q. Yang, X. Wu, and Y. Guo, "Online adaptive optimal control for continuous-time nonlinear systems with completely unknown dynamics," *Int. J. Control*, vol. 89, no. 1, pp. 99–112, Jan. 2016.

[43] M. Mozaffar, S. Liao, X. Xie, S. Saha, C. Park, J. Cao, W. K. Liu, and Z. Gan, "Mechanistic artificial intelligence (mechanistic-AI) for modeling, design, and control of advanced manufacturing processes: Current state and perspectives," *J. Mater. Process. Technol.*, vol. 302, Apr. 2022, Art. no. 117485. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0924013621004453

[44] M. E. H. Korner, M. P. Lambán, J. A. Albajez, J. Santolaria, L. D. C. N. Corrales, and J. Royo, "Systematic literature review: Integration of additive manufacturing and Industry 4.0," *Metals*, vol. 10, no. 8, p. 1061, Aug. 2020. [Online]. Available: https://www.mdpi.com/2075-4701/10/8/1061

[45] Y. Kobayashi, T. Takahashi, T. Nakazato, H. Sakurai, H. Tamaru, K. L. Ishikawa, K. Sakaue, and S. Tani, "Fully automated data acquisition for laser production cyber-physical system," *IEEE J. Sel. Topics Quantum Electron.*, vol. 27, no. 6, pp. 1–8, Nov. 2021.

[46] T. Herzog, M. Brandt, A. Trinchi, A. Sola, and A. Molotnikov, "Process monitoring and machine learning for defect detection in laser-based metal additive manufacturing," *J. Intell. Manuf.*, vol. 35, no. 4, pp. 1407–1437, Apr. 2024, doi: 10.1007/s10845-023-02119-y.

[47] Z. Zhang and Z. Chen, "Modeling and control of robotic manipulators based on symbolic regression," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 34, no. 5, pp. 2440–2450, May 2023.

[48] O. J. Fisher, N. J. Watson, J. E. Escrig, R. Witt, L. Porcu, D. Bacon, M. Rigley, and R. L. Gomes, "Considerations, challenges and opportunities when developing data-driven models for process manufacturing systems," *Comput. Chem. Eng.*, vol. 140, Sep. 2020, Art. no. 106881. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0098135419308373

[49] J. Haley, C. Leach, B. Jordan, R. Dehoff, and V. Paquit, "In-situ digital image correlation and thermal monitoring in directed energy deposition additive manufacturing," *Opt. Exp.*, vol. 29, no. 7, p. 9927, 2021.

[50] T. Özel, "A review on in-situ process sensing and monitoring systems for fusion-based additive manufacturing," *Int. J. Mechatronics Manuf. Syst.*, vol. 16, nos. 2–3, pp. 115–154, 2023, doi: 10.1504/ijmms.2023.133390.

[51] T. Sahar, M. Rauf, A. Murtaza, L. A. Khan, H. Ayub, S. M. Jameel, and I. U. Ahad, "Anomaly detection in laser powder bed fusion using machine learning: A review," *Results Eng.*, vol. 17, Mar. 2023, Art. no. 100803. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S259012302200473X

[52] L. Chen, G. Bi, X. Yao, J. Su, C. Tan, W. Feng, M. Benakis, Y. Chew, and S. K. Moon, "In-situ process monitoring and adaptive quality enhancement in laser additive manufacturing: A critical review," *J. Manuf. Syst.*, vol. 74, pp. 527–574, Jun. 2024, doi: 10.1016/j.jmsy.2024.04.013.

[53] H. Wang, W. Liu, Z. Tang, Y. Wang, X. Mei, K. M. Saleheen, Z. Wang, and H. Zhang, "Review on adaptive control of laser-directed energy deposition," *Opt. Eng.*, vol. 59, no. 7, Jul. 2020, Art. no. 070901.

[54] T. Phillips, T. Ricker, S. Fish, and J. Beaman, "Design of a laser control system with continuously variable power and its application in additive manufacturing," *Additive Manuf.*, vol. 34, Aug. 2020, Art. no. 101173.

[55] S. L. Brunton and J. N. Kutz, *Data-Driven Science and Engineering: Machine Learning, Dynamical Systems, and Control*. Cambridge, U.K.: Cambridge Univ. Press, 2019.

[56] C. Das, P. Sreeramagiri, and G. Balasubramanian, "Phase and thermodynamics-informed predictive model for laser beam additive manufacturing of a multi-principal element alloy," *Frontiers Met. Alloys*, vol. 2, Sep. 2023, Art. no. 1252115.

[57] M. D. Khomenko, N. W. Makoana, F. K. Mirzade, and S. Pityana, "Coupled heat transfer, fluid flow and solidification kinetics for laser additive manufacturing applications," *J. Manuf. Processes*, vol. 67, pp. 611–618, Jul. 2021.

[58] M. Mandolini, M. Sartini, C. Favi, and M. Germani, "Cost sensitivity analysis for laser powder bed fusion," *Proc. Des. Soc.*, vol. 2, pp. 1411–1420, May 2022.

[59] S. Greenhill, S. Rana, S. Gupta, P. Vellanki, and S. Venkatesh, "Bayesian optimization for adaptive experimental design: A review," *IEEE Access*, vol. 8, pp. 13937–13948, 2020.

[60] C. A. Duchanoy, H. Calvo, and M. A. Moreno-Armendáriz, "ASAMS: An adaptive sequential sampling and automatic model selection for artificial intelligence surrogate modeling," *Sensors*, vol. 20, no. 18, p. 5332, Sep. 2020. [Online]. Available: https://www.mdpi.com/1424-8220/20/18/5332

[61] H. Liu, Y.-S. Ong, and J. Cai, "A survey of adaptive sampling for global metamodeling in support of simulation-based complex engineering design," *Struct. Multidisciplinary Optim.*, vol. 57, no. 1, pp. 393–416, Jan. 2018, doi: 10.1007/s00158-017-1739-8.

[62] S. Falkner, A. Klein, and F. Hutter, "BOHB: Robust and efficient hyperparameter optimization at scale," 2018, *arXiv:1807.01774*.

[63] F. Berkenkamp, A. Krause, and A. P. Schoellig, "Bayesian optimization with safety constraints: Safe and automatic parameter tuning in robotics," *Mach. Learn.*, vol. 112, no. 10, pp. 3713–3747, Oct. 2023, doi: 10.1007/s10994-021-06019-1.

[64] B. G. Galuzzi, I. Giordani, A. Candelieri, R. Perego, and F. Archetti, "Bayesian optimization for recommender system," in *Optimization of Complex Systems: Theory, Models, Algorithms and Applications* (Advances in Intelligent Systems and Computing), H. A. L. Thi, H. M. Le, and T. P. Dinh, Eds., Cham, Switzerland: Springer, 2020, pp. 751–760.

[65] M. Zhang, A. Parnell, D. Brabazon, and A. Benavoli, "Bayesian optimisation for sequential experimental design with applications in additive manufacturing," 2021, *arXiv:2107.12809*.

[66] T. Chepiga, P. Zhilyaev, A. Ryabov, A. P. Simonov, O. N. Dubinin, D. G. Firsov, Y. O. Kuzminova, and S. A. Evlashin, "Process parameter selection for production of stainless steel 316L using efficient multi-objective Bayesian optimization algorithm," *Materials*, vol. 16, no. 3, p. 1050, Jan. 2023. [Online]. Available: https://www.mdpi.com/1996-1944/16/3/1050

[67] Y. Cai, J. Xiong, H. Chen, and G. Zhang, "A review of in-situ monitoring and process control system in metal-based laser additive manufacturing," *J. Manuf. Syst.*, vol. 70, pp. 309–326, Oct. 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0278612523001504

[68] R. McCann, M. A. Obeidi, C. Hughes, É. McCarthy, D. S. Egan, R. K. Vijayaraghavan, A. M. Joshi, V. Acinas Garzon, D. P. Dowling, P. J. McNally, and D. Brabazon, "In-situ sensing, process monitoring and machine control in laser powder bed fusion: A review," *Additive Manuf.*, vol. 45, Sep. 2021, Art. no. 102058. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2214860421002232

[69] H. Yan, J.-F. Cai, Y. Zhao, Z. Jiang, Y. Zhang, H. Ren, Y. Zhang, H. Li, and Y. Long, "A lightweight high-resolution algorithm based on deep learning for layer-wise defect detection in laser powder bed fusion," *Meas. Sci. Technol.*, vol. 35, no. 2, Feb. 2024, Art. no. 025604.

[70] B. Shi and Z. Chen, "A layer-wise multi-defect detection system for powder bed monitoring: Lighting strategy for imaging, adaptive segmentation and classification," *Mater. Des.*, vol. 210, Nov. 2021, Art. no. 110035.

[71] S. Fathizadan, F. Ju, and Y. Lu, "Deep representation learning for process variation management in laser powder bed fusion," *Additive Manuf.*, vol. 42, Jun. 2021, Art. no. 101961.

[72] Q. Fang, Z. Tan, H. Li, S. Shen, S. Liu, C. Song, X. Zhou, Y. Yang, and S. Wen, "In-situ capture of melt pool signature in selective laser melting using U-Net-based convolutional neural network," *J. Manuf. Processes*, vol. 68, pp. 347–355, Aug. 2021.

[73] L. Chen, X. Yao, W. Feng, Y. Chew, and S. K. Moon, "Multimodal sensor fusion for real-time location-dependent defect detection in laser-directed energy deposition," in *Proc. 43rd Comput. Inf. Eng. Conf. (CIE)*, vol. 2, Aug. 2023, pp. 1–35.

[74] V. Pandiyan, D. Cui, R. A. Richter, A. Parrilli, and M. Leparoux, "Real-time monitoring and quality assurance for laser-based directed energy deposition: Integrating co-axial imaging and self-supervised deep learning framework," *J. Intell. Manuf.*, vol. 36, no. 2, pp. 909–933, Feb. 2025, doi: 10.1007/s10845-023-02279-x.

[75] M. Obara, K. Sato, H. Sakamoto, T. Okuno, and A. Takeda, "Stable linear system identification with prior knowledge by Riemannian sequential quadratic optimization," 2021, *arXiv:2112.14043*.

[76] G. Pillonetto, A. Aravkin, D. Gedon, L. Ljung, A. H. Ribeiro, and T. B. Schön, "Deep networks for system identification: A survey," 2023, *arXiv:2301.12832*.

[77] M. Cardona and F. E. Serrano, "Autoregressive model for identification of nonlinear dynamics systems with the GNU octave control toolbox," in *Proc. IEEE Central Amer. Panama Student Conf. (CONESCAPAN)*, Oct. 2022, pp. 1–6.

[78] D. Ivanov and Z. Yakoub, "Overview of identification methods of autoregressive model in presence of additive noise," *Mathematics*, vol. 11, no. 3, p. 607, Jan. 2023. [Online]. Available: https://www.mdpi.com/2227-7390/11/3/607

[79] J. Harris, F. Arthurs, J. V. Henrickson, and J. Valasek, "Aircraft system identification using artificial neural networks with flight test data," in *Proc. Int. Conf. Unmanned Aircr. Syst. (ICUAS)*, Jun. 2016, pp. 679–688.

[80] M. Forgione, A. Muni, D. Piga, and M. Gallieri, "On the adaptation of recurrent neural networks for system identification," 2022, *arXiv:2201.08660*.

[81] R. Yin and J. Ren, "Sequence-to-sequence LSTM-based dynamic system identification of piezo-electric actuators," in *Proc. Amer. Control Conf. (ACC)*, May 2023, pp. 673–678.

[82] J. H. Tu, C. W. Rowley, D. M. Luchtenburg, S. L. Brunton, and J. N. Kutz, "On dynamic mode decomposition: Theory and applications," *J. Comput. Dyn.*, vol. 1, no. 2, pp. 391–421, 2014, doi: 10.3934/jcd.2014.1.391.

[83] S. L. Brunton, J. L. Proctor, and J. N. Kutz, "Discovering governing equations from data by sparse identification of nonlinear dynamical systems," *Proc. Nat. Acad. Sci. USA*, vol. 113, no. 15, pp. 3932–3937, Mar. 2016, doi: 10.1073/pnas.1517384113.

[84] M. I. Jordan and T. M. Mitchell, "Machine learning: Trends, perspectives, and prospects," *Science*, vol. 349, no. 6245, pp. 255–260, Jul. 2015.

[85] A. L. Tarca, V. J. Carey, X.-W. Chen, R. Romero, and S. Drăghici, "Machine learning and its applications to biology," *PLoS Comput. Biol.*, vol. 3, no. 6, p. e116, Jun. 2007.

[86] L. Cheng, Z. Wang, F. Jiang, and J. Li, "Adaptive neural network control of nonlinear systems with unknown dynamics," *Adv. Space Res.*, vol. 67, no. 3, pp. 1114–1123, Feb. 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0273117720307821

[87] P. J. Fleming and R. C. Purshouse, "Evolutionary algorithms in control systems engineering: A survey," *Control Eng. Pract.*, vol. 10, no. 11, pp. 1223–1241, Nov. 2002. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0967066102000813

[88] X. Wang, S. Wang, X. Liang, D. Zhao, J. Huang, X. Xu, B. Dai, and Q. Miao, "Deep reinforcement learning: A survey," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 4, pp. 5064–5078, Sep. 2024.

[89] K. H. Ang, G. Chong, and Y. Li, "PID control system analysis, design, and technology," *IEEE Trans. Control Syst. Technol.*, vol. 13, no. 4, pp. 559–576, Jul. 2005.

[90] P. B. D. M. Oliveira and J. B. Cunha, "Blending artificial intelligence into PID controller design: A biomedical engineering experiment," *IFAC-PapersOnLine*, vol. 49, no. 6, pp. 366–371, 2016. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2405896316304116

[91] D. Somwanshi, M. Bundele, G. Kumar, and G. Parashar, "Comparison of fuzzy-PID and PID controller for speed control of DC motor using LabVIEW," *Proc. Comput. Sci.*, vol. 152, pp. 252–260, Jan. 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1877050919306702

[92] B. Maaloul and S. Elloumi, "Adaptive PID controller of a quadrotor," in *Proc. IEEE Int. Conf. Adv. Syst. Emergent Technol. (IC_ASET)*, Apr. 2023, pp. 1–6.

[93] R. Kumar, S. Srivastava, and J. R. P. Gupta, "Artificial neural network based PID controller for online control of dynamical systems," in *Proc. IEEE 1st Int. Conf. Power Electron., Intell. Control Energy Syst. (ICPEICES)*, Jul. 2016, pp. 1–6.

[94] U. M. Nath, C. Dey, and R. K. Mudi, "Desired characteristic equation based PID controller tuning for lag-dominating processes with real-time realization on level control system," *IEEE Control Syst. Lett.*, vol. 5, no. 4, pp. 1255–1260, Oct. 2021.

[95] M. Schwenzer, M. Ay, T. Bergs, and D. Abel, "Review on model predictive control: An engineering perspective," *Int. J. Adv. Manuf. Technol.*, vol. 117, nos. 5–6, pp. 1327–1349, Aug. 2021.

[96] J. H. Hoekstra, B. Cseppento, G. I. Beintema, M. Schoukens, Z. Kollár, and R. Tóth, "Computationally efficient predictive control based on ANN state-space models," 2023, *arXiv:2303.17305*.

[97] I. Pappas, N. A. Diangelakis, and E. N. Pistikopoulos, "Multiparametric/explicit nonlinear model predictive control for quadratically constrained problems," *J. Process Control*, vol. 103, pp. 55–66, Jul. 2021.

[98] L. Chen, P. Wu, K. Chitta, B. Jaeger, A. Geiger, and H. Li, "End-to-end autonomous driving: Challenges and frontiers," 2023, *arXiv:2306.16927*.

[99] H. Haavaldsen, M. Aasboe, and F. Lindseth, "Autonomous vehicle control: End-to-end learning in simulated urban environments," 2019, *arXiv:1905.06712*.

[100] R. Hasani, M. Lechner, A. Amini, L. Liebenwein, A. Ray, M. Tschaikowski, G. Teschl, and D. Rus, "Closed-form continuous-time neural networks," *Nature Mach. Intell.*, vol. 4, no. 11, pp. 992–1003, Nov. 2022, doi: 10.1038/s42256-022-00556-7.

[101] N. Akalin and A. Loutfi, "Reinforcement learning approaches in social robotics," *Sensors*, vol. 21, no. 4, p. 1292, Feb. 2021.

[102] S. Sharma, A. Srinivas, and B. Ravindran, "Deep reinforcement learning," in *Proc. 14th Int. Conf. Comput. Commun. Netw. Technol. (ICCCNT)*, 2023, pp. 1–7.

[103] W. Saeed and C. Omlin, "Explainable AI (XAI): A systematic meta-survey of current challenges and future opportunities," *Knowl.-Based Syst.*, vol. 263, Mar. 2023, Art. no. 110273.

[104] M. C. McKenzie and M. D. McDonnell, "Modern value based reinforcement learning: A chronological review," *IEEE Access*, vol. 10, pp. 134704–134725, 2022.

[105] C. J. C. H. Watkins and P. Dayan, "Q-learning," *Mach. Learn.*, vol. 8, nos. 3–4, pp. 279–292, May 1992, doi: 10.1007/bf00992698.

[106] M. Hu, *Policy Gradient Methods*. Berkeley, CA, USA: Apress, 2023, pp. 177–196, doi: 10.1007/978-1-4842-9606-6_9.

[107] I. Grondman, L. Busoniu, G. A. D. Lopes, and R. Babuska, "A survey of actor-critic reinforcement learning: Standard and natural policy gradients," *IEEE Trans. Syst. Man, Cybern., C, Appl. Rev.*, vol. 42, no. 6, pp. 1291–1307, Nov. 2012.

[108] Z. Zhang, Y. Chen, J. D. Lee, and S. S. Du, "Settling the sample complexity of online reinforcement learning," 2023, *arXiv:2307.13586*.

[109] N. Zolman, U. Fasel, J. N. Kutz, and S. L. Brunton, "SINDy-RL: Interpretable and efficient model-based reinforcement learning," 2024, *arXiv:2403.09110*.

[110] T. M. Moerland, J. Broekens, A. Plaat, and C. M. Jonker, "Model-based reinforcement learning: A survey," 2020, *arXiv:2006.16712*.

[111] B. Zheng, S. Verma, J. Zhou, I. W. Tsang, and F. Chen, "Imitation learning: Progress, taxonomies and challenges," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 5, pp. 6322–6337, May 2024.

[112] W. Xue, P. Kolaric, J. Fan, B. Lian, T. Chai, and F. L. Lewis, "Inverse reinforcement learning in tracking control based on inverse optimal control," *IEEE Trans. Cybern.*, vol. 52, no. 10, pp. 10570–10581, Oct. 2022.

[113] S. Byeon, D. Sun, and I. Hwang, "An inverse optimal control approach for learning and reproducing under uncertainties," *IEEE Control Syst. Lett.*, vol. 7, pp. 787–792, 2023.

[114] P. Rashidinejad, B. Zhu, C. Ma, J. Jiao, and S. Russell, "Bridging offline reinforcement learning and imitation learning: A tale of pessimism," *IEEE Trans. Inf. Theory*, vol. 68, no. 12, pp. 8156–8196, Dec. 2022.

[115] B. Xu, X. Wang, Y. Shou, P. Shi, and Z. Shi, "Finite-time robust intelligent control of strict-feedback nonlinear systems with flight dynamics application," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 33, no. 11, pp. 6173–6182, Nov. 2022.

[116] M. Han, K. Wong, J. Euler-Rolle, L. Zhang, and R. K. Katzschmann, "Robust learning-based control for uncertain nonlinear systems with validation on a soft robot," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 36, no. 1, pp. 510–524, Jan. 2025.

[117] K. Zhang, J. Zhang, P.-D. Xu, T. Gao, and D. W. Gao, "Explainable AI in deep reinforcement learning models for power system emergency control," *IEEE Trans. Computat. Social Syst.*, vol. 9, no. 2, pp. 419–427, Apr. 2022.

[118] J. Gawlikowski, C. R. N. Tassi, M. Ali, J. Lee, M. Humt, J. Feng, A. Kruspe, R. Triebel, P. Jung, R. Roscher, M. Shahzad, W. Yang, R. Bamler, and X. X. Zhu, "A survey of uncertainty in deep neural networks," *Artif. Intell. Rev.*, vol. 56, no. S1, pp. 1513–1589, Oct. 2023, doi: 10.1007/s10462-023-10562-9.

[119] J. Liu and Y. Jin, "A comprehensive survey of robust deep learning in computer vision," *J. Autom. Intell.*, vol. 2, no. 4, pp. 175–195, Nov. 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S294985542300045X

[120] S. Lundberg and S.-I. Lee, "A unified approach to interpreting model predictions," 2017, *arXiv:1705.07874*.

[121] M. T. Ribeiro, S. Singh, and C. Guestrin, "'Why should I trust you?': Explaining the predictions of any classifier," 2016, *arXiv:1602.04938*.

[122] N. Friedman and I. Nachman, "Gaussian process networks," 2013, *arXiv:1301.3857*.

[123] F. Laakom, J. Raitoharju, A. Iosifidis, J. Nikkanen, and M. Gabbouj, "Monte Carlo dropout ensembles for robust illumination estimation," 2020, *arXiv:2007.10114*.

[124] P. Zhai, J. Luo, Z. Dong, L. Zhang, S. Wang, and D. Yang, "Robust adversarial reinforcement learning with dissipation inequation constraint," in *Proc. AAAI Conf. Artif. Intell.*, Jun. 2022, vol. 36, no. 5, pp. 5431–5439. [Online]. Available: https://ojs.aaai.org/index.php/AAAI/article/view/20481

[125] J. Tack, S. Yu, J. Jeong, M. Kim, S. J. Hwang, and J. Shin, "Consistency regularization for adversarial robustness," 2021, *arXiv:2103.04623*.

[126] M. J. Page, "PRISMA 2020 explanation and elaboration: Updated guidance and exemplars for reporting systematic reviews," *BMJ*, vol. 372, p. n160, Mar. 2021. [Online]. Available: https://www.bmj.com/content/372/bmj.n160

[127] M. R. Dehaghani, A. Sahraeidolatkhaneh, M. Nilsen, F. Sikström, P. Sajadi, Y. Tang, and G. G. Wang, "System identification and closed-loop control of laser hot-wire directed energy deposition using the parameter-signature-quality modeling scheme," *J. Manuf. Processes*, vol. 112, pp. 1–13, Feb. 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1526612524000409

[128] I. Jeon, P. Liu, and H. Sohn, "Real-time melt pool depth estimation and control during metal-directed energy deposition for porosity reduction," *Int. J. Adv. Manuf. Technol.*, pp. 1–16, Jun. 2023, doi: 10.1007/s00170-023-11689-3.

[129] B. Park, A. Chen, and S. Mishra, "Real-time melt pool homogenization through geometry-informed control in laser powder bed fusion using reinforcement learning," *IEEE Trans. Autom. Sci. Eng.*, vol. 22, pp. 2986–2997, 2025.

[130] A. W. Malik, M. A. Mahmood, and F. Liou, "Digital twin–driven optimization of laser powder bed fusion processes: A focus on lack-of-fusion defects," *Rapid Prototyping J.*, vol. 30, no. 10, pp. 1977–1988, Nov. 2024, doi: 10.1108/rpj-02-2024-0091.

[131] V. Karkaria, A. Goeckner, R. Zha, J. Chen, J. Zhang, Q. Zhu, J. Cao, R. X. Gao, and W. Chen, "Towards a digital twin framework in additive manufacturing: Machine learning and Bayesian optimization for time series process optimization," *J. Manuf. Syst.*, vol. 75, pp. 322–332, Aug. 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S027861252400089X

[132] X. Cao, C. Duan, X. Luo, S. Zheng, H. Xu, X. Hao, and Z. Zhang, "Deep learning-based rapid prediction of temperature field and intelligent control of molten pool during directed energy deposition process," *Additive Manuf.*, vol. 94, Aug. 2024, Art. no. 104501. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2214860424005475

[133] S. Zhu, W. Xia, H. Kamali, L. Ouyang, L. Xie, Z. Huang, and Z. Jiang, "Deep learning-driven precision control of dilution rate in multi-pass laser cladding: Experiment and simulation," *Int. J. Adv. Manuf. Technol.*, vol. 127, nos. 11–12, pp. 5353–5371, Aug. 2023, doi: 10.1007/s00170-023-11732-3.

[134] Z. Xi, "Model predictive control of melt pool size for the laser powder bed fusion process under process uncertainty," *ASCE-ASME J. Risk Uncertainty Eng. Syst., B, Mech. Eng.*, vol. 8, no. 1, Mar. 2022, Art. no. 011103, doi: 10.1115/1.4051746. [Online]. Available: https://asmedigitalcollection.asme.org/risk/article-pdf/8/1/011103/6736135/risk008111103.pdf

[135] C. Reiff, W. Bubeck, D. Krawczyk, M. Steeb, A. Lechler, and A. Verl, "Learning feedforward control for laser powder bed fusion," *Proc. CIRP*, vol. 96, pp. 127–132, Jan. 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2212827121000883

[136] Y. Zhang, M. Yin, W. Li, J. Xiang, and X. Ding, "Layered and subregional control strategy based on model-free adaptive iterative learning for laser additive manufacturing process," *J. Manuf. Processes*, vol. 102, pp. 806–813, Sep. 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1526612523007715

[137] C. Ma, D. Wang, K. Zhao, J. Gao, H. Wang, A. Zhang, L. Cheng, and Y. Zhang, "Layer-wise surface quality improvement in laser powder bed fusion through surface anomaly detection and control," *Comput. Ind. Eng.*, vol. 191, May 2024, Art. no. 110098. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360835224002195

[138] C. Ma and Y. Zhang, "A layer-wise melting defects mitigation method in laser powder bed fusion process based on machine learning and fuzzy inference," *ISA Trans.*, vol. 156, pp. 698–711, Jan. 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0019057824005214

[139] S. Shi, X. Liu, Z. Wang, H. Chang, Y. Wu, R. Yang, and Z. Zhai, "An intelligent process parameters optimization approach for directed energy deposition of nickel-based alloys using deep reinforcement learning," *J. Manuf. Processes*, vol. 120, pp. 1130–1140, Jun. 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1526612524004559

[140] E. Malekipour, H. El-Mounayri, and D. Hagedorn-Hansen, "Monitoring and control framework for intelligent real-time optimization of printing sequence of powder bed fusion," *J. Intell. Manuf.*, vol. 36, no. 1, pp. 375–398, Jan. 2025, doi: 10.1007/s10845-023-02218-w.

[141] Q. Zhong, X. Tian, X. Huang, C. Huo, and D. Li, "Using feedback control of thermal history to improve quality consistency of parts fabricated via large-scale powder bed fusion," *Additive Manuf.*, vol. 42, Jun. 2021, Art. no. 101986. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2214860421001512

[142] C. Knaak, L. Masseling, E. Duong, P. Abels, and A. Gillner, "Improving build quality in laser powder bed fusion using high dynamic range imaging and model-based reinforcement learning," *IEEE Access*, vol. 9, pp. 55214–55231, 2021.

[143] J. Schmidhuber, "On learning to think: Algorithmic information theory for novel combinations of reinforcement learning controllers and recurrent neural world models," 2015, *arXiv:1511.09249*.

[144] D. Silver, S. Singh, D. Precup, and R. S. Sutton, "Reward is enough," *Artif. Intell.*, vol. 299, Oct. 2021, Art. no. 103535. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0004370221000862

[145] Y. LeCun, "A path towards autonomous machine intelligence version 0.9. 2, 2022-06-27," *Open Rev.*, vol. 62, no. 1, pp. 1–62, 2022.

[146] J. Sousa, A. Sousa, F. Brueckner, L. P. Reis, and A. Reis, "Human-in-the-loop multi-objective Bayesian optimization for directed energy deposition with in-situ monitoring," *Robot. Comput.-Integr. Manuf.*, vol. 92, Apr. 2025, Art. no. 102892. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0736584524001790

[147] J. Sousa, R. Darabi, A. Sousa, F. Brueckner, L. Paulo Reis, and A. Reis, "JEMA: A joint embedding framework for scalable co-learning with multimodal alignment," 2024, *arXiv:2410.23988*.

[148] M. Schänzel, D. Shakirov, A. Ilin, and V. Ploshikhin, "Coupled thermo-mechanical process simulation method for selective laser melting considering phase transformation steels," *Comput. Math. With Appl.*, vol. 78, no. 7, pp. 2230–2246, Oct. 2019.

[149] T. Taniguchi, S. Murata, M. Suzuki, D. Ognibene, P. Lanillos, E. Ugur, L. Jamone, T. Nakamura, A. Ciria, B. Lara, and G. Pezzulo, "World models and predictive coding for cognitive and developmental robotics: Frontiers and challenges," *Adv. Robot.*, vol. 37, no. 13, pp. 780–806, Jul. 2023.

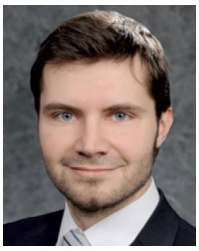
[150] A. Hu, "Neural world models for computer vision," 2023, *arXiv:2306.09179*.

JOÃO SOUSA received the master's degree in mechanical engineering from the University of Porto, where he is currently pursuing the Ph.D. degree. He is currently a member of the Artificial Intelligence and Computer Science Laboratory (LIACC) and affiliated with the Associate Laboratory for Energy, Transport, and Aerospace (LAETA), Institute of Science and Innovation in Mechanical and Industrial Engineering (INEGI). He is also a Visiting Researcher with Fraunhofer IWS and an invited Professor with the University of Porto.

BENEDIKT BRANDAU received the master's degree in material science from the Technical University of Ilmenau. He is currently pursuing the Ph.D. degree in monitoring techniques for additive manufacturing with Luleå University of Technology, Sweden. He began his career as an Optical Engineer with JENOPTIK, Jena, Germany, where he gained experience in coating technology and laser material processing. He has a strong background in material science and optical engineering, where he applies to improve manufacturing processes across various industries.

ROYA DARABI received the Ph.D. degree in computational mechanics from the University of Porto, in 2024. Currently, she is a Postdoctoral Researcher with the University of Porto and the Mechanics of Materials Laboratory, Engineering Department, Oxford University. Her research interest includes multiscale-multiphysics process modeling, with a strong background in phase field methods.

ARMANDO SOUSA received the Ph.D. degree in electrical and computer engineering and in robotics and automation from the Faculty of Engineering, University of Porto, in 2004. Currently, he is an Associate Professor with the ECE Department, FEUP, and an Integrated Researcher with the Centre for Intelligent and Industrial Systems (CRIIS), INESC TEC. His research interests include intelligent robotics, robot learning, and higher education.



FRANK BRUECKNER received the Ph.D. degree in theoretical aspects of laser material processing from the Technical University of Dresden. He studied automation and control technology and business administration with the Technical University of Dresden. Currently, he leads the Additive Manufacturing and Surface Technology Division, Fraunhofer IWS, focusing on additive manufacturing, heat treatment, coating processes, biosystems technology, and digitalization. Additionally, he supervises Ph.D. students with Luleå University of Technology and delivers lecture series in these areas with TU Dresden.

ANA REIS received the Ph.D. degree in mechanical engineering from the University of Porto. She is currently a Professor with the Department of Mechanical Engineering (DEMec), University of Porto (FEUP), and an Integrated Researcher with the Associated Laboratory for Energy, Transport, and Aeronautics (LAETA). Her research interests include applied mechanics and product development. As a member of the Materials and Technological Processes Section of DEMec, she teaches courses related to advanced manufacturing technologies.

LUÍS PAULO REIS (Senior Member, IEEE) received the Licentiate, master's, and Ph.D. degrees in electrical and computers engineering (specializations in informatics and systems, industrial informatics, artificial intelligence/robotics) from the University of Porto, in 1993, 1995, and 2003, respectively. He is currently an Associate Professor with the Department of Informatics Engineering, Faculty of Engineering, University of Porto (FEUP), Portugal, and the Director of LIACC—Artificial Intelligence and Computer Science Laboratory. He has held positions, such as the President of Portuguese Society for Robotics (SPR) and the Vice President of Portuguese Association for Artificial Intelligence (APPIA). His research interests include artificial intelligence, intelligent robotics, multi-agent systems, and intelligent simulation.