Materials & Design 244 (2024) 113086

Contents lists available at ScienceDirect

Materials & Design

journal homepage: www.elsevier.com/locate/matdes

Big data, machine learning, and digital twin assisted additive manufacturing: A review

Liuchao Jin [a,b,c], Xiaoya Zhai [d,a], Kang Wang [e,f], Kang Zhang [a,g], Dazhong Wu [h], Aamer Nazir [i,j], Jingchao Jiang [k,*], Wei-Hsin Liao [a,l,*]

[a] Department of Mechanical and Automation Engineering, The Chinese University of Hong Kong, Hong Kong, China
[b] Department of Mechanical and Energy Engineering, Southern University of Science and Technology, Shenzhen, 518055, China
[c] Shenzhen Key Laboratory of Soft Mechanics & Smart Manufacturing, Southern University of Science and Technology, Shenzhen, 518055, China
[d] School of Mathematical Sciences, University of Science and Technology of China, Hefei, 230026, China
[e] School of Nursing, The Hong Kong Polytechnical University, Hong Kong, China
[f] School of Mechanical Engineering, Zhejiang University, Hangzhou, 310027, China
[g] Nano and Advanced Materials Institute Limited, Hong Kong Science Park, Hong Kong, China
[h] Department of Mechanical and Aerospace Engineering, University of Central Florida, Orlando, 32816, FL, USA
[i] Department of Mechanical Engineering, King Fahd University of Petroleum & Minerals, Dhahran, 31261, Saudi Arabia
[j] Interdisciplinary Research Center for Advanced Materials, King Fahd University of Petroleum & Minerals, Dhahran, 31261, Saudi Arabia
[k] Department of Engineering, University of Exeter, Exeter, United Kingdom
[l] Institute of Intelligent Design and Manufacturing, The Chinese University of Hong Kong, Hong Kong, China

ARTICLE INFO

Keywords:
Additive manufacturing
Big data
Machine learning
Digital twin
Data-driven

ABSTRACT

Additive manufacturing (AM) has undergone significant development over the past decades, resulting in vast amounts of data that carry valuable information. Numerous research studies have been conducted to extract insights from AM data and utilize it for optimizing various aspects such as the manufacturing process, supply chain, and real-time monitoring. Data integration into proposed digital twin frameworks and the application of machine learning techniques is expected to play pivotal roles in advancing AM in the future. In this paper, we provide an overview of machine learning and digital twin-assisted AM. On one hand, we discuss the research domain and highlight the machine-learning methods utilized in this field, including material analysis, design optimization, process parameter optimization, defect detection and monitoring, and sustainability. On the other hand, we examine the status of digital twin-assisted AM from the current research status to the technical approach and offer insights into future developments and perspectives in this area. This review paper aims to examine present research and development in the convergence of big data, machine learning, and digital twin-assisted AM. Although there are numerous review papers on machine learning for additive manufacturing and others on digital twins for AM, no existing paper has considered how these concepts are intrinsically connected and interrelated. Our paper is the first to integrate the three concepts big data, machine learning, and digital twins and propose a cohesive framework for how they can work together to improve the efficiency, accuracy, and sustainability of AM processes. By exploring latest advancements and applications within these domains, our objective is to emphasize the potential advantages and future possibilities associated with integration of these technologies in AM.

1. Introduction

Additive manufacturing (AM), also known as 3D printing, has revolutionized the manufacturing industry by offering unprecedented design freedom [1–5], reducing material waste [6–11], and enabling the production of complex geometries that were once impractical or impossible with traditional manufacturing methods [12–21]. This transformative technology has found applications in various sectors, including aerospace [22–31], automotive [32–40], healthcare [41–54], food industry [55–69], and even construction industry [70–83]. As AM contin-

* Corresponding authors.
E-mail addresses: j.jiang2@exeter.ac.uk (J. Jiang), whliao@cuhk.edu.hk (W.-H. Liao).

https://doi.org/10.1016/j.matdes.2024.113086
Received 15 March 2024; Received in revised form 26 May 2024; Accepted 11 June 2024
Available online 25 June 2024

ues to evolve and gain wider adoption in various industries, the focus has shifted towards optimizing the manufacturing process, enhancing product quality, and accurately predicting material properties [84,85]. The complex nature of AM, with its intricate geometries, diverse materials, and intricate interplay of process parameters, poses challenges in achieving consistent and reliable outcomes. To address these challenges, the integration of advanced data-driven technologies such as big data analytics, machine learning (ML), and digital twin (DT) simulations becomes crucial. The vast amount of data generated during the AM process provides valuable insights into process performance, material behavior, and product characteristics. By harnessing big data analytics, these data can be analyzed and interpreted to identify patterns, correlations, and hidden trends that may impact the final product quality.

Big data plays a pivotal role in AM by enabling the collection, storage, and analysis of vast amounts of data generated during the manufacturing process [86,87]. By leveraging big data analytics techniques, valuable insights and patterns can be extracted so that they can be used to optimize process parameters [88–90], monitor product quality [91], and improve overall performance [92]. The utilization of big data in AM has the potential to enhance efficiency, reduce costs, and facilitate innovation.

In recent years, machine learning, a subset of artificial intelligence (AI), has also emerged as a game-changer in the AM domain. ML algorithms and techniques enable computers to learn from data patterns and make data-driven decisions [93], optimizing manufacturing processes [94], enhancing product quality [95], and reducing costs [96]. The integration of machine learning methods into AM has opened up new possibilities for material analysis, design optimization, process optimization, defect detection, real-time monitoring, and sustainable manufacturing [97–99].

Additionally, the concept of digital twins has emerged as a transformative technology in the manufacturing industry [100–102]. A digital twin is a virtual representation of a physical object or system, capturing its behavior, performance, and lifecycle in real-time. This technology has found diverse applications in healthcare [103–108], smart cities [109–112], and, more importantly, AM [113–115]. Digital twins enable real-time monitoring, predictive maintenance, and optimization of AM processes, paving the way for data-driven decision-making and increased operational efficiency.

There have been a lot of review papers exploring the application of these three techniques in AM [116–127]. (1). For big data, Bi et al. [90] conducted a comprehensive review of the integration of big data in AM, highlighting its potential impact on design, production, and supply chain processes. They explored how big data analytics can effectively handle the vast data generated by AM, benefiting both research and production. Additionally, big data methods were identified as aiding designers, engineers, and customers through valuable information collection. Wang & Alexander [128] reviewed the utilization of big data in AM, emphasizing its influence on supply chains and production efficiency. They explored the advantages, applications, and technological advancements of AM, including its limitations and cybersecurity considerations. Additionally, the integration of big data and the application of big data analytics in AM were discussed to underscore their significance in enhancing the overall AM process. (2). For machine learning, Wang et al. [98] examined the use of machine learning in AM. They explored how machine learning enhances various aspects of AM, from design optimization to production quality assessment and data security. Meng et al. [129] extensively assessed the utilization of machine learning in AM, categorizing applications like parameter optimization and anomaly detection into distinct machine learning tasks such as regression, classification, and clustering. Qin et al. [130] conducted an in-depth review of the role of machine learning in addressing challenges within AM. They recognized the potential of AM for revolutionizing manufacturing and emphasized the obstacles related to complex systems, product quality, and adoption. They employed systematic methods, including keyword co-occurrence and cluster analysis, to analyze literature on various aspects of AM, such as design for AM, material analytics, monitoring, defect detection, property prediction, and sustainability. Guo et al. [131] addressed the challenge of interpreting machine learning outcomes within the context of complex thermodynamics governing AM. To address this, the concept of physics-informed machine learning was introduced, integrating data-driven methods with underlying physical principles. Chinchanikar et al. [132] provided a comprehensive review of recent advancements in the application of machine learning to AM, with a focus on the aerospace industry. (3). For digital twins, Phua et al. [133] critically examined the application of digital twin technology in the context of metal AM. They explored how digital twins offer a viable solution to the challenges inherent in metal AM, particularly related to part qualification, certification, and optimization. The evaluation encompassed diverse aspects such as modeling, sensing, control, and machine intelligence. They identified a four-level hierarchy for the development of a digital twin for metal AM, highlighting essential components like surrogate modeling, in-situ sensing, hardware control systems, and intelligent control policies. Zhang et al. [134] delved into the potential of digital twin applications in AM. They recognized the challenges posed by the trial-and-error approach to achieve optimal structural integrity and mechanical properties in AM-produced components. They proposed that digital twins could address these challenges by offering a comprehensive digital representation of production systems or products. Digital twins were identified as a potential solution to enhance part quality, shorten product qualification time, and improve overall production efficiency. Chen et al. [135] proposed a novel, service-oriented framework for AM digital twin development, addressing challenges stemming from the uniqueness of each AM process. They outlined the discrepancies in defining and developing AM digital twins, which often lead to high costs and low adaptability. To mitigate these issues, They summarized existing AM digital twin approaches and introduces a four-layered framework: service, model, data, and interface. This framework aimed to enhance reusability across different levels of AM digital twin development. Ladani [136] explored the applications of artificial intelligence and machine learning in metal AM. They highlighted the potential synergies between AI and AM due to the vast amount of digital data generated in AM processes. Specifically focusing on powder bed AM technology, they discussed the types and sources of data, potential variabilities in experimental and simulation data, and how these data can be utilized in ML algorithms. They also presented several innovative ideas that demonstrate how combining AI and AM could significantly impact various fields.

Although there are numerous review papers on machine learning for additive manufacturing and others on digital twins for AM, no existing paper has considered how these concepts are intrinsically connected and interrelated. Our paper is the first to integrate the three concepts—big data, machine learning, and digital twins—and propose a cohesive framework for how they can work together to improve the efficiency, accuracy, and sustainability of additive manufacturing processes as demonstrated in Fig. 1. This distinct approach is lacking in current literature, where the interplay between these three elements is often overlooked. By amalgamating the capabilities of big data, machine learning, and digital twin, our review provides an integrated framework that demonstrates their symbiotic relationship. Our comprehensive analysis not only highlights the individual strengths of each technology but also elucidates their collective potential. This inclusive review not only offers insights into their individual significance but also unveils how they synergistically shape the future of AM. In doing so, our paper not only aims to contribute to the academic discourse but also presents a forward-looking perspective that is aligned with the evolving landscape of advanced manufacturing technologies. The objective of this review paper is to provide a comprehensive overview of the current state of research and development in the intersection of big data analytics, machine learning, and digital twin-assisted AM. By examining the latest advancements and applications in these areas, we aim to

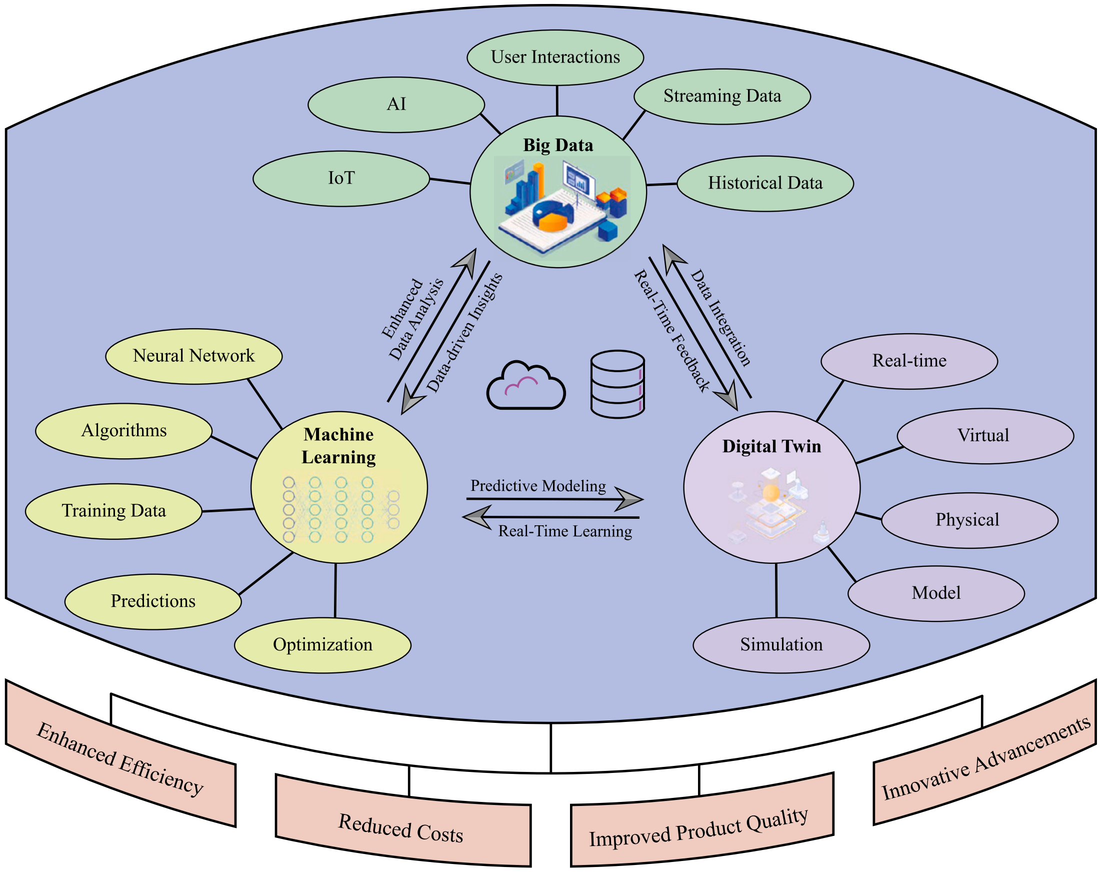

Fig. 1. Interconnected landscape: big data, machine learning, and digital twin.

highlight the potential benefits, challenges, and future prospects of integrating these technologies in the AM process.

The subsequent sections of this review paper are structured as follows: In Section 2, we will provide a detailed discussion of the concepts of big data analytics, machine learning, and digital twin technology, emphasizing their relevance and significance in the AM domain. We will delve into the specific application areas of machine learning in AM in Section 3. This includes material analysis, where machine learning techniques can be employed to optimize material properties and enhance material selection processes. We will also explore design optimization, where geometric and topology optimization methods driven by machine learning can revolutionize how products are designed and manufactured. This section will also delve into the realm of process optimization, discussing how machine learning algorithms can be utilized to achieve better control over AM processes, leading to improved efficiency and reduced defects. Additionally, we will discuss the significance of defect detection and real-time monitoring in ensuring the quality of the AM process. Moreover, we will explore the concept of sustainability in AM, emphasizing how machine learning and digital twin technologies can contribute to environmentally friendly practices through energy consumption modeling, waste reduction, and optimization of support structures. Section 4 will assess the current research status of digital twin-assisted AM and discuss the technical approaches being used to integrate digital twins into the AM workflow. Additionally, we will explore future development directions and perspectives to highlight the potential of this transformative technology in revolutionizing the manufacturing industry. Finally, Section 5 presents a comprehensive discussion on the implications and potential areas of future research, followed by a conclusion. Through this comprehensive review, we aim to highlight the challenges, opportunities, and future prospects of leveraging big data, machine learning, and digital twin technologies in AM. Because big data analysis is usually interspersed with the application of machine learning and digital twins, this review does not list the application of big data analysis in AM as a separate section. By shedding light on the latest advancements and applications, we seek to underscore the potential benefits of these integrated technologies and inspire further research and innovation in this exciting and rapidly evolving field.

2. Basic concepts

In this section, we will explore the basic concepts of AM, big data, machine learning, and digital twins.

2.1. Additive manufacturing

ISO/ASTM categorizes additive manufacturing into seven distinct groups, namely vat photopolymerization, material jetting, binder jetting, powder bed fusion, material extrusion, directed energy deposition, and sheet lamination [137]. In this subsection, we will introduce the concept of AM through reviewing the developments of seven different categories of AM demonstrated in Fig. 2.

2.1.1. Vat photopolymerization

Vat photopolymerization is an AM process that uses a vat of liquid photopolymer resin that is selectively cured (hardened) by exposing it to a UV light source, usually in the range of 350-405 nm [138]. This process is also known as stereolithography (SLA) or digital light processing (DLP) 3D printing. In SLA, a laser is used to selectively cure the resin. In DLP, a digital projector is used to project a pattern of light onto the resin.

The process involves a build platform that is lowered into the vat of liquid photopolymer resin, and a UV light source that selectively cures the resin layer by layer, creating a solid object. Once a layer has been

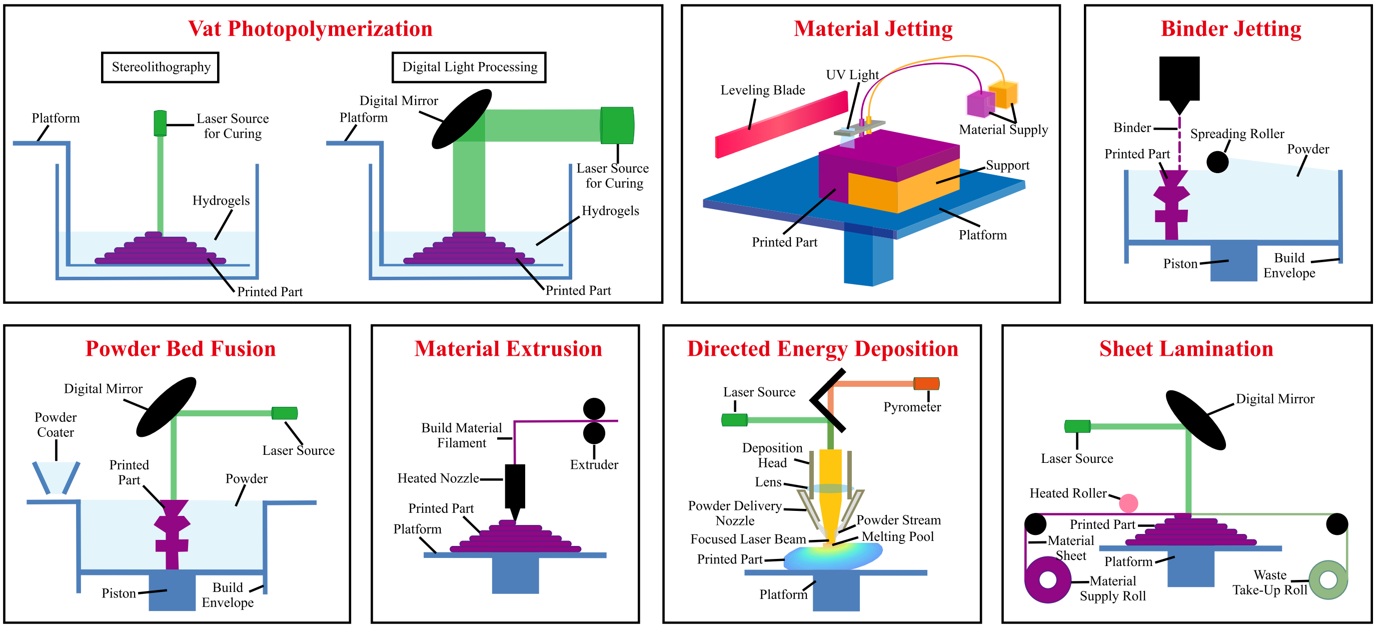

Fig. 2. Additive manufacturing process categories.

cured, the build platform is lowered into the vat by a small amount, typically in the range of 0.05-0.15 mm, and the next layer of resin is spread on top of the cured layer [139]. The process is repeated until the entire object has been printed. After printing is complete, the object is removed from the vat and washed to remove any uncured resin. The object may also be post-processed to smooth or finish the surface, or to add additional features or colors.

Vat photopolymerization produces high-resolution, detailed parts with smooth surfaces and high accuracy. It is commonly used in industries such as jewelry, dentistry, and prototyping. However, the process can be slow compared to other 3D printing techniques, and the cost of the photopolymer resin can be relatively high [140]. In addition, the cured resin may be brittle and have limited mechanical properties, depending on the specific material used [141].

2.1.2. *Material jetting*

Material jetting is a 3D printing technology that uses a print head to deposit small droplets of material onto a build platform. This process is similar to inkjet printing, where tiny droplets of ink are deposited onto paper. In material jetting, the print head can deposit droplets of multiple materials, such as plastics, metals, or ceramics, onto the build platform. The droplets are then cured using heat, light, or other methods to solidify the material and create a 3D object [142].

One of the key advantages of material jetting is its ability to produce parts with very high resolution and accuracy [143]. This makes it well-suited for applications that require fine details, such as jewelry, dental and medical devices, and small mechanical parts. Material jetting also allows for the creation of parts with multiple materials, which can be useful for creating parts with varying properties, such as parts that need to be both rigid and flexible [144]. However, material jetting can be relatively slow compared to other 3D printing technologies, particularly for larger parts [145]. It can also be more expensive, as it typically requires specialized equipment and materials. Despite these limitations, material jetting remains an important 3D printing technology, particularly in industries such as product design, prototyping, and the creation of high-precision parts for aerospace and automotive applications. Ongoing research is also exploring ways to improve the speed, cost, and versatility of material jetting.

2.1.3. *Binder jetting*

Binder jetting is an AM process that uses a binder material to fuse together a powdered material, such as metal, plastic, or ceramic, to create a solid object. It works by depositing a liquid binder onto a thin layer of powder, which then solidifies and binds the particles together. The process is repeated layer by layer until the object is complete. Once the object is printed, it is typically sintered or cured to strengthen the final product. Binder jetting is often used in industries such as aerospace, automotive, and medical device manufacturing. It has been used to produce parts such as engine components, dental implants, and surgical instruments [146].

One of the main advantages of binder jetting is its ability to print with a wide range of materials, including metals, plastics, and ceramics. This makes it a versatile manufacturing method for creating a variety of parts and components. While binder jetting is a relatively fast process, it does have some limitations. The resolution and accuracy of the final product can be lower than other 3D printing methods, which may limit its use for certain applications [147]. Additionally, post-processing steps such as sintering or curing may be required to strengthen the final product [148]. Ongoing research is focused on improving the resolution and accuracy of the final product, as well as developing new materials and applications for binder jetting [149].

2.1.4. *Powder bed fusion*

Powder bed fusion is a 3D printing technology that uses a laser or electron beam to selectively melt or fuse together layers of powdered material, such as metal, plastic, or ceramic, to create a solid object. There are two main types of powder bed fusion: selective laser melting (SLM) and electron beam melting (EBM). SLM uses a high-powered laser to selectively melt the powder, while EBM uses an electron beam to melt the powder. The process begins with a thin layer of powder spread evenly over a build platform. A laser or electron beam is then used to selectively melt or fuse together the powder in the desired areas, creating a solid layer. The build platform then moves down by a layer thickness, and the process is repeated layer by layer until the object is complete. Powder bed fusion is typically used to create small to medium-sized parts, although larger parts can be created by using multiple machines or by printing and joining individual components together. The process can be relatively slow compared to other 3D printing technologies, particularly for parts with complex geometries [150].

One of the main advantages of powder bed fusion is its ability to create parts with very high accuracy and resolution [151]. This makes it an excellent choice for creating parts with intricate geometries and fine details. Additionally, powder bed fusion can be used with a wide range of materials, including metals [152], plastics [153], and ceramics [154]. Powder bed fusion has some limitations, including the need for post-processing steps such as heat treatment to improve the strength of the final product [155–159]. Additionally, the process can be relatively expensive, as it requires specialized equipment and materials [160]. Ongoing research is focused on multi-material printing [161], reducing residual stresses and distortions [162], and new materials development [163].

2.1.5. Material extrusion

Material extrusion is a 3D printing technology that uses a heated nozzle to melt and extrude a thermoplastic material, such as ABS or PLA, layer by layer, to create a solid object. The process begins with a 3D model that is sliced into thin layers using 3D printing software. The printer then extrudes the melted material through a nozzle, building up the object layer by layer. Material extrusion is typically used for creating prototypes, low-volume production runs, and one-off parts. It is also commonly used in education and hobbyist applications, as desktop 3D printers using material extrusion technology can be relatively affordable and easy to use [164].

One of the main advantages of material extrusion is its ability to print with a wide range of thermoplastic materials, including PLA, ABS, PETG, and nylon [165]. This makes it a versatile manufacturing method for creating a variety of parts and components. However, material extrusion does have some limitations. The resolution and accuracy of the final product can be lower than other 3D printing methods, particularly for parts with complex geometries [166]. Additionally, the layer-by-layer construction of parts can result in a visible texture on the final product [167]. Despite these limitations, material extrusion remains an important 3D printing technology, particularly for creating simple, functional parts quickly and affordably. Ongoing research is focused on bioprinting and tissue engineering [168–173], multi-axis printing [174–178], as well as advanced filament materials that can be used [179–181].

2.1.6. Directed energy deposition

Directed energy deposition is a 3D printing technology that uses a high-energy heat source, such as a laser or electron beam, to melt and fuse together metal powders or wire feedstock to create a solid object. There are two main types of directed energy deposition: laser-based and electron beam-based. Laser-based directed energy deposition uses a high-powered laser to melt and fuse the metal material, while electron beam-based directed energy deposition uses an electron beam to achieve the same result. The process begins with a 3D model that is sliced into thin layers using 3D printing software. The printer then directs the heat source to melt and fuse the metal material onto the build platform, layer by layer, until the object is complete. Directed energy deposition can be used with a wide range of metal materials, including titanium, stainless steel, and aluminum [182]. It is often used in industries such as aerospace, automotive, and medical device manufacturing to create complex, high-performance parts and components.

One of the advantages of directed energy deposition is its ability to create large, complex parts with a high degree of accuracy and precision [183]. It is also well-suited for repairing or adding material to existing parts, making it a popular choice for maintenance and repair applications. However, directed energy deposition does have some limitations. The process can be relatively slow compared to other 3D printing technologies, particularly for parts with complex geometries. Additionally, post-processing steps such as machining or polishing may be required to achieve the desired surface finish and tolerances [184]. Despite these limitations, directed energy deposition remains an important 3D printing technology, particularly for creating complex, high-performance metal parts and components. Ongoing research is focused on improving the speed and efficiency of the process, as well as expanding the range of materials and geometries that can be used.

2.1.7. Sheet lamination

Sheet lamination is a 3D printing technology that involves bonding together thin layers of material, usually paper or plastic, to create a solid object. The process begins with a 3D model that is sliced into thin layers using 3D printing software. The printer then applies adhesive to each layer and bonds them together, layer by layer, until the object is complete. Sheet lamination is a relatively low-cost and low-tech 3D printing technology, making it accessible to a wide range of users. It is often used in educational settings, such as schools and libraries, as well as for rapid prototyping and small-scale production runs [185].

One of the main advantages of sheet lamination is its low cost and accessibility [186]. The materials used are relatively inexpensive, and the process does not require sophisticated equipment or technical expertise. This makes it a popular choice for users who are new to 3D printing or who have limited resources. Another advantage of sheet lamination is its ability to create objects with full-color graphics or images [187]. This is achieved by printing the color or image onto the surface of each layer before bonding them together. This makes it well-suited for creating models or prototypes of products that require detailed visual representations. However, sheet lamination also has some limitations. The resolution of the final object is typically lower than other 3D printing technologies, as the layers are relatively thick compared to other methods [188]. Additionally, the materials used may not be as strong or durable as those used in other methods [189], which limits the range of applications for which it is suitable.

Despite these limitations, sheet lamination remains an important 3D printing technology, particularly for applications that require full-color graphics or images. Ongoing research is focused on improving the resolution and strength of the final product, as well as expanding the range of materials that can be used. Newer techniques, such as hybrid lamination, which combines sheet lamination with other AM or subtractive manufacturing techniques, are also being explored to further improve the capabilities of the technology.

The comparison of seven different kinds of AM technologies, including advantages, disadvantages, materials, and applications, is listed in Table 1.

Most AM systems typically align with one of the seven established categories outlined in current industry standards. However, there are latest exceptions to this categorization [255], such as cold spray technology. Cold spray, unlike traditional AM methods, involves the deposition of metal or composite particles onto a substrate at supersonic velocities, forming a solid build-up without melting the material. This could require an update to the ISO/ASTM 52900 standard.

2.2. Big data

Big data refers to the presence of extremely large and complex data sets that are challenging to manage, process, and analyze using traditional data processing tools and methods [256]. Big data is characterized by its volume (enormous amounts of data), velocity (high speed of data generation and processing), and variety (diversity of data types and sources) [257]. The term “big data” encompasses various entities, including social phenomena, information assets, data sets, analytical techniques, storage technologies, processes, and infrastructures. Microsoft describes big data as the application of “serious computing power” to massive amounts of information, while the National Institute of Standards and Technology (NIST) emphasizes the need for a “scalable architecture for efficient storage, manipulation, and analysis” when defining big data [258]. The development histories of big data are listed in Table 2 and the core concept of big data can be expressed through the following key aspects:

Table 1
Comparison of additive manufacturing technologies.

Process	Advantages	Disadvantages	Printable Materials	Applications	Ref
Vat photopoly-merization	• high-resolution • smooth surfaces • high accuracy	• long process time • expensive • weak parts	pure photopolymer or pure waxes, or they can contain ceramic or metal particles	Industries such as jewelry, dentistry, and prototyping	[190–199]
Material jetting	• high accurate parts • smooth surface • low wastage	• weak parts • expensive • material limitation	pure photopolymer or pure waxes, or they can contain ceramic or metal particles	Industries such as product design, prototyping, high-precision parts for aerospace and automotive applications	[200–204]
Binder jetting	• create large, complex parts quickly • low cost	• low resolution • brittle parts	metals, ceramics, and polymers	Industries such as aerospace, automotive, and medical device manufacturing	[205–214]
Powder bed fusion	• high-resolution • wide range of materials used	• need for post processing steps • expensive • long process time	metals including titanium alloys, stainless steel, aluminum alloys; polymers including nylon, PA	Rapid prototyping of parts; aerospace components; high complex and delicate objects	[215–233]
Material extrusion	• wide range of materials used • easy to use • low cost	• low resolution • visible texture surface	thermoplastic polymer, including PLA, TPU, ABS; elastomers; graphite; metals	Creating prototypes, low-volume production runs, and one-off parts	[234–242]
Directed energy deposition	• create large, complex parts • high-resolution • easy for repairing or adding material to existing parts	• long process time • post processing steps • material limitation	metals including titanium alloys, stainless steel, aluminum alloys	Industries such as aerospace, automotive, and medical device manufacturing to create complex, high-performance parts and components	[243–251]
Sheet lamination	• easy to use • low cost	• low resolution • weak parts • material limitation	paper, plastic film, metal foil, composites including carbon fiber composites, glass fiber composites	Rapid prototyping and small-scale production runs; educational settings	[252–254]

- "Volume," "Velocity," and "Variety": These terms describe the characteristics of the involved information, highlighting the vast amounts of data, the high speed at which it is generated and processed, and the diverse types and sources of data.
- Specific "Technology" and "Analytical Methods": Big data necessitates unique requirements to effectively utilize such vast amounts of information, including specialized technologies and analytical methods designed to handle the complexities and challenges associated with big data.
- Transformation into insights and creation of economic value: The primary impact of big data on companies and society lies in its ability to extract valuable insights from the data, leading to the generation of economic value. By leveraging the power of big data analytics, organizations can uncover meaningful patterns, trends, and correlations within the data, enabling informed decision-making and driving innovation.

Overall, big data represents a paradigm shift in the way data is managed and analyzed, emphasizing the importance of scalable technologies, advanced analytics, and the potential for generating valuable insights and economic benefits.

2.3. Machine learning

Machine learning is a specialized field focused on developing and understanding methods that enable machines to "learn" and improve their performance on specific tasks by leveraging data [269,270]. It is a subfield of artificial intelligence that emphasizes the creation of algorithms and models capable of autonomously learning, making predictions, and making decisions without explicit programming [271]. ML involves the development of computer systems that can analyze and interpret large volumes of data, identify patterns, and extract meaningful insights to enhance their performance over time [272]. ML tasks are typically categorized into different types based on learning approaches (supervised/unsupervised), learning models (classification, regression, clustering, dimensionality reduction), or the specific algorithms employed for a given task. The evolution histories of ML are demonstrated in Table 2.

Machine learning models can be classified into various types based on their learning algorithms, objectives, and underlying mathematical techniques. Some commonly used machine learning models include:

- Supervised Learning Models: Linear Regression, Logistic Regression, Decision Trees, Random Forest, Support Vector Machines, Gradient Boosting models (e.g., XGBoost, LightGBM), Neural Networks (e.g., Multi-layer Perceptron).
- Unsupervised Learning Models: K-means Clustering, Hierarchical Clustering, Principal Component Analysis (PCA), Gaussian Mixture Models (GMM), Self-Organizing Maps (SOM), Autoencoders.
- Reinforcement Learning Models: Q-Learning, Deep Q-Networks (DQN), Policy Gradient Methods, Actor-Critic Methods, Monte Carlo Tree Search (MCTS).
- Deep Learning Models: Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Generative Adversarial Networks (GAN), Transformers.
- Bayesian Models: Naive Bayes, Bayesian Networks, Hidden Markov Models (HMM), Gaussian Processes.
- Ensemble Learning Models: Bagging (Bootstrap Aggregating), Boosting (e.g., AdaBoost, Gradient Boosting), Stacking, Voting.
- Dimensionality Reduction Models: Principal Component Analysis (PCA), t-Distributed Stochastic Neighbor Embedding (t-SNE), Linear Discriminant Analysis (LDA).
- Recommender Systems Models: Collaborative Filtering, Content-Based Filtering, Hybrid Approaches.

These models represent a range of techniques used in machine learning, each with its own strengths and areas of application. Researchers and practitioners select appropriate models based on the specific problem they are addressing and the characteristics of their data.

Table 2
Evolution of big data, machine learning, and digital twins.

Time	Big Data	Machine Learning	Digital Twin
1950-1980	• Development of relational database systems like IBM's IMS and Oracle. • Creation of the World Wide Web by Tim Berners-Lee in 1989.	• Development of the perceptron algorithm by Frank Rosenblatt [259] in 1957, one of the earliest machine learning algorithms inspired by biological neurons. • Introduction of decision tree learning algorithms like ID3 by Ross Quinlan [260] in the 1980s.	– – – – – – –
1980-2000		• Introduction of support vector machines (SVM) by Vladimir Vapnik [261] in the 1990s, providing a powerful method for classification and regression tasks.	
2000-2010	• Google's publication of the MapReduce and GFS papers in 2004, laying the groundwork for distributed computing and the Hadoop ecosystem. • Apache Hadoop project launch in 2006, providing an open-source framework for distributed storage and processing of big data.	• Emergence of ensemble learning methods like random forests [262] and gradient boosting machines [263], improving predictive performance by combining multiple models.	• Introduction of the "Digital Twin" concept by Michael Grieves [264] in 2002, highlighting the potential for virtual replicas of physical assets. • Adoption of simulation and modeling techniques in manufacturing and aerospace industries for virtual prototyping and testing.
2010-2020	• Introduction of Apache Spark in 2014, offering faster and more versatile big data processing compared to MapReduce. • Growth of cloud computing platforms like Amazon Web Services (AWS), Google Cloud Platform (GCP), and Microsoft Azure.	• Breakthroughs in deep learning, including the development of convolutional neural networks (CNNs) [265] for image recognition and recurrent neural networks (RNNs) [266] for sequential data. • Introduction of the Transformer architecture by Vaswani et al. [267] in 2017, revolutionizing natural language processing (NLP) by enabling efficient training on large datasets through attention mechanisms.	• Implementation of digital twins in industries like energy, healthcare, and transportation for predictive maintenance and performance optimization. • Development of IoT platforms and sensors for collecting real-time data from physical assets and environments.
2020-	• Advancements in real-time data processing technologies like Apache Kafka and Apache Flink.	• Continued research in areas like reinforcement learning, generative adversarial networks (GANs) [268], and self-supervised learning. • Advanced multimodal models like GPT, DALL-E, Sora demonstrated integration across text, images, and other data types, enabling more sophisticated and contextually aware outputs.	• Expansion of digital twins into smart cities and urban planning, enabling holistic management of infrastructure and resources. • Integration of AI and machine learning into digital twins for advanced analytics, anomaly detection, and scenario simulation.

2.4. Digital twin

The initial definition of Digital Twin was formulated by NASA (Table 2), describing it as "an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that utilizes the best available physical models, sensor updates, fleet history, etc., to replicate the life of its flying counterpart" [273]. According to this definition, the DT consists of three principal components: (i) physical objects in the Physical World, (ii) digital objects in the Digital World, and (iii) the connections that link the digital and physical elements together.

While the research on DT primarily focused on the aerospace field initially, in 2013, there were initial studies exploring its application in the manufacturing sector. Lee and colleagues proposed the DT to be the virtual representation of production resources, extending beyond just the product itself. This sparked a discussion about the role of DT in advanced manufacturing environments, particularly in relation to Industry 4.0, which encompasses core technologies like big data analytics and cloud platforms [274]. This ongoing debate forms the context for the present work.

It became evident that the significance of DT in the manufacturing industry lies in its definition as the virtual counterpart of physical devices. These virtual representations are based on semantic data models and enable simulations across various disciplines. They facilitate not only static prognostic assessments during the design stage but also the continuous updating of the virtual representation through real-time synchronization with sensed data. This enables the representation to reflect the current state of the system, facilitating real-time optimization, decision-making, and predictive maintenance based on the sensed conditions.

A widely acknowledged and utilized concept of DT is presented in [275]. According to this concept, a DT is a comprehensive, physical, unified, and stochastic simulation of an as-built system, made possible by the utilization of a Digital Thread. The Digital Thread incorporates the best available models (physical, behavioral, etc.) and updated information to emulate the life cycle, actions, and operations of its real counterpart [276]. This concept is widely embraced because it offers a broad and inclusive definition, encompassing all the key characteristics and elements of a DT, while also governing its performance. Importantly, unlike the initial NASA definition, this concept can be applied to various development areas, as its primary objective is not limited to replicating the life of an aircraft but rather capturing the life cycle of any element, product, or system that serves as its physical twin.

3. Machine learning assisted additive manufacturing

3.1. Overview

Machine learning has revolutionized AM by enabling advancements in defect detection, process parameter optimization, design optimization, material analysis, and sustainability. Through the application of various machine learning algorithms such as k-nearest neighbors [277], support vector machines [278,279], deep learning [280,281], decision trees [282], and genetic algorithms [283], researchers and industry professionals have been able to improve the quality, efficiency, and overall performance of AM processes. By harnessing the power of machine learning, they have successfully detected defects [277–279,284], optimized process parameters [283,285–293], generated optimized designs [294–301], analyzed materials [302–304], and made significant strides towards sustainable manufacturing practices [305,306]. These developments showcase the tremendous potential of machine learning in transforming AM into a more reliable, cost-effective, and environmentally friendly production method.

Furthermore, machine learning algorithms play a pivotal role in refining AM processes by adjusting parameters based on insights learned from historical data, thus ensuring higher quality outputs and improved operational efficiency [277–279,281,282,284,307–311]. These algorithms significantly augment defect detection mechanisms and quality assurance practices by enabling automated inspection of manufactured parts, drastically reducing human errors and time spent on manual assessments [277–279,281,284,307–310]. By leveraging operational data patterns, machine learning can foresee potential equipment failures, facilitating a proactive approach to maintenance and consequently reducing unexpected downtime [277–279,281,284,307–310]. Machine learning also accelerates the materials research segment of AM by predicting the properties of potential materials, substantially speeding up the discovery and testing processes [282,311]. In addition, the amalgamation of machine learning with design tools introduces an avenue for design optimization in AM, taking into account factors like manufacturability, material usage, and performance characteristics [294–301]. Machine learning also extends its capabilities to real-time monitoring of AM processes, ensuring consistency and quality of production by identifying and rectifying anomalies instantaneously [277–279,281,284,307–310]. Finally, by optimizing manufacturing processes and improving defect detection, machine learning has a substantial impact on waste reduction, leading to considerable cost savings and environmental benefits [283,285–293,312–327]. Thus, the confluence of machine learning and AM unlocks a realm of opportunities, leading to more efficient processes, improved quality, and innovative possibilities in design and materials. In this section, we endeavor to present a comprehensive overview of the applications of machine learning techniques within the diverse domains of AM processes. This synthesis draws on the most recent scholarly literature, offering a critical examination of current trends. Additionally, this discussion includes our insightful projections on promising and impactful research directions that are either currently under active exploration or possess significant potential for the future development of AM.

3.1.1. Research domain

In this section, we will explore the wide-ranging applications of machine learning in AM. Machine learning techniques have revolutionized the AM landscape, offering significant advancements in material analysis and selection, design optimization, process parameter optimization, defect detection and real-time monitoring, and sustainability as shown in Fig. 3. By harnessing the power of machine learning algorithms, researchers and industry professionals have been able to enhance the quality, efficiency, and overall performance of AM processes.

One of the primary applications of machine learning in AM is in the domain of defect detection and real-time monitoring. With the ability to analyze large volumes of data and detect subtle patterns, machine learning algorithms enable automated inspection of manufactured parts, ensuring high-quality outputs and minimizing human errors [277]. These algorithms can quickly identify defects or anomalies in the manufacturing process, allowing for timely corrective actions [278,279,284]. By reducing the reliance on manual inspection and streamlining the quality assurance process, machine learning significantly improves the efficiency and reliability of AM [281,307–310].

Another crucial research domain where machine learning has made significant contributions is process parameter optimization. AM processes involve a multitude of parameters that can affect the final product's quality and performance. Machine learning algorithms can analyze historical data on process parameters and their corresponding outcomes to identify the optimal parameter settings [283,285–293]. By leveraging insights learned from the data, machine learning algorithms can adjust the parameters in real-time, leading to improved process efficiency, reduced material waste, and enhanced product quality [312–340].

In addition to defect detection and process parameter optimization, machine learning techniques have found applications in design optimization [294–301]. By integrating machine learning algorithms with design tools, engineers and designers can explore vast design space

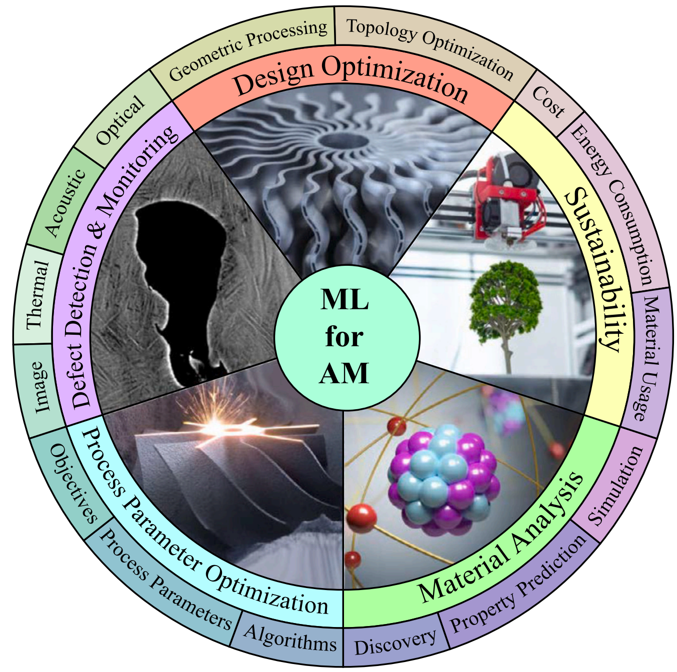

Fig. 3. Research domain of machine learning in additive manufacturing.

and identify optimal designs for AM. Machine learning algorithms can consider various factors such as manufacturability, material usage, and performance characteristics to generate designs that are both functional and efficient in terms of AM processes. This approach enables the creation of complex geometries and customized designs that maximize the capabilities of AM.

Material analysis is another domain where machine learning plays a vital role in AM [302–304]. Machine learning algorithms have been employed to analyze the properties of different materials used in AM processes. By considering various material characteristics, such as strength, thermal properties, and chemical composition, machine learning models can assist in identifying the most suitable materials for specific applications, optimizing material selection, and even predicting material behavior under different conditions.

Furthermore, sustainability is a growing concern in the field of AM, and machine learning can contribute to addressing these challenges [305,306,341–347]. Machine learning is being employed to enhance sustainability in AM by reducing material waste and energy consumption. By predicting potential sources of waste and inefficiencies in the process, machine learning models can guide process improvements that lead to a more environmentally friendly and sustainable AM practice.

In conclusion, machine learning has significantly advanced AM by enhancing defect detection, process parameter optimization, design optimization, material analysis, and sustainability. It has greatly improved the quality, efficiency, and sustainability of AM processes, offering new opportunities for complex designs. Continued research in this field holds great potential for further advancements in AM with the help of machine learning techniques.

3.1.2. Machine learning methods

Machine learning methods commonly used in AM encompass various approaches. These include supervised learning methods such as k-Nearest Neighbors (k-NN) [322], Support Vector Machines (SVM) [322,330], Random Forests (RF) [322], Decision Trees (DTree) [295,297,304,346], Linear Regression (LR) [322], and Gaussian Process Regression (GPR) [322,327]. Deep Learning (DL) methods, such as neural networks (NN) [296,299–301] and Convolutional Neural Networks (CNN) [337,339], are also prevalent. Gaussian Process (GP) methods utilize Gaussian distributions for regression and optimization tasks [324,325,331,333–335]. Additionally, Particle Swarm Optimization (PSO) [342] and Bayesian Networks (BN) [338] are employed. These methods are utilized for defect detection, real-time monitoring, quality assessment, process parameter optimization, design optimization, material analysis, and sustainability aspects in AM.

The selection of a specific method depends on the goals and requirements of the application at hand. In supervised learning, machine learning models are used to predict the properties of interest based on a labeled dataset. The model is trained on a collection of data-label pairs. Data can take various forms, such as fields, vectors, images, and graphs. Supervised learning is typically divided into two main categories: regression and classification, depending on the type of labels. In the context of data-driven additive manufacturing, supervised learning is often employed to establish relationships between parameters and performance. The data set usually describes a shape, represented by its parameterization, and describes the quantity of interest, such as elastic components or response spectra. A key motivation for supervised learning is to replace resource-intensive cell evaluation processes with faster alternative models. The types of models are primarily based on neural networks, sometimes also based on Gaussian Processes. Once trained on a large dataset, data-driven models can instantly predict the properties of unseen cells.

In contrast to supervised learning, unsupervised learning extracts information from unlabeled data and is mainly applied to learning the complex processes of additive manufacturing. Common unsupervised learning models include autoencoders, variational autoencoders, and generative adversarial networks. An autoencoder is a type of neural network that uses an encoder-decoder architecture to extract low-dimensional latent variables from input data. Variational autoencoders are a type of deep generative model that generates new data by sampling low-dimensional latent variables that follow well-defined distributions. Therefore, compared to traditional additive manufacturing optimization, the latent representations learned by variational autoencoders are often more efficient and interpretable, especially considering high design complexity and degrees of freedom. Semi-supervised learning is a machine learning method trained on partially labeled data so that the model can predict the labels of unlabeled data.

Compared to pure supervised and unsupervised learning, the advantage of semi-supervised learning lies in its ability to leverage additional information provided by unlabeled data to improve model performance. Semi-supervised learning bridges the gap between these two approaches by incorporating both labeled and unlabeled data into the training process. The presence of unlabeled data allows the model to learn from a larger dataset, capturing more comprehensive and nuanced patterns within the data. This can be particularly beneficial in scenarios where obtaining labeled data is challenging or costly, but unlabeled data is abundant.

The core idea of reinforcement learning is to simulate an agent interacting with an environment, learning how to maximize cumulative rewards by trying different actions. Typically, reinforcement learning is used to solve sequential decision-making problems, where the agent needs to select the optimal action among a series of decisions to achieve specific goals.

The machine learning methods that are commonly used in AM are listed in Fig. 4 and the machine learning methods for different research domains and different goals are shown in Table 3.

3.1.3. Data limitation in additive manufacturing

Collecting extensive datasets for AM processes presents a significant challenge due to various factors, including process diversity and the resource-intensive nature of experimentation. Unlike sectors like retail or streaming services, where vast amounts of data are readily available from millions of customers, manufacturing, including AM, is characterized by its segmented nature. Moreover, within the realm of AM, there exist numerous categories based on material, technology, and hardware, further complicating data collection efforts. Consequently, AM primarily deals with what can be termed as "small data."

The limitations posed by small data in AM necessitate the development of techniques to overcome these challenges. Machine learning models typically perform more robustly when trained on large volumes of data. Therefore, strategies must be devised to augment datasets and address data imbalances, enabling the effective utilization of ML algorithms for process optimization and quality control. Several approaches have been proposed to mitigate data limitations in AM [357], including experiment modularization, physics-informed machine learning, data augmentation, synthetic data generation, transfer learning, data-centric machine learning models.

3.2. Material analysis

AM has revolutionized the manufacturing industry by enabling the production of complex parts with unprecedented design freedom. Various materials, including polymers [358–369], metal [370–376], ceramics [377–381], concrete [382–384], ice [385–387], wood [388–390], and even sugar [391,392], as well as their combinations, are utilized in AM applications, and ongoing efforts are focused on developing new materials to expand the capabilities of the technology. The choice of materials in AM significantly impacts the performance and properties of the final parts [393]. To optimize the manufacturing process and ensure high-quality results, it is crucial to analyze and understand the relationships between material chemistry, material characteristics, and the performance of the printed parts using the available material data.

Most of the current material analysis for AM using machine learning focuses on metal powder material analysis in metal 3D printing [394]. This is because metals AM has brought about a paradigm shift in the manufacturing of metal components, offering unique advantages such as the simultaneous fabrication of materials and parts using a single machine and the ability to produce highly complex geometries. However, ensuring the consistency and quality of parts and materials remains an ongoing challenge in many applications of metal AM. To address this challenge, Integrated Computational Materials Engineering (ICME) approaches have been instrumental in accelerating the development and adoption of materials technologies [395–398]. Traditionally, ICME approaches have relied on physics-based experimental data and simulations to understand the relationship between material properties and processing conditions [399]. However, in the context of metals AM, where the physics are still being discovered, the development of computationally feasible physics-first ICME approaches remains an open challenge. Additionally, the wealth of data generated in the field of AM presents its own challenges, as the ability to store and analyze this data is being pushed to its limits. Nevertheless, this abundance of data has sparked a paradigm shift towards incorporating machine learning into ICME approaches, enabling the extraction of valuable insights and the development of comprehensive and computationally feasible models. Motaman et al. [400] demonstrated a multi-scale and multi-physics ICME approach, highlighting the linkages between the different stages of the process–structure–properties–performance chain. They also proposed a hybrid physics-based and data-driven strategy for optimal component design. Wang & Xiong [401] developed a method to optimize the composition of pre-alloyed powders in AM by employing a CALPHAD-based ICME framework. The high-strength low-alloy steel was used as a case study, and process–structure–property relationships were analyzed for various compositions. Critical properties, including yield strength, impact transition temperature, and weldability, were evaluated to optimize the composition. The optimized composition increased the probability of successful AM builds by 44.7%. While current machine learning applications in material analysis for AM largely focus on metal powder characterization, further exploration, and research are needed to unlock the full potential of leveraging machine learning for material analysis, including analyzing material composition for alloy

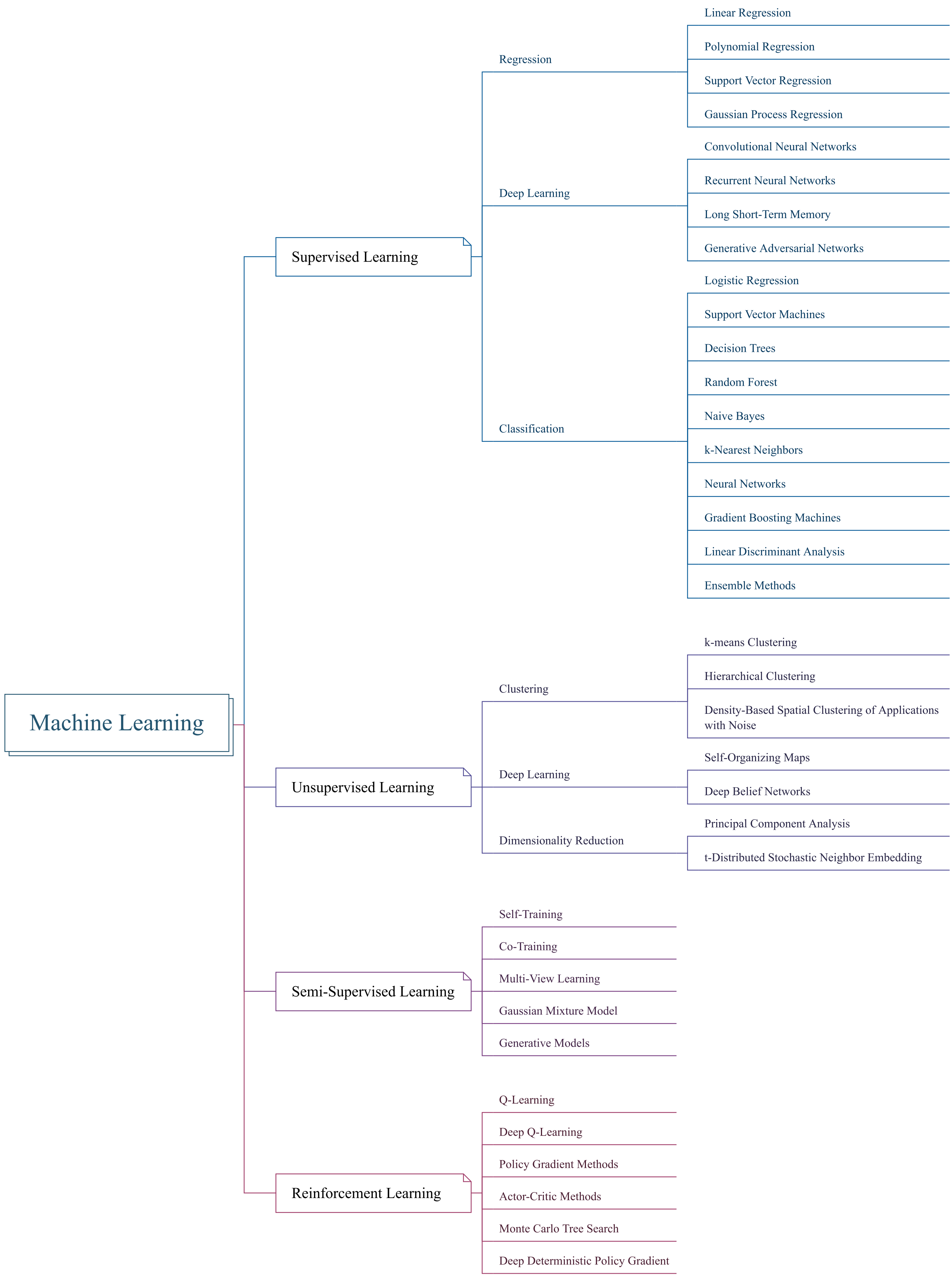

Fig. 4. Machine learning methods for additive manufacturing.

Table 3
Application of machine learning in additive manufacturing.

Direction	AM processes	Materials	Data type	ML methods	Goal	Refs
Defect detection & real-time monitoring	Powder bed fusion	SS316L	acoustic emission	k-NN, DL, GPR	quality	[277]
			images	CA	quality	[279]
			images	SVM, ANN	quality	[278]
			printing parameters	SVM	quality	[284]
		SS304L	acoustic emission	SVM	quality	[307]
		Ti-6Al-4V	images	SVM	quality	[308]
			images	SVM, k-NN, ANN	quality	[281]
			images	k-NN, SVM	quality	[309]
			acoustic emission	ANN	quality	[310]
		Inconel 625	printing parameters	ANN	quality	[311]
		Al-5083	image	DTree	quality	[282]
	Material extrusion	Carbon fiber reinforced polymer	real-time images	DL	quality	[280]
		ABS	images	k-NN, SVM, RF	quality	[348]
			process parameter	SVM	quality	[349]
	Binder jetting	SS316L	images	CNN	quality	[350]
	Directed energy deposition	Ti-6Al-4V	images, optical data	SVM	quality	[351]
			optical emission	DL, CA	quality	[352]
	Vat photo-polymerization	Liquid resin	videos	DL	quality	[353]
			image	GPR	quality	[354]
	Material jetting	liquefied metal	video	DL	quality	[355]
		Dimatix	images	ANN	quality	[356]
Process parameter optimization	Powder bed fusion	SS316L	process parameters	GPR	quality	[283]
			process parameters	GPR	quality	[285]
			process parameters	DTree, k-NN, LR	quality	[286]
			process parameters	BN	quality	[287]
			process parameters	SVM, DL, DTree, GPR	quality	[288]
			images & data	DL	quality	[289]
			process parameters	GPR	property	[290]
			process parameters	GPR	quality	[291]
			process parameters	GPR	quality	[283]
			process parameters	GPR	quality	[292]
			process parameters	ANN, RF, SVM	property	[293]
		Inconel 625 & 718	process parameters	SVM, DTree, LR	quality	[312]
		Inconel 625	process parameters	GA	quality	[313]
		Inconel 718	process parameters	DL	property	[314]
			process parameters	GA	quality	[315]
		NiTi SMA	process parameters	DL	quality	[316]
		AlSi10Mg	process parameters	GPR	property	[317]
		Ti-6Al-4V	process parameters	ANN	property	[319]
			process parameters	GA	property	[318]
			process parameters	ANN	property	[319]
			process parameters	GPR	property	[320]
		CoCr	process parameters	SVM	quality	[321]
	Material extrusion	PLA	sensor data	SVM, LR	quality	[322]
			process parameter	DL	property	[323]
			process parameter	GPR	quality	[324]
			shape	GPR	quality	[325]
		ABS	process parameter	GA	quality	[326]
		Silicone	process parameter	GPR	property	[327]
	Binder jetting	Co-Cr-Mo	process parameters	ANN	quality	[328]
	Directed energy deposition	Copper alloy	process parameters	SVM	quality	[329]
		Al 4043	process parameters	SVM	model	[330]
		Al 5356	process parameters	GPR	quality	[331]
		SS304L	process parameters	GA	property	[332]
		SS316L	process parameters	GPR	quality	[333]
		Ti–Mn alloy	process parameters	GPR	property	[334]
	Material jetting	Silver	process parameters	GPR	quality	[335]
		Glycerol	process parameters	DL	quality	[336]
	Vat photo-polymerization	Liquid resin	images	DL	property	[337]
			CAD model	BN	quality	[338]
			CAD model	DL	quality	[339]
			process parameter	GA	quality	[340]
Design optimization	Powder bed fusion	AlSi10Mg	CAD model	SVM	design	[294]
		Inconel 625	images	DTree	design	[295]
	Material extrusion	ABS	3D coordinates	DL	design	[296]
			build orientation	ANN, BN	design	[297]
	–	–	CAD model	DL	property	[298]
			CAD model	GPR	design	[299]
			CAD model	DL	design	[300]
			images	DL	design	[301]

(continued on next page)

Table 3 (*continued*)

Direction	AM processes	Materials	Data type	ML methods	Goal	Refs
Material analysis	Powder bed fusion	–	radiation	SVM	classify	[302]
			images	SVM	classify	[303]
			features	DTree	classify	[304]
Sustainability	Material extrusion	PLA	process parameter	GA	cost	[305]
		ABS	process parameter	GA	cost	[306]
	Directed energy deposition	Inconel 718, Ti–6Al–4V	process parameter	GA	efficiency	[341]
	Vat photo-polymerization	Liquid resin	process parameter	PSO	efficiency	[342]
			process parameter	DL	efficiency	[343]
			process parameter	XGBoost, CA	efficiency	[344]
	–	–	CAD model	GA	cost	[345]
			CAD model	DTree	efficiency	[346]
			process parameter	DL	efficiency	[347]

development and modeling the intricate relationships between material chemistry, properties, and the performance of the final printed parts.

Some other researches focus on the material properties prediction of AM. Jiang et al. [402] utilized machine learning models to predict the amorphization of crystalline drug formulations and the chemical stability of subsequent amorphous solid dispersions (ASDs) prepared through hot-melt extrusion (HME). They trained the ML models using a dataset of 760 formulations containing 49 active pharmaceutical ingredients (APIs) and various excipients. The best ML model achieved an accuracy of 92.8% in predicting amorphization and 96.0% in estimating chemical stability. Feature importance analyses revealed critical processing parameters and material attributes for accurate predictions. The study highlights the potential of ML in facilitating the development of chemically stable ASDs through HME, reducing the laborious trial-and-error approach traditionally used in ASD development. Chernyavsky et al. [403] developed a heteroscedastic Gaussian process (HGP) model to predict microstructural properties, specifically amorphicity, of a glass-forming alloy fabricated through laser powder bed fusion. The HGP model accurately predicted mean amorphicity and quantified uncertainty, facilitating the assessment of dataset quality and identification of underlying physical phenomena. The results of HGP prediction are demonstrated in Fig. 5.

Additionally, machine learning also has a broad application in the material classification of AM. Schmidt et al. [404] utilized acoustic emissions for material classification and quality monitoring in laser AM. Acoustic emissions were recorded and processed using fast Fourier transformation. Machine learning models were trained and achieved high accuracy in classifying materials (up to 0.99) and process quality (up to 0.81). Vrábel et al. [302] explored the use of laser-induced breakdown spectroscopy (LIBS) for material analysis in SLM. The elemental composition of raw materials and constructed parts is obtained from LIBS measurements. Multivariate data analysis algorithms, including principal component analysis and support vector machines, are employed for data processing and classification.

In conclusion, material analysis plays a crucial role in AM to optimize the manufacturing process and ensure high-quality results. Machine learning techniques have been applied to analyze and understand the relationships between material chemistry, characteristics, and performance in AM. Current research in material analysis has primarily focused on metal powder characterization, while further exploration is needed to leverage machine learning for material composition analysis and modeling the relationships between material properties and final part performance. Additionally, machine learning has been applied in predicting material properties and classifying materials in AM processes, offering potential improvements in efficiency and quality control. The integration of machine learning with integrated computational materials engineering approaches has shown promise in advancing the understanding and optimization of AM processes.

3.3. Design optimization

Design optimization for AM [299] takes advantage of the unique capabilities of AM technologies to optimize the design of parts or products that are stronger, lighter, and more efficient than traditional manufacturing methods. Design optimization for AM is a critical aspect of AM, as it can significantly impact the performance and functionality of the final product [405].

The entire AM pipeline is shown in Fig. 6. In our paper, design optimization for AM mainly focuses on shape computational optimization [406] adopting machine learning methods. This can include optimizing the shape [407], topology [408] of the part to improve its strength, reduce its weight or improve its functionality. According to the pipeline of AM, the process of computational optimization is divided into the following steps:

- Input optimization including macrostructure/material (microstructure) optimization [409–413]. AM processes, such as 3D printing, can produce intricate geometries that are difficult or impossible to achieve using traditional manufacturing methods. Input optimization can help take advantage of these capabilities by designing structures that are optimized for the specific AM process being used while obtaining higher stiffness.
- Segmentation/package optimization [414,415]. These techniques involve breaking down a large part into smaller segments or optimizing the layout of multiple parts within a build volume to achieve better use of the available space.
- Optimization of the print direction [416–418]. It is to optimize the orientation of a part during printing, with the goal of improving its mechanical properties and reducing the need for support structures.
- Slice optimization [419–421]. It involves breaking down a 3D model into individual layers for printing. The goal of slice optimization is to achieve better print quality and reduce printing time and material usage.
- Path planning optimization [422–425]. It involves analyzing the geometry of the part being printed and selecting the optimal path for the print head to follow during printing. The goal of path planning optimization is to reduce printing time, improve print quality, and reduce the wear and tear on the print head.

3.3.1. Geometric processing based on machine learning

This section delves into the remarkable synergy between geometric processing and ML, focusing on key optimization domains. From package segmentation to path planning, the integration of ML not only enhances these processes but also marks a paradigm shift in how AM leverages computational intelligence to propel manufacturing excellence. Through a comprehensive exploration of package/segmentation optimization, printing orientation optimization, slicing optimization, and path planning optimization, this section unveils the transformative power of ML-driven geometric processing, underscoring its potential to

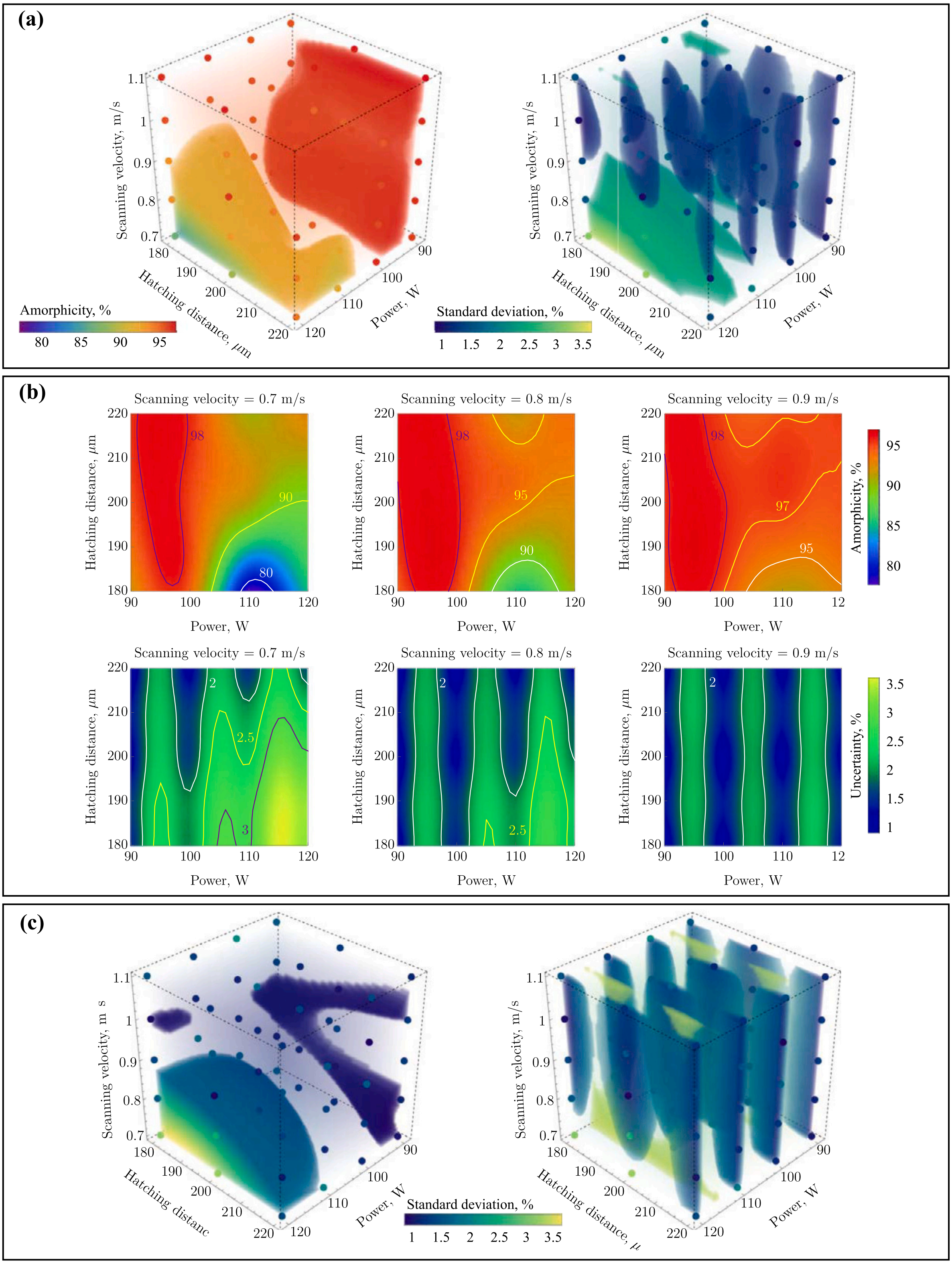

Fig. 5. Predicting materials characteristics and their uncertainty by HGP [403]. (a). HGP model predictions for mean values of amorphicity and its total uncertainty. (b). Two-dimensional contour maps of HGP model predictions for mean values of amorphicity and its total uncertainty. (c). Position-resolved aleatoric and epistemic uncertainties predicted by the HGP model.

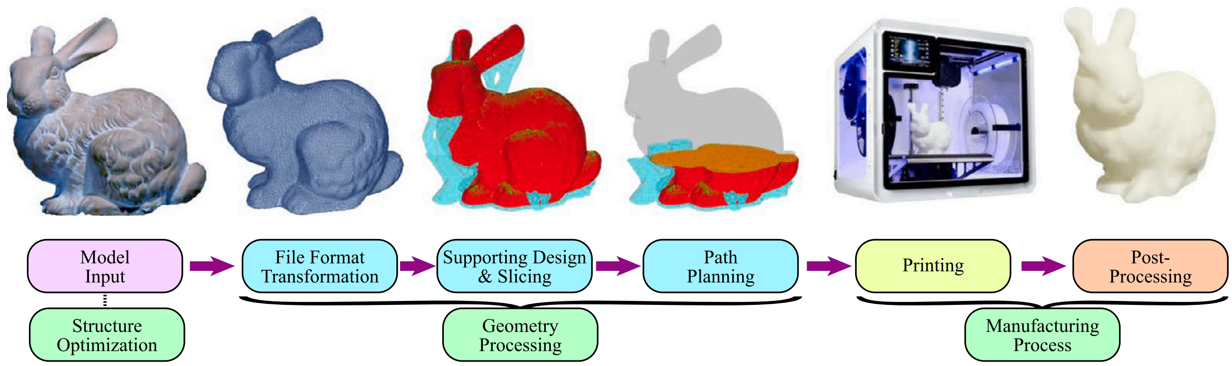

Fig. 6. Design process of additive manufacturing technology.

revolutionize the landscape of AM. Fig. 7 illustrates a selection of representative research examples in the field.

3.3.1.1. Package/segmentation optimization For larger objects, it may be possible to print the object in smaller sections and then assemble them together. This requires breaking down the object into smaller pieces and then printing each section separately. Once all sections are printed, they can be assembled to create the final object. However, this requires careful planning and assembly to ensure that the pieces fit together correctly. Object segmentation from AM is an extensive task in deep learning. Guo et al. [426] proposed a new method to find the optimal build orientation for each submodel, based on a modified curvature shift strategy and weight factors for every flat facet of the regions. The aim is to improve surface quality, reduce printing costs, and eliminate the need for support structures. Li et al. [415] proposed a 3D model segmentation method based on deep learning to improve the surface quality and reduce the support structure of 3D printed models. The proposed method uses pre-segmentation and an Affinity Propagation clustering method to segment a product model into several parts, which is validated by printing samples. Ng et al. [432] explored the integration of deep learning into 3D bioprinting, from image segmentation to tissue maturation. The paper discusses practical guidelines and potential applications, highlighting synergistic interactions between biology, materials, and computational design.

3.3.1.2. Printing orientation optimization Optimizing the orientation of a 3D model for printing involves considering various factors such as stability, support requirements, surface details, and print time. To ensure maximum stability during printing, the orientation should be chosen carefully. Similarly, minimizing the need for support structures is important, as is ensuring that the surface details of the final product are as smooth as possible. Finally, minimizing print time is essential to keep costs low and avoid quality problems.

Based on these factors, the 3D model can be rotated and adjusted in the 3D printing software to find the optimal orientation for printing. The software can also simulate the printing process to check for stability and identify areas that may require additional support structures. Zhang et al. [427] proposed a perceptual model to find optimal 3D printing orientations that avoid placing supports in perceptually significant regions, resulting in fewer surface artifacts. The model is formulated as a combination of metrics that include support area, visual saliency, preferred viewpoint, and smoothness preservation. The study demonstrates the performance of this model on natural and man-made objects. Malviya et al. [297] proposed a machine learning-based framework to optimize the build orientation in FDM components by maximizing the minimum Factor of Safety. An ANN coupled with a Bayesian algorithm is used for acceleration, and experiments show effective optimization with limitations. Rezaei et al. [433] proposed an autonomous system that utilizes artificial intelligence to decide the build orientation of a shape based on similar parts previously encountered. Orientation of the part to be printed is very important for reducing energy consumption. Based on this, the paper [434] explored the use of twelve machine learning algorithms to optimize energy consumption in AM processes, specifically the FDM process. The Gaussian process regressor model was found to estimate energy consumption with high accuracy. Shi et al. [428] proposed a reinforcement learning (RL) framework for optimal build orientation in 3D printing to address local optimization and trial and error issues. The proposed method outperforms existing approaches and can quickly discover optimal global solutions and generalize beyond the training environment.

3.3.1.3. Slicing optimization Slicing optimization is used to convert the CAD model into a series of layers depending on the type of slicing strategy used. The most commonly used slicing method is planner slicing which slices the model into parallel layers. The thickness of each layer can be adjusted to control the objects' details. By optimizing the slicing parameters, it is possible to achieve higher quality and accuracy in the final 3D print, while minimizing material usage and print time. Checa et al. [435] proposed a strategy to select the best cutting tool design and cutting parameters using experimental tests, machine learning modeling, and virtual reality visualization to optimize power consumption. Tamir et al. [436] presented open-loop and closed-loop machine learning models to monitor the effects of processing parameters on the quality of 3D printed parts, allowing a closed-loop control system in AM. Jin et al. [437] proposed machine learning algorithms to precisely detect and localize in-plane printing conditions such as over-extrusion and under-extrusion in fused filament fabrication. The system provides real-time defect information and has the potential for automated control and correction.

3.3.1.4. Path planning optimization 3D printing path planning based on machine learning involves developing a model that learns from previous 3D printing jobs to suggest the most efficient printing path for a new object. To do this, the machine learning model analyzes the characteristics of the object being printed, such as its shape and size, and takes into account factors such as the type of material being used, the printer's capabilities, and any design constraints. It then uses this information to generate a printing path that minimizes printing time, reduces material waste, and improves the overall quality of the final product. Patrick et al. [438] proposed the use of reinforcement learning, a type of machine learning, to generate toolpaths for 3D printing. RL involves two agents, the actor and the critic, learning to maximize a score based on the actions of the actor in a defined space, and in this context, the actor will learn to find the optimal toolpath to reduce printhead lifts and print time. Fok et al. [439] introduced using artificial neural networks to improve the efficiency of the optimization process. The optimization process is computationally intensive, and heuristics and metaheuristics are typically used to generate suboptimal results. Ge et al. [430] described an intelligent path planning method called Q-Path, which uses reinforcement learning to find optimal so-

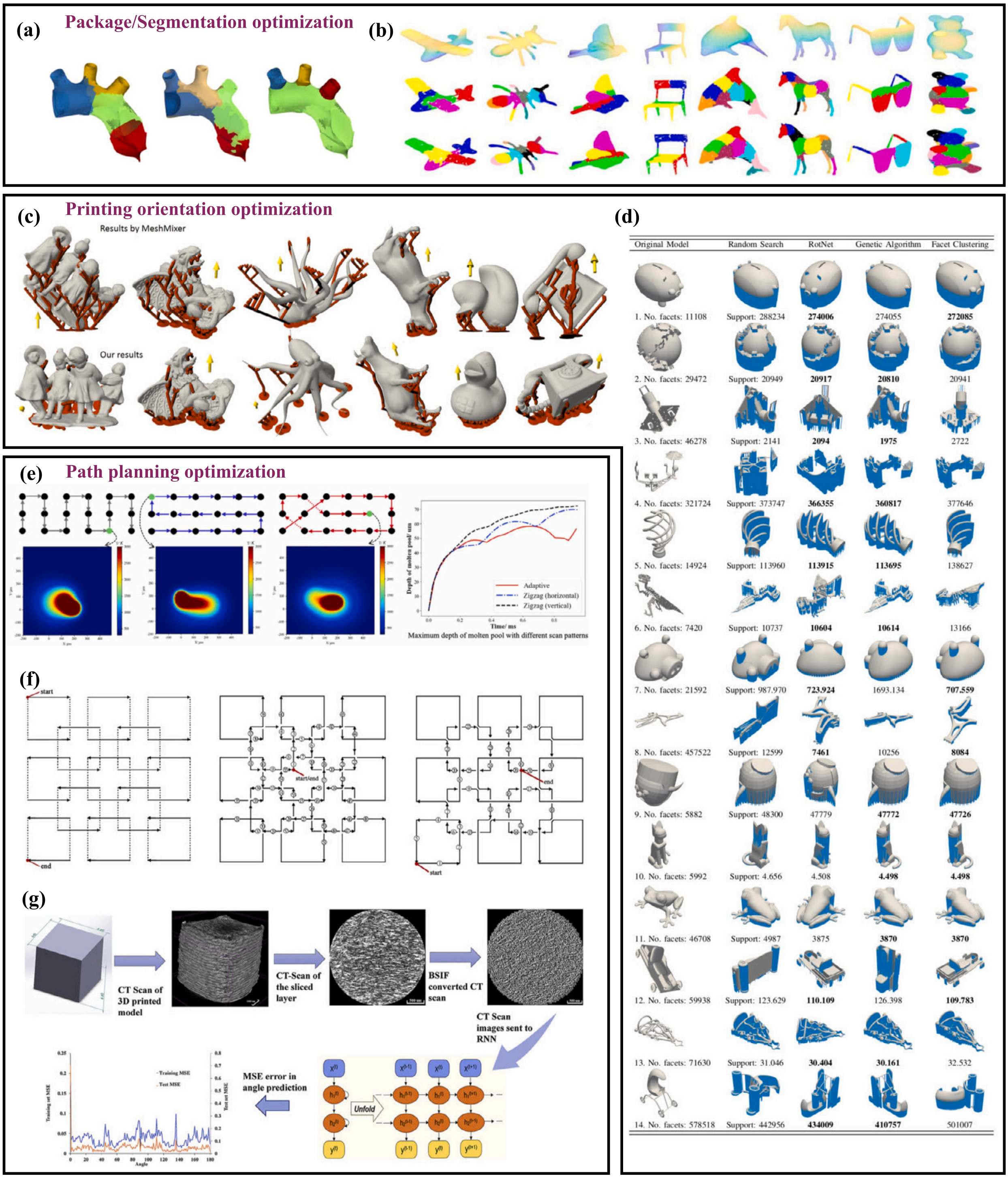

Fig. 7. Geometric optimization based on machine learning. (a). Segmentation methods using k-means, modified Cs and the Reeb graph method [426]. (b). Segmentation methods using clustering [415]. (c). Optimal 3D printing orientations generated by MeshMixer (top) and Perceptual Models (bottom) [427]. (d) Support optimization with different build orientations by random search, RotNet, genetic algorithm, and facet clustering [428]. (e). Zigzag toolpath along the vertical and horizontal direction and selected temperature distribution (green point) and adaptive toolpath calculated by objective functions and selected temperature distribution (green point) [429]. (f). The path plans using three algorithms in order: ZigZag-Path, Fleury-Path, and Q-Path [430]. (g). Reverse engineering of additive manufactured composite part by toolpath reconstruction using imaging and machine learning [431].

lutions while adhering to 3D printing constraints, such as minimizing printhead lifts and turns. Xie et al. [440] presented a tool path pattern recommendation method based on deep learning neural networks that utilize 3D point cloud segmentation and classification and transfer learning to identify object features and improve performance. Yanamandra et al. [431] focused on using imaging and machine learning to reverse engineer composite material parts made through AM. The aim is to reconstruct not only the geometry, but also the tool path of 3D printing, to prevent unauthorized production. The method achieves a high level of dimensional accuracy. Crockett et al. [441] proposed a variation of k-means clustering for object division to reduce print time in 3D printing. The algorithm considers the balance of workload and discrete build areas for parallel construction. The method is tested on several models to compare workload across the number of build points. Qin et al. [429] proposed adaptive toolpath generation algorithms for laser powder bed fusion to reduce part distortion. The algorithms are based on minimizing thermal gradients and include collision-free and smoothing constraints. Experimental results show that the proposed algorithms reduce distortion compared to traditional zigzag- and chessboard-based patterns and can be extended to fabricate complex 3D geometries.

3.3.2. Topology optimization for properties based on machine learning

Topology optimization is a layout optimization method to find the shape and material distribution of a structure to achieve the best performance targeting minimizes weight, maximizes stiffness or strength, and minimizes stress concentrations under certain constraints. It is a promising field in engineering and computational mechanics, which emerged in the 1980s [442] and 1990s [443]. However, the idea of optimizing structures for maximum performance has been around for centuries. When combined with AM and machine learning, topology optimization can become even more powerful, allowing for the creation of parts that are optimized specifically for AM processes quickly and efficiently.

Machine learning has the potential to significantly enhance topology optimization by providing more accurate and efficient optimization algorithms, as well as enabling new types of design and material optimizations. One benefit of using machine learning in topology optimization is the ability to incorporate large amounts of data into the design process. Machine learning algorithms can be trained on data from previous designs and simulations to learn patterns and correlations that can be used to inform new designs. This can lead to faster and more accurate optimization results, as well as the discovery of new design possibilities that might not have been apparent through traditional optimization techniques. Another benefit of machine learning in topology optimization is the ability to optimize material distributions and designs for multiple objectives simultaneously. This is particularly useful in multiphysics problems where there are multiple competing objectives, such as minimizing weight while maximizing stiffness or reducing cost while maintaining performance. Machine learning algorithms can optimize designs for these multiple objectives simultaneously, resulting in more efficient and effective designs. Overall, the benefits of machine learning in topology optimization include faster and more accurate optimization results, the discovery of new design possibilities, and the ability to optimize for multiple objectives simultaneously. Machine learning can also optimize the manufacturing process for topology-optimized designs, leading to more efficient and cost-effective manufacturing.

Despite the promising potential of machine learning in topology optimization, there are still several limitations that require attention in current research. A notable limitation pertains to the scarcity of ML applications specifically tailored for AM in topology optimization. While deep learning techniques have made progress in generating topologically-optimized designs, the majority of these efforts have concentrated on 2D structures [444–457]. Given that AM encompasses three-dimensional fabrication, the extension of topology optimization to 3D structures becomes imperative for fully capitalizing on the advantages of AM. However, the introduction of an additional dimension in the design space presents challenges for machine learning algorithms to effectively conduct TO. Furthermore, the resolution of optimized structures remains constrained [458], thereby impeding the implementation of topology optimization in more intricate designs.

In this section, we will explore the application of machine learning in topology optimization from two aspects: macro-structure and micro-structure topology optimization.

3.3.2.1. Macro-structures topology optimization Macro-scale topology optimization is a design approach that seeks to optimize the overall shape and layout of large structures, such as buildings or bridges, in order to achieve a desired performance objective [459,460]. Machine learning-based macro-scale topology optimization methods use algorithms that can learn from data to generate optimized designs based on those data [461,462]. Machine learning has been developed to automatically detect patterns in the data to accurately predict the distribution of material under different forces and boundary conditions. Recent years have witnessed a number of studies devoted to applying ML techniques to solve topology optimization problems as illustrated in Fig. 8.

Some research work [97,98,469–472] reviewed the progress in using deep learning for photonic design and highlights key applications, challenges, and perspectives. Sosnovik and Oseledets [463] adopted the convolution neural network to determine the distribution of the material. The deep learning method is used to speed up the whole optimization process. Lei et al. [464] adopted machine learning to achieve real-time structural topology optimization using an explicit framework and regression models, resulting in reduced training data and the potential for intuitive understanding. Examples demonstrate effectiveness. Yu et al. [465] proposed a deep learning-based method for predicting optimized structures without iterative schemes. Using an open source optimization code, a CNN-based encoder and cGAN network are trained to produce near-optimal structures with negligible computational time. Wang et al. [454] proposed a lightweight and high-efficiency CNN, the convolutional block attention (Cba-U-Net) model, for predicting topology-optimized configurations in real time, achieving accuracy rates of 91.42%, and being suitable for various optimization algorithms. It demonstrates the potential of combining deep learning with topology optimization for large-scale projects. Xing et al. [473] adopted an autonomous learning and prediction (ALP) scheme for machine learning-assisted structural optimization (MLaSO) to reduce total computational time while maintaining prediction accuracy. Four numerical examples demonstrate the benefits of integrating ALP with gradient-based MLaSO. Yoo et al. [474] presented a topology control system for drone networks to optimize connectivity between drones from the perspective of interference and energy consumption. The system uses reinforcement learning (DDPG) to adaptively conduct connectivity optimization, minimizing learning time by changing the number of learning steps. The proposed system was verified through simulation experiments and theoretical analysis on various topologies consisting of multiple UAVs.

Overall, machine learning-based macro-scale topology optimization has the potential to significantly improve the design process for large structures, but it requires careful consideration of computational resources and validation to ensure the accuracy and feasibility of the resulting designs. Additionally, the incorporation of expert knowledge and engineering principles is still necessary to ensure that the designs are practical and can be implemented.

3.3.2.2. Micro-structure topology optimization Meta-materials have unique properties that make them useful in a variety of applications, including aerospace, biomedical, and marine engineering. However, designing meta-materials with desired properties can be challenging, because of the complex and intricate structure of these materials. Machine learning has been explored as a potential solution to this challenge. Researchers have developed various methods to use machine learning algorithms to generate meta-materials with specific properties, such as high refractive index or negative permittivity [475],

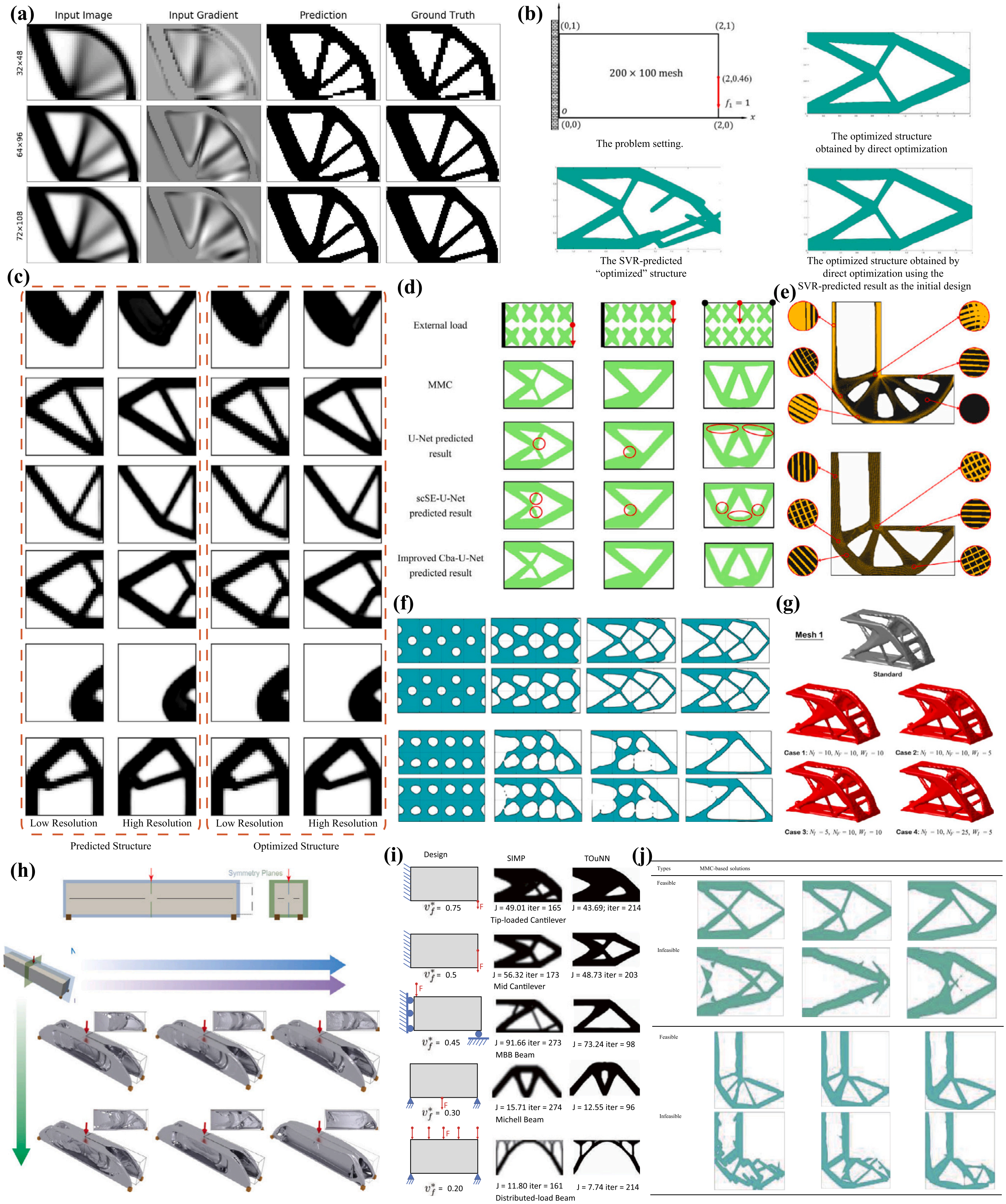

Fig. 8. Topology optimization based on machine learning. (a). Results of the application of neural networks for topology optimization [463]. (b). Using ML-predicted results as initial design for direct optimization [464]. (c). Deep learning for determining a near-optimal topological design without any iteration [465]. (d). Topology optimization results of MMC and three deep learning models [454]. (e). Post-processed results of L-shaped beam design with machine learning combined topology optimization for the functionally graded composite structure with cross-shaped fiber layout and the fiber-reinforced composite structure with fixed fiber volume fraction [466]. (f). Cantilever model optimization and MBB beam model using machine learning combined topology optimization with 1, 30, 80, 200 steps [410]. (g). The final bridge designs obtained from the standard and machine learning-based approaches for cases [444]. (h). Results for the MBB beam domain obtained through the ML-driven topology optimization. [449] (i). Optimized results for topology optimization using neural networks [467]. (j). Machine learning-based parameter tuning strategy for MMC-based topology optimization [468].

auxetic properties [476], maximum bulk/shear modulus [446], which are demonstrated in Fig. 9. These methods include the use of adversarial generative networks [477–479], deep neural networks [480–482], and reinforcement learning [483–486].

While these approaches have shown promise, there are still some limitations to using machine learning for meta-materials generation. One limitation is the need for large amounts of training data to train the machine learning algorithms effectively. Another limitation is the computational resources required to run the algorithms, which can be time-consuming and costly. Overall, the use of machine learning for meta-materials generation is an exciting area of research with promising potential. Further advancements in this area could lead to the development of new and improved meta-materials with tailored properties for specific applications.

3.3.3. Section conclusion

Design optimization is a pivotal aspect of AM, harnessing the unique capabilities of AM technologies to produce stronger, lighter, and more efficient parts compared to traditional manufacturing methods. By adopting machine learning methods, researchers and industry professionals have made significant advancements in shaping computational optimization for AM. This optimization encompasses various steps, including macrostructure/material (microstructure) optimization, segmentation/package optimization, print direction optimization, slice optimization, and path planning optimization.

Geometric processing based on machine learning has shown promising results in package/segmentation optimization, enabling the design of complex structures while reducing support structures and improving surface quality. Moreover, machine learning has proven valuable in printing orientation optimization, predicting optimal orientations to achieve stability, minimize support structures, and enhance surface details. Slicing optimization has benefited from machine learning techniques, leading to improved 3D print quality, reduced material usage, and shorter print times. Additionally, machine learning-based path planning optimization has enabled the selection of efficient printing paths, further enhancing print quality and minimizing print time and material consumption.

At the macrostructures level, machine learning-driven topology optimization has demonstrated the ability to optimize the overall shape and layout of large structures with multiple objectives and constraints, offering a powerful tool for engineering design. However, addressing computational complexity and ensuring interpretability remains a focus of ongoing research. On the microstructure front, machine learning methods have been applied to design metamaterials with tailored properties, showcasing potential for various applications. Challenges, such as the need for substantial training data and computational resources, persist and call for further investigation.

As AM and machine learning technologies continue to evolve, design optimization is set to play an increasingly critical role in revolutionizing various industries. By combining the strengths of AM and machine learning, researchers aim to create innovative products with improved performance and sustainability, advancing the realm of AM and its real-world applications.

3.4. Process optimization

Process parameter optimization (PPO) is a crucial aspect of AM that can lead to significant benefits for manufacturers. First, the optimization of process parameters in AM can help improve the quality of the finished product [130]. This is because the right combination of process parameters can result in reduced porosity, improved surface finish, and better dimensional accuracy. By optimizing process parameters, manufacturers can ensure that their products meet the required specifications, and are free from defects that may arise due to improper process parameter settings. PPO can also help to reduce manufacturing costs. By identifying the optimal settings for process parameters, manufacturers can achieve better process efficiency, reduce material waste, and minimize the need for post-processing operations. This can result in significant cost savings, particularly for high-volume production runs.

However, the optimization of process parameters in AM is a complex problem. One of the challenges is that AM processes involve a multitude of variables that can impact the quality of the final product [491]. Another challenge in optimizing process parameters is the need to balance conflicting objectives [492]. There are often trade-offs between different aspects of the print. For example, optimizing for print strength may require sacrificing print speed or resolution. Similarly, optimizing for print quality may require sacrificing production speed or material usage. These trade-offs can make it difficult to find the optimal set of parameters that balance all of the competing objectives. Also, the range of materials and techniques that are used in AM is one of the reasons for this complexity. Each material and technique has its own unique set of process parameters that need to be optimized for the best results. Another challenge in optimizing process parameters is the lack of standardization in the industry [493]. While there are some general guidelines for process parameters, each manufacturer and printer model may have different optimal settings. This means that optimization often requires a great deal of trial and error, as well as careful observation and analysis of the results. Besides, the optimization of process parameters is not a one-time event. As materials, printer models, and techniques continue to evolve, the optimal process parameters will also change. This means that manufacturers and researchers must continually monitor and update their process parameter settings to ensure that they are using the most up-to-date and effective methods. As a result, researchers are exploring various optimization methods to find the best set of parameters that achieve the desired trade-off between these objectives.

In this section, we will thoroughly explore the concept of process parameter optimization for AM, addressing it from three distinct but interconnected perspectives. Firstly, optimization objectives will be discussed, that is the specific goals and performance benchmarks we aim to achieve with optimization, as these factors directly influence the quality and applicability of the printed part. Secondly, optimization process parameters in the AM process that can be adjusted to drive better outcomes will be examined in detail. The careful control and adjustment of these parameters is crucial to ensure optimal results. The overview of optimized process parameters and optimization objectives in process parameter optimization of AM is illustrated in Fig. 10. Lastly, optimization methods will be explored into the computational and mathematical models or strategies employed to systematically determine the best combination of parameters that yield optimal results. This segment focuses on the role of advanced techniques like machine learning in modeling the complex relationship between process parameters and the properties of the final part. These three components together form a holistic approach to process parameter optimization in AM, providing a nuanced understanding of how to achieve the best possible product performance and quality.

3.4.1. Optimization objectives

The main objectives of optimization in AM can be divided into three principal categories: cost-efficiency, qualities, and properties. These categories represent key targets that need to be achieved to ensure an effective and high-quality production process. Each category covers a range of parameters that are subject to optimization in order to enhance production efficiency, product quality, and suitability for specific applications.

The first category, cost-efficiency, is concerned with making the manufacturing process more economical and sustainable. Key factors that need optimization in this category are the building time [305,306,313,324,326,331,333,494–508], energy consumption [341,342,501,509–516], and material usage [517]. By optimizing these factors, we can significantly increase production efficiency and reduce the

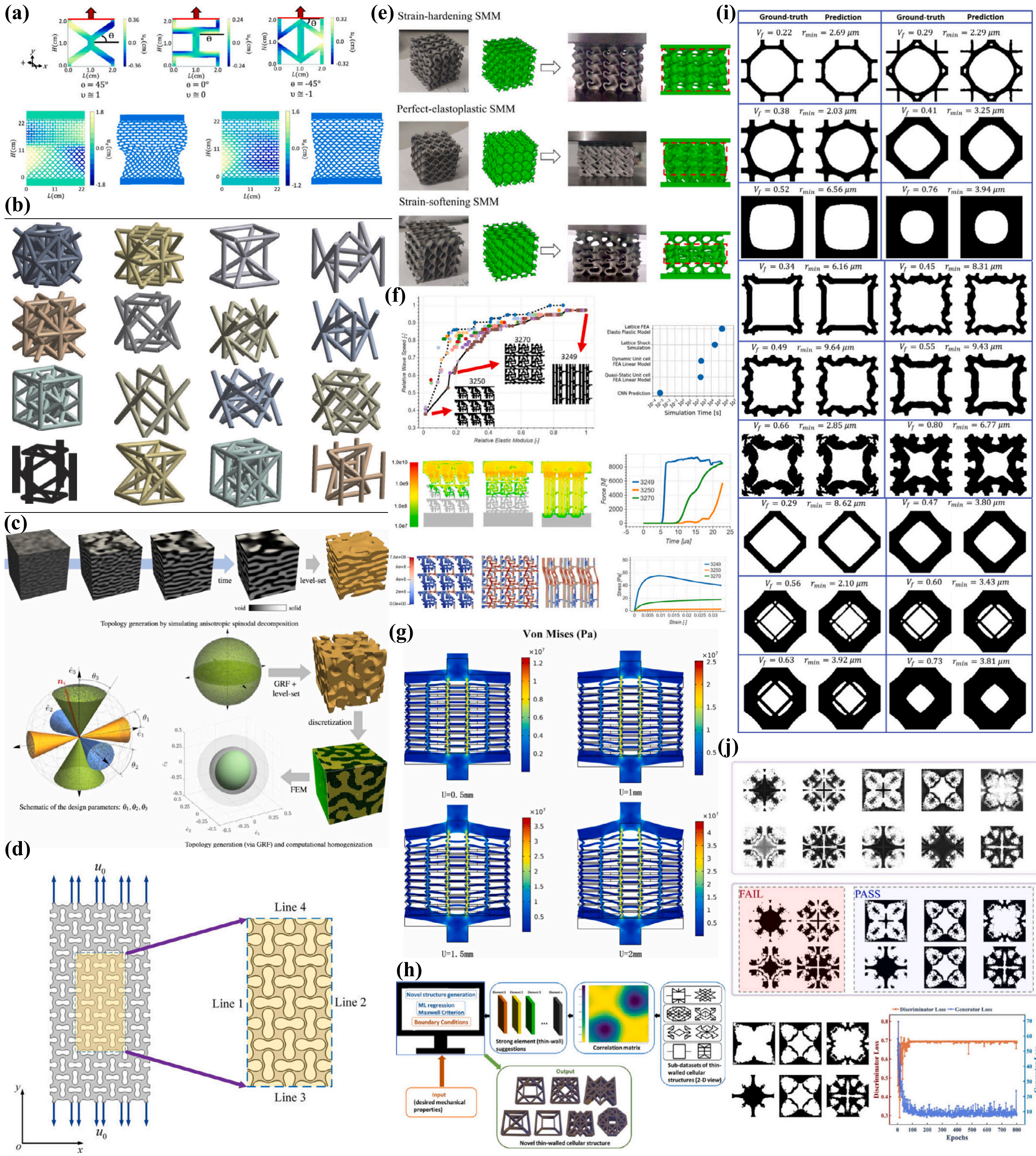

Fig. 9. Materials design based on machine learning. (a). Metamaterial design with deep learning [476]. (b). Optimized results for the inverse machine learning framework to optimize lightweight metamaterials [479]. (c). Inverse-designed spinodoid metamaterials using machine learning [487]. (d). New planar auxetic metamaterial perforated with orthogonally aligned oval-shaped holes using machine learning [447]. (e). Inverse design of mechanical metamaterial based on shell structures with customized loading curves based on machine learning and genetic algorithm [488]. (f). Pragmatic generative optimization of novel structural lattice metamaterials with machine learning [489]. (g). Inverse design based on machine learning of auxetic metamaterial with zero Poisson's ratio [490]. (h). Inverse machine learning discovered metamaterials with record high recovery stress [448]. (i). Topology optimization of 2D metamaterials for the case of maximizing the bulk modulus, minimizing the Poisson's ratio, and maximizing the shear modulus [446]. (j). Machine learning-based prediction and inverse design of 2D metamaterial structures with tunable deformation-dependent Poisson's ratio [445].

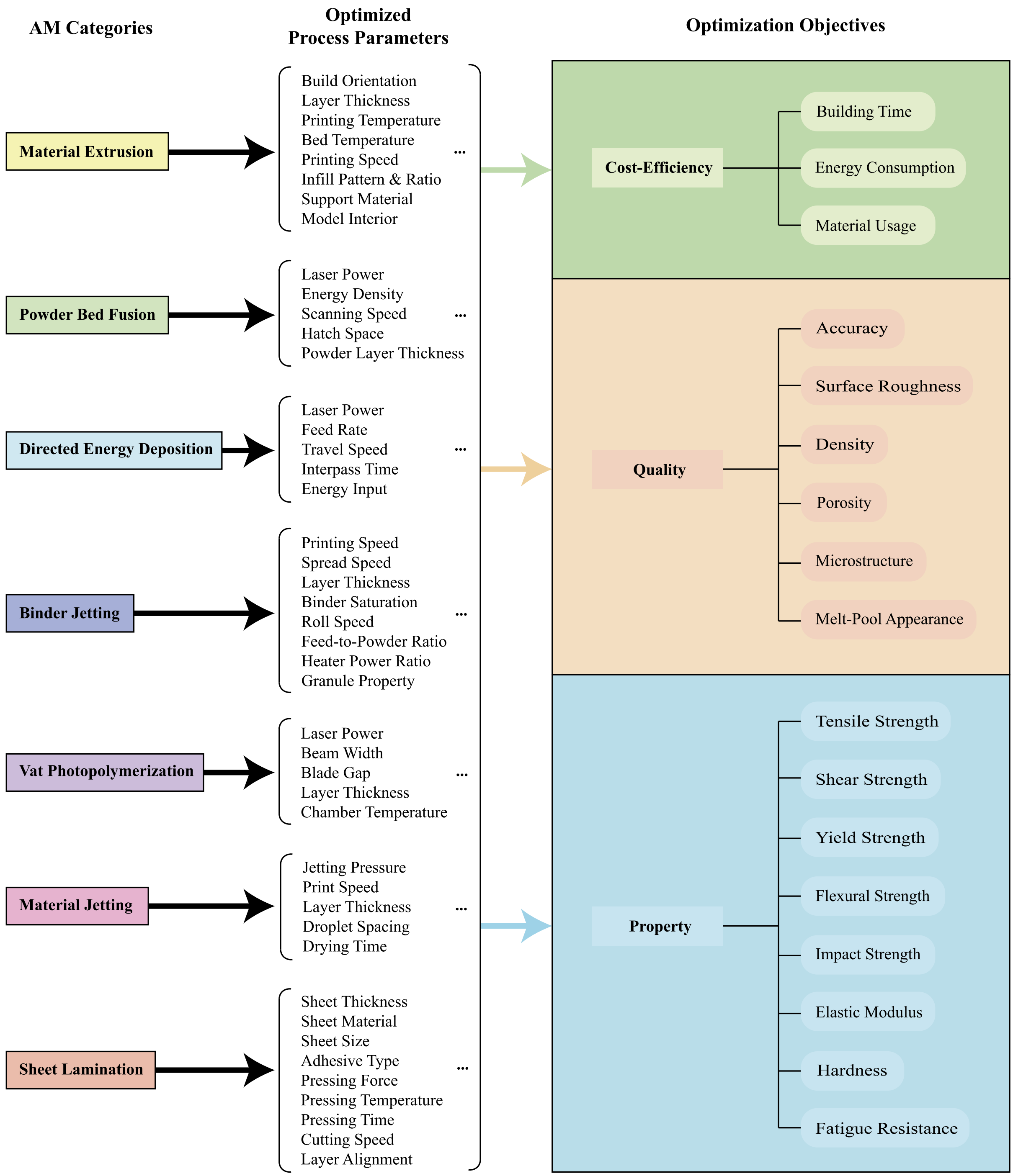

Fig. 10. Optimized process parameters and optimization objectives in process parameter optimization of additive manufacturing.

operational costs involved in manufacturing, which in turn makes the process more sustainable.

The second category focuses on the quality of the products manufactured. This category encompasses parameters such as accuracy [291,326,327,494,498,518–526], surface roughness [291,306,329,340,495,497,520,527–539], density [328,520,527,530,540–542], porosity [320,321,331,520,543–551], microstructure [313,315,552,553], and melt-pool appearance [283,292,554–556]. The optimization of these qualities plays a crucial role in determining both the aesthetic and functional aspects of the final product. By enhancing precision in these areas, we ensure that products are manufactured to meet the highest standards and suit specific application requirements.

Lastly, the third category revolves around the properties of the manufactured products, with a particular focus on mechanical and thermal properties. These properties include tensile strength [290,317–320,327,332,334,501,518,528,541,542,557–580], shear strength [581], yield strength [518,558,567,581,582], flexural strength [558–561,565,566,583–585], impact strength [558–561,565,566,586], elastic modulus [518,528,558,562,563,567,568,581], hardness [509,528,552,573,587–589], and fatigue resistance [293,564,590] among others. These attributes determine the product's durability, lifespan, and suitability for various applications. By optimizing these properties, we can ensure that the manufactured products meet the required performance standards in their intended applications, providing long-lasting reliability and overall value.

3.4.2. Optimization process parameters

In this section, we will delve into the crucial aspect of optimizing process parameters in AM. The optimization of process parameters is essential for achieving high-quality, efficient, and cost-effective production. However, due to the diverse nature of various printing methods, the parameters that require optimization vary for each AM category. Hence, we will explore the optimization process parameters individually for seven distinct AM categories.

The optimization of the material extrusion process requires careful consideration of various parameters such as build orientation [499,500,518,528,557,559,560,565,591–596] and layer thickness [498–500,518,525,528,559,560,562,565–567,581,591,592,595–598]. Also, parameters like printing temperature [324,501,518], bed temperature [327], and air gap [499,500,559,560,591,592,595–597] play crucial roles in determining the characteristics of the part being manufactured. Parameters like printing speed [498,518,525,566,597] have also been investigated for their impact on the extrusion process. Infill pattern and infill ratio play a significant role in both the cost and mechanical properties of the final part [499–501,518,525,528,557–562,564,565,567,581,591–593,595–597,599–602]. Furthermore, support material and model interior are also optimized for hardness, flexural modulus, tensile strength, and surface roughness [528]. Gao et al. [603] compared two optimization approaches–the Taguchi method and RSM. They identified four operating parameters and their interaction terms as control variables, and tensile strength and compressive strength as responses. The experimental results showed that the conclusions regarding the significant ranking of parameters differed between the Taguchi method and RSM. Mohamed et al. [604] examined the effects of FDM fabrication conditions on the dimensional accuracy of cylindrical parts. A combination of a second-order definitive screening design (DSD) and an artificial neural network (ANN) was proposed for experimental design and prediction. The study successfully determined the optimum fabrication conditions for improved dimensional accuracies of cylindrical parts.

For powder bed fusion, parameters like laser power [580,605–615], energy density [616,617], scanning speed [580,605,607,609,612,613,615,618,619], hatch space [610,615,619], and powder layer thickness [615,620,621] are pivotal to the success of the process. When considering the process parameter optimization of powder bed fusion, heat treatment emerges as a significant parameter that sets this method apart from other kinds of AM. The role of heat treatment in the powder bed fusion process is a multifaceted one and demands careful consideration, as it has far-reaching implications on the properties and performance of the final product. The heat treatment process in powder bed fusion plays an instrumental role in defining the microstructure of the manufactured parts, which is a determining factor of their mechanical properties. The application of heat, both in terms of magnitude and duration, impacts the atomic arrangement within the product, which can lead to variations in properties like tensile strength, hardness, ductility, and resistance to wear and tear. Specifically, the appropriate control and regulation of heat treatment can enhance the tensile strength of the printed parts, making them more durable and capable of withstanding higher mechanical stresses. This underscores the significance of heat treatment as a parameter in the powder bed fusion process and emphasizes its influence on the functional characteristics of the products [622–630]. Liu et al. [631] developed a machine learning approach based on Gaussian process regression to optimize the LPBF process in AM. The optimized processing window for manufacturing fully dense AlSi10Mg samples was determined, resulting in previously unattainable combinations of high strength and ductility. Gu et al. [632] utilized small dataset of 33 experiments to predict relative density and surface roughness of LPBF process. The ML models were improved by curating the input data and using volumetric energy density as a universal predictor. This approach reduced the mean absolute percentage error and increased the translation capability of the models across different machines and materials. Muhammad et al. [633] developed a DL framework to predict the process-induced surface roughness of AlSi10Mg aluminum alloy fabricated using LPBF. The framework involved the fabrication of specimens, surface topography measurement, data extraction and engineering, and the development of a deep neural network model. Different scanning strategies and process parameters were considered, and the inputs to the model were the AM process parameters. Lapointe et al. [634] focused on applying machine learning to optimize laser process parameters in AM. The irregular quality of parts produced through laser powder bed fusion was addressed, with a focus on dimensional inaccuracies and defects in complex geometries. A data-driven approach was employed, utilizing experimental diagnostics to create a training dataset for supervised learning models. These models, a forward and an inverse model, were developed to predict photodiode signals and laser parameters based on track-wise geometry features. The inverse model enabled the determination of required laser parameters for desired photodiode signals. The whole process and results are demonstrated in Fig. 11.

In directed energy deposition, laser power [635,636], feed rate [333,635,636], travel speed [333,635–637], interpass time [333], and energy input [521,637] are among the parameters to optimize. Effective management of these parameters can control the quality of the deposited material and the subsequent cooling process, thus influencing the mechanical properties and dimensional accuracy of the final product. By tuning these parameters, manufacturers can enhance process efficiency and improve the performance characteristics of the final products. Heat treatment also assumes a key role in the process optimization of directed energy deposition. While directed energy deposition distinguishes itself from powder bed fusion through its distinct method of material deposition and melting, the fundamental importance of heat treatment remains. It contributes significantly to the modulation of the microstructure, and by extension, the mechanical properties of the produced parts. In the directed energy deposition process, the feedstock material, typically in the form of powder or wire, is melted using a focused thermal energy source such as a laser or electron beam. The manipulation of heat treatment parameters during this process can significantly alter the thermal gradients and cooling rates experienced by the material, thus influencing the microstructural evolution within the part. As a consequence, mechanical attributes such as tensile strength, hardness, ductility, and fatigue resistance can be finely tuned. Much like in powder bed fusion, optimizing heat treatment in directed energy deposition is a complex and delicate task that requires a deep understanding of material science and the relationship between heat treatment conditions and resulting material properties. Strategies such as preheating the substrate, controlling the interpass temperature, and post-process heat treatment can all be deployed to manipulate the material microstructure and achieve the desired mechanical properties [638–645]. Era et al. [646] applied machine learning algorithms (XGBoost and Random Forest) to predict the tensile behaviors of stainless steel 316L parts fabricated using laser-based directed energy deposition (L-DED). The process parameters, including laser power, scanning speed, and layer thickness, were optimized to control the properties of the fabricated parts. The models successfully predicted the tensile properties, with XGBoost demonstrating superior accuracy compared to Ridge Regression and Random Forest. Jamnikar et al. [647] developed a deep learning-based multi-modality convolutional neural network for in-process geometry monitoring in wire-feed laser AM. The network was trained to estimate the geometric properties of the build bead using real-time molten pool sensing data. The effect of using temperature data from different positions of the molten pool on the prediction performance of the CNN model was analyzed. Pham et al. [648] proposed a feedforward neural network surrogate model was developed for fast and accurate prediction of temperature evolutions and melting pool sizes in metal bulk samples manufactured by the DED process. The surrogate model was trained using high-fidelity data from finite element models and validated with experiments. The FFNN model achieved high accuracy, with 99% and 98% accuracy for temperature evolutions and melting pool sizes, respectively.

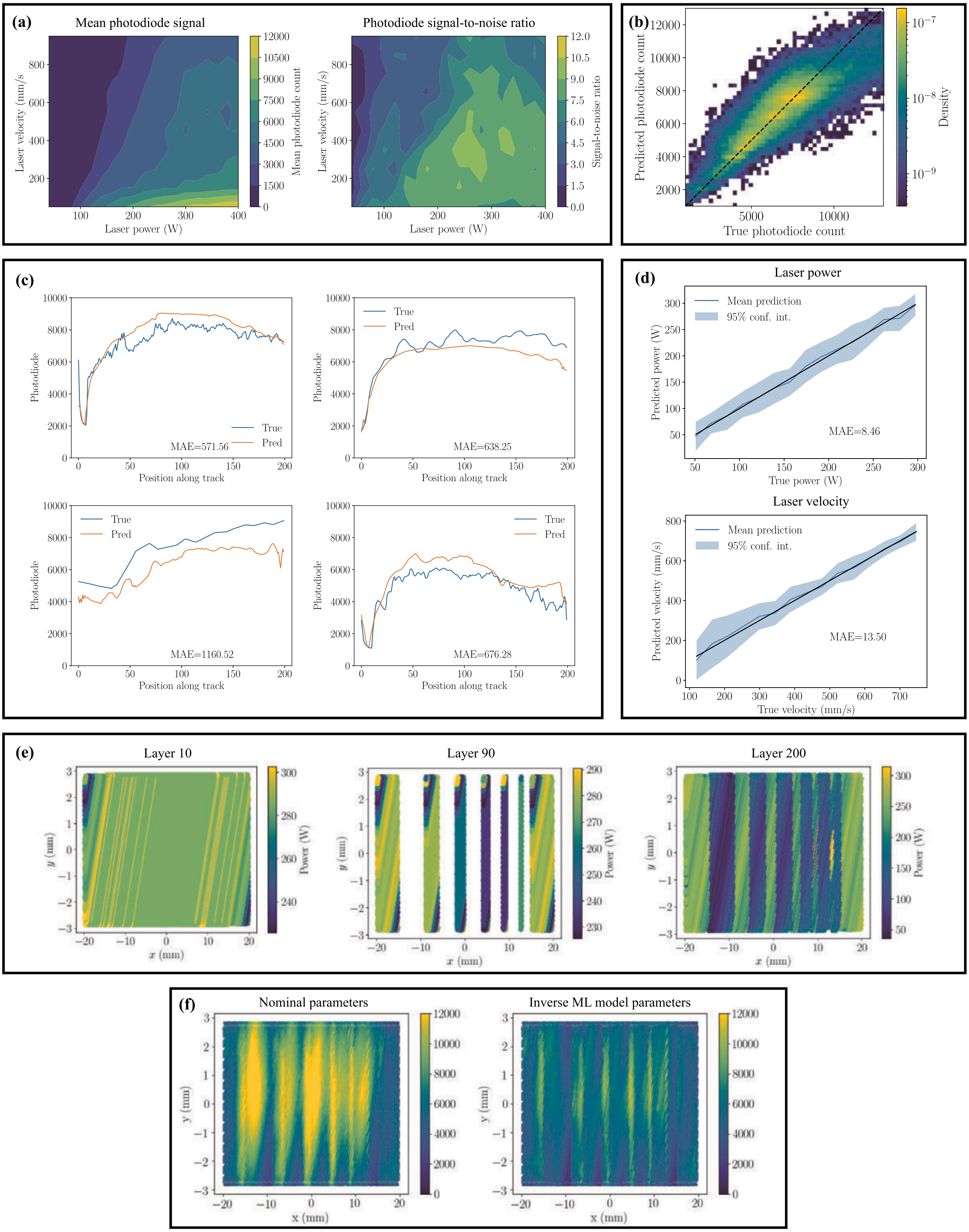

Fig. 11. Photodiode-based machine learning for optimization of laser powder bed fusion parameters in complex geometries [634]. (a). Mean and signal-to-noise ratio of the photodiode signal for single tracks printed at different laser powers and velocities. (b). Joint probability density function of the predicted and true photodiode signal intensities. (c). Comparison of true and predicted photodiode signal for four tracks from the test set. (d). Comparison of the true and predicted laser powers and velocities. (e). Laser power predicted by the inverse ML model for three layers of the test geometry. (f). Comparison of the photodiode signal on the first layer above the overhang (layer 200) for a part printed with nominal laser parameters and a part printed with laser parameters predicted by the inverse model.

In the binder jetting process, various process parameters play pivotal roles in influencing the quality and characteristics of the final product. Layer thickness and binder saturation are two of the most frequently optimized parameters, which significantly impact the structural integrity and dimensional accuracy of printed parts [328,523,527,583,649–654]. Other parameters, such as roll speed and the feed-to-powder ratio, also require careful calibration for optimal performance [583]. In addition, heater power ratio affects the drying time, which in turn impacts the part strength and the rate of production [328,523]. The properties of the granules used, such as particle size and morphology, and the powder bed's characteristics, including roughness and packing density, also significantly affect the printing process and the final part characteristics [527,655]. Lastly, printing speed and spread speed are parameters that influence the printing efficiency and surface finish of the product [328,649]. By optimizing these process parameters, manufacturers can significantly enhance the quality and efficiency of binder jetting processes. Onler et al. [328] developed a robust approach to identify optimal process parameters for binder jetting of Co-Cr-Mo alloy. Experimental investigations and machine learning techniques were used to establish the relationship between process parameters and output quality, including density, dimensions, and surface quality of green parts. Artificial neural networks were employed to model this relationship, and the weighted k-NN algorithm was used for qualitative classification. A genetic algorithm-based multi-objective optimization was applied to determine the optimum process parameters, achieving over 90% accuracy in predicting part quality. Jimenez et al. [656] conducted a parametric study to investigate the influence of seven process inputs on the relative densities of printed alumina parts. Multivariable linear and Gaussian process regression models were developed to predict green densities based on process inputs. The study identified recoat speed and oscillator speed as key parameters affecting green densities.

Process parameter optimization research in vat photopolymerization, material jetting, and sheet lamination is relatively scarce compared to other techniques, possibly due to perceived limited opportunities for substantial quality improvement [657–659]. These methods already yield high-resolution products with smooth finishes, especially in the realm of polymers. Consequently, the quality benefits achievable through process optimization might not be seen as profound enough to justify the extensive time and resources required for in-depth study. The inherent limitations of these technologies, such as the restricted range of materials applicable in vat photopolymerization and material jetting, or the weak interlayer bonding in Sheet Lamination, might also inhibit broad-scale enhancements. Thus, research efforts may be directed more towards other aspects like new material development or integration with other techniques rather than process parameter optimization, which might be seen as offering minimal potential for significant quality advancements in these specific techniques. Segura et al. [336] developed a machine-learning approach to predict droplet behaviors in MJ AM. The Network of Tensor Time Series was used to capture the underlying relationships shared across diverse material and process parameters. The Tensor Graph Convolutional Network and Tensor Recurrent Neural Network were employed to capture cross-linked and temporal relationships, respectively. The features extracted from these networks were fed into a Multilayer Perceptron for predicting future droplet behaviors. The proposed methodology demonstrated accurate and efficient predictions for both known and unknown material/process parameters using simulated and experimental droplet evolution data.

3.4.3. Optimization algorithms

Optimization algorithms play a critical role in process parameter optimization for AM [285]. After the relationships between process parameters and output qualities are determined, the optimization algorithms need to be applied to figure out the optimal solutions to obtain the desired qualities. The quality and efficiency of an AM process can be improved by optimizing the process parameters that control the manufacturing process.

Indeed, process parameter optimization in AM is often approached as a multi-objective optimization problem [660]. The multi-objective optimization problem is a class of optimization problems that involve optimizing multiple, often conflicting, objectives simultaneously. In the context of process parameter optimization in AM, a multi-objective optimization problem arises when multiple quality measures need to be optimized simultaneously. For example, in metal AM, the quality measures include porosity, surface roughness, tensile strength, and fatigue strength. Each quality measure is typically optimized individually in a single-objective optimization problem. However, in practice, these quality measures are often interdependent, and optimizing one measure may lead to a degradation in another measure. Thus, optimizing these measures simultaneously requires a multi-objective optimization problem. The typical multi-objective optimization problem is given in Equation (1).

$$\begin{aligned} \min F(x) = \textstyle\sum_{i=1}^{T} \omega_i f_i(x) \quad & x \in \Omega \in \mathbb{R}^n \\ \text{s.t.}\, g_i(x) \le 0 \quad & i = 1, 2, ..., k \\ h_i(x) = 0 \quad & i = 1, 2, ..., k \end{aligned} \tag{1}$$

where $f_i(x)$ is the objective function that needs to be optimized subject to the constraints, and $g_i(x) \le 0$ and $h_i(x) = 0$ are constraints that are required to be satisfied (these are called hard constraints).

Multi-objective optimization methods can be broadly categorized into three groups: priori methods, posteriori methods, and interactive methods [661].

Priori methods are also known as pre-decision methods or offline methods [662]. These methods involve solving the multi-objective optimization problem before the decision-maker is faced with making a choice. The solutions obtained from the pre-decision methods are presented to the decision-maker, who then chooses the best solution based on their preferences. Some examples of priori methods include weighting methods [663], goal programming [664], and lexicographic methods [665].

Posteriori methods are also known as post-decision methods or online methods [666]. These methods involve solving the multi-objective optimization problem in real-time as the decision-maker makes choices. The solutions obtained from the post-decision methods are presented to the decision-maker, who then chooses the best solution based on their preferences. Some examples of post-decision methods include non-dominated sorting genetic algorithm-II (NSGA-II) [306,318,515,667], and Pareto archive evolution strategy (PAES) [668]. Peng et al. [515] developed a predictive model for specific energy consumption and metallic powder usage rate in laser cladding using three different methods. The comparison revealed that the method that demonstrated the highest fitting performance was the integrated Tabu search and GEP. The predictive models were then used to determine the Pareto front using NSGA-II, which provided the optimal set of processing parameters. Results showed that NSGA-II was effective in maximizing energy and metallic powder efficiency. This study emphasizes the importance and effectiveness of NSGA-II in the process optimization of AM. Asadollahi-Yazdi et al. [306] proposed a method to simultaneously analyze critical attributes and drawbacks of AM and optimize the manufacturing parameters for AM products. The study focuses on FDM and formulates a multi-objective optimization problem with layer thickness and part orientation as decision variables. NSGA-II is utilized to find optimal solutions. The approach is demonstrated through a case study and emphasizes the effectiveness of NSGA-II in AM process optimization. Meng et al. [318] focused on optimizing multilayer bio-inspired sandwich structures of Ti-6Al-4V alloy fabricated by SLM. The results showed that NSGA-II can effectively optimize the bio-inspired sandwich structures with a relative error rate of less than 10%. The study further demonstrated the comprehensive mechanical performances of the bio-inspired sandwich structures and identified the optimal configuration as the two-layered structure under cross-arranged configurations, emphasizing the effectiveness of NSGA-II in optimizing AM structures.

Interactive methods involve the decision-maker actively participating in the optimization process [669]. These methods involve presenting the decision-maker with a set of solutions and asking them to choose the best solution based on their preferences. The optimization process is then updated based on the decision-maker's choices. Some examples of interactive decision-making methods include interactive particle swarm optimization (PSO) [342,533], interactive genetic algorithms (GA) [313,332,341,670], and interactive evolutionary strategies [671–673]. Selvam et al. [533] used PSO to optimize FFF printing parameters for improving surface quality and reducing the printing time of ABS polymer. The study employed RSM and PSO techniques to predict the optimum process parameter values. Through the PSO method, high surface quality with a minimum printing time of 24 minutes was achieved, showing finer optimal values compared to RSM. Kumar & Maji [332] discussed the optimization of WAAM through the use of multi-objective GA to minimize void and excess material. The focus is on developing a single-bead geometry model using RSM and Box-Behenken DoE for the deposition of SS304L. The study found that the optimal processing conditions and deposition planning determined by multi-objective GA led to the minimum void and maximum material yield. Additionally, it was discovered that optimal bead sizes and degrees of overlapping are different for different geometries. The study also highlights the benefits of double wire feed deposition, which can deliver a higher deposition rate and superior mechanical properties of the deposited material compared to single wire feed deposition.

Each of these categories of multi-objective optimization methods has its advantages and disadvantages. Priori methods can be more computationally efficient as they solve the optimization problem only once. However, they may not provide the decision-maker with enough flexibility to make the best choice. Posteriori methods provide more flexibility to the decision-maker, but they can be more computationally expensive as the optimization problem is solved in real-time. Interactive methods provide the most flexibility to the decision-maker but can be time-consuming as the decision-maker must actively participate in the optimization process.

3.4.4. Section conclusion

In this section, the concept of process parameter optimization in AM is explored comprehensively from three interconnected perspectives. Firstly, the optimization objectives, encompassing cost-efficiency, qualities, and properties, are discussed. These objectives cover a range of parameters that need optimization to enhance production efficiency, product quality, and suitability for specific applications. Secondly, the optimization of process parameters in the AM process is examined in detail. Various parameters, such as build orientation, layer thickness, printing temperature, and infill pattern, are explored for their impact on the characteristics of the manufactured part. Lastly, optimization methods, including computational and mathematical models, are explored, with a focus on advanced techniques like machine learning for modeling the complex relationship between process parameters and the properties of the final part.

Additionally, we delve into the crucial aspect of optimizing process parameters in AM to achieve significant benefits for manufacturers. The optimization of process parameters plays a vital role in improving the quality of the finished product, including reducing porosity, enhancing surface finish, and improving dimensional accuracy. This optimization helps ensure that products meet required specifications and are free from defects arising from improper process parameter settings. Moreover, process parameter optimization contributes to reducing manufacturing costs by achieving better process efficiency, minimizing material waste, and reducing the need for post-processing operations.

However, optimizing process parameters in AM presents several challenges. AM processes involve numerous variables that impact the final product's quality, and balancing conflicting objectives poses a significant challenge. Trade-offs between different aspects of the print, such as strength, speed, resolution, and quality, can make it challenging to find the optimal parameter settings. Additionally, the lack of standardization in the industry adds complexity to the optimization process, as optimal settings may vary among manufacturers and printer models.

Furthermore, the range of materials and techniques used in AM further contributes to the complexity of process parameter optimization. Each material and technique have its own unique set of process parameters that must be optimized for optimal results. Additionally, process parameter optimization is an ongoing process, as materials, printer models, and techniques evolve over time, necessitating continual monitoring and updates to achieve the most effective methods.

3.5. Defect detection & real-time monitoring

Defect detection and real-time monitoring in AM hold significant importance across various aspects of the manufacturing process [674]. It ensures quality assurance by identifying and addressing defects that can compromise the structural integrity and functional performance of AM parts [675]. Moreover, defect detection enhances reliability and safety, particularly in industries where structural integrity is critical [676]. By minimizing defects, manufacturers can achieve cost savings through reduced material waste and improved efficiency. Defect analysis also provides valuable insights for process optimization [677], enabling manufacturers to fine-tune parameters, materials, and designs. Compliance with regulatory standards is ensured through defect detection, and continuous improvement is fostered by identifying areas for enhancement. Ultimately, defect detection plays a crucial role in enhancing the overall quality, reliability, cost-efficiency, and compliance of additively manufactured components.

3.5.1. Defect types

AM processes are susceptible to various types of defects that can impact the quality and performance of manufactured components. These defects can arise at different stages, including material preparation, part fabrication, and post-processing. Common defect types in AM include geometric defects, surface defects, porosity and voids, inadequate fusion or bonding, inclusions and contaminants, residual stresses, and microstructural defects [674,678]. Fig. 12 provides an overview of defect detection within the context of AM. The explanations for each defect are demonstrated below:

- Geometric defects: Warping [679], distortion [680], overhangs [681,682], undercuts [682], and shape inaccuracies affecting the geometric accuracy and dimensional deviations of printed parts.
- Surface defects: Rough surfaces [683,684], pits [685,686], cracks [687,688], and surface porosity [689] impacting the surface finish and smoothness of printed parts.
- Porosity and voids: Small voids or air pockets within the printed material, which can negatively impact mechanical properties and structural integrity [547,690–695].
- Inadequate fusion or bonding: Insufficient fusion or inadequate bonding between successive layers or material interfaces, leading to weak or delaminated regions within the part [696–699].
- Inclusions and contaminants: Foreign particles or impurities incorporated into the printed material during manufacturing, causing defects like weak spots or reduced properties [700–702].
- Residual stresses: Stresses remaining within printed parts due to rapid heating and cooling cycles, potentially resulting in distortion, warping, or cracking [493,680,703–706].
- Microstructural defects: Variations in grain size, phase transformations, or uneven distribution of alloying elements, affecting material properties and performance [547,707–710].

3.5.2. Data types

Defect detection in AM relies on the analysis of various signals, which can be categorized into two main types: image-based signals and sensor-based signals [711]. Image-based signals involve visual data,

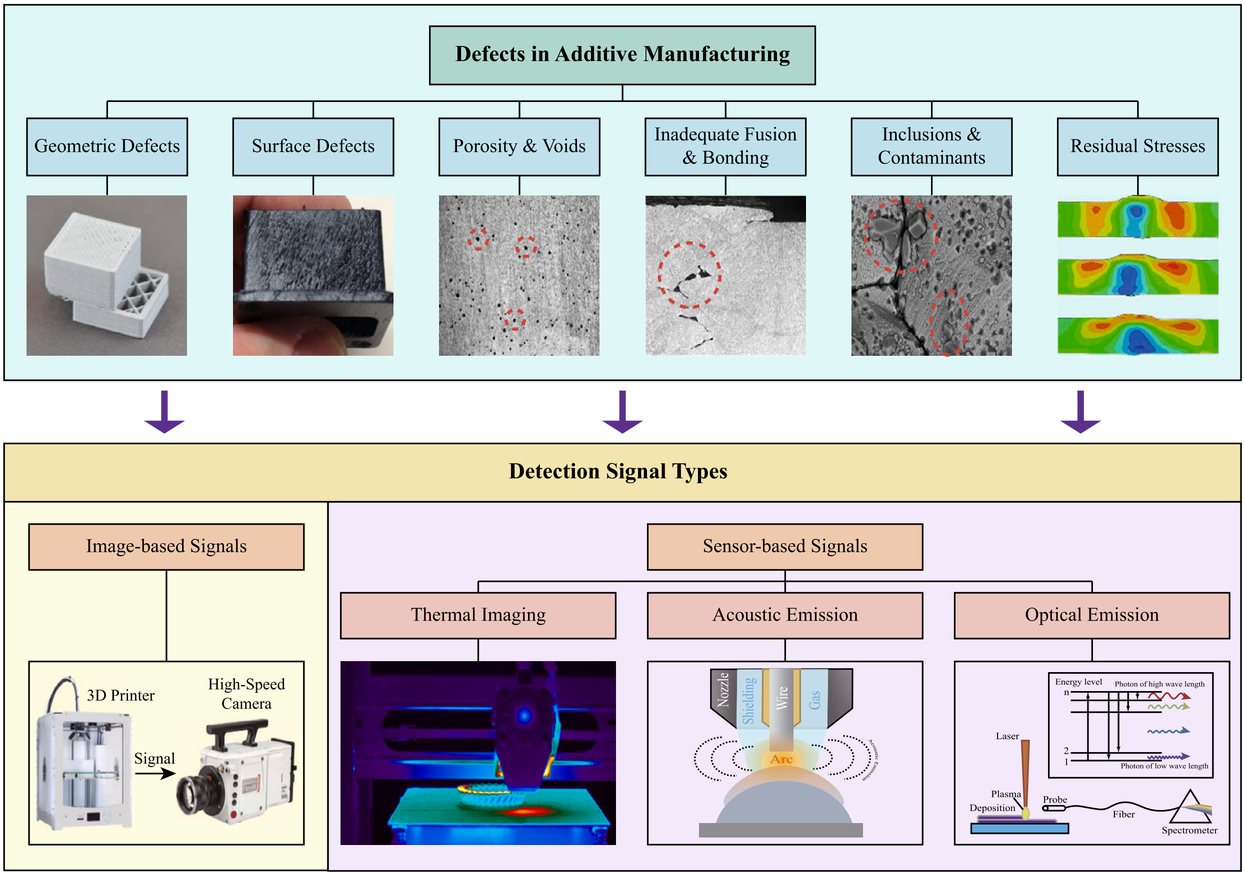

Fig. 12. Machine learning assisted defect detection & real-time monitoring in additive manufacturing.

such as images or videos, that capture surface irregularities, cracks, or other visual defects. These images can be acquired using high-resolution cameras or microscopy techniques [712,713]. Advanced image processing algorithms can then be applied to analyze the images, detect defects, and assess their severity. Image-based defect detection techniques provide valuable information about surface quality and visual anomalies [678]. Sensor-based signals, on the other hand, involve the use of various sensors to capture different aspects of the manufactured part. Thermal imaging sensors can detect variations in temperature distribution, which may indicate inadequate fusion or cooling issues [714–716]. Acoustic sensors can capture acoustic emissions or ultrasonic waves to assess the structural integrity of the part, detecting anomalies such as voids or delaminations [277,713,717–720]. X-ray or CT scanning employs sensors to capture internal images, revealing defects like porosity or incomplete fusion [721–728]. Mechanical testing sensors, such as tensile testers or hardness testers, can measure the mechanical properties of the part, detecting deviations from the desired material behavior.

3.5.3. Current research

As mentioned before, defect detection and real-time monitoring are one of the most popular research domains for the application of machine learning in AM. Therefore, in this section, we will explore the current research for defect detection and real-time monitoring according to the data type used in the process. Some representative research is demonstrated in Fig. 13.

3.5.3.1. Image-based signals Image-based signals in defect detection of AM play a crucial role in capturing visual data that reveals surface irregularities, cracks, and other visual defects. High-resolution cameras or microscopy techniques are employed to acquire detailed images or videos of the manufactured parts. These visual data serve as a rich source of information for analyzing the surface quality and identifying any anomalies present. Advanced image processing algorithms are then applied to these images, enabling the detection and characterization of defects with high accuracy and precision. By leveraging image-based signals, AM processes can be monitored in real-time, enabling early detection of defects and facilitating quality control throughout the manufacturing process. The utilization of image-based defect detection techniques provides valuable insights into the visual aspects of the printed parts, ensuring the overall quality and integrity of the manufactured components. Scime & Beuth [314] utilized a high-speed camera to monitor the morphology of LPBF melt pools in the Inconel 718 material system. Computer Vision techniques were employed to construct a scale-invariant description of melt pool morphology, and unsupervised machine learning was applied to differentiate between observed melt pools. In-situ signatures indicating flaws were identified through the linkage of ex-situ and in-situ morphology. Supervised machine learning was then used to classify melt pools observed during the fusion of non-bulk geometries, such as overhangs. Zhang et al. [734] applied a deep-learning-based approach to detect porosity in laser AM. A high-speed digital camera captured melt-pool data during the process, and CNN models were trained to analyze the features of the melt-pool and predict porosity attributes in the deposited specimens. The developed image processing tools automated the extraction of porosity information from raw quality inspection data. The compact CNN models achieved a high classification accuracy of 91.2% for porosity occurrence detection and demonstrated predictive capability for micro pores. Furthermore, the models accurately predicted local volume porosity with a low root mean square error, showcasing their effectiveness for both high and low-porosity specimens. Wright et al. [735] developed a novel optimization framework using computer vision and DL for the defect detection and optimization of extrusion AM of thermoset composites. The framework dynamically adjusted printing parameters during extrusion to achieve optimal results. A DL-integrated extrusion AM system was

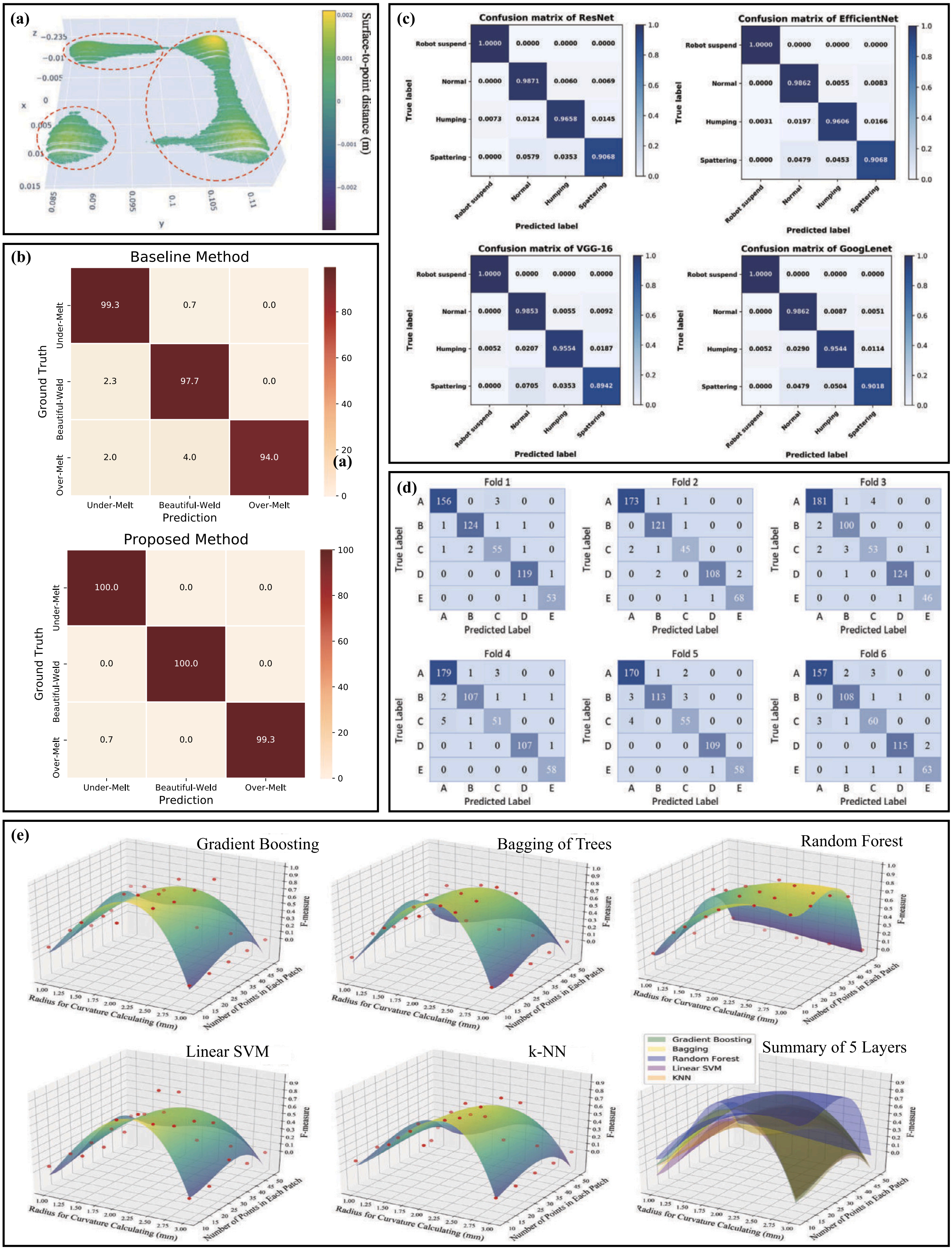

Fig. 13. Current research for defect detection and real-time monitoring in additive manufacturing based on machine learning. (a). Clustering result showing surface defects in 3D with in-situ point cloud processing and machine learning [729]. (b). Confusion matrix for deep learning-based quality identification method for metal AM process [730]. (c). Confusion matrix for vision-based melt pool monitoring for wire-arc additive manufacturing using deep learning method [731]. (d). Confusion matrix for A hybrid deep learning model of process-build interactions in additive manufacturing [732]. (e). 3D fitted surface of five ML algorithms for geometrical defect detection on additive manufacturing parts with curvature feature and machine learning [733].

used, along with in-situ imaging and high-accuracy CNN, to determine the ideal process parameters for composite AM.

3.5.3.2. Sensor-based signals Sensor-based signals can provide parameters such as temperature, pressure, vibration, sound, or electromagnetic signals during the AM process. In the context of defect detection in AM, sensor-based signals provide valuable information for identifying and characterizing defects and abnormalities.

3.5.3.2.1. Thermal imaging By capturing thermal images of the printed part or the surrounding environment, thermal imaging sensors provide valuable information for defect detection and quality control.

One of the key applications of thermal imaging in defect detection is the identification of inadequate fusion or incomplete melting. Thermal anomalies, such as cold spots or hot spots, can indicate regions where the material has not properly fused or melted, leading to weak or defective bonds between layers. By analyzing thermal images, machine learning algorithms can be employed to identify and classify these areas of inadequate fusion, allowing for timely intervention or adjustment of process parameters to ensure the production of defect-free parts. Tian et al. [736] described a deep learning-based data fusion approach for predicting porosity in LBAM. The melt pool thermal history, captured by high-speed thermal imaging, was used to monitor the process and detect potential defects. Two deep-learning neural networks, PyroNet and IRNet, were developed to correlate in-process pyrometry images and sequential thermal images from an infrared camera with layer-wise porosity. The predictions from PyroNet and IRNet were fused at the decision level to improve the accuracy of porosity detection. Khanzadeh et al. [309] developed a real-time porosity prediction method using morphological characteristics of the melt pool boundary, obtained through functional principal component analysis (FPCA). Thermal imaging was used to capture the time-varying melt pool signal, which was labeled as either pores or normal melt pools using X-ray tomography. Supervised learning methods were employed to build a black-box model that predicts the probability distribution of porosity based on melt pool characteristics.

In addition to inadequate fusion, thermal imaging can also help identify cooling-related issues during the AM process. Rapid cooling or uneven cooling can result in thermal gradients across the printed part, leading to residual stresses, warping, or distortion. By capturing thermal images at different stages of the cooling process, thermal imaging sensors can detect and visualize these temperature gradients, enabling the identification of potential defects or areas of concern. This information can guide the optimization of cooling strategies or the implementation of post-processing techniques to mitigate these defects and improve the overall quality of the printed parts. Estalaki et al. [737] developed ML models to predict micropore defects in LPBF stainless steel materials using in-situ thermographic data. Two key features, the time above the apparent melting threshold and the maximum radiance, were used as inputs for the ML models. The models were trained and tested for binary classification, considering the state of each voxel as either defective or normal. The inclusion of thermal features from neighboring voxels improved the prediction accuracy.

3.5.3.2.2. Acoustic emission Acoustic emission (AE) signals play a crucial role in the defect detection of AM. By utilizing acoustic sensors, the emitted acoustic waves or vibrations can be captured and analyzed to assess the structural integrity of the printed part. These sensors are sensitive to the acoustic emissions produced during the manufacturing process and can detect anomalies such as voids, cracks, or delaminations. The AE signals provide valuable information about the internal structural quality of the part, allowing for early detection of defects that may compromise its performance or durability. Advanced signal processing techniques, such as pattern recognition and machine learning algorithms, can be applied to analyze the AE signals and distinguish between normal and defective conditions. This enables real-time monitoring and quality control of AM processes, ensuring the production of high-quality parts with minimal defects. Kononenko et al. [738] designed a situ crack detection in LPBF fabricated parts. Machine learning models were developed to differentiate crack AE events from background noise sound, achieving high classification accuracy of up to 99%. Wang et al. [739] proposed an in situ quality monitoring method, combining machine learning with an improved variational modal decomposition (VMD) technique. The AE signals were adaptively decomposed using VMD with adjusted parameters based on the whale optimization algorithm and average energy entropy. Xu et al. [740] developed a real-time monitoring system, combining AE and laser scanning technology, to detect warpage defects during the printing process. The AE signal captured variations in vibration, indicating changes in internal tension and reflecting real-time part characteristics. The AE signal was processed, and frequency and time domain features were extracted for training machine learning models. Laser scanning depth images were used to quantify dimensional changes and measure warpage. Machine learning models, including support vector machine, naïve Bayes classifier, and decision tree, were employed to accurately identify warpage in real-time. Shevchik et al. [718] utilized an AE sensor to capture acoustic signals during the selective laser melting process, with intentionally varied process parameters to induce different levels of pore formation in the workpiece. The collected AE signals were divided into training and testing datasets, and the relative energies of narrow frequency bands were extracted as acoustic features. A spectral convolutional neural network classifier was trained to differentiate between different quality levels based on these features. The classifier achieved confidence levels between 83% and 89% in quality classification.

3.5.3.2.3. Optical emission Optical emission signals play a crucial role in the defect detection of AM. These signals are obtained through optical sensors that capture the emission of light or other electromagnetic radiation during the manufacturing process. By analyzing the optical emission characteristics, such as intensity, wavelength, and spectral patterns, it is possible to identify various defects and anomalies in the printed parts [219,741,742]. Optical emission signals can provide valuable insights into phenomena such as overheating, improper melting, lack of fusion, and surface irregularities. Machine learning algorithms can be applied to process and analyze optical emission data, enabling automated defect detection and classification. This enables real-time monitoring and quality control during AM, helping to ensure the production of high-quality parts with minimal defects. Atwya & Panoutsos [691] developed a data-driven neural network framework to achieve in-situ micro-porosity localization in laser powder bed fusion using exclusively within hatch stripe optical emission data. The proposed method leveraged prior-guided neural networks to incorporate process physics and utilize nominal data. Ren et al. [352] developed a novel unsupervised recognition model for in-situ defect detection in DED. The model, which combines a long short-term memory-based autoencoder (LSTM-Autoencoder) and k-means clustering, analyzes the optical emission collected during the DED process to extract features and classify the deposition quality. Petrich et al. [743] proposed a comprehensive concept and validation scheme for inter-layer flaw detection in powder bed fusion using supervised machine learning. The research established a statistical correlation between the multi-modal sensor footprint collected during the build process and the presence of flaws identified through post-build X-ray Computed Tomography scans. Various sensor modalities, including layerwise imagery, acoustic and multi-spectral emissions, and scan vector trajectory information, were integrated using data registration techniques. A neural network was employed to fuse the modalities and distinguish flaws from nominal build conditions using only in-situ data.

3.5.4. Control and real-time intervention

For AM, the ability to control and intervene in real-time during the manufacturing process is crucial for ensuring high-quality outputs and optimizing performance. Optimization, defect detection, and real-time monitoring are prerequisites for effective control and intervention. Optimization and real-time monitoring lay the groundwork by ensuring that the manufacturing process is well-understood and that any deviations or anomalies can be detected promptly. These steps are essential to gather the necessary data and insights that enable informed control decisions. Gunasegaram et al. [357] discussed the application of machine learning in closed-loop control (CLC) strategies for metal AM. It highlights the limitations of traditional deterministic and rule-based CLC solutions in addressing the stochastic nature of the AM process. They proposed a framework for ML-assisted CLC in AM, focusing on defect and anomaly control through three scenarios: avoidance, mitigation, and repair. It identified reinforcement learning and inverse ML models as promising approaches for rapid, situation-aware control decisions. They emphasized the need for seamless integration of various technologies to advance autonomous in-situ control in industrial settings.

3.5.5. Section conclusion

In conclusion, the research in defect detection of AM using machine learning techniques has made significant progress in recent years. Various types of defects, including geometric defects, surface defects, porosity and voids, inadequate fusion or bonding, inclusions and contaminants, residual stresses, and microstructural defects, have been identified and characterized. Image-based signals, such as high-resolution cameras and microscopy techniques, have been utilized to capture visual data and detect surface irregularities and cracks. Sensor-based signals, including thermal imaging, acoustic emission, and optical emission, have been employed to monitor temperature variations, assess structural integrity, and identify anomalies in the manufacturing process. Machine learning algorithms have been applied to analyze the collected data and classify defects with high accuracy. The integration of multiple sensor modalities and the use of prior-guided neural networks have improved the reliability and efficiency of defect detection. Real-time monitoring and quality control based on these techniques have the potential to enhance the reliability and performance of AM processes. Further research and development in this field will continue to advance the application of machine learning in defect detection of AM, contributing to the production of high-quality parts and the widespread adoption of AM technology.

3.6. Design for sustainability

Undoubtedly, ensuring the sustainability of present-day technology is vital for meeting the needs of future generations [744]. It is worth noting that historically, sustainability received serious attention with a considerable delay of 50 years from the introduction of numerically controlled machining and mass production [269]. As for AM technologies, while research on their sustainability is currently being expedited, the available documented knowledge remains limited [745]. Therefore, it is imperative to conduct careful and comprehensive studies on the sustainability aspects of AM in parallel with the further development of the industry.

AM holds significant promise for reducing energy and resource-intensive manufacturing processes [269]. It offers notable advantages over conventional subtractive manufacturing, particularly when fabricating parts with complex geometries, structures, and compositions. The ease of manufacturing such intricate components using AM contributes to improved materials efficiency, as many AM processes employ powder materials that are highly reusable and recyclable. This efficiency leads to reduced material waste, thereby helping to lower the carbon footprint [746]. Additionally, AM's potential for decentralized production brings production closer to the point of consumption. Consequently, supply chains can be compressed and simplified [747]. This reduction in complexity may lead to lower environmental impact and easier management. Overall, AM is widely recognized as a green technology for small-to-medium batch production, offering superior time and cost efficiency compared to conventional manufacturing processes.

However, it is essential to exercise caution when considering the seemingly evident benefits that AM may offer. There are instances documented in the literature where AM does not align perfectly with the notion of being a wholly "green" technology. Here are some examples: (1) Economies of scale typically favor conventional mass production, leading to lower incremental costs compared to one-off AM production [748]. This aspect raises concerns about the cost-effectiveness of AM for certain production scenarios. (2) A comprehensive evaluation of the entire operating procedure, which includes accounting for stages like equipment warm-up/cool-down, may reveal that AM does not necessarily outperform conventional manufacturing processes in terms of energy consumption [749]. This aspect challenges the assumption of AM being inherently more energy-efficient. (3) AM often necessitates the use of additional support structures for overhanging parts. These support structures can lead to wastage of material, time, and energy [6], further highlighting the need to consider the overall environmental impact of AM processes.

In conclusion, while AM has undeniably demonstrated several environmental benefits, it is crucial to acknowledge and address these concerns to ensure its sustainable and responsible implementation. Careful consideration of the specific manufacturing requirements and the overall ecological impact of AM is essential for making informed decisions about its usage in different contexts. The main concerns for the sustainability of AM are listed in Fig. 14. By considering sustainability from the outset, designers can create products that not only meet functional requirements but also contribute to environmental and resource conservation goals. Herein, we shine a spotlight on two aspects of design for sustainability, including energy consumption modeling and material waste reduction.

3.6.1. Energy consumption modeling

In general, recent approaches for energy consumption modeling in AM technologies can be broadly divided into two groups: physics modeling and machine learning methods [750,751]. Physics-modeling approaches aim to uncover the relationships between energy consumption and relevant parameters by using rigorous formulas. For instance, Gutierrez-Osorio et al. [752] introduced a mathematical model to predict energy consumption directly during the system stage, covering processes such as extrusion, deposition, selection, gluing, and curing. Garcia et al. [753] used life cycle assessment and unit process life cycle inventory methodology to evaluate the potential environmental impacts of injection molding and fused deposition modeling. Yi et al. [754] developed an energy simulation of a desktop AM system based on the bond graph modeling approach. Ramesh et al. [755] presented an interpretive structural energy consumption model that considers 18 influencing factors in the material extrusion-based AM process. Despite their potential, physics-modeling approaches face challenges in AM due to their complex nature and the involvement of multiple data sources, including model designers and manufacturers. This complexity makes it difficult for physics-based methods to comprehensively account for all relevant factors in AM's energy consumption.

As a result, machine learning methods have emerged as an alternative approach [756]. These methods rely on large datasets and machine learning techniques to identify patterns and correlations between input parameters and energy consumption [269]. Machine learning approaches can handle the intricacies and multivariate nature of AM processes more effectively, providing valuable insights for energy consumption minimization. Unlike physics-modeling approaches, ML specializes in learning potential rules solely from data, making it particularly well-suited for tackling the complexities of AM processes. For example, Wang et al. [756] proposed a novel approach that involves constructing a multisource dataset comprising pixel-source, motion-source, and processing-source data generated from the AM design stage. They then employed a deep network called 3DPECP-Net to map the learned rep-

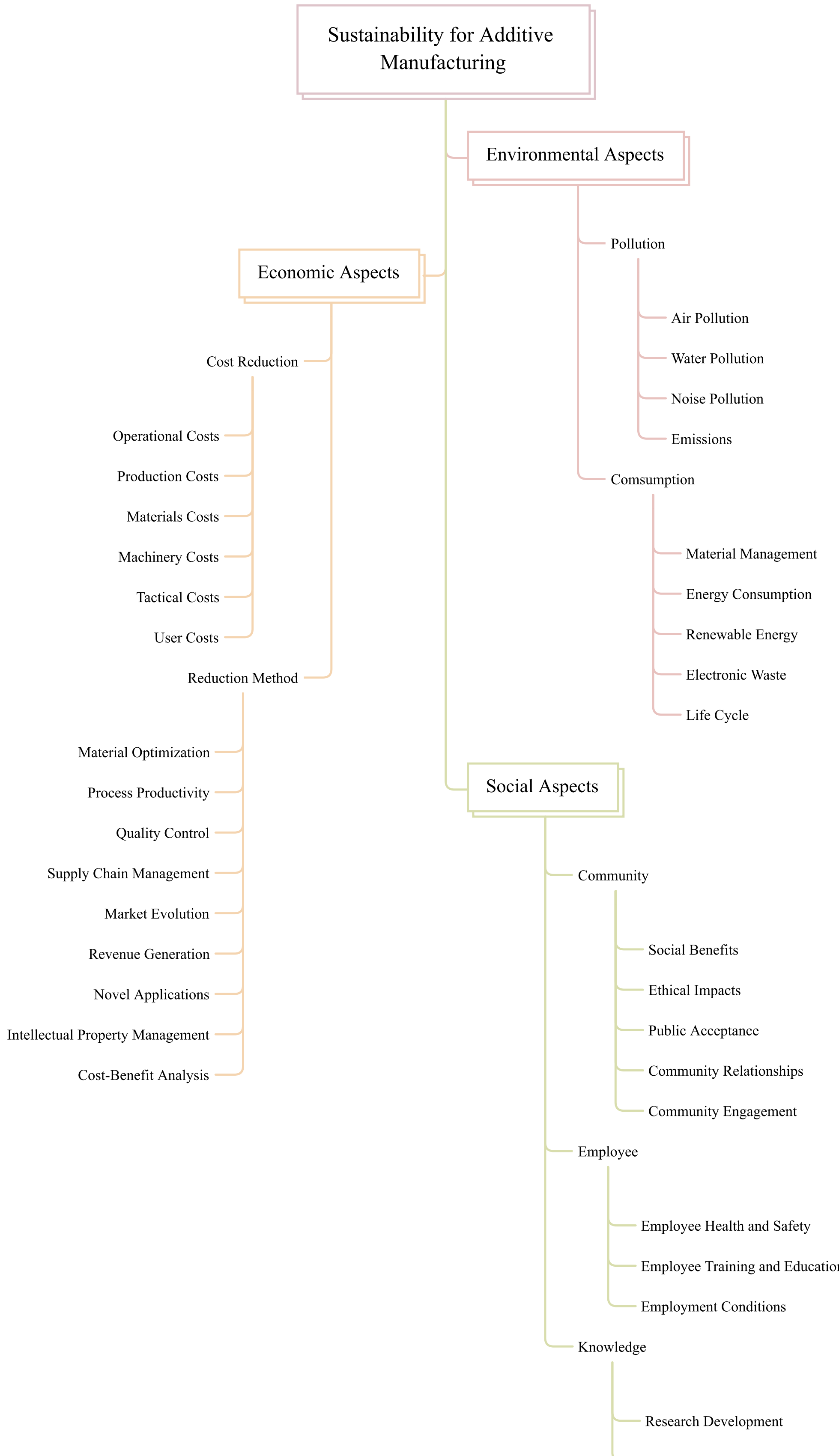

Fig. 14. Main concerns for the sustainability of additive manufacturing.

resentation from this dataset to energy consumption values, achieving accurate predictions with moderate computation requirements. Wang et al. [751] also focused on addressing energy consumption (EC) and material waste concerns associated with AM processes. A new energy efficiency design method was proposed, utilizing a Multimodal Attention Fusion Network (MAFN) to optimize the AM process. The study developed a mathematical EC model for AM and used the MAFN to predict EC by integrating data from computer-aided design and the manufacturing process. The MAFN included a Multimodal Fusion Framework and an Attentional Feature Fusion Module to effectively combine and analyze diverse data sources. The whole process is demonstrated in Fig. 15. Similarly, Yang et al. [343] utilized ML to explore the relationships between energy consumption and various hand-crafted features of printing layers, such as layer thickness, surface areas, and shapes. Barrionuevo et al. [757] applied three ML methods, including gaussian process regressor, extreme gradient boosting regressor, and multi-layer perceptron, to assess energy consumption in the wire arc AM process using input variables such as wire diameter, wire feed speed, travel speed, and net power. Majeed et al. [89] proposed a big data-driven framework for sustainable and smart AM, which assists AM industry leaders in making better decisions during the beginning of the product life cycle.

These examples illustrate the potential of ML in providing valuable insights into energy consumption patterns in AM. By leveraging large datasets and powerful learning algorithms, ML approaches contribute to advancing energy-efficient practices in AM. Combining both physics-modeling and data-driven methods allows researchers to develop more accurate and comprehensive tools for assessing and reducing energy consumption in AM processes, further promoting the sustainable development of AM technology.

3.6.2. Material waste reduction

AM technology is not entirely waste-free, and thus, material waste reduction becomes a critical aspect of sustainable AM [758–760]. Reducing material waste not only has a direct impact on the environmental dimension of sustainable AM by minimizing resource depletion and waste generation, but it also significantly influences the economic dimension of the process. In numerous AM processes, support structures are a significant source of waste in AM processes [6]. Due to the nature of AM, some complex geometries may require support structures to ensure the integrity of the object during the manufacturing process. However, these additional support structures often result in material waste, as they are removed and discarded after the printing is complete. Moreover, the presence of support structures leads to increased print time and energy consumption. Printing these extra structures not only extends the overall manufacturing time but also consumes additional energy, further contributing to the environmental impact.

Optimizing the geometry and topology of support structures is indeed a potential solution to reduce waste and improve the efficiency of AM processes [415,418,502]. Recent studies have explored innovative approaches to achieve self-supporting designs or to minimize the need for excessive support structures. One method involves using genetic algorithms to prune supporting lattice structures without compromising their supporting functionality [345]. This approach identifies and removes unnecessary elements from the support structure, optimizing it for minimal material usage while still providing the necessary support to the printed object. Another technique is designing self-supporting parts that eliminate the need for external support during the AM process. In a recent study, explicit topology optimization was employed to generate self-supporting designs by optimizing explicit geometry parameters [761]. This approach involves adjusting the geometry of the design in a way that allows it to be printed without requiring additional support structures. Moreover, combining topology optimization with machine learning techniques has shown promising results in reducing the need for inner and outer support structures. For instance, a recent study proposed a data-driven topology optimization method for AM that leverages microstructure libraries containing various microstructures and their corresponding mechanical properties. The use of a multiresponse latent-variable Gaussian process in this approach allows for efficient optimization of the AM design, considering both performance and support structure requirements [762].

By leveraging advanced optimization techniques and integrating machine learning with topology optimization, researchers and engineers can significantly reduce waste, material consumption, and printing time, thus contributing to the overall sustainability and efficiency of AM processes.

4. Digital twin assisted additive manufacturing

In recent years, the concept of the Metaverse has gained immense popularity and captured the attention of various sectors, including academia, business, and technology enthusiasts [763–768]. The industrial version of Metaverse–the digital twin–has also attracted significant attention as a powerful tool for improving the efficiency and reliability of manufacturing processes [769–781]. The adoption of digital twin technology has experienced a rapid surge, driven by its potential to revolutionize the manufacturing landscape. The digital twin technology involves the creation of a virtual replica of a physical object or system that can be used for monitoring, analysis, and optimization. This technology offers a novel approach to bridge the gap between the physical and digital worlds, enabling manufacturers to create virtual replicas of their physical assets. These virtual representations are continuously updated with real-time data from their physical counterparts [276,782]. By harnessing this wealth of information, manufacturers can gain a deep understanding of their assets' performance, behavior, and condition.

Digital twins serve as powerful tools for monitoring, analysis, and simulation of manufacturing processes [783]. They provide real-time insights into the operation of physical systems, allowing manufacturers to optimize process parameters, identify inefficiencies, and enhance overall efficiency. By capturing and analyzing data from sensors and IoT devices embedded within the physical assets, digital twins facilitate predictive maintenance strategies [784]. This enables proactive identification of potential faults or malfunctions, thereby reducing unplanned downtime and improving overall equipment effectiveness.

Furthermore, digital twins hold tremendous potential for decision-making [785–787] in AM. AM processes often involve intricate geometries and complex material interactions, which can lead to challenges in achieving desired part quality and performance. The use of digital twins allows manufacturers to simulate and analyze the entire AM workflow, from design to post-processing [788,789]. By virtually testing different design iterations, material choices, and process parameters, manufacturers can identify optimal settings that result in improved part quality, reduced waste, and enhanced production efficiency.

By integrating digital twin technology into AM, manufacturers can achieve greater control and visibility over the entire production lifecycle. Real-time data gathered from sensors during the AM process can be utilized to validate and calibrate the digital twin, ensuring a high degree of accuracy and reliability [790–794]. This integration facilitates the identification of potential process variations or deviations and enables real-time adjustments to maintain consistency and quality throughout production. The main components and principles of digital twins are demonstrated in Fig. 16.

In this section, we will explore the key components and functionalities of digital twins and their integration into the AM workflow. We will examine the diverse ways in which digital twins are utilized for process optimization, predictive maintenance, quality assurance, iterative design, and lifecycle management in the context of AM. Furthermore, we will analyze the benefits, limitations, and future prospects of digital twin technology in this rapidly evolving field.

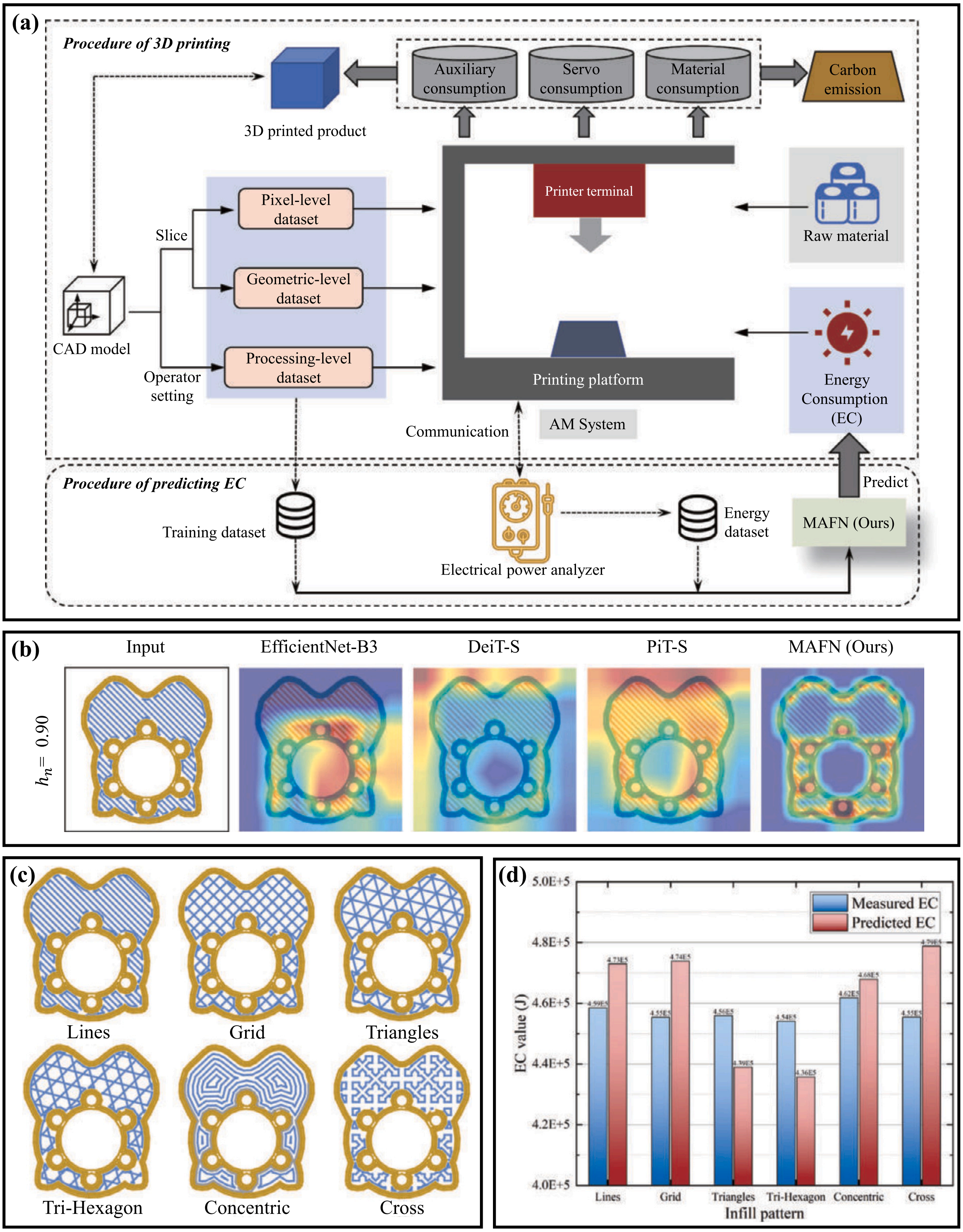

Fig. 15. Energy efficiency design for eco-friendly additive manufacturing based on multimodal attention fusion [751]. (a). The energy efficiency design and EC prediction frameworks during the AM process. (b). Grad-CAM overlaps with the corresponding LCI to interpret the diverse methods during the test phase in EC prediction. (c). Sliced LCIs with six infill patterns. (d). Comparison results of measured EC and predicted EC by the proposed MAFN on the wheel support models with diverse infill patterns.

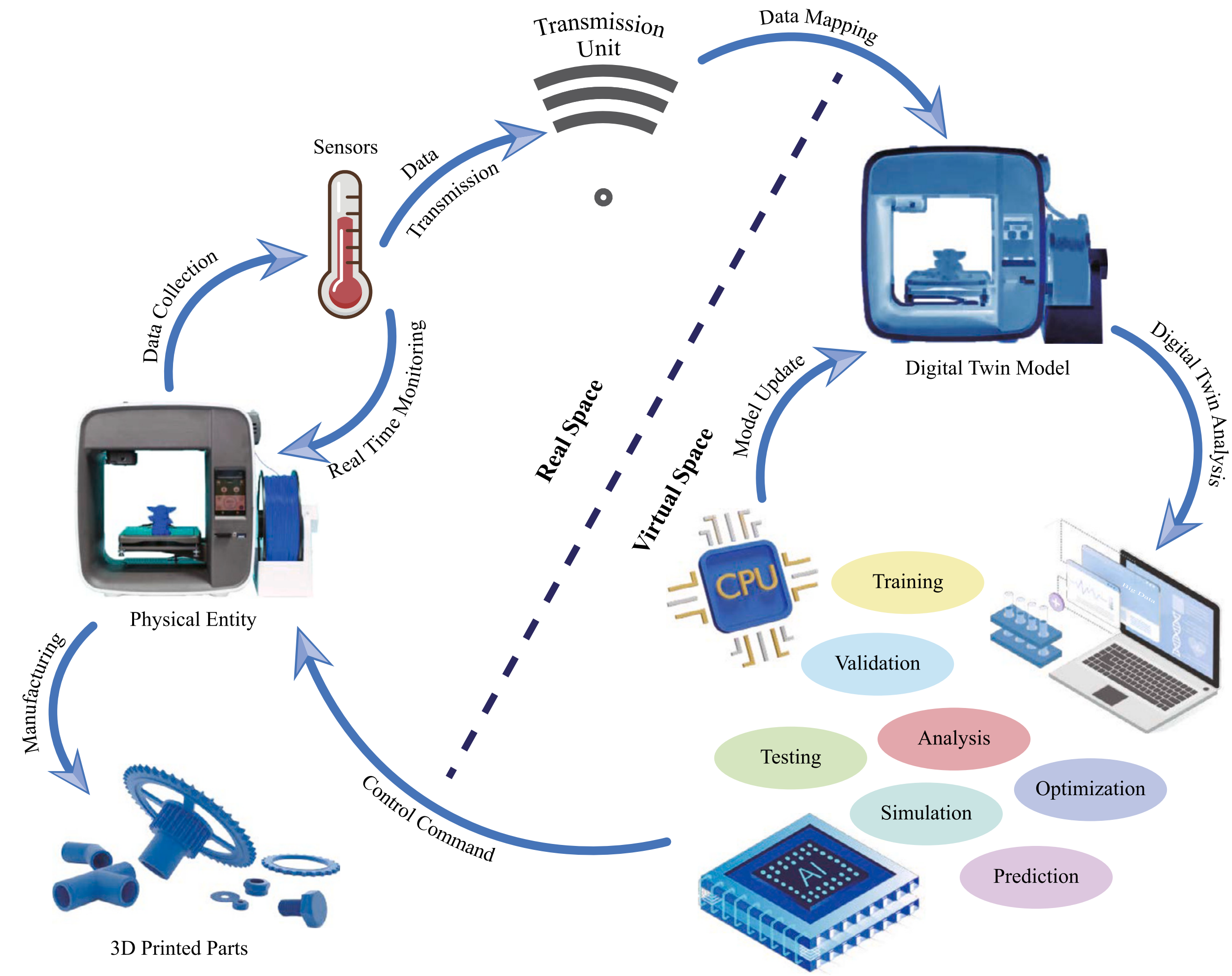

Fig. 16. Components and principles of digital twins for additive manufacturing.

4.1. Research status of digital twins

The current research status of digital twin technology remains highly active and dynamic, with a growing number of studies exploring its various applications and potential in different industries. Researchers and practitioners still do not agree on a standardized definition of digital twin, leading to variations in its interpretations and applications based on specific use cases and industries. Some recent research studies have focused on establishing common definitions and components of digital twins. For instance, Tao et al. [769] conducted a comprehensive analysis of digital twin models from various perspectives and classified studies based on six modeling aspects within the digital twin modeling theoretical system. Enabling technologies and tools for digital twin modeling were also investigated and summarized. Additionally, Liu et al. [779] did a systematic research on the basic components of digital twins, focusing on common definitions and characteristics. It clarified the relationship between digital twins and cyber-physical systems. The research methodology for core components (physical entities, virtual models, and twin data) was examined, and application areas of digital twins were explored.

As industries undergo significant digital transformations and embrace Industry 4.0 technologies, the adoption of digital twin is expected to increase [795]. The advancements in data collection, storage, and exchange, driven by technologies like the Internet of Things and big data, are enhancing the capabilities of digital twins [796]. Moreover, the integration of augmented reality provides an optimal human-machine interface, making digital twin information easily accessible and understandable for both technical and non-technical users [797].

Although the development of digital twins is very popular now, there are still some challenges that have to be faced. One of the challenges is the lack of existing physical data for new products [85,798]. Developing digital twins for new products that are still in the design phase can be challenging due to the lack of historical data. Unlike existing products, where data from past interactions and performance are available, new products do not have a track record to rely on. This scarcity of physical data makes it difficult to accurately model the behavior and characteristics of the digital twin. Without this data, designers may face uncertainties in making informed decisions during the design and conceptualization process. Also, the reliance on accurate data of digital twins also sets a threshold for its development. The accuracy of the data collected from sensors embedded on physical entities is paramount to the effectiveness of digital twins. In industries like manufacturing, aerospace, and healthcare, where precise measurements and monitoring are critical, any inaccuracies in data collection can result in faulty simulations and unreliable predictions. To ensure the fidelity of the digital twin, rigorous data validation processes and calibration of sensors are necessary. Additionally, the integration of real-time data updates is essential to maintain accurate synchronization between the physical counterpart and its virtual replica [799,800].

While the potential benefits of the digital twin in improving process management, monitoring, and predictive maintenance are promising, its implementation can be costly [778,801–803]. Creating a digital twin requires significant investments in technology, infrastructure, and skilled personnel. The costs associated with acquiring and integrating sensors, setting up data storage systems, and developing the digital twin software can be substantial. Consequently, potential users need to carefully evaluate the cost and benefits of adopting DTs, often leading to their utilization in high-value projects or those that heavily rely on digital twin-specific functionalities.

Besides, the lack of standardized guidelines and specifications for digital twins still poses a challenge to their widespread adoption [804–807]. Establishing a standardized framework for DTs is crucial to building confidence in the technology's validity, accuracy, and interoperability. Furthermore, the ease of integrating digital twins into existing manufacturing setups is an important issue that requires addressing, as seamless data exchange between different digital twin components is essential for realizing their full potential.

As research in the field of digital twin technology continues to progress, there is a particular focus on its application in manufacturing environments. Many recent studies have explored how DTs can be integrated into various stages of a product's life cycle, from conceptualization and design to production, post-production, and retirement stages [770,773,808–810]. Researchers are investigating the potential of digital twins to interact and influence each phase of the product life cycle, with a special emphasis on AM settings. Researchers are exploring how digital twins can revolutionize various stages of the product life cycle, placing particular emphasis on their applications within AM settings. The integration of digital twins in the AM allows for accurate prototyping, rapid iterations, and virtual testing, enabling more efficient and cost-effective product development. During the production phase, digital twins facilitate real-time monitoring, predictive maintenance, and quality control, optimizing manufacturing processes and minimizing downtime. Furthermore, in the post-production phase, digital twins continue to play a vital role in monitoring product performance, collecting valuable data for product improvements, and enabling sustainable lifecycle management. By harnessing the power of digital twins in AM, researchers aim to enhance productivity, reduce waste, and pave the way for a more agile and intelligent manufacturing ecosystem. Gaikwad et al. [793] researched defect-free production of AM parts by combining predictions from a physical model with in-situ sensor data in a machine learning framework. They demonstrated the effectiveness of a digital twin approach, combining physics-based predictions and sensor data, for real-time flaw detection in AM processes. The integration of these approaches resulted in an statistical fidelity-score approaching 90%, outperforming using either approach alone (statistical fidelity-score of nearly 80%). Liu et al. [789] proposed a digital twin-enabled collaborative data management framework for metal AM systems. The framework was validated through practical implementation in a distributed metal AM system, showcasing its potential to enhance process understanding, develop simulation models, reduce development times and costs, and improve product quality and production efficiency. The representative application scenario of cloud-based and deep learning-enabled metal AM layer defect analysis demonstrated the effectiveness of the digital twin approach in supporting intelligent process monitoring and optimization. Mandolla et al. [811] proposed a digital twin for AM in the aircraft industry, utilizing Blockchain solutions to secure and track the data generated throughout the end-to-end AM process. This approach ensures compliance with stringent technical standards and facilitates the rapid prototyping of components, leading to reduced time-to-market, improved quality, and cost containment. The digital twin application enhances the security and organization of data, allowing companies to build secure and connected manufacturing infrastructure in the aircraft industry. Cai et al. [812] developed a methodology using augmented reality (AR) to communicate layout information between a reconfigurable AM system and its digital twin. The AR technique facilitated toolpath planning and simulation for concurrent material deposition using multiple independent actuators. The study demonstrated that this approach enabled rapid retrieval of position information from the physical system into the digital twin, supporting layout optimization and convenient deployment of the optimized layout back to the physical system. Pantelidakis et al. [791] implemented a novel digital twin ecosystem for AM using two data-driven approaches. One approach used an open-source 3D printer web controller application to capture status and parameters, while the other relied on externally mounted sensors for accurate synchronization between the physical and virtual 3D printers. Near-real-time synchronization was achieved, and the digital twin was validated for position, temperature, and run duration. The cost-efficient and reliable digital twin ecosystem can provide legacy equipment with digital twin capabilities, collect historical data, and generate analytics.

In conclusion, the research status of digital twin technology is still in its infancy, with a focus on its applications in various industries, including AM. Despite challenges such as the lack of standardized definitions and guidelines, researchers are exploring common components and definitions for digital twins. The integration of digital twins in AM shows promising potential in optimizing the entire product life cycle, from design to production and post-production phases. By combining physics-based models with in-situ sensor data, researchers have successfully developed digital twins for flaw detection in AM processes, improving the accuracy of predictions and reducing production defects.

4.2. Technical approach

Digital twin is a system integration, which contains a lot of technologies from data analytics to virtual modeling and simulation. In this section, we will introduce the whole process of building digital twin from a technical point of view, providing insights into the diverse range of technologies involved and their interconnections to create an effective and comprehensive digital twin system.

4.2.1. Virtual modeling and simulation

Virtual modeling and simulation are pivotal in the construction of the digital twin, serving as essential tools to bridge the gap between theoretical research and practical implementation. At the core of the digital twin lies its model, which is fundamental for the successful application of digital twin technology. Within the realm of virtual space, the digital twin model is composed of four critical dimensions: shape and structure, physical properties, dynamic response, and historical data and knowledge [769]. The shape and structure model precisely captures the geometric shape and intricate assembly relationships of the physical entity. On the other hand, the physical model meticulously reflects the comprehensive physical properties, characteristics, and constraints of the actual entity. By simulating the dynamic behavior of the physical entity in response to internal and external influences, the dynamic response model offers valuable insights into its performance under varying conditions. Moreover, the historical data and knowledge model enriches the digital twin's intelligence by integrating historical data and leveraging tacit knowledge, contributing to a smarter digital twin model. Through the amalgamation of multidisciplinary knowledge, the multidimensional digital twin model becomes empowered to perform advanced functions such as prognostication, optimization, and control within the digital realm. As a result, virtual modeling and simulation play a critical role in shaping the capabilities of the digital twin and unlocking its immense potential in various real-world applications. Knapp et al. [813] developed and validated a first-generation digital twin for laser-based directed energy deposition AM. The digital twin utilized a transient, three-dimensional model to calculate temperature and velocity fields, cooling rates, solidification parameters, and deposit geometry. The predictions of metallurgical parameters, such as cooling rates, temperature gradients, solidification rates, secondary dendrite arm spacing, and micro-hardness values, were found to be more accurate compared to conventional heat conduction calculations. This digital twin provides a practical and efficient tool to optimize AM processes and improve the properties and serviceability of additively manufactured components. Gunasegaram et al. [814] emphasized the application of digital twin modeling in metal AM to embed artificial intelligence capabilities. They highlighted the value of high-fidelity multiscale-multiphysics models for AM processes, addressing technical hurdles related to model complexity and scarcity of experimental data. Machine learning-based surrogate models were proposed for real-time problem-solving. Non-technical barriers, including standardization and collaboration difficulties, were identified, and potential solutions were offered. Phua et al. [115] developed a new framework for the application of digital twin modeling in metal AM, using Bayesian optimization to build and train surrogate models for real-time control of the layering process. The Smart Recoating approach demonstrated the potential of the digital twin control system to mitigate process variation and achieve consistent print quality in each layer, revealing new strategies for controlling the recoater and print stage displacements. Gamdha et al. [815] developed a general framework for creating a digital twin of the dynamic printing process in extrusion-based AM. Their approach involved performing geometric modeling physics-based simulations with intermediate print geometries, using parallel adaptive octree meshes for real-time predictions. The method demonstrated scalability to high voxel resolutions and accurate predictions of transient heat distribution during the printing process. This work establishes the foundations for real-time digital twins, enabling rapid virtual print sequence exploration to enhance print quality and reduce material waste.

In the construction of digital twin models, model lightweight is indeed a crucial and significant research direction [769,816–820]. As digital twins are virtual replicas of physical assets, systems, or processes, they often involve complex and detailed models to accurately represent their real-world counterpart. However, creating and working with highly detailed models can be computationally intensive and resource-consuming, especially for large-scale systems and simulations. Model lightweighting addresses this challenge by developing techniques to create simplified yet efficient digital twin models. These lightweight models retain essential features and information necessary for accurate simulations and analysis while reducing the memory and computational requirements. By optimizing the digital twin's model, it becomes easier to handle large datasets, process real-time data, and achieve higher performance in simulations. Some common methods for model lightweight are listed here:

- Level of Detail (LOD) models [821–824]: Creating different versions of the model with varying levels of detail. For example, a high-level LOD model may include only the main features, while a low-level LOD model contains fewer details for quicker processing.
- Decimation [825–827]: Removing certain elements or vertices from the 3D model, reducing its polygon count while retaining the overall shape.
- Feature suppression [828–830]: Temporarily hiding or simplifying specific features, annotations, or metadata that are not critical for the current analysis or simulation.
- Subdivision surfaces [826,831,832]: Representing complex surfaces using a lower number of control points, resulting in a more lightweight model.
- Parameterization [833–835]: Using mathematical parameterization techniques to represent complex shapes with simpler equations.
- Simplified physics models [836]: Employing reduced or approximated physics models for simulations, sacrificing some accuracy for faster computations.
- Data aggregation [837–839]: Grouping similar data points together or using statistical methods to reduce the overall data volume.

The benefits of model lightweighting in digital twin construction are multi-fold. Firstly, it enables real-time or near-real-time simulations, making it possible to monitor and control physical assets and processes in an agile and responsive manner. Secondly, lightweight models are particularly valuable in fields like AM, where precise and rapid simulations are essential for optimizing designs and production processes. Additionally, model lightweight allows for seamless integration of digital twins with other systems and technologies, facilitating data exchange and collaboration.

Research efforts in model lightweighting focus on developing advanced algorithms, compression techniques, and data reduction methods to efficiently represent complex physical systems without sacrificing accuracy. These advancements contribute to the broader adoption and implementation of digital twins across various industries, enabling them to leverage the full potential of this technology for enhanced decision-making, predictive maintenance, and process optimization. As digital twin technology continues to evolve, model lightweighting will remain a crucial aspect in building practical and scalable digital twin solutions for real-world applications.

4.2.2. In-situ monitoring and data analytics

In-situ monitoring of the digital twin in AM refers to the real-time data collection and analysis of the physical manufacturing process, which is then used to update and synchronize the corresponding virtual model or digital twin [793]. This process involves the continuous monitoring of various process parameters, such as temperature, pressure, material deposition rates, and other relevant variables during the AM process. The data collected from sensors and monitoring devices on the physical AM system are fed back to the digital twin, allowing it to dynamically adjust and simulate the evolving conditions of the physical process. In-situ monitoring plays a crucial role in ensuring accurate and up-to-date representations of the manufacturing process in the digital twin, enabling more informed decision-making, quality control, and optimization throughout the AM lifecycle. In-situ quality monitoring in digital twin-assisted AM goes beyond just being an objective; it serves as a comprehensive method to enhance the overall system, encompassing both the virtual and physical aspects. By integrating real-time data from various sensors into the digital twin, the virtual replica can continuously monitor and analyze the manufacturing process. This data-driven approach enables the digital twin to identify defects, anomalies, or deviations as they occur during the physical manufacturing process. Phua et al. [133] evaluated and reviewed the application of in-situ monitoring in the development of a digital twin for metal AM. They organized the research into four levels of increasing complexity, focusing on surrogate modeling, in-situ sensing, hardware control systems, and intelligent control policies. The proposed digital twin hierarchy offers a framework for engineering digital twins in AM and other intelligent manufacturing systems. Chen et al. [840,841] developed a multisensor fusion-based digital twin for in-situ quality monitoring and defect correction in AM. They synchronized and registered data from multiple sensors, including an acoustic sensor, an infrared thermal camera, a coaxial vision camera, and a laser line scanner, to predict location-specific quality using machine learning. This allowed for on-the-fly identification of regions requiring material addition or removal and enabled auto-tuned process parameters for defect correction.

Absolutely, data analytics is also a crucial aspect of the digital twin of AM. It involves several key components, including:

- Data Collection: The data collection process during additive manufacturing involves utilizing various technologies, including Industrial IoT [842–844], sensors, digital gauges [845–847], RFID (Radio Frequency Identification) [848,849], cameras [850–852], and 3D scanning devices [853–855]. These technologies capture essential data during the additive manufacturing process.
- Data Mapping: Once the data is collected, it needs to be organized and mapped in a way that makes sense for the digital twin. Data mapping is essential for organizing and structuring the collected data. Commonly used data mapping technologies include XML (Extensible Markup Language) [856–860], AutomationML [861–863], OPUUA (Open Platform Communications Unified Architecture) [864–866], and MT connect [867–869]. These technologies facilitate data standardization and efficient data exchange between the physical system and the digital twin.

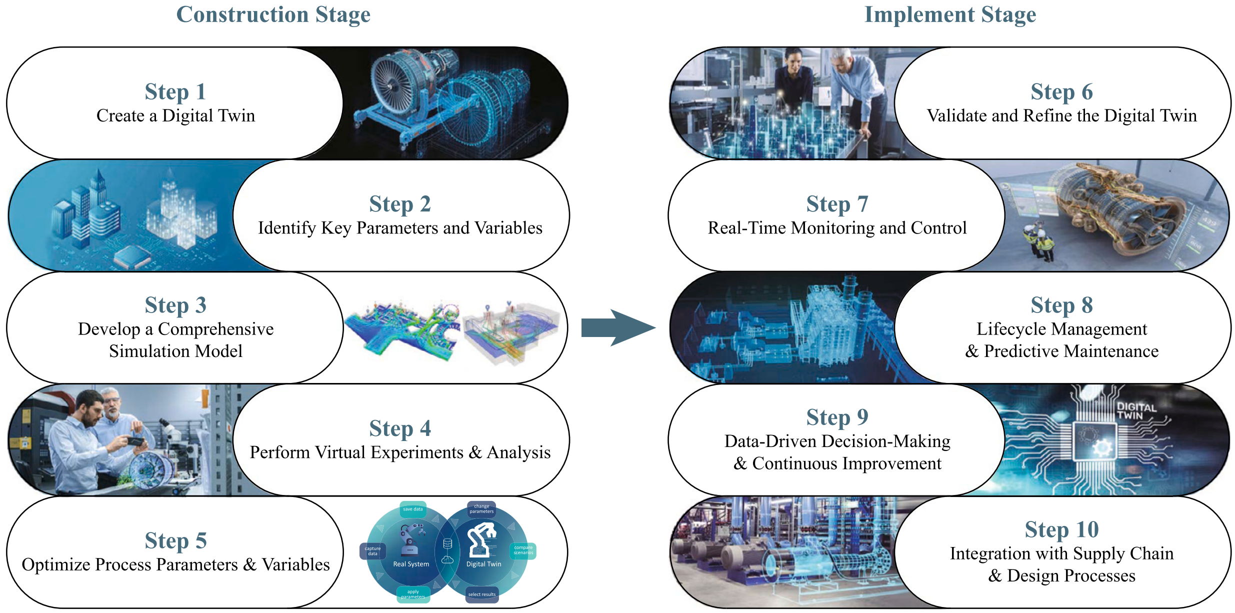

Fig. 17. Digital twins for additive manufacturing workflow.

- Data Processing: Data processing techniques are applied to analyze and interpret the collected data. This includes data fusion [870–873], where data from multiple sources are integrated to provide a comprehensive view. Blockchain technology may also be used for data security and integrity [874–879]. Edge computing is used for local processing, reducing the burden on central servers [880–884]. Signal processing is employed to extract meaningful information from raw data [885–888].
- Data Transmission: The collected and processed data need to be transmitted between the physical system and the digital twin. For this purpose, various data transmission technologies are used, such as Bluetooth [889–891], wireless sensor networks [892–895], fieldbus networks [896–898], and 5G [899–901]. These technologies enable real-time or near-real-time data exchange, ensuring seamless communication between the physical and virtual environments.

4.2.3. Whole workflow

According to the existing research on digital twins, the main steps to construct digital twins for AM are demonstrated in Fig. 17 and also summarized as follows [114,133,134,790,793,814,902–907]:

Step 1: Create a Digital Twin The first step in utilizing digital twin technology for AM is to create a digital twin of the entire manufacturing process. A digital twin is a virtual representation of the physical system, encompassing the equipment, materials, and process parameters involved in AM. Creating a digital twin requires specialized software and expertise in modeling and simulation to accurately capture the complexities of the manufacturing process.

Step 2: Identify Key Parameters and Variables Once the digital twin has been created, the next step is to identify the key parameters and variables that have a significant impact on the AM process. These can include process parameters, material properties, equipment settings, environmental conditions, and other relevant factors. Each parameter and variable must be carefully analyzed and understood to ensure their accurate representation within the digital twin model.

Step 3: Develop a Comprehensive Simulation Model Using the digital twin and the identified parameters and variables, a comprehensive simulation model is developed to simulate the AM process. The simulation model should incorporate the physics, mechanics, and dynamics of the process, accurately reflecting the interactions and dependencies between various components. Developing a simulation model requires expertise in modeling and simulation software, as well as a deep understanding of the AM process.

Step 4: Perform Virtual Experiments and Analysis Utilizing the simulation model within the digital twin, virtual experiments can be performed to simulate and analyze the AM process under various conditions. Virtual experiments allow for the exploration of different scenarios, the evaluation of alternative process settings, and the prediction of manufacturing outcomes. The results of these virtual experiments are thoroughly analyzed to gain insights into the process performance, quality, efficiency, and other relevant metrics.

Step 5: Optimize Process Parameters and Variables Based on the analysis of the virtual experiments, the digital twin enables the optimization of process parameters and variables for AM. The insights gained from the simulation model help identify optimal settings that result in improved product quality, reduced production time, enhanced efficiency, and minimized waste. The optimization process involves adjusting and fine-tuning the parameters and variables within the digital twin to achieve the desired manufacturing objectives.

Step 6: Validate and Refine the Digital Twin The optimized process parameters and variables obtained from the digital twin simulation are validated through physical experiments and actual manufacturing runs. The physical validation allows for the comparison of the digital twin's predictions with real-world results, validating the accuracy and reliability of the digital twin model. Any discrepancies or deviations between the digital twin and the physical outcomes and physical results are carefully analyzed to identify potential gaps or areas for improvement in the digital twin. The insights gained from the validation process are used to refine and update the digital twin model, ensuring its accuracy and reliability for future AM processes.

Step 7: Real-Time Monitoring and Control To enhance the effectiveness of the digital twin-assisted AM process, real-time monitoring and control systems can be implemented. By integrating sensors and data acquisition systems into the manufacturing setup, real-time data on process parameters, equipment performance, material properties, and product quality can be collected. This real-time data is fed into the digital twin, enabling continuous monitoring and control of the AM process. Real-time monitoring allows for proactive identification of deviations, timely adjustments, and optimization to maintain optimal manufacturing conditions and product quality.

Step 8: Lifecycle Management and Predictive Maintenance In addition to process optimization, the digital twin can be utilized for lifecycle management and predictive maintenance. By incorporating data on equipment condition, maintenance history, and usage patterns into the digital twin model, manufacturers can monitor the health and performance of the manufacturing equipment. Predictive maintenance algorithms can analyze the data from the digital twin to predict equipment failures and recommend maintenance actions, minimizing downtime and optimizing equipment utilization.

Step 9: Data-Driven Decision-Making and Continuous Improvement Leveraging the wealth of data generated from the digital twin, real-time monitoring, and other sources, manufacturers can employ data analytics and machine learning techniques to extract insights and make data-driven decisions. By analyzing historical data, identifying patterns, and detecting correlations, manufacturers can gain a deeper understanding of the AM process. This allows for continuous improvement through the identification of optimization opportunities, root cause analysis of issues, and the implementation of strategies to enhance overall operational efficiency and productivity.

Step 10: Integration with Supply Chain and Design Processes To fully harness the potential of digital twin-assisted AM, the digital twin can be integrated with other aspects of the supply chain and design processes. By connecting the digital twin with supply chain management systems, manufacturers can optimize material flow, inventory management, and production scheduling. Furthermore, integrating the digital twin with design software enables design optimization, rapid prototyping, and design-for-manufacturability analysis, leading to improved product designs and reduced time-to-market.

4.3. Future development and perspective

The future development directions of digital twin-assisted AM encompass a multi-faceted approach that leverages advancements in various domains to enhance its capabilities and impact on the manufacturing industry. To fully capitalize on this potential, several critical areas require focused attention.

Firstly, the research has shown that digital twins have tremendous potential for optimizing build speed and part performance in metal AM systems. To unlock this potential, future work needs to focus on improving surrogate modeling techniques to enable deeper integration with higher levels of the digital twin hierarchy. Multi-physics validation and enhancement of surrogate model performance, facilitated by larger datasets and emerging machine learning methods, are key areas to address. Additionally, sensor development for AM-specific monitoring, such as computer vision for defect detection, requires further refinement and integration into digital twins to enable real-time monitoring and control of the AM process.

Secondly, there is a need for a unified ontology for digital twin development in AM. Efforts should be made to bridge the gap between low digital design levels and the high demand for digital twin technology. This includes developing mathematical and simulation models to support digital twin construction and integration across various stakeholders. Blockchain technology can be used to ensure seamless data access while protecting intellectual property.

Thirdly, the construction of digital twins requires the integration of a vast amount of manufacturing data from various sources, including 5M1E data (Manpower, Machine, Material, Method, Measurement, Environment) that affects product quality. Complex manufacturing system phenomena, including external factors like orders and supply chains and internal factors like machine degradation and workers' skills, need to be considered for a comprehensive understanding of manufacturing systems.

Fourthly, when digital twins come to implement, they are critical for understanding the lifecycle of products and enabling predictive maintenance, fault detection, and diagnosis. Efforts should be made to connect digital twins with physical twins, considering the decentralized nature of products, and integrate data from different stakeholders and lifecycle phases. Digital twins can also serve as "soft sensors" to extend the measurement range and facilitate information flow throughout the entire lifecycle.

Finally, to accelerate the adoption of digital twins in metal AM, a suggested high-level roadmap involves forming a global partnership in research through international collaboration. Key topics for discussion and research include software and hardware challenges in multiscale-multiphysics modeling, standardization, uncertainty quantification, verification and validation, and the use of machine learning for developing surrogate models for real-time queries by digital twins.

5. Conclusions

In this essay, we presented a comprehensive review of the intersection between big data, machine learning, and digital twins in the context of AM and examined how they can work together to improve the efficiency, accuracy, and sustainability of additive manufacturing processes. For machine learning, we explored its application in AM from five aspects, including material analysis, design optimization, process optimization, defect detection and real-time monitoring, and design for sustainability. The ability to leverage big data from various sources further reinforces the effectiveness of machine learning in providing data-driven insights and decision-making capabilities. For digital twin, we reviewed its current research status and the technical approach to build the digital twins for additive manufacturing. We also outlined future development directions of application of digital twins to additive manufacturing. The combination of big data, machine learning, and digital twins has the potential to reshape the AM landscape, fostering innovation, sustainability, and efficiency. As this field continues to evolve, further research and collaboration among academia, industry, and policymakers are essential to realize the full potential of these technologies in AM.

CRediT authorship contribution statement

Liuchao Jin: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Xiaoya Zhai:** Writing – review & editing, Writing – original draft, Validation, Investigation, Conceptualization. **Kang Wang:** Writing – original draft, Validation, Investigation, Formal analysis. **Kang Zhang:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis. **Dazhong Wu:** Writing – review & editing, Validation, Investigation, Formal analysis. **Aamer Nazir:** Writing – review & editing, Validation, Investigation, Formal analysis. **Jingchao Jiang:** Writing – review & editing, Writing – original draft, Validation, Supervision, Investigation. **Wei-Hsin Liao:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data supporting the findings of this study are available within the article.

Acknowledgements

This work is supported by Research Grants Council (C4074-22G), Hong Kong Special Administrative Region, China, The Chinese University of Hong Kong (Project ID: 3110174). For the purpose of open

Table 4
Acronym used in this paper.

Term	Acronym	Term	Acronym
Accelerated Process Optimization	APO	k-Nearest Neighbors	k-NN
Acrylonitrile Butadiene Styrene	ABS	Laser-Based Additive Manufacturing	LBAM
Acoustic Emission	AE	Laser Powder-Bed Fusion	LPBF
Additive Manufacturing	AM	Linear Regression	LR
Analysis of Variance	ANOVA	Machine Learning	ML
Artificial Intelligence	AI	Multi-Objective Genetic Algorithm	MOGA
Artificial Neural Networks	ANN	Neural Networks	NN
Augmented Reality	AR	Non-dominated Sorting Genetic Algorithm	NSGA
Bayesian Networks	BN	Particle Swarm Optimization	PSO
Cluster Analysis	CA	Process Parameter Optimization	PPO
Central Composite Design	CCD	Random Forest	RF
Computational Fluid Dynamics	CFD	Reinforcement Learning	RL
Convolutional Neural Networks	CNN	Response Surface Modeling	RSM
Directed Energy Deposition	DED	Stereolithography	SLA
Digital Light Processing	DLP	Selective Laser Melting	SLM
Design of Experiments	DoE	Selective Laser Sintering	SLS
Digital Twin	DT	Simulated Annealing	SA
Decision Tree	DTree	Stainless Steel 316L	SS316L
Electron Beam Melting	EBM	Stereolithography	SLA
Full Factorial Design	FFD	Support Vector Machines	SVM
Fused Deposition Modeling	FDM	Support Vector Regression	SVR
Gaussian Process Regression	GPR	Wire Arc Additive Manufacturing	WAAM
Genetic Algorithms	GA	Extreme Gradient Boosting	XGBoost

Appendix A

The main terms and their acronyms used in this paper are listed in Table 4.

References

[1] J. Liu, V. Nguyen-Van, B. Panda, K. Fox, A. du Plessis, P. Tran, Additive manufacturing of sustainable construction materials and form-finding structures: a review on recent progresses, 3D Print. Addit. Manuf. 9 (1) (2022) 12–34.
[2] B.H. Jared, M.A. Aguilo, L.L. Beghini, B.L. Boyce, B.W. Clark, A. Cook, B.J. Kaehr, J. Robbins, Additive manufacturing: toward holistic design, Scr. Mater. 135 (2017) 141–147.
[3] C. Tan, R. Li, J. Su, D. Du, Y. Du, B. Attard, Y. Chew, H. Zhang, E.J. Lavernia, Y. Fautrelle, et al., Review on field assisted metal additive manufacturing, Int. J. Mach. Tools Manuf. (2023) 104032.
[4] R. Citarella, V. Giannella, Additive manufacturing in industry, Appl. Sci. 11 (2) (2021) 840.
[5] X. Zhai, L. Jin, J. Jiang, A survey of additive manufacturing reviews, Mater. Sci. Addit. Manuf. 1 (4) (2022) 21.
[6] J. Jiang, X. Xu, J. Stringer, Support structures for additive manufacturing: a review, J. Manuf. Mater. Process. 2 (4) (2018) 64.
[7] J. Jiang, X. Xu, J. Stringer, Optimization of process planning for reducing material waste in extrusion based additive manufacturing, Robot. Comput.-Integr. Manuf. 59 (2019) 317–325.
[8] J. Jiang, X. Xu, J. Stringer, Optimisation of multi-part production in additive manufacturing for reducing support waste, Virtual Phys. Prototyp. 14 (3) (2019) 219–228.
[9] J. Jiang, J. Stringer, X. Xu, R.Y. Zhong, Investigation of printable threshold overhang angle in extrusion-based additive manufacturing for reducing support waste, Int. J. Comput. Integr. Manuf. 31 (10) (2018) 961–969.
[10] J. Jiang, X. Xu, J. Stringer, A new support strategy for reducing waste in additive manufacturing, in: The 48th International Conference on Computers and Industrial Engineering (CIE 48), 2018, pp. 1–7.
[11] A. Ghobadian, I. Talavera, A. Bhattacharya, V. Kumar, J.A. Garza-Reyes, N. O'regan, Examining legitimatisation of additive manufacturing in the interplay between innovation, lean manufacturing and sustainability, Int. J. Prod. Econ. 219 (2020) 457–468.
[12] J. Jiang, X. Zhai, K. Zhang, L. Jin, Q. Lu, Z. Shen, W.-H. Liao, Low-melting-point alloys integrated extrusion additive manufacturing, Addit. Manuf. (2023) 103633.
[13] J. Gardan, Additive manufacturing technologies: state of the art and trends, in: Additive Manufacturing Handbook, 2017, pp. 149–168.
[14] M. Pérez, D. Carou, E.M. Rubio, R. Teti, Current advances in additive manufacturing, Proc. CIRP 88 (2020) 439–444.
[15] W. Gao, Y. Zhang, D. Ramanujan, K. Ramani, Y. Chen, C.B. Williams, C.C. Wang, Y.C. Shin, S. Zhang, P.D. Zavattieri, The status, challenges, and future of additive manufacturing in engineering, Comput. Aided Des. 69 (2015) 65–89.
[16] C. Druzgalski, A. Ashby, G. Guss, W. King, T.T. Roehling, M.J. Matthews, Process optimization of complex geometries using feed forward control for laser powder bed fusion additive manufacturing, Addit. Manuf. 34 (2020) 101169.
[17] S. Verma, C.-K. Yang, C.-H. Lin, J.Y. Jeng, Additive manufacturing of lattice structures for high strength mechanical interlocking of metal and resin during injection molding, Addit. Manuf. 49 (2022) 102463.
[18] M.J. Prajapati, A. Kumar, S.-C. Lin, J.-Y. Jeng, Multi-material additive manufacturing with lightweight closed-cell foam-filled lattice structures for enhanced mechanical and functional properties, Addit. Manuf. 54 (2022) 102766.
[19] X. Zhang, H. Tang, J. Wang, L. Jia, Y. Fan, M. Leary, M. Qian, Additive manufacturing of intricate lattice materials: ensuring robust strut additive continuity to realize the design potential, Addit. Manuf. 58 (2022) 103022.
[20] A. De Marzi, M. Vibrante, M. Bottin, G. Franchin, Development of robot assisted hybrid additive manufacturing technology for the freeform fabrication of lattice structures, Addit. Manuf. 66 (2023) 103456.
[21] B. Jagadeesh, M. Duraiselvam, K. Prashanth, Deformation behavior of metallic lattice structures with symmetrical gradients of porosity manufactured by metal additive manufacturing, Vacuum 211 (2023) 111955.
[22] U. Fasel, D. Keidel, L. Baumann, G. Cavolina, M. Eichenhofer, P. Ermanni, Composite additive manufacturing of morphing aerospace structures, Manuf. Lett. 23 (2020) 85–88.
[23] V. Mohanavel, K.A. Ali, K. Ranganathan, J.A. Jeffrey, M. Ravikumar, S. Rajkumar, The roles and applications of additive manufacturing in the aerospace and automobile sector, Mater. Today Proc. 47 (2021) 405–409.
[24] V. Madhavadas, D. Srivastava, U. Chadha, S.A. Raj, M.T.H. Sultan, F.S. Shahar, A.U.M. Shah, A review on metal additive manufacturing for intricately shaped aerospace components, CIRP J. Manuf. Sci. Technol. 39 (2022) 18–36.
[25] S. Mohd Yusuf, S. Cutler, N. Gao, The impact of metal additive manufacturing on the aerospace industry, Metals 9 (12) (2019) 1286.
[26] M. Khorasani, A. Ghasemi, B. Rolfe, I. Gibson, Additive manufacturing a powerful tool for the aerospace industry, Rapid Prototyping J. 28 (1) (2022) 87–100.
[27] F.H. Froes, R. Boyer, Additive Manufacturing for the Aerospace Industry, Elsevier, Amsterdam, Netherlands; Cambridge, Ma, United States, 2019.
[28] J.C. Najmon, S. Raeisi, A. Tovar, Review of additive manufacturing technologies and applications in the aerospace industry, Addit. Manuf. Aerospace Indust. (2019) 7–31.
[29] S.C. Altıparmak, B. Xiao, A market assessment of additive manufacturing potential for the aerospace industry, J. Manuf. Process. 68 (2021) 728–738.
[30] B. Blakey-Milner, P. Gradl, G. Snedden, M. Brooks, J. Pitot, E. Lopez, M. Leary, F. Berto, A. du Plessis, Metal additive manufacturing in aerospace: a review, Mater. Des. 209 (2021) 110008.
[31] L. Jin, Y. Lou, L.-A. Chen, Q. Lu, The unified tracking controller for a tilt-rotor unmanned aerial vehicle based on the dual quaternion, in: 2022 IEEE International Conference on Unmanned Systems (ICUS), IEEE, 2022, pp. 1356–1363.
[32] V. Juechter, M. Franke, T. Merenda, A. Stich, C. Körner, R. Singer, Additive manufacturing of Ti-45Al-4Nb-C by selective electron beam melting for automotive applications, Addit. Manuf. 22 (2018) 118–126.

[33] M.S. Muhammad, L. Kerbache, A. Elomri, Potential of additive manufacturing for upstream automotive supply chains, Supply Chain Forum 23 (2022) 1–19, Taylor & Francis.
[34] S. Salifu, D. Desai, O. Ogunbiyi, K. Mwale, Recent development in the additive manufacturing of polymer-based composites for automotive structures—a review, Int. J. Adv. Manuf. Technol. 119 (11–12) (2022) 6877–6891.
[35] M. Delic, 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. 228 (2020) 107689.
[36] G. Dwivedi, S.K. Srivastava, R.K. Srivastava, Analysis of barriers to implement additive manufacturing technology in the indian automotive sector, Int J. Phys. Distrib. Logist. Manag. 47 (10) (2017) 972–991.
[37] S.G. Sarvankar, S.N. Yewale, Additive manufacturing in automobile industry, Int. J. Res. Aeronaut. Mech. Eng. 7 (4) (2019) 1–10.
[38] D. Böckin, A.-M. Tillman, Environmental assessment of additive manufacturing in the automotive industry, J. Clean. Prod. 226 (2019) 977–987.
[39] J.C. Vasco, Additive manufacturing for the automotive industry, in: Additive Manufacturing, Elsevier, 2021, pp. 505–530.
[40] R. Leal, F. Barreiros, L. Alves, F. Romeiro, J. Vasco, M. Santos, C. Marto, Additive manufacturing tooling for the automotive industry, Int. J. Adv. Manuf. Technol. 92 (2017) 1671–1676.
[41] E. Alabort, D. Barba, R.C. Reed, Design of metallic bone by additive manufacturing, Scr. Mater. 164 (2019) 110–114.
[42] X. Wang, S. Xu, S. Zhou, W. Xu, M. Leary, P. Choong, M. Qian, M. Brandt, Y.M. Xie, Topological design and additive manufacturing of porous metals for bone scaffolds and orthopaedic implants: a review, Biomaterials 83 (2016) 127–141.
[43] Y. Yang, G. Wang, H. Liang, C. Gao, S. Peng, L. Shen, C. Shuai, Additive manufacturing of bone scaffolds, Int. J. Bioprint. 5 (1) (2019).
[44] A.P.M. Madrid, S.M. Vrech, M.A. Sanchez, A.P. Rodriguez, Advances in additive manufacturing for bone tissue engineering scaffolds, Mater. Sci. Eng. C 100 (2019) 631–644.
[45] D. Barba, E. Alabort, R. Reed, Synthetic bone: design by additive manufacturing, Acta Biomater. 97 (2019) 637–656.
[46] Y. Huang, S.R. Schmid, Additive manufacturing for health: state of the art, gaps and needs, and recommendations, J. Manuf. Sci. Eng. 140 (9) (2018).
[47] H.K. Celik, O. Kose, M.-E. Ulmeanu, A.E. Rennie, T.N. Abram, I. Akinci, Design and additive manufacturing of medical face shield for healthcare workers battling coronavirus (covid-19), Int. J. Bioprint. 6 (4) (2020).
[48] E. Özceylan, C. Çetinkaya, N. Demirel, O. Sabırlıoğlu, Impacts of additive manufacturing on supply chain flow: a simulation approach in healthcare industry, Logistics 2 (1) (2017) 1.
[49] P.K. Arora, R. Arora, A. Haleem, H. Kumar, Application of additive manufacturing in challenges posed by covid-19, Mater. Today Proc. 38 (2021) 466–468.
[50] M. Ramola, V. Yadav, R. Jain, On the adoption of additive manufacturing in healthcare: a literature review, Int. J. Manuf. Technol. Manag. 30 (1) (2019) 48–69.
[51] E.R. Ghomi, F. Khosravi, R.E. Neisiany, S. Singh, S. Ramakrishna, Future of additive manufacturing in healthcare, Current Opin. Biomed. Eng. 17 (2021) 100255.
[52] G. Liu, Y. He, P. Liu, Z. Chen, X. Chen, L. Wan, Y. Li, J. Lu, Development of bioimplants with 2D, 3D, and 4D additive manufacturing materials, Engineering 6 (11) (2020) 1232–1243.
[53] Q. Yan, H. Dong, J. Su, J. Han, B. Song, Q. Wei, Y. Shi, A review of 3D printing technology for medical applications, Engineering 4 (5) (2018) 729–742.
[54] K. Wang, C.-C. Ho, C. Zhang, B. Wang, A review on the 3D printing of functional structures for medical phantoms and regenerated tissue and organ applications, Engineering 3 (5) (2017) 653–662.
[55] N. Nachal, J. Moses, P. Karthik, C. Anandharamakrishnan, Applications of 3D printing in food processing, Food Eng. Rev. 11 (3) (2019) 123–141.
[56] I. Tomašević, P. Putnik, F. Valjak, B. Pavlić, B. Šojić, A.B. Markovinović, D.B. Kovačević, 3D printing as novel tool for fruit-based functional food production, Current Opin. Food Sci. 41 (2021) 138–145.
[57] T. Pereira, S. Barroso, M.M. Gil, Food texture design by 3D printing: a review, Foods 10 (2) (2021) 320.
[58] S. Caulier, E. Doets, M. Noort, An exploratory consumer study of 3D printed food perception in a real-life military setting, Food Qual. Prefer. 86 (2020) 104001.
[59] L. Liu, O.N. Ciftci, Effects of high oil compositions and printing parameters on food paste properties and printability in a 3D printing food processing model, J. Food Eng. 288 (2021) 110135.
[60] A. Baiano, 3D printed foods: a comprehensive review on technologies, nutritional value, safety, consumer attitude, regulatory framework, and economic and sustainability issues, Food Rev. Int. 38 (5) (2022) 986–1016.
[61] B. Pérez, H. Nykvist, A.F. Brøgger, M.B. Larsen, M.F. Falkeborg, Impact of macronutrients printability and 3D-printer parameters on 3D-food printing: a review, Food Chem. 287 (2019) 249–257.
[62] T. Manstan, M.B. McSweeney, Consumers' attitudes towards and acceptance of 3D printed foods in comparison with conventional food products, Int. J. Food Sci. Technol. 55 (1) (2020) 323–331.
[63] C. He, M. Zhang, Z. Fang, 3D printing of food: pretreatment and post-treatment of materials, Crit. Rev. Food Sci. Nutr. 60 (14) (2020) 2379–2392.
[64] A. Le-Bail, B.C. Maniglia, P. Le-Bail, Recent advances and future perspective in additive manufacturing of foods based on 3D printing, Current Opin. Food Sci. 35 (2020) 54–64.
[65] C. Guo, M. Zhang, B. Bhandari, Model building and slicing in food 3D printing processes: a review, Compr. Rev. Food Sci. Food Saf. 18 (4) (2019) 1052–1069.
[66] S. Zhu, M.A. Stieger, A.J. van der Goot, M.A. Schutyser, Extrusion-based 3D printing of food pastes: correlating rheological properties with printing behaviour, Innov. Food Sci. Emerg. Technol. 58 (2019) 102214.
[67] R. Kumar, R. Kumar, et al., 3D printing of food materials: a state of art review and future applications, Mater. Today Proc. 33 (2020) 1463–1467.
[68] A.F. Ghazal, M. Zhang, Z. Liu, Spontaneous color change of 3D printed healthy food product over time after printing as a novel application for 4D food printing, Food Bioprocess Technol. 12 (2019) 1627–1645.
[69] P. Rando, M. Ramaioli, Food 3D printing: effect of heat transfer on print stability of chocolate, J. Food Eng. 294 (2021) 110415.
[70] A. Siddika, M.A.A. Mamun, W. Ferdous, A.K. Saha, R. Alyousef, 3D-printed concrete: applications, performance, and challenges, J. Sustain. Cement-Based Mater. 9 (3) (2020) 127–164.
[71] S.J. Schuldt, J.A. Jagoda, A.J. Hoisington, J.D. Delorit, A systematic review and analysis of the viability of 3D-printed construction in remote environments, Autom. Constr. 125 (2021) 103642.
[72] D. Lee, H. Kim, J. Sim, D. Lee, H. Cho, D. Hong, Trends in 3D printing technology for construction automation using text mining, Int. J. Prec. Eng. Manuf. 20 (2019) 871–882.
[73] F. Tahmasebinia, S.M.E. Sepasgozar, S. Shirowzhan, M. Niemela, A. Tripp, S. Nagabhyrava, K. Ko, Z. Mansuri, F. Alonso-Marroquin, Criteria development for sustainable construction manufacturing in construction industry 4.0: theoretical and laboratory investigations, Constr. Inn. 20 (3) (2020) 379–400.
[74] M.A. Hossain, A. Zhumabekova, S.C. Paul, J.R. Kim, A review of 3D printing in construction and its impact on the labor market, Sustainability 12 (20) (2020) 8492.
[75] R.G. Rivera, R.G. Alvarado, A. Martinez-Rocamora, F. Auat Cheein, A comprehensive performance evaluation of different mobile manipulators used as displaceable 3D printers of building elements for the construction industry, Sustainability 12 (11) (2020) 4378.
[76] P. Shakor, S. Nejadi, G. Paul, S. Malek, Review of emerging additive manufacturing technologies in 3D printing of cementitious materials in the construction industry, Front. Built Env. 4 (2019) 85.
[77] S. Pessoa, A.S. Guimarães, S.S. Lucas, N. Simões, 3D printing in the construction industry-a systematic review of the thermal performance in buildings, Renew. Sustain. Energy Rev. 141 (2021) 110794.
[78] R. Duballet, O. Baverel, J. Dirrenberger, Classification of building systems for concrete 3D printing, Autom. Constr. 83 (2017) 247–258.
[79] R. García-Alvarado, G. Moroni-Orellana, P. Banda-Pérez, Architectural evaluation of 3D-printed buildings, Buildings 11 (6) (2021) 254.
[80] M. Sakin, Y.C. Kiroglu, 3D printing of buildings: construction of the sustainable houses of the future by BIM, Energy Proc. 134 (2017) 702–711.
[81] I. Hager, A. Golonka, R. Putanowicz, 3D printing of buildings and building components as the future of sustainable construction?, Proc. Eng. 151 (2016) 292–299.
[82] Y.W.D. Tay, B. Panda, S.C. Paul, N.A. Noor Mohamed, M.J. Tan, K.F. Leong, 3D printing trends in building and construction industry: a review, Virtual Phys. Prototyp. 12 (3) (2017) 261–276.
[83] B. Lu, Y. Weng, M. Li, Y. Qian, K.F. Leong, M.J. Tan, S. Qian, A systematical review of 3D printable cementitious materials, Constr. Build. Mater. 207 (2019) 477–490.
[84] R. Ashima, A. Haleem, S. Bahl, M. Javaid, S.K. Mahla, S. Singh, Automation and manufacturing of smart materials in additive manufacturing technologies using internet of things towards the adoption of industry 4.0, Mater. Today Proc. 45 (2021) 5081–5088.
[85] F. Tao, J. Cheng, Q. Qi, M. Zhang, H. Zhang, F. Sui, Digital twin-driven product design, manufacturing and service with big data, Int. J. Adv. Manuf. Technol. 94 (2018) 3563–3576.
[86] Y. Cui, S. Kara, K.C. Chan, Manufacturing big data ecosystem: a systematic literature review, Robot. Comput.-Integr. Manuf. 62 (2020) 101861.
[87] F. Tao, Q. Qi, A. Liu, A. Kusiak, Data-driven smart manufacturing, J. Manuf. Syst. 48 (2018) 157–169.
[88] A. Majeed, J. Lv, T. Peng, A framework for big data driven process analysis and optimization for additive manufacturing, Rapid Prototyping J. 25 (2) (2018) 308–321.
[89] A. Majeed, Y. Zhang, S. Ren, J. Lv, T. Peng, S. Waqar, E. Yin, A big data-driven framework for sustainable and smart additive manufacturing, Robot. Comput.-Integr. Manuf. 67 (2021) 102026.
[90] K. Bi, D. Lin, Y. Liao, C.-H. Wu, P. Parandoush, Additive manufacturing embraces big data, Progr. Addit. Manuf. 6 (2021) 181–197.
[91] D. Gu, X. Shi, R. Poprawe, D.L. Bourell, R. Setchi, J. Zhu, Material-structure-performance integrated laser-metal additive manufacturing, Science 372 (6545) (2021) eabg1487.
[92] J.F. Arinez, Q. Chang, R.X. Gao, C. Xu, J. Zhang, Artificial intelligence in advanced manufacturing: current status and future outlook, J. Manuf. Sci. Eng. 142 (11) (2020) 110804.
[93] S.S. Razvi, S. Feng, A. Narayanan, Y.-T.T. Lee, P. Witherell, A Review of Machine Learning Applications in Additive Manufacturing, International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, vol. 59179, American Society of Mechanical Engineers, 2019, V001T02A040.

[94] S. Kumar, T. Gopi, N. Harikeerthana, M.K. Gupta, V. Gaur, G.M. Krolczyk, C. Wu, Machine learning techniques in additive manufacturing: a state of the art review on design, processes and production control, J. Intell. Manuf. 34 (1) (2023) 21–55.
[95] X. Li, M. Zhang, M. Zhou, J. Wang, W. Zhu, C. Wu, X. Zhang, Qualify assessment for extrusion-based additive manufacturing with 3D scan and machine learning, J. Manuf. Process. 90 (2023) 274–285.
[96] J. Jiang, Y. Xiong, Z. Zhang, D.W. Rosen, Machine learning integrated design for additive manufacturing, J. Intell. Manuf. 33 (4) (2022) 1073–1086.
[97] Z. Jin, Z. Zhang, K. Demir, G.X. Gu, Machine learning for advanced additive manufacturing, Matter 3 (5) (2020) 1541–1556.
[98] C. Wang, X. Tan, S.B. Tor, C. Lim, Machine learning in additive manufacturing: state-of-the-art and perspectives, Addit. Manuf. 36 (2020) 101538.
[99] J. Jiang, A survey of machine learning in additive manufacturing technologies, Int. J. Comput. Integr. Manuf. 36 (9) (2023) 1258–1280.
[100] D. Guo, S. Ling, H. Li, D. Ao, T. Zhang, Y. Rong, G.Q. Huang, A framework for personalized production based on digital twin, blockchain and additive manufacturing in the context of industry 4.0, in: 2020 IEEE 16th International Conference on Automation Science and Engineering (CASE), IEEE, 2020, pp. 1181–1186.
[101] R.B. Roy, D. Mishra, S.K. Pal, T. Chakravarty, S. Panda, M.G. Chandra, A. Pal, P. Misra, D. Chakravarty, S. Misra, Digital twin: current scenario and a case study on a manufacturing process, Int. J. Adv. Manuf. Technol. 107 (2020) 3691–3714.
[102] D.P. Möller, H. Vakilzadian, W. Hou, Intelligent manufacturing with digital twin, in: 2021 IEEE International Conference on Electro Information Technology (EIT), IEEE, 2021, pp. 413–418.
[103] A. Croatti, M. Gabellini, S. Montagna, A. Ricci, On the integration of agents and digital twins in healthcare, J. Med. Syst. 44 (2020) 1–8.
[104] G. Ahmadi-Assalemi, H. Al-Khateeb, C. Maple, G. Epiphaniou, Z.A. Alhaboby, S. Alkaabi, D. Alhaboby, Digital twins for precision healthcare, in: Cyber Defence in the Age of AI, Smart Societies and Augmented Humanity, 2020, pp. 133–158.
[105] M. Alazab, L.U. Khan, S. Koppu, S.P. Ramu, M. Iyapparaja, P. Boobalan, T. Baker, P.K.R. Maddikunta, T.R. Gadekallu, A. Aljuhani, Digital twins for healthcare 4.0-recent advances, architecture, and open challenges, IEEE Cons. Electron. Mag. (2022).
[106] R. Kaul, C. Ossai, A.R.M. Forkan, P.P. Jayaraman, J. Zelcer, S. Vaughan, N. Wickramasinghe, The role of AI for developing digital twins in healthcare: the case of cancer care, Wiley Interdiscip. Rev. Data Min. Knowl. Discov. 13 (1) (2023) e1480.
[107] Y. Wang, Q. Tan, F. Pu, D. Boone, M. Zhang, A review of the application of additive manufacturing in prosthetic and orthotic clinics from a biomechanical perspective, Engineering 6 (11) (2020) 1258–1266.
[108] C. Li, D. Pisignano, Y. Zhao, J. Xue, Advances in medical applications of additive manufacturing, Engineering 6 (11) (2020) 1222–1231.
[109] S.P. Ramu, P. Boopalan, Q.-V. Pham, P.K.R. Maddikunta, T. Huynh-The, M. Alazab, T.T. Nguyen, T.R. Gadekallu, Federated learning enabled digital twins for smart cities: concepts, recent advances, and future directions, Sustain. Cities Soc. 79 (2022) 103663.
[110] G. Mylonas, A. Kalogeras, G. Kalogeras, C. Anagnostopoulos, C. Alexakos, L. Muñoz, Digital twins from smart manufacturing to smart cities: a survey, IEEE Access 9 (2021) 143222–143249.
[111] L. Deren, Y. Wenbo, S. Zhenfeng, Smart city based on digital twins, Comput. Urban Sci. 1 (2021) 1–11.
[112] F. Dembski, U. Wössner, M. Letzgus, M. Ruddat, C. Yamu, Urban digital twins for smart cities and citizens: the case study of Herrenberg, Germany, Sustainability 12 (6) (2020) 2307.
[113] F. Oettl, S. Hörbrand, T. Wittmeir, J. Schilp, Method for evaluating the monetary added value of the usage of a digital twin for additive manufacturing, Proc. CIRP 118 (2023) 717–722.
[114] H. Mu, F. He, L. Yuan, P. Commins, H. Wang, Z. Pan, Toward a smart wire arc additive manufacturing system: a review on current developments and a framework of digital twin, J. Manuf. Syst. 67 (2023) 174–189.
[115] A. Phua, P.S. Cook, C.H. Davies, G.W. Delaney, Smart recoating: a digital twin framework for optimisation and control of powder spreading in metal additive manufacturing, J. Manuf. Process. 99 (2023) 382–391.
[116] K. Zhu, J.Y.H. Fuh, X. Lin, Metal-based additive manufacturing condition monitoring: a review on machine learning based approaches, IEEE/ASME Trans. Mechatron. (2021).
[117] D. Mahmoud, M. Magolon, J. Boer, M. Elbestawi, M.G. Mohammadi, Applications of machine learning in process monitoring and controls of L-PBF additive manufacturing: a review, Appl. Sci. 11 (24) (2021) 11910.
[118] M. Parsazadeh, S. Sharma, N. Dahotre, Towards the next generation of machine learning models in additive manufacturing: a review of process dependent material evolution, Prog. Mater. Sci. (2023) 101102.
[119] M.D. Xames, F.K. Torsha, F. Sarwar, A systematic literature review on recent trends of machine learning applications in additive manufacturing, J. Intell. Manuf. 34 (6) (2023) 2529–2555.
[120] A. Raza, K.M. Deen, R. Jaafreh, K. Hamad, A. Haider, W. Haider, Incorporation of machine learning in additive manufacturing: a review, Int. J. Adv. Manuf. Technol. 122 (3–4) (2022) 1143–1166.
[121] G.K. Sarkon, B. Safaei, M.S. Kenevisi, S. Arman, Q. Zeeshan, State-of-the-art review of machine learning applications in additive manufacturing; from design to manufacturing and property control, Arch. Comput. Methods Eng. 29 (7) (2022) 5663–5721.
[122] X. Qi, G. Chen, Y. Li, X. Cheng, C. Li, Applying neural-network-based machine learning to additive manufacturing: current applications, challenges, and future perspectives, Engineering 5 (4) (2019) 721–729.
[123] F.W. Baumann, A. Sekulla, M. Hassler, B. Himpel, M. Pfeil, Trends of machine learning in additive manufacturing, Int. J. Rapid Manuf. 7 (4) (2018) 310–336.
[124] A. Hamrani, A. Agarwal, A. Allouhi, D. McDaniel, Applying machine learning to wire arc additive manufacturing: a systematic data-driven literature review, J. Intell. Manuf. (2023) 1–33.
[125] Y. Zhang, M. Safdar, J. Xie, J. Li, M. Sage, Y.F. Zhao, A systematic review on data of additive manufacturing for machine learning applications: the data quality, type, preprocessing, and management, J. Intell. Manuf. (2022) 1–36.
[126] J. Akhavan, S. Manoochehri, Sensory data fusion using machine learning methods for in-situ defect registration in additive manufacturing: a review, in: 2022 IEEE International IOT, Electronics and Mechatronics Conference (IEMTRONICS), IEEE, 2022, pp. 1–10.
[127] J. Breitenbach, F. Seidenspinner, F. Vural, P. Beisswanger, R. Buettner, A systematic literature review of machine learning approaches for optimization in additive manufacturing, in: 2022 IEEE 46th Annual Computers, Software, and Applications Conference (COMPSAC), IEEE, 2022, pp. 1147–1152.
[128] L. Wang, C.A. Alexander, Additive manufacturing and big data, Int. J. Math. Eng. Manag. Sci. 1 (3) (2016) 107.
[129] L. Meng, B. McWilliams, W. Jarosinski, H.-Y. Park, Y.-G. Jung, J. Lee, J. Zhang, Machine learning in additive manufacturing: a review, JOM 72 (2020) 2363–2377.
[130] J. Qin, F. Hu, Y. Liu, P. Witherell, C.C. Wang, D.W. Rosen, T.W. Simpson, Y. Lu, Q. Tang, Research and application of machine learning for additive manufacturing, Addit. Manuf. 52 (2022) 102691.
[131] S. Guo, M. Agarwal, C. Cooper, Q. Tian, R.X. Gao, W.G. Grace, Y. Guo, Machine learning for metal additive manufacturing: towards a physics-informed data-driven paradigm, J. Manuf. Syst. 62 (2022) 145–163.
[132] S. Chinchanikar, A.A. Shaikh, A review on machine learning, big data analytics, and design for additive manufacturing for aerospace applications, J. Mater. Eng. Perform. 31 (8) (2022) 6112–6130.
[133] A. Phua, C. Davies, G. Delaney, A digital twin hierarchy for metal additive manufacturing, Comput. Ind. 140 (2022) 103667.
[134] L. Zhang, X. Chen, W. Zhou, T. Cheng, L. Chen, Z. Guo, B. Han, L. Lu, Digital twins for additive manufacturing: a state-of-the-art review, Appl. Sci. 10 (23) (2020) 8350.
[135] Z. Chen, K. Surendraarcharyagie, C. Granland, Keenan Chen, X. Xu, Y. Xiong, C. Davies, Y. Tang, Service oriented digital twin for additive manufacturing process, J. Manuf. Syst. 74 (2024) 762–776.
[136] L.J. Ladani, Applications of artificial intelligence and machine learning in metal additive manufacturing, J. Phys. Mater. 4 (4) (2021) 042009.
[137] International Organization for Standardization, ASTM International, Additive manufacturing – general principles – terminology, ISO/ASTM 52900, 2021.
[138] F. Zhang, L. Zhu, Z. Li, S. Wang, J. Shi, W. Tang, N. Li, J. Yang, The recent development of vat photopolymerization: a review, Addit. Manuf. 48 (2021) 102423.
[139] A. Al Rashid, W. Ahmed, M.Y. Khalid, M. Koc, Vat photopolymerization of polymers and polymer composites: processes and applications, Addit. Manuf. 47 (2021) 102279.
[140] R.V. Pazhamannil, P. Govindan, Current state and future scope of additive manufacturing technologies via vat photopolymerization, Mater. Today Proc. 43 (2021) 130–136.
[141] I. Cazin, M.O. Gleirscher, M. Fleisch, M. Berer, M. Sangermano, S. Schlögl, Spatially controlling the mechanical properties of 3D printed objects by dual-wavelength vat photopolymerization, Addit. Manuf. 57 (2022) 102977.
[142] S. Tyagi, A. Yadav, S. Deshmukh, Review on mechanical characterization of 3D printed parts created using material jetting process, Mater. Today Proc. 51 (2022) 1012–1016.
[143] A. Elkaseer, K.J. Chen, J.C. Janhsen, O. Refle, V. Hagenmeyer, S.G. Scholz, Material jetting for advanced applications: a state-of-the-art review, gaps and future directions, Addit. Manuf. (2022) 103270.
[144] A. Pugalendhi, R. Ranganathan, S. Ganesan, Impact of process parameters on mechanical behaviour in multi-material jetting, Mater. Today Proc. 46 (2021) 9139–9144.
[145] H. Yang, J.C. Lim, Y. Liu, X. Qi, Y.L. Yap, V. Dikshit, W.Y. Yeong, J. Wei, Performance evaluation of projet multi-material jetting 3D printer, Virtual Phys. Prototyp. 12 (1) (2017) 95–103.
[146] M. Yakout, M. Elbestawi, S.C. Veldhuis, A review of metal additive manufacturing technologies, Solid State Phenom. 278 (2018) 1–14.
[147] X. Lv, F. Ye, L. Cheng, S. Fan, Y. Liu, Binder jetting of ceramics: powders, binders, printing parameters, equipment, and post-treatment, Ceram. Int. 45 (10) (2019) 12609–12624.
[148] Y. Bai, C.B. Williams, Binder jetting additive manufacturing with a particle-free metal ink as a binder precursor, Mater. Des. 147 (2018) 146–156.
[149] X. Shen, H.E. Naguib, A robust ink deposition system for binder jetting and material jetting, Addit. Manuf. 29 (2019) 100820.
[150] N.D. Dejene, H.G. Lemu, Current status and challenges of powder bed fusion-based metal additive manufacturing: literature review, Metals 13 (2) (2023) 424.
[151] S. Qu, J. Ding, J. Fu, M. Fu, B. Zhang, X. Song, High-precision laser powder bed fusion processing of pure copper, Addit. Manuf. 48 (2021) 102417.

[152] N. Sanaei, A. Fatemi, N. Phan, Defect characteristics and analysis of their variability in metal L-PBF additive manufacturing, Mater. Des. 182 (2019) 108091.
[153] S. Yu, S. Park, D.Y. Kang, G.S. Shin, M.W. Lee, S.Y. Moon, J.Y. Hwang, Strategic dual laser 3D printing of structural metal-plastic hybrid materials, Composites, Part B, Eng. 261 (2023) 110794.
[154] S. Mu, Y. Hong, H. Huang, A. Ishii, J. Lei, Y. Song, Y. Li, K.S. Brinkman, F. Peng, H. Xiao, et al., A novel laser 3D printing method for the advanced manufacturing of protonic ceramics, Membranes 10 (5) (2020) 98.
[155] J. Rindler, C. Slone, E. Herderick, M. Mills, A. Ramirez, Investigation on the potential effects of laser stitching and subsequent heat treatment on the microstructure and mechanical properties of Nickel Alloy 718 produced via Laser Powder Bed Fusion (L-PBF), Addit. Manuf. 57 (2022) 102906.
[156] W. Yang, Y.-G. Jung, T. Kwak, S.K. Kim, H. Lim, D.-H. Kim, Microstructure and mechanical properties of an Al–Mg–Si–Zr alloy processed by L-PBF and subsequent heat treatments, Materials 15 (15) (2022) 5089.
[157] H. Javidrad, S. Salemi, Effect of the volume energy density and heat treatment on the defect, microstructure, and hardness of L-PBF Inconel 625, Metall. Mater. Trans. A 51 (2020) 5880–5891.
[158] W. Qin, C. Man, K. Pang, H. Zhang, Z. Cui, L. Wang, D. Kong, C. Dong, H. Cui, Corrosion behavior of L-PBF Ti6Al4V with heat treatments in the F–containing environments, Corros. Sci. 210 (2023) 110811.
[159] M. Avateffazeli, S.I. Shakil, M.F. Khan, H. Pirgazi, N. Shamsaei, M. Haghshenas, The effect of heat treatment on fatigue response of laser powder bed fused Al-Cu-Mg-Ag-TiB2 (A20X) alloy, Mater. Today Commun. 35 (2023) 106009.
[160] L. Wang, C. Shen, P. Zhang, X. Hua, Y. Zhang, F. Li, J. Xin, K. Wu, Fabrication of Fe–30Al alloy using plasma arc welding powered twin-wire directed energy deposition-arc process: droplet transfer, microstructure, and mechanical property investigation, Intermetallics 161 (2023) 107961.
[161] A. Nazir, O. Gokcekaya, K.M.M. Billah, O. Ertugrul, J. Jiang, J. Sun, S. Hussain, Multi-material additive manufacturing: a systematic review of design, properties, applications, challenges, and 3D Printing of materials and cellular metamaterials, Mater. Des. (2023) 111661.
[162] R.J. Williams, C.M. Davies, P.A. Hooper, A pragmatic part scale model for residual stress and distortion prediction in powder bed fusion, Addit. Manuf. 22 (2018) 416–425.
[163] M.A. Dechet, J.S.G. Bonilla, M. Grünewald, K. Popp, J. Rudloff, M. Lang, J. Schmidt, A novel, precipitated polybutylene terephthalate feedstock material for powder bed fusion of polymers (PBF): material development and initial PBF processability, Mater. Des. 197 (2021) 109265.
[164] A.M. Gohn, D. Brown, G. Mendis, S. Forster, N. Rudd, M. Giles, Mold inserts for injection molding prototype applications fabricated via material extrusion additive manufacturing, Addit. Manuf. 51 (2022) 102595.
[165] D.E. Samoylenko, K.S. Rodygin, V.P. Ananikov, Sustainable application of calcium carbide residue as a filler for 3D printing materials, Sci. Rep. 13 (1) (2023) 4465.
[166] K.M. Agarwal, P. Shubham, D. Bhatia, P. Sharma, H. Vaid, R. Vajpeyi, Analyzing the impact of print parameters on dimensional variation of ABS specimens printed using fused deposition modelling (FDM), Sensors Int. 3 (2022) 100149.
[167] B.S. Shim, J.H. Choe, J.-U. Hou, Source identification of 3D printer based on layered texture encoders, IEEE Trans. Multimed. (2023).
[168] S.Y. Hann, H. Cui, N.C. Zalud, T. Esworthy, K. Bulusu, Y.-L. Shen, M.W. Plesniak, L.G. Zhang, An in vitro analysis of the effect of geometry-induced flows on endothelial cell behavior in 3D printed small-diameter blood vessels, Biomater. Adv. 137 (2022) 212832.
[169] S.Y. Hann, H. Cui, T. Esworthy, L.G. Zhang, 4D thermo-responsive smart hiPSC-CM cardiac construct for myocardial cell therapy, Int. J. Nanomed. (2023) 1809–1821.
[170] Y. Wang, H. Cui, T. Esworthy, D. Mei, Y. Wang, L.G. Zhang, Emerging 4D printing strategies for next-generation tissue regeneration and medical devices, Adv. Mater. 34 (20) (2022) 2109198.
[171] W. Zhu, N.J. Castro, Y.-L. Shen, L.G. Zhang, Nanotechnology and 3D/4D bioprinting for neural tissue regeneration, in: 3D Bioprinting and Nanotechnology in Tissue Engineering and Regenerative Medicine, Elsevier, 2022, pp. 427–458.
[172] S.Y. Hann, H. Cui, G. Chen, M. Boehm, T. Esworthy, L.G. Zhang, 3D printed biomimetic flexible blood vessels with iPS cell-laden hierarchical multilayers, Biomed. Eng. Adv. 4 (2022) 100065.
[173] L.G. Zhang, K. Leong, J.P. Fisher, 3D Bioprinting and Nanotechnology in Tissue Engineering and Regenerative Medicine, Academic Press, 2022.
[174] C. Wu, C. Dai, G. Fang, Y.-J. Liu, C.C. Wang, General support-effective decomposition for multi-directional 3-D printing, IEEE Trans. Autom. Sci. Eng. 17 (2) (2019) 599–610.
[175] M. Qin, S. Gao, C.C. Wang, W.-H. Liao, Multi-axis direct metal deposition process with effective regrouping strategy, J. Manuf. Process. 81 (2022) 707–716.
[176] Z. Zhang, C. Wu, C. Dai, Q. Shi, G. Fang, D. Xie, X. Zhao, Y.-J. Liu, C.C. Wang, X.-J. Wang, A multi-axis robot-based bioprinting system supporting natural cell function preservation and cardiac tissue fabrication, Bioactive Mater. 18 (2022) 138–150.
[177] G. Fang, T. Zhang, S. Zhong, X. Chen, Z. Zhong, C.C. Wang, Reinforced FDM: multi-axis filament alignment with controlled anisotropic strength, ACM Trans. Graph. 39 (6) (2020) 1–15.
[178] T. Zhang, G. Fang, Y. Huang, N. Dutta, S. Lefebvre, Z.M. Kilic, C.C. Wang, S3-slicer: a general slicing framework for multi-axis 3D printing, ACM Trans. Graph. 41 (6) (2022) 1–15.
[179] M. Alhijjaj, J. Nasereddin, P. Belton, S. Qi, Impact of processing parameters on the quality of pharmaceutical solid dosage forms produced by fused deposition modeling (FDM), Pharmaceutics 11 (12) (2019) 633.
[180] A. Sharma, A. Rai, Fused deposition modelling (FDM) based 3D & 4D Printing: a state of art review, Mater. Today Proc. 62 (2022) 367–372.
[181] M.S. Alsoufi, M.W. Alhazmi, D.K. Suker, T.A. Alghamdi, R.A. Sabbagh, M.A. Felemban, F.K. Bazuhair, Experimental characterization of the influence of nozzle temperature in FDM 3D printed pure PLA and advanced PLA+, Am. J. Mech. Eng. 7 (2) (2019) 45–60.
[182] J. Zhou, X. Zhou, H. Li, J. Hu, X. Han, S. Liu, In-situ laser shock peening for improved surface quality and mechanical properties of laser-directed energy-deposited AlSi10Mg alloy, Addit. Manuf. 60 (2022) 103177.
[183] T. Feldhausen, L. Heinrich, K. Saleeby, A. Burl, B. Post, E. MacDonald, C. Saldana, L. Love, Review of computer-aided manufacturing (cam) strategies for hybrid directed energy deposition, Addit. Manuf. (2022) 102900.
[184] D. De Oliveira, M.C. Gomes, A.G. Dos Santos, K.S.B. Ribeiro, I.J. Vasques, R.T. Coelho, M.B. Da Silva, N.W. Hung, Abrasive and non-conventional post-processing techniques to improve surface finish of additively manufactured metals: a review, Progr. Addit. Manuf. (2022) 1–18.
[185] A. Pilipović, Sheet lamination, in: Polymers for 3D Printing, Elsevier, 2022, pp. 127–136.
[186] M.A.M. Asri, W.C. Mak, S.A. Norazman, A.N. Nordin, Low-cost and rapid prototyping of integrated electrochemical microfluidic platforms using consumer-grade off-the-shelf tools and materials, Lab Chip 22 (9) (2022) 1779–1792.
[187] J. Yuan, G. Chen, H. Li, H. Prautzsch, K. Xiao, Accurate and computational: a review of color reproduction in full-color 3D printing, Mater. Des. 209 (2021) 109943.
[188] S.M. El Awad Azrak, C.M. Clarkson, R.J. Moon, G.T. Schueneman, J.P. Youngblood, Wet-stacking lamination of multilayer mechanically fibrillated cellulose nanofibril (CNF) sheets with increased mechanical performance for use in high-strength and lightweight structural and packaging applications, ACS Appl. Polym. Mater. 1 (9) (2019) 2525–2534.
[189] P. Kiss, W. Stadlbauer, C. Burgstaller, H. Stadler, S. Fehringer, F. Haeuserer, V.-M. Archodoulaki, In-house recycling of carbon-and glass fibre-reinforced thermoplastic composite laminate waste into high-performance sheet materials, Composites, Part A, Appl. Sci. Manuf. 139 (2020) 106110.
[190] X. Wu, J. Teng, X. Ji, C. Xu, D. Ma, S. Sui, Z. Zhang, Research progress of the defects and innovations of ceramic vat photopolymerization, Addit. Manuf. (2023) 103441.
[191] M. Pagac, J. Hajnys, Q.-P. Ma, L. Jancar, J. Jansa, P. Stefek, J. Mesicek, A review of vat photopolymerization technology: materials, applications, challenges, and future trends of 3D printing, Polymers 13 (4) (2021) 598.
[192] A. Andreu, P.-C. Su, J.-H. Kim, C.S. Ng, S. Kim, I. Kim, J. Lee, J. Noh, A.S. Subramanian, Y.-J. Yoon, 4D printing materials for vat photopolymerization, Addit. Manuf. 44 (2021) 102024.
[193] U. Shaukat, E. Rossegger, S. Schlögl, A review of multi-material 3D printing of functional materials via vat photopolymerization, Polymers 14 (12) (2022) 2449.
[194] X. Xu, A. Awad, P. Robles-Martinez, S. Gaisford, A. Goyanes, A.W. Basit, Vat photopolymerization 3D printing for advanced drug delivery and medical device applications, J. Control. Release 329 (2021) 743–757.
[195] I. Sachdeva, S. Ramesh, U. Chadha, H. Punugoti, S.K. Selvaraj, Computational AI models in VAT photopolymerization: a review, current trends, open issues, and future opportunities, Neural Comput. Appl. 34 (20) (2022) 17207–17229.
[196] A. Medellin, W. Du, G. Miao, J. Zou, Z. Pei, C. Ma, Vat photopolymerization 3D printing of nanocomposites: a literature review, J. Micro Nano-Manuf. 7 (3) (2019).
[197] N.A. Chartrain, C.B. Williams, A.R. Whittington, A review on fabricating tissue scaffolds using vat photopolymerization, Acta Biomater. 74 (2018) 90–111.
[198] H. Liu, D. Mei, S. Qian, Y. Wang, Vat photopolymerization of polymer-derived SiC ceramic with triply periodic minimal surface structure for hydrogen production, Addit. Manuf. (2023) 103694.
[199] J. Cheng, R. Wang, Z. Sun, Q. Liu, X. He, H. Li, H. Ye, X. Yang, X. Wei, Z. Li, et al., Centrifugal multimaterial 3D printing of multifunctional heterogeneous objects, Nat. Commun. 13 (1) (2022) 7931.
[200] S. Mora, N.M. Pugno, D. Misseroni, 3D printed architected lattice structures by material jetting, Mater. Today (2022).
[201] I. Gibson, D. Rosen, B. Stucker, M. Khorasani, I. Gibson, D. Rosen, B. Stucker, M. Khorasani, Material jetting, Addit. Manuf. Technol. (2021) 203–235.
[202] Y.L. Yap, C. Wang, S.L. Sing, V. Dikshit, W.Y. Yeong, J. Wei, Material jetting additive manufacturing: an experimental study using designed metrological benchmarks, Precis. Eng. 50 (2017) 275–285.
[203] O. Gülcan, K. Günaydın, A. Tamer, The state of the art of material jetting—a critical review, Polymers 13 (16) (2021) 2829.
[204] J. Dilag, T. Chen, S. Li, S.A. Bateman, Design and direct additive manufacturing of three-dimensional surface micro-structures using material jetting technologies, Addit. Manuf. 27 (2019) 167–174.
[205] K. Sen, T. Mehta, S. Sansare, L. Sharifi, A.W. Ma, B. Chaudhuri, Pharmaceutical applications of powder-based binder jet 3D printing process–a review, Adv. Drug Deliv. Rev. 177 (2021) 113943.
[206] P. Shakor, S. Chu, A. Puzatova, E. Dini, Review of binder jetting 3D printing in the construction industry, Progr. Addit. Manuf. 7 (4) (2022) 643–669.

[207] S. Mirzababaei, S. Pasebani, A review on binder jet additive manufacturing of 316L stainless steel, J. Manuf. Mater. Process. 3 (3) (2019) 82.
[208] W. Du, X. Ren, Z. Pei, C. Ma, Ceramic binder jetting additive manufacturing: a literature review on density, J. Manuf. Sci. Eng. 142 (4) (2020) 040801.
[209] W. Du, X. Ren, C. Ma, Z. Pei, Binder jetting additive manufacturing of ceramics: a literature review, in: ASME International Mechanical Engineering Congress and Exposition, vol. 58493, American Society of Mechanical Engineers, 2017, V014T07A006.
[210] F. Dini, S.A. Ghaffari, J. Jafar, R. Hamidreza, S. Marjan, A review of binder jet process parameters: powder, binder, printing and sintering condition, Metal Powder Rep. 75 (2) (2020) 95–100.
[211] A. Lores, N. Azurmendi, I. Agote, E. Zuza, A review on recent developments in binder jetting metal additive manufacturing: materials and process characteristics, Powder Metall. 62 (5) (2019) 267–296.
[212] A. Mostafaei, A.M. Elliott, J.E. Barnes, F. Li, W. Tan, C.L. Cramer, P. Nandwana, M. Chmielus, Binder jet 3D printing: process parameters, materials, properties, modeling, and challenges, Prog. Mater. Sci. 119 (2021) 100707.
[213] M. Li, W. Du, A. Elwany, Z. Pei, C. Ma, Metal binder jetting additive manufacturing: a literature review, J. Manuf. Sci. Eng. 142 (9) (2020).
[214] M. Ziaee, N.B. Crane, Binder jetting: a review of process, materials, and methods, Addit. Manuf. 28 (2019) 781–801.
[215] Z. Snow, A.R. Nassar, E.W. Reutzel, Invited review article: review of the formation and impact of flaws in powder bed fusion additive manufacturing, Addit. Manuf. 36 (2020) 101457.
[216] A. Awad, F. Fina, A. Goyanes, S. Gaisford, A.W. Basit, Advances in powder bed fusion 3D printing in drug delivery and healthcare, Adv. Drug Deliv. Rev. 174 (2021) 406–424.
[217] W.E. King, A.T. Anderson, R.M. Ferencz, N.E. Hodge, C. Kamath, S.A. Khairallah, A.M. Rubenchik, Laser powder bed fusion additive manufacturing of metals; physics, computational, and materials challenges, Appl. Phys. Rev. 2 (4) (2015).
[218] M. Khorasani, I. Gibson, A.H. Ghasemi, E. Hadavi, B. Rolfe, Laser subtractive and laser powder bed fusion of metals: review of process and production features, Rapid Prototyping J. 29 (5) (2023) 935–958.
[219] M. Grasso, A. Remani, A. Dickins, B. Colosimo, R.K. Leach, In-situ measurement and monitoring methods for metal powder bed fusion: an updated review, Meas. Sci. Technol. 32 (11) (2021) 112001.
[220] C. Zitelli, P. Folgarait, A. Di Schino, Laser powder bed fusion of stainless steel grades: a review, Metals 9 (7) (2019) 731.
[221] A. Aversa, G. Marchese, A. Saboori, E. Bassini, D. Manfredi, S. Biamino, D. Ugues, P. Fino, M. Lombardi, New aluminum alloys specifically designed for laser powder bed fusion: a review, Materials 12 (7) (2019) 1007.
[222] S. Sanchez, P. Smith, Z. Xu, G. Gaspard, C.J. Hyde, W.W. Wits, I.A. Ashcroft, H. Chen, A.T. Clare, Powder bed fusion of nickel-based superalloys: a review, Int. J. Mach. Tools Manuf. 165 (2021) 103729.
[223] E. Malekipour, H. El-Mounayri, Common defects and contributing parameters in powder bed fusion am process and their classification for online monitoring and control: a review, Int. J. Adv. Manuf. Technol. 95 (2018) 527–550.
[224] A. Khorasani, I. Gibson, J.K. Veetil, A.H. Ghasemi, A review of technological improvements in laser-based powder bed fusion of metal printers, Int. J. Adv. Manuf. Technol. 108 (2020) 191–209.
[225] R. Singh, A. Gupta, O. Tripathi, S. Srivastava, B. Singh, A. Awasthi, S. Rajput, P. Sonia, P. Singhal, K.K. Saxena, Powder bed fusion process in additive manufacturing: an overview, Mater. Today Proc. 26 (2020) 3058–3070.
[226] M. Mehrpouya, D. Tuma, T. Vaneker, M. Afrasiabi, M. Bambach, I. Gibson, Multi-material powder bed fusion techniques, Rapid Prototyping J. (2022).
[227] J.L. Bartlett, X. Li, An overview of residual stresses in metal powder bed fusion, Addit. Manuf. 27 (2019) 131–149.
[228] L. Dowling, J. Kennedy, S. O'Shaughnessy, D. Trimble, A review of critical repeatability and reproducibility issues in powder bed fusion, Mater. Des. 186 (2020) 108346.
[229] A.T. Sutton, C.S. Kriewall, M.C. Leu, J.W. Newkirk, Powder characterisation techniques and effects of powder characteristics on part properties in powder-bed fusion processes, Virtual Phys. Prototyp. 12 (1) (2017) 3–29.
[230] M. Grasso, B.M. Colosimo, Process defects and in situ monitoring methods in metal powder bed fusion: a review, Meas. Sci. Technol. 28 (4) (2017) 044005.
[231] V. Bhavar, P. Kattire, V. Patil, S. Khot, K. Gujar, R. Singh, A review on powder bed fusion technology of metal additive manufacturing, Addit. Manuf. Handb. (2017) 251–253.
[232] D.D. Singh, T. Mahender, A.R. Reddy, Powder bed fusion process: a brief review, Mater. Today Proc. 46 (2021) 350–355.
[233] S. Vock, B. Klöden, A. Kirchner, T. Weißgärber, B. Kieback, Powders for powder bed fusion: a review, Progr. Addit. Manuf. 4 (2019) 383–397.
[234] I.J. Solomon, P. Sevvel, J. Gunasekaran, A review on the various processing parameters in FDM, Mater. Today Proc. 37 (2021) 509–514.
[235] M.E. Lamm, L. Wang, V. Kishore, H. Tekinalp, V. Kunc, J. Wang, D.J. Gardner, S. Ozcan, Material extrusion additive manufacturing of wood and lignocellulosic filled composites, Polymers 12 (9) (2020) 2115.
[236] P. Zhuo, S. Li, I.A. Ashcroft, A.I. Jones, Material extrusion additive manufacturing of continuous fibre reinforced polymer matrix composites: a review and outlook, Composites, Part B, Eng. 224 (2021) 109143.
[237] A. Oleff, B. Küster, M. Stonis, L. Overmeyer, Process monitoring for material extrusion additive manufacturing: a state-of-the-art review, Progr. Addit. Manuf. 6 (4) (2021) 705–730.
[238] C. Suwanpreecha, A. Manonukul, A review on material extrusion additive manufacturing of metal and how it compares with metal injection moulding, Metals 12 (3) (2022) 429.
[239] J. Huang, Q. Chen, H. Jiang, B. Zou, L. Li, J. Liu, H. Yu, A survey of design methods for material extrusion polymer 3D printing, Virtual Phys. Prototyp. 15 (2) (2020) 148–162.
[240] J. Gonzalez-Gutierrez, S. Cano, S. Schuschnigg, C. Kukla, J. Sapkota, C. Holzer, Additive manufacturing of metallic and ceramic components by the material extrusion of highly-filled polymers: a review and future perspectives, Materials 11 (5) (2018) 840.
[241] G. Hsiang Loh, E. Pei, J. Gonzalez-Gutierrez, M. Monzón, An overview of material extrusion troubleshooting, Appl. Sci. 10 (14) (2020) 4776.
[242] G.D. Goh, Y.L. Yap, H. Tan, S.L. Sing, G.L. Goh, W.Y. Yeong, Process–structure–properties in polymer additive manufacturing via material extrusion: a review, Crit. Rev. Solid State Mater. Sci. 45 (2) (2020) 113–133.
[243] A. Jinoop, C. Paul, K. Bindra, Laser-assisted directed energy deposition of nickel super alloys: a review, Proc. Inst. Mech. Eng., Part L: J. Mater. Des. Appl. 233 (11) (2019) 2376–2400.
[244] A. Saboori, D. Gallo, S. Biamino, P. Fino, M. Lombardi, An overview of additive manufacturing of titanium components by directed energy deposition: microstructure and mechanical properties, Appl. Sci. 7 (9) (2017) 883.
[245] A. Saboori, A. Aversa, G. Marchese, S. Biamino, M. Lombardi, P. Fino, Application of directed energy deposition-based additive manufacturing in repair, Appl. Sci. 9 (16) (2019) 3316.
[246] D. Feenstra, R. Banerjee, H. Fraser, A. Huang, A. Molotnikov, N. Birbilis, Critical review of the state of the art in multi-material fabrication via directed energy deposition, Curr. Opin. Solid State Mater. Sci. 25 (4) (2021) 100924.
[247] D. Svetlizky, M. Das, B. Zheng, A.L. Vyatskikh, S. Bose, A. Bandyopadhyay, J.M. Schoenung, E.J. Lavernia, N. Eliaz, Directed energy deposition (DED) additive manufacturing: physical characteristics, defects, challenges and applications, Mater. Today 49 (2021) 271–295.
[248] A. Singh, S. Kapil, M. Das, A comprehensive review of the methods and mechanisms for powder feedstock handling in directed energy deposition, Addit. Manuf. 35 (2020) 101388.
[249] Z.-j. Tang, W.-w. Liu, Y.-w. Wang, K.M. Saleheen, Z.-c. Liu, S.-t. Peng, Z. Zhang, H.-c. Zhang, A review on in situ monitoring technology for directed energy deposition of metals, Int. J. Adv. Manuf. Technol. 108 (2020) 3437–3463.
[250] D.-G. Ahn, Directed energy deposition (DED) process: state of the art, Int. J. Precis. Eng. Manuf.-Green Technol. 8 (2021) 703–742.
[251] A. Dass, A. Moridi, State of the art in directed energy deposition: from additive manufacturing to materials design, Coatings 9 (7) (2019) 418.
[252] P.M. Bhatt, A.M. Kabir, M. Peralta, H.A. Bruck, S.K. Gupta, A robotic cell for performing sheet lamination-based additive manufacturing, Addit. Manuf. 27 (2019) 278–289.
[253] Y. Zhang, L. Wu, X. Guo, S. Kane, Y. Deng, Y.-G. Jung, J.-H. Lee, J. Zhang, Additive manufacturing of metallic materials: a review, J. Mater. Eng. Perform. 27 (2018) 1–13.
[254] C. Thakar, S.P. Deshmukh, T. Mulla, A review on selective deposition lamination 3D printing technique, Int. J. Adv. Sci. Res. Eng. Trends 4 (2020) 7–11.
[255] L. Ladani, Additive Manufacturing of Metals: Materials, Processes, Tests, and Standards, DEStech Publications, 2021.
[256] J. Fan, F. Han, H. Liu, Challenges of big data analysis, Nat. Sci. Rev. 1 (2) (2014) 293–314.
[257] S. Sagiroglu, D. Sinanc, Big data: a review, in: 2013 International Conference on Collaboration Technologies and Systems (CTS), IEEE, 2013, pp. 42–47.
[258] W.L. Chang, N. Grady, Nist Big Data Interoperability Framework: Volume 1, Definitions, 2019.
[259] F. Rosenblatt, et al., Principles of Neurodynamics: Perceptrons and the Theory of Brain Mechanisms, vol. 55, Spartan Books, Washington, DC, 1962.
[260] J.R. Quinlan, Induction of decision trees, Mach. Learn. 1 (1986) 81–106.
[261] O. Chapelle, P. Haffner, V.N. Vapnik, Support vector machines for histogram-based image classification, IEEE Trans. Neural Netw. 10 (5) (1999) 1055–1064.
[262] L. Breiman, Random forests, Mach. Learn. 45 (2001) 5–32.
[263] J.H. Friedman, Greedy function approximation: a gradient boosting machine, Ann. Stat. (2001) 1189–1232.
[264] M. Grieves, J. Vickers, Digital twin: mitigating unpredictable, undesirable emergent behavior in complex systems, in: Transdisciplinary Perspectives on Complex Systems: New Findings and Approaches, 2017, pp. 85–113.
[265] A. Krizhevsky, I. Sutskever, G.E. Hinton, Imagenet classification with deep convolutional neural networks, Adv. Neural Inf. Process. Syst. 25 (2012).
[266] M. Schuster, K.K. Paliwal, Bidirectional recurrent neural networks, IEEE Trans. Signal Process. 45 (11) (1997) 2673–2681.
[267] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A.N. Gomez, Ł. Kaiser, I. Polosukhin, Attention is all you need, Adv. Neural Inf. Process. Syst. 30 (2017).
[268] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, Y. Bengio, Generative adversarial nets, Adv. Neural Inf. Process. Syst. 27 (2014).

[269] K. Wang, J. Xu, S. Zhang, J. Tan, J. Qin, Towards low-budget energy efficiency design in additive manufacturing based on variational scale-aware transformer, J. Clean. Prod. 393 (2023) 136168.
[270] T.M. Mitchell, et al., Machine Learning, vol. 1, McGraw-Hill, New York, 2007.
[271] K. Wang, Contrastive learning-based semantic segmentation for in-situ stratified defect detection in additive manufacturing, J. Manuf. Syst. 68 (2023) 465–476.
[272] M.I. Jordan, T.M. Mitchell, Machine learning: trends, perspectives, and prospects, Science 349 (6245) (2015) 255–260.
[273] M. Shafto, M. Conroy, R. Doyle, E. Glaessgen, C. Kemp, J. LeMoigne, L. Wang, Modeling, simulation, information technology & processing roadmap, Nat. Aeronaut. Space Adm. 32 (2012) (2012) 1–38.
[274] J. Lee, E. Lapira, B. Bagheri, H.-a. Kao, Recent advances and trends in predictive manufacturing systems in big data environment, Manuf. Lett. 1 (1) (2013) 38–41.
[275] E.M. Kraft, The air force digital thread/digital twin-life cycle integration and use of computational and experimental knowledge, in: 54th AIAA Aerospace Sciences Meeting, 2016, p. 0897.
[276] E. Negri, L. Fumagalli, M. Macchi, A review of the roles of digital twin in CPS-based production systems, Proc. Manuf. 11 (2017) 939–948.
[277] M.G. Mohammadi, D. Mahmoud, M. Elbestawi, On the application of machine learning for defect detection in L-PBF additive manufacturing, Opt. Laser Technol. 143 (2021) 107338.
[278] Y. Zhang, G.S. Hong, D. Ye, K. Zhu, J.Y. Fuh, Extraction and evaluation of melt pool, plume and spatter information for powder-bed fusion am process monitoring, Mater. Des. 156 (2018) 458–469.
[279] X. Zhang, J. Saniie, A. Heifetz, Detection of defects in additively manufactured stainless steel 316L with compact infrared camera and machine learning algorithms, JOM 72 (12) (2020) 4244–4253.
[280] L. Lu, J. Hou, S. Yuan, X. Yao, Y. Li, J. Zhu, Deep learning-assisted real-time defect detection and closed-loop adjustment for additive manufacturing of continuous fiber-reinforced polymer composites, Robot. Comput.-Integr. Manuf. 79 (2023) 102431.
[281] F. Imani, A. Gaikwad, M. Montazeri, P. Rao, H. Yang, E. Reutzel, Process mapping and in-process monitoring of porosity in laser powder bed fusion using layerwise optical imaging, J. Manuf. Sci. Eng. 140 (10) (2018).
[282] A.-I. García-Moreno, J.-M. Alvarado-Orozco, J. Ibarra-Medina, E. Martínez-Franco, Image-based porosity classification in Al-alloys by laser metal deposition using random forests, Int. J. Adv. Manuf. Technol. 110 (2020) 2827–2845.
[283] G. Tapia, S. Khairallah, M. Matthews, W.E. King, A. Elwany, Gaussian process-based surrogate modeling framework for process planning in laser powder-bed fusion additive manufacturing of 316L stainless steel, Int. J. Adv. Manuf. Technol. 94 (2018) 3591–3603.
[284] Z. Lu, D. Li, B. Lu, A. Zhang, G. Zhu, G. Pi, The prediction of the building precision in the laser engineered net shaping process using advanced networks, Opt. Lasers Eng. 48 (5) (2010) 519–525.
[285] L. Meng, J. Zhang, Process design of laser powder bed fusion of stainless steel using a gaussian process-based machine learning model, JOM 72 (1) (2020) 420–428.
[286] C. Kamath, Y.J. Fan, Regression with small data sets: a case study using code surrogates in additive manufacturing, Knowl. Inf. Syst. 57 (2018) 475–493.
[287] N. Hertlein, S. Deshpande, V. Venugopal, M. Kumar, S. Anand, Prediction of selective laser melting part quality using hybrid bayesian network, Addit. Manuf. 32 (2020) 101089.
[288] G.O. Barrionuevo, J.A. Ramos-Grez, M. Walczak, C.A. Betancourt, Comparative evaluation of supervised machine learning algorithms in the prediction of the relative density of 316L stainless steel fabricated by selective laser melting, Int. J. Adv. Manuf. Technol. 113 (2021) 419–433.
[289] A. Gaikwad, B. Giera, G.M. Guss, J.-B. Forien, M.J. Matthews, P. Rao, Heterogeneous sensing and scientific machine learning for quality assurance in laser powder bed fusion–a single-track study, Addit. Manuf. 36 (2020) 101659.
[290] K. Huang, C. Kain, N. Diaz-Vallejo, Y. Sohn, L. Zhou, High throughput mechanical testing platform and application in metal additive manufacturing and process optimization, J. Manuf. Process. 66 (2021) 494–505.
[291] L. Cao, J. Li, J. Hu, H. Liu, Y. Wu, Q. Zhou, Optimization of surface roughness and dimensional accuracy in LPBF additive manufacturing, Opt. Laser Technol. 142 (2021) 107246.
[292] S. Mondal, D. Gwynn, A. Ray, A. Basak, Investigation of melt pool geometry control in additive manufacturing using hybrid modeling, Metals 10 (5) (2020) 683.
[293] L. Song, W. Huang, X. Han, J. Mazumder, Real-time composition monitoring using support vector regression of laser-induced plasma for laser additive manufacturing, IEEE Trans. Ind. Electron. 64 (1) (2016) 633–642.
[294] X. Yao, S.K. Moon, G. Bi, A hybrid machine learning approach for additive manufacturing design feature recommendation, Rapid Prototyping J. (2017).
[295] H. Ko, P. Witherell, Y. Lu, S. Kim, D.W. Rosen, Machine learning and knowledge graph based design rule construction for additive manufacturing, Addit. Manuf. 37 (2021) 101620.
[296] J.D. Alejandrino, R.S. Concepcion II, S.C. Lauguico, R.R. Tobias, L. Venancio, D. Macasaet, A.A. Bandala, E.P. Dadios, A machine learning approach of lattice infill pattern for increasing material efficiency in additive manufacturing processes, Int. J. Mech. Eng. Robot. Res. 9 (9) (2020) 1253–1263.
[297] M. Malviya, K. Desai, Build orientation optimization for strength enhancement of FDM parts using machine learning based algorithm, Comput-Aided Des. Appl. 17 (2019) 783–796.
[298] N. Després, E. Cyr, P. Setoodeh, M. Mohammadi, Deep learning and design for additive manufacturing: a framework for microlattice architecture, JOM 72 (2020) 2408–2418.
[299] G. Liu, Y. Xiong, D.W. Rosen, Multidisciplinary design optimization in design for additive manufacturing, J. Comput. Des. Eng. 9 (1) (2022) 128–143.
[300] J. Huang, T.-H. Kwok, C. Zhou, W. Xu, Surfel convolutional neural network for support detection in additive manufacturing, Int. J. Adv. Manuf. Technol. 105 (2019) 3593–3604.
[301] N. Hertlein, P.R. Buskohl, A. Gillman, K. Vemaganti, S. Anand, Generative adversarial network for early-stage design flexibility in topology optimization for additive manufacturing, J. Manuf. Syst. 59 (2021) 675–685.
[302] J. Vrábel, P. Pořízka, J. Klus, D. Prochazka, J. Novotnỳ, D. Koutnỳ, D. Paloušek, J. Kaiser, Classification of materials for selective laser melting by laser-induced breakdown spectroscopy, Chem. Pap. 73 (2019) 2897–2905.
[303] B.L. DeCost, H. Jain, A.D. Rollett, E.A. Holm, Computer vision and machine learning for autonomous characterization of am powder feedstocks, JOM 69 (3) (2017) 456–465.
[304] R. Valente, A. Ostapenko, B.C. Sousa, J. Grubbs, C.J. Massar, D.L. Cote, R. Neamtu, Classifying powder flowability for cold spray additive manufacturing using machine learning, in: 2020 IEEE International Conference on Big Data, IEEE, 2020, pp. 2919–2928.
[305] X. Wang, J. Cao, A novel multi-objective optimization of 3D printing adaptive layering algorithm based on improved NSGA-II and fuzzy set theory, Int. J. Adv. Manuf. Technol. 123 (3–4) (2022) 957–972.
[306] E. Asadollahi-Yazdi, J. Gardan, P. Lafon, Multi-objective optimization of additive manufacturing process, IFAC-PapersOnLine 51 (11) (2018) 152–157.
[307] D.S. Ye, Y. Fuh, Y. Zhang, G. Hong, K.P. Zhu, Defects Recognition in Selective Laser Melting with Acoustic Signals by svm Based on Feature Reduction, IOP Conference Series: Materials Science and Engineering, vol. 436, IOP Publishing, 2018, p. 012020.
[308] S.H. Seifi, W. Tian, H. Doude, M.A. Tschopp, L. Bian, Layer-wise modeling and anomaly detection for laser-based additive manufacturing, J. Manuf. Sci. Eng. 141 (8) (2019) 081013.
[309] M. Khanzadeh, S. Chowdhury, M. Marufuzzaman, M.A. Tschopp, L. Bian, Porosity prediction: supervised-learning of thermal history for direct laser deposition, J. Manuf. Syst. 47 (2018) 69–82.
[310] H. Gaja, F. Liou, Defect classification of laser metal deposition using logistic regression and artificial neural networks for pattern recognition, Int. J. Adv. Manuf. Technol. 94 (2018) 315–326.
[311] T. Özel, A. Altay, B. Kaftanoğlu, R. Leach, N. Senin, A. Donmez, Focus variation measurement and prediction of surface texture parameters using machine learning in laser powder bed fusion, J. Manuf. Sci. Eng. 142 (1) (2020) 011008.
[312] S. Lee, J. Peng, D. Shin, Y.S. Choi, Data analytics approach for melt-pool geometries in metal additive manufacturing, Sci. Technol. Adv. Mater. 20 (1) (2019) 972–978.
[313] Y.M. Arısoy, L.E. Criales, T. Özel, B. Lane, S. Moylan, A. Donmez, Influence of scan strategy and process parameters on microstructure and its optimization in additively manufactured nickel alloy 625 via laser powder bed fusion, Int. J. Adv. Manuf. Technol. 90 (2017) 1393–1417.
[314] L. Scime, J. Beuth, Using machine learning to identify in-situ melt pool signatures indicative of flaw formation in a laser powder bed fusion additive manufacturing process, Addit. Manuf. 25 (2019) 151–165.
[315] W. Halsey, J. Ferguson, A. Plotkowski, R. Dehoff, V. Paquit, Geometry-independent microstructure optimization for electron beam powder bed fusion additive manufacturing, Addit. Manuf. 35 (2020) 101354.
[316] M. Mehrpouya, A. Gisario, A. Rahimzadeh, M. Nematollahi, K.S. Baghbaderani, M. Elahinia, A prediction model for finding the optimal laser parameters in additive manufacturing of NiTi shape memory alloy, Int. J. Adv. Manuf. Technol. 105 (2019) 4691–4699.
[317] P. He, Q. Liu, J.J. Kruzic, X. Li, Machine-learning assisted additive manufacturing of a TiCN reinforced AlSi10Mg composite with tailorable mechanical properties, Mater. Lett. 307 (2022) 131018.
[318] L. Meng, J. Zhao, X. Lan, H. Yang, Z. Wang, Multi-objective optimisation of bio-inspired lightweight sandwich structures based on selective laser melting, Virtual Phys. Prototyp. 15 (1) (2020) 106–119.
[319] E. Maleki, S. Bagherifard, M. Guagliano, Application of artificial intelligence to optimize the process parameters effects on tensile properties of Ti-6Al-4V fabricated by laser powder-bed fusion, Int. J. Mech. Mater. Des. (2021) 1–24.
[320] Z. Wang, P. Liu, Y. Xiao, X. Cui, Z. Hu, L. Chen, A data-driven approach for process optimization of metallic additive manufacturing under uncertainty, J. Manuf. Sci. Eng. 141 (8) (2019).
[321] K. Aoyagi, H. Wang, H. Sudo, A. Chiba, Simple method to construct process maps for additive manufacturing using a support vector machine, Addit. Manuf. 27 (2019) 353–362.
[322] D. Wu, Y. Wei, J. Terpenny, Predictive modelling of surface roughness in fused deposition modelling using data fusion, Int. J. Prod. Res. 57 (12) (2019) 3992–4006.
[323] J. Zhang, P. Wang, R.X. Gao, Deep learning-based tensile strength prediction in fused deposition modeling, Comput. Ind. 107 (2019) 11–21.
[324] F. Wang, S. Fathizadan, F. Ju, K. Rowe, N. Hofmann, Print surface thermal modeling and layer time control for large-scale additive manufacturing, IEEE Trans. Autom. Sci. Eng. 18 (1) (2020) 244–254.

[325] Z. Zhu, N. Anwer, Q. Huang, L. Mathieu, Machine learning in tolerancing for additive manufacturing, CIRP Ann. 67 (1) (2018) 157–160.
[326] N.A. Fountas, N.M. Vaxevanidis, Optimization of fused deposition modeling process using a virus-evolutionary genetic algorithm, Comput. Ind. 125 (2021) 103371.
[327] E. Luis, H.M. Pan, S.L. Sing, A.K. Bastola, G.D. Goh, G.L. Goh, H.K.J. Tan, R. Bajpai, J. Song, W.Y. Yeong, Silicone 3D printing: process optimization, product biocompatibility, and reliability of silicone meniscus implants, 3D Print. Addit. Manuf. 6 (6) (2019) 319–332.
[328] R. Onler, A.S. Koca, B. Kirim, E. Soylemez, Multi-objective optimization of binder jet additive manufacturing of Co-Cr-Mo using machine learning, Int. J. Adv. Manuf. Technol. 119 (1–2) (2022) 1091–1108.
[329] Y. Li, Y. Sun, Q. Han, G. Zhang, I. Horváth, Enhanced beads overlapping model for wire and arc additive manufacturing of multi-layer multi-bead metallic parts, J. Mater. Process. Technol. 252 (2018) 838–848.
[330] D. Ding, F. He, L. Yuan, Z. Pan, L. Wang, M. Ros, The first step towards intelligent wire arc additive manufacturing: an automatic bead modelling system using machine learning through industrial information integration, J. Ind. Inf. Integr. 23 (2021) 100218.
[331] M. Naveen Srinivas, K. Vimal, N. Manikandan, G. Sritharanandh, Parametric optimization and multiple regression modelling for fabrication of aluminium alloy thin plate using wire arc additive manufacturing, Int. J. Interact. Des. Manuf. (2022) 1–11.
[332] A. Kumar, K. Maji, Selection of process parameters for near-net shape deposition in wire arc additive manufacturing by genetic algorithm, J. Mater. Eng. Perform. 29 (2020) 3334–3352.
[333] S.H. Lee, Optimization of cold metal transfer-based wire arc additive manufacturing processes using gaussian process regression, Metals 10 (4) (2020) 461.
[334] X. Gong, Y.C. Yabansu, P.C. Collins, S.R. Kalidindi, Evaluation of Ti-Mn alloys for additive manufacturing using high-throughput experimental assays and Gaussian process regression, Materials 13 (20) (2020) 4641.
[335] H. Zhang, S.K. Moon, T.H. Ngo, Hybrid machine learning method to determine the optimal operating process window in aerosol jet 3D printing, ACS Appl. Mater. Interfaces 11 (19) (2019) 17994–18003.
[336] L.J. Segura, Z. Li, C. Zhou, H. Sun, Droplet evolution prediction in material jetting via tensor time series analysis, Addit. Manuf. 66 (2023) 103461.
[337] A. Khadilkar, J. Wang, R. Rai, Deep learning–based stress prediction for bottom-up SLA 3D printing process, Int. J. Adv. Manuf. Technol. 102 (2019) 2555–2569.
[338] R. d, S.B. Ferreira, A. Sabbaghi, Q. Huang, Automated geometric shape deviation modeling for additive manufacturing systems via bayesian neural networks, IEEE Trans. Autom. Sci. Eng. 17 (2) (2019) 584–598.
[339] Z. Shen, X. Shang, M. Zhao, X. Dong, G. Xiong, F.-Y. Wang, A learning-based framework for error compensation in 3D printing, IEEE Trans. Cybern. 49 (11) (2019) 4042–4050.
[340] G. Strano, L. Hao, R. Everson, K. Evans, Multi-objective optimization of selective laser sintering processes for surface quality and energy saving, Proc. Inst. Mech. Eng., B J. Eng. Manuf. 225 (9) (2011) 1673–1682.
[341] J. Yan, I. Battiato, G.M. Fadel, A mathematical model-based optimization method for direct metal deposition of multimaterials, J. Manuf. Sci. Eng. 139 (8) (2017).
[342] J. Qin, Y. Liu, R. Grosvenor, F. Lacan, Z. Jiang, Deep learning-driven particle swarm optimisation for additive manufacturing energy optimisation, J. Clean. Prod. 245 (2020) 118702.
[343] Y. Yang, M. He, L. Li, Power consumption estimation for mask image projection stereolithography additive manufacturing using machine learning based approach, J. Clean. Prod. 251 (2020) 119710.
[344] Y. Li, F. Hu, J. Qin, M. Ryan, R. Wang, Y. Liu, A hybrid machine learning approach for energy consumption prediction in additive manufacturing, in: Pattern Recognition. ICPR International Workshops and Challenges: Virtual Event, January 10–15, 2021, Proceedings, Part IV, Springer, 2021, pp. 622–636.
[345] B. Vaissier, J.-P. Pernot, L. Chougrani, P. Véron, Genetic-algorithm based framework for lattice support structure optimization in additive manufacturing, Comput. Aided Des. 110 (2019) 11–23.
[346] F. Hu, Y. Liu, J. Qin, X. Sun, P. Witherell, Feature-level data fusion for energy consumption analytics in additive manufacturing, in: 2020 IEEE 16th International Conference on Automation Science and Engineering (CASE), IEEE, 2020, pp. 612–617.
[347] F. Hu, J. Qin, Y. Li, Y. Liu, X. Sun, Deep fusion for energy consumption prediction in additive manufacturing, Proc. CIRP 104 (2021) 1878–1883.
[348] R. Li, M. Jin, V.C. Paquit, Geometrical defect detection for additive manufacturing with machine learning models, Mater. Des. 206 (2021) 109726.
[349] H. Hu, K. He, T. Zhong, Y. Hong, Fault diagnosis of FDM process based on support vector machine (SVM), Rapid Prototyping J. 26 (2) (2020) 330–348.
[350] N. Satterlee, E. Torresani, E. Olevsky, J.S. Kang, Automatic detection and characterization of porosities in cross-section images of metal parts produced by binder jetting using machine learning and image augmentation, J. Intell. Manuf. (2023) 1–23.
[351] M. Montazeri, A.R. Nassar, C.B. Stutzman, P. Rao, Heterogeneous sensor-based condition monitoring in directed energy deposition, Addit. Manuf. 30 (2019) 100916.
[352] W. Ren, G. Wen, Z. Zhang, J. Mazumder, Quality monitoring in additive manufacturing using emission spectroscopy and unsupervised deep learning, Mater. Manuf. Process. 37 (11) (2022) 1339–1346.
[353] X.Y. Lee, S.K. Saha, S. Sarkar, B. Giera, Automated detection of part quality during two-photon lithography via deep learning, Addit. Manuf. 36 (2020) 101444.
[354] Y. Shan, A. Krishnakumar, Z. Qin, H. Mao, Smart Resin vat: Real-Time Detecting Failures, Defects, and Curing Area in vat Photopolymerization 3D Printing, International Manufacturing Science and Engineering Conference, vol. 85802, American Society of Mechanical Engineers, 2022, V001T01A030.
[355] T. Wang, T.-H. Kwok, C. Zhou, S. Vader, In-situ droplet inspection and closed-loop control system using machine learning for liquid metal jet printing, J. Manuf. Syst. 47 (2018) 83–92.
[356] M. Ogunsanya, J. Isichei, S.K. Parupelli, S. Desai, Y. Cai, In-situ droplet monitoring of inkjet 3D printing process using image analysis and machine learning models, Proc. Manuf. 53 (2021) 427–434.
[357] D. Gunasegaram, A. Barnard, M. Matthews, B. Jared, A. Andreaco, K. Bartsch, A. Murphy, Machine learning-assisted in-situ adaptive strategies for the control of defects and anomalies in metal additive manufacturing, Addit. Manuf. (2024) 104013.
[358] Z.U. Arif, M.Y. Khalid, A. Zolfagharian, M. Bodaghi, 4D bioprinting of smart polymers for biomedical applications: recent progress, challenges, and future perspectives, React. Funct. Polym. (2022) 105374.
[359] S. Park, W. Shou, L. Makatura, W. Matusik, K.K. Fu, 3D printing of polymer composites: materials, processes, and applications, Matter 5 (1) (2022) 43–76.
[360] S. Singh, S. Ramakrishna, F. Berto, 3D Printing of polymer composites: a short review, Mater. Des. Process. Commun. 2 (2) (2020) e97.
[361] S.C. Ligon, R. Liska, J. Stampfl, M. Gurr, R. Mülhaupt, Polymers for 3D printing and customized additive manufacturing, Chem. Rev. 117 (15) (2017) 10212–10290.
[362] J.W. Stansbury, M.J. Idacavage, 3D printing with polymers: challenges among expanding options and opportunities, Dent. Mater. 32 (1) (2016) 54–64.
[363] M. Askari, M.A. Naniz, M. Kouhi, A. Saberi, A. Zolfagharian, M. Bodaghi, Recent progress in extrusion 3D bioprinting of hydrogel biomaterials for tissue regeneration: a comprehensive review with focus on advanced fabrication techniques, Biomater. Sci. 9 (3) (2021) 535–573.
[364] Q. Ge, A.H. Sakhaei, H. Lee, C.K. Dunn, N.X. Fang, M.L. Dunn, Multimaterial 4D printing with tailorable shape memory polymers, Sci. Rep. 6 (1) (2016) 31110.
[365] Q. Ge, Z. Chen, J. Cheng, B. Zhang, Y.-F. Zhang, H. Li, X. He, C. Yuan, J. Liu, S. Magdassi, et al., 3D printing of highly stretchable hydrogel with diverse UV curable polymers, Sci. Adv. 7 (2) (2021) eaba4261.
[366] H. Ye, Q. Liu, J. Cheng, H. Li, B. Jian, R. Wang, Z. Sun, Y. Lu, Q. Ge, Multimaterial 3D printed self-locking thick-panel origami metamaterials, Nat. Commun. 14 (1) (2023) 1607.
[367] M. Lalegani Dezaki, M. Bodaghi, Sustainable 4D printing of magneto-electroactive shape memory polymer composites, Int. J. Adv. Manuf. Technol. 126 (1–2) (2023) 35–48.
[368] M.Y. Khalid, Z.U. Arif, R. Noroozi, A. Zolfagharian, M. Bodaghi, 4D printing of shape memory polymer composites: a review on fabrication techniques, applications, and future perspectives, J. Manuf. Process. 81 (2022) 759–797.
[369] L. Jin, X. Zhai, J. Jiang, K. Zhang, W.-H. Liao, Optimizing stimuli-based 4D printed structures: a paradigm shift in programmable material response, in: Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2024, vol. 12949, SPIE, 2024, pp. 321–332.
[370] Q. Wei, H. Li, G. Liu, Y. He, Y. Wang, Y.E. Tan, D. Wang, X. Peng, G. Yang, N. Tsubaki, Metal 3D printing technology for functional integration of catalytic system, Nat. Commun. 11 (1) (2020) 1–8.
[371] C. Buchanan, L. Gardner, Metal 3D printing in construction: a review of methods, research, applications, opportunities and challenges, Eng. Struct. 180 (2019) 332–348.
[372] S. Das, D.L. Bourell, S. Babu, Metallic materials for 3D printing, Mater. Res. Soc. Bull. 41 (10) (2016) 729–741.
[373] T. Duda, L.V. Raghavan, 3D metal printing technology, IFAC-PapersOnLine 49 (29) (2016) 103–110.
[374] J. Ding, S. Qu, L. Zhang, M.Y. Wang, X. Song, Geometric deviation and compensation for thin-walled shell lattice structures fabricated by high precision laser powder bed fusion, Addit. Manuf. 58 (2022) 103061.
[375] J. Xu, Y. Ding, Y. Gao, B. Liu, S. Xue, Y. Hu, D. Zhang, X. Song, Improving high-temperature mechanical properties of laser powder bed-fused Inconel 738 alloy by hot isostatic pressing: tailoring precipitates and healing defects, Mater. Sci. Eng. A 862 (2023) 144285.
[376] J. Jiang, X. Zhai, L. Jin, K. Zhang, J. Chen, Q. Lu, W.-H. Liao, Design for reversed additive manufacturing low-melting-point alloys, J. Eng. Des. (2023) 1–14.
[377] Z. Chen, X. Sun, Y. Shang, K. Xiong, Z. Xu, R. Guo, S. Cai, C. Zheng, Dense ceramics with complex shape fabricated by 3D printing: a review, J. Adv. Ceram. 10 (2) (2021) 195–218.
[378] S.M. Sajadi, L. Vásárhelyi, R. Mousavi, A.H. Rahmati, Z. Kónya, Á. Kukovecz, T. Arif, T. Filleter, R. Vajtai, P. Boul, et al., Damage-tolerant 3D-printed ceramics via conformal coating, Sci. Adv. 7 (28) (2021) eabc5028.
[379] Z. Chen, Z. Li, J. Li, C. Liu, C. Lao, Y. Fu, C. Liu, Y. Li, P. Wang, Y. He, 3D printing of ceramics: a review, J. Eur. Ceram. Soc. 39 (4) (2019) 661–687.
[380] L.C. Hwa, S. Rajoo, A.M. Noor, N. Ahmad, M. Uday, Recent advances in 3D printing of porous ceramics: a review, Curr. Opin. Solid State Mater. Sci. 21 (6) (2017) 323–347.

[381] Z.C. Eckel, C. Zhou, J.H. Martin, A.J. Jacobsen, W.B. Carter, T.A. Schaedler, Additive manufacturing of polymer-derived ceramics, Science 351 (6268) (2016) 58–62.
[382] Y. Weng, M. Li, T.N. Wong, M.J. Tan, Synchronized concrete and bonding agent deposition system for interlayer bond strength enhancement in 3D concrete printing, Autom. Constr. 123 (2021) 103546.
[383] J.H. Lim, Y. Weng, Q.-C. Pham, 3D printing of curved concrete surfaces using Adaptable Membrane Formwork, Constr. Build. Mater. 232 (2020) 117075.
[384] Y. Weng, M. Li, S. Ruan, T.N. Wong, M.J. Tan, K.L.O. Yeong, S. Qian, Comparative economic, environmental and productivity assessment of a concrete bathroom unit fabricated through 3D printing and a precast approach, J. Clean. Prod. 261 (2020) 121245.
[385] P.P. Kamble, S. Chavan, R. Hodgir, G. Gote, K. Karunakaran, Multi-jet ice 3D printing, Rapid Prototyping J. (2021).
[386] F. Zheng, Z. Wang, J. Huang, Z. Li, Inkjet printing-based fabrication of microscale 3D ice structures, Microsyst. Nanoeng. 6 (1) (2020) 1–10.
[387] A. Pronk, Y. Moonen, C. Ao, P. Luo, Y. Wu, 3D printing of ice, in: Proceedings of IASS Annual Symposia, vol. 2017, International Association for Shell and Spatial Structures (IASS), 2017, pp. 1–8.
[388] A.K. Das, D.A. Agar, M. Rudolfsson, S.H. Larsson, A review on wood powders in 3D printing: processes, properties and potential applications, J. Mater. Res. Technol. 15 (2021) 241–255.
[389] A. Le Duigou, M. Castro, R. Bevan, N. Martin, 3D printing of wood fibre biocomposites: from mechanical to actuation functionality, Mater. Des. 96 (2016) 106–114.
[390] K. Henke, S. Treml, Wood based bulk material in 3D printing processes for applications in construction, Eur. J. Wood Prod. 71 (1) (2013) 139–141.
[391] B.N. Johnson, A sweet solution to complex microprinting, Science 378 (6622) (2022) 826–827.
[392] P.Y.V. Leung, Sugar 3D printing: additive manufacturing with molten sugar for investigating molten material fed printing, 3D Print. Addit. Manuf. 4 (1) (2017) 13–18.
[393] A. Dey, I.N. Roan Eagle, N. Yodo, A review on filament materials for fused filament fabrication, J. Manuf. Mater. Process. 5 (3) (2021) 69.
[394] N. Johnson, P. Vulimiri, A. To, X. Zhang, C. Brice, B. Kappes, A. Stebner, Invited review: machine learning for materials developments in metals additive manufacturing, Addit. Manuf. 36 (2020) 101641.
[395] J.H. Panchal, S.R. Kalidindi, D.L. McDowell, Key computational modeling issues in integrated computational materials engineering, Comput. Aided Des. 45 (1) (2013) 4–25.
[396] P.-A. Pires, O. Desmaison, M. Megahed, Icme manufacturability assessment in powder bed fusion additive manufacturing, JOM 70 (2018) 1677–1685.
[397] R. Kannan, G.L. Knapp, P. Nandwana, R. Dehoff, A. Plotkowski, B. Stump, Y. Yang, V. Paquit, Data mining and visualization of high-dimensional icme data for additive manufacturing, Integr. Mater. Manuf. Innov. 11 (1) (2022) 57–70.
[398] M. Seifi, A. Salem, J. Beuth, O. Harrysson, J.J. Lewandowski, Overview of materials qualification needs for metal additive manufacturing, JOM 68 (2016) 747–764.
[399] W.Y. Wang, J. Li, W. Liu, Z.-K. Liu, Integrated computational materials engineering for advanced materials: a brief review, Comput. Mater. Sci. 158 (2019) 42–48.
[400] S.A.H. Motaman, F. Kies, P. Köhnen, M. Létang, M. Lin, A. Molotnikov, C. Haase, Optimal design for metal additive manufacturing: an integrated computational materials engineering (icme) approach, JOM 72 (2020) 1092–1104.
[401] X. Wang, W. Xiong, Uncertainty quantification and composition optimization for alloy additive manufacturing through a calphad-based icme framework, npj Comput. Mater. 6 (1) (2020) 188.
[402] J. Jiang, A. Lu, X. Ma, D. Ouyang, R.O. Williams III, The applications of machine learning to predict the forming of chemically stable amorphous solid dispersions prepared by hot-melt extrusion, Int. J. Pharm. X 5 (2023) 100164.
[403] D. Chernyavsky, D.Y. Kononenko, J.H. Han, H.J. Kim, J. van den Brink, K. Kosiba, Machine learning for additive manufacturing: predicting materials characteristics and their uncertainty, Mater. Des. 227 (2023) 111699.
[404] R.R. Schmidt, J. Hildebrand, I. Kraljevski, F. Duckhorn, C. Tschöpe, A study for laser additive manufacturing quality and material classification using machine learning, in: 2022 IEEE Sensors, IEEE, 2022, pp. 1–4.
[405] S. Yang, Y.F. Zhao, Additive manufacturing-enabled design theory and methodology: a critical review, Int. J. Adv. Manuf. Technol. 80 (2015) 327–342.
[406] K.V. Bhat, G. Capasso, S. Coniglio, J. Morlier, C. Gogu, On some applications of Generalized Geometric Projection to optimal 3D printing, Comput. Graph. 102 (2022) 199–212.
[407] V. Hassani, Z. Khabazi, F. Raspall, C. Banon, D. Rosen, Form-finding and structural shape optimization of the metal 3D-printed node, in: Proceedings of CAD'19, Singapore, 2019, pp. 24–28.
[408] G. Kazakis, I. Kanellopoulos, S. Sotiropoulos, N.D. Lagaros, Topology optimization aided structural design: interpretation, computational aspects and 3D printing, Heliyon 3 (10) (2017) e00431.
[409] Y. Wang, W. Du, H. Wang, Y. Zhao, Intelligent generation method of innovative structures based on topology optimization and deep learning, Materials 14 (24) (2021) 7680.
[410] Y. Maksum, A. Amirli, A. Amangeldi, M. Inkarbekov, Y. Ding, A. Romagnoli, S. Rustamov, B. Akhmetov, Computational acceleration of topology optimization using parallel computing and machine learning methods–analysis of research trends, J. Ind. Inf. Integr. 28 (2022) 100352.
[411] N.A. Kallioras, N.D. Lagaros, Mlgen: generative design framework based on machine learning and topology optimization, Appl. Sci. 11 (24) (2021) 12044.
[412] D.W. Abueidda, S. Koric, N.A. Sobh, Topology optimization of 2D structures with nonlinearities using deep learning, Comput. Struct. 237 (2020) 106283.
[413] N.S. Iyer, A.M. Mirzendehdel, S. Raghavan, Y. Jiao, E. Ulu, M. Behandish, S. Nelaturi, D.M. Robinson, Pato: producibility-aware topology optimization using deep learning for metal additive manufacturing, preprint, arXiv:2112.04552, 2021.
[414] X. Chen, H. Zhang, J. Lin, R. Hu, L. Lu, Q.-X. Huang, B. Benes, D. Cohen-Or, B. Chen, Dapper: decompose-and-pack for 3D printing, ACM Trans. Graph. 34 (6) (2015) 213–1.
[415] R. Li, Q. Peng, Deep learning-based optimal segmentation of 3D printed product for surface quality improvement and support structure reduction, J. Manuf. Syst. 60 (2021) 252–264.
[416] B. Ezair, F. Massarwi, G. Elber, Orientation analysis of 3D objects toward minimal support volume in 3D-printing, Comput. Graph. 51 (2015) 117–124.
[417] W.M. Wang, C. Zanni, L. Kobbelt, Improved Surface Quality in 3D Printing by Optimizing the Printing Direction, Computer Graphics Forum, vol. 35, Wiley Online Library, 2016, pp. 59–70.
[418] H. Shen, X. Ye, G. Xu, L. Zhang, J. Qian, J. Fu, 3D printing build orientation optimization for flexible support platform, Rapid Prototyping J. 26 (1) (2020) 59–72.
[419] W. Wang, H. Chao, J. Tong, Z. Yang, X. Tong, H. Li, X. Liu, L. Liu, Saliency-Preserving Slicing Optimization for Effective 3D Printing, Computer Graphics Forum, vol. 34, Wiley Online Library, 2015, pp. 148–160.
[420] W. Wang, H. Shao, X. Liu, B. Yin, Printing direction optimization through slice number and support minimization, IEEE Access 8 (2020) 75646–75655.
[421] N. Umetani, R.M. Schmidt, Cross-sectional structural analysis for 3D printing optimization, in: SIGGRAPH Asia Technical Briefs, Citeseer, 2013, pp. 5–1.
[422] T. Wang, N. Li, G. Link, J. Jelonnek, J. Fleischer, J. Dittus, D. Kupzik, Load-dependent path planning method for 3D printing of continuous fiber reinforced plastics, Composites, Part A, Appl. Sci. Manuf. 140 (2021) 106181.
[423] R.D. Weeks, R.L. Truby, S.G. Uzel, J.A. Lewis, Embedded 3D printing of multimaterial polymer lattices via graph-based print path planning, Adv. Mater. 35 (5) (2023) 2206958.
[424] S. Elagandula, L. Poudel, Z. Sha, W. Zhou, Multi-robot path planning for cooperative 3D printing, in: International Manufacturing Science and Engineering Conference, vol. 84256, American Society of Mechanical Engineers, 2020, V001T01A034.
[425] A.V. Shembekar, Y.J. Yoon, A. Kanyuck, S.K. Gupta, Trajectory planning for conformal 3D printing using non-planar layers, in: International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, vol. 51722, American Society of Mechanical Engineers, 2018, V01AT02A026.
[426] H. Guo, J. Xu, S. Zhang, Y. Zhang, J. Tan, Multi-orientation optimization of complex parts based on model segmentation in additive manufacturing, J. Mech. Sci. Technol. (2023) 1–15.
[427] X. Zhang, X. Le, A. Panotopoulou, E. Whiting, C.C. Wang, Perceptual models of preference in 3D printing direction, ACM Trans. Graph. 34 (6) (2015) 1–12.
[428] P. Shi, Q. Qi, Y. Qin, F. Meng, S. Lou, P.J. Scott, X. Jiang, Learn to rotate: part orientation for reducing support volume via generalizable reinforcement learning, IEEE Trans. Ind. Inform. (2023).
[429] M. Qin, S. Qu, J. Ding, X. Song, S. Gao, C.C. Wang, W.-H. Liao, Adaptive toolpath generation for distortion reduction in laser powder bed fusion process, Addit. Manuf. 64 (2023) 103432.
[430] J. Ge, Y. Wang, J. Li, H. Bai, L. Liu, S. Wang, X. Xue, F. Li, A reinforcement learning-based path planning method for complex thin-walled structures in 3D printing, in: 2021 the 5th International Conference on Innovation in Artificial Intelligence, 2021, pp. 234–240.
[431] K. Yanamandra, G.L. Chen, X. Xu, G. Mac, N. Gupta, Reverse engineering of additive manufactured composite part by toolpath reconstruction using imaging and machine learning, Compos. Sci. Technol. 198 (2020) 108318.
[432] W.L. Ng, A. Chan, Y.S. Ong, C.K. Chua, Deep learning for fabrication and maturation of 3D bioprinted tissues and organs, Virtual Phys. Prototyp. 15 (3) (2020) 340–358.
[433] M.R. Rezaei, M. Houshmand, O. Fatahi Valilai, An autonomous intelligent framework for optimal orientation detection in 3D printing, Int. J. Comput. Integr. Manuf. (2023) 1–39.
[434] M.A. El youbi El idrissi, L. Laaouina, A. Jeghal, H. Tairi, M. Zaki, Energy consumption prediction for fused deposition modelling 3D printing using machine learning, Appl. Syst. Innov. 5 (4) (2022) 86.
[435] D. Checa, G. Urbikain, A. Beranoagirre, A. Bustillo, L.N. Lopez de Lacalle, Using machine-learning techniques and virtual reality to design cutting tools for energy optimization in milling operations, Int. J. Comput. Integr. Manuf. 35 (9) (2022) 951–971.
[436] T.S. Tamir, G. Xiong, Q. Fang, Y. Yang, Z. Shen, M. Zhou, J. Jiang, Machine-learning-based monitoring and optimization of processing parameters in 3D printing, Int. J. Comput. Integr. Manuf. (2022) 1–17.
[437] Z. Jin, Z. Zhang, J. Ott, G.X. Gu, Precise localization and semantic segmentation detection of printing conditions in fused filament fabrication technologies using machine learning, Addit. Manuf. 37 (2021) 101696.
[438] S. Patrick, A. Nycz, M. Noakes, Reinforcement learning for generating toolpaths in additive manufacturing, in: 2018 International Solid Freeform Fabrication Symposium, University of Texas at Austin, 2018.

[439] K.-Y. Fok, N. Ganganath, C.-T. Cheng, H.H.-C. Iu, K.T. Chi, Tool-path optimization using neural networks, in: 2019 IEEE International Symposium on Circuits and Systems (ISCAS), IEEE, 2019, pp. 1–5.
[440] Z. Xie, N. Somani, Y.J.S. Tan, J.C.Y. Seng, Automatic toolpath pattern recommendation for various industrial applications based on deep learning, in: 2021 IEEE/SICE International Symposium on System Integration (SII), IEEE, 2021, pp. 60–65.
[441] B. Crockett, M. Borish, Toolpath planning for multiple build points using k-means clustering, in: 2022 International Solid Freeform Fabrication Symposium, 2022.
[442] M.P. Bendsøe, N. Kikuchi, Generating optimal topologies in structural design using a homogenization method, Comput. Methods Appl. Mech. Eng. 71 (2) (1988) 197–224.
[443] O. Sigmund, On the design of compliant mechanisms using topology optimization, J. Struct. Mech. 25 (4) (1997) 493–524.
[444] H. Chi, Y. Zhang, T.L.E. Tang, L. Mirabella, L. Dalloro, L. Song, G.H. Paulino, Universal machine learning for topology optimization, Comput. Methods Appl. Mech. Eng. 375 (2021) 112739.
[445] J. Tian, K. Tang, X. Chen, X. Wang, Machine learning-based prediction and inverse design of 2D metamaterial structures with tunable deformation-dependent Poisson's ratio, Nanoscale 14 (35) (2022) 12677–12691.
[446] H.T. Kollmann, D.W. Abueidda, S. Koric, E. Guleryuz, N.A. Sobh, Deep learning for topology optimization of 2D metamaterials, Mater. Des. 196 (2020) 109098.
[447] H. Wang, S.-H. Xiao, C. Zhang, Novel planar auxetic metamaterial perforated with orthogonally aligned oval-shaped holes and machine learning solutions, Adv. Eng. Mater. 23 (7) (2021) 2100102.
[448] A. Challapalli, J. Konlan, G. Li, Inverse machine learning discovered metamaterials with record high recovery stress, Int. J. Mech. Sci. 244 (2023) 108029.
[449] F.V. Senhora, H. Chi, Y. Zhang, L. Mirabella, T.L.E. Tang, G.H. Paulino, Machine learning for topology optimization: physics-based learning through an independent training strategy, Comput. Methods Appl. Mech. Eng. 398 (2022) 115116.
[450] Z. Xia, H. Zhang, Z. Zhuang, C. Yu, J. Yu, L. Gao, A machine-learning framework for isogeometric topology optimization, Struct. Multidiscip. Optim. 66 (4) (2023) 83.
[451] H. Jeong, J. Bai, C.P. Batuwatta-Gamage, C. Rathnayaka, Y. Zhou, Y. Gu, A physics-informed neural network-based topology optimization (pinnto) framework for structural optimization, Eng. Struct. 278 (2023) 115484.
[452] J. Seo, R.K. Kapania, Topology optimization with advanced cnn using mapped physics-based data, Struct. Multidiscip. Optim. 66 (1) (2023) 21.
[453] C.M. Parrott, D.W. Abueidda, K.A. James, Multidisciplinary topology optimization using generative adversarial networks for physics-based design enhancement, J. Mech. Des. 145 (6) (2023) 061704.
[454] L. Wang, D. Shi, B. Zhang, G. Li, W.M. Helal, M. Qi, Deep learning driven real time topology optimization based on improved convolutional block attention (Cba-U-Net) model, Eng. Anal. Bound. Elem. 147 (2023) 112–124.
[455] A. Chandrasekhar, A. Mirzendehdel, M. Behandish, K. Suresh, Frc-tounn: topology optimization of continuous fiber reinforced composites using neural network, Comput. Aided Des. 156 (2023) 103449.
[456] A. Chandrasekhar, S. Sridhara, K. Suresh, Graded multiscale topology optimization using neural networks, Adv. Eng. Softw. 175 (2023) 103359.
[457] S. Liu, Q. Li, J. Liu, W. Chen, Y. Zhang, A realization method for transforming a topology optimization design into additive manufacturing structures, Engineering 4 (2) (2018) 277–285.
[458] W. Wang, D. Feng, L. Yang, S. Li, C.C. Wang, Topology optimization of self-supporting lattice structure, Addit. Manuf. 67 (2023) 103507.
[459] H. Li, Z. Luo, L. Gao, Q. Qin, Topology optimization for concurrent design of structures with multi-patch microstructures by level sets, Comput. Methods Appl. Mech. Eng. 331 (2018) 536–561.
[460] C. Lu, M. Hsieh, Z. Huang, C. Zhang, Y. Lin, Q. Shen, F. Chen, L. Zhang, Architectural design and additive manufacturing of mechanical metamaterials: a review, Engineering 17 (2022) 44–63.
[461] S. Qian, H. Liu, Y. Wang, D. Mei, Structural optimization of 3D printed SiC scaffold with gradient pore size distribution as catalyst support for methanol steam reforming, Fuel 341 (2023) 127612.
[462] Z. Gan, H. Li, S.J. Wolff, J.L. Bennett, G. Hyatt, G.J. Wagner, J. Cao, W.K. Liu, Data-driven microstructure and microhardness design in additive manufacturing using a self-organizing map, Engineering 5 (4) (2019) 730–735.
[463] I. Sosnovik, I. Oseledets, Neural networks for topology optimization, Russ. J. Numer. Anal. Math. Model. 34 (4) (2019) 215–223.
[464] X. Lei, C. Liu, Z. Du, W. Zhang, X. Guo, Machine learning-driven real-time topology optimization under moving morphable component-based framework, J. Appl. Mech. 86 (1) (2019) 011004.
[465] Y. Yu, T. Hur, J. Jung, I.G. Jang, Deep learning for determining a near-optimal topological design without any iteration, Struct. Multidiscip. Optim. 59 (3) (2019) 787–799.
[466] C. Kim, J. Lee, J. Yoo, Machine learning-combined topology optimization for functionary graded composite structure design, Comput. Methods Appl. Mech. Eng. 387 (2021) 114158.
[467] A. Chandrasekhar, K. Suresh, Tounn: topology optimization using neural networks, Struct. Multidiscip. Optim. 63 (2021) 1135–1149.
[468] X. Jiang, H. Wang, Y. Li, K. Mo, Machine Learning based parameter tuning strategy for MMC based topology optimization, Adv. Eng. Softw. 149 (2020) 102841.
[469] W. Ma, Z. Liu, Z.A. Kudyshev, A. Boltasseva, W. Cai, Y. Liu, Deep learning for the design of photonic structures, Nat. Photonics 15 (2) (2021) 77–90.
[470] H. Liu, Z. Fu, K. Yang, X. Xu, M. Bauchy, Machine learning for glass science and engineering: a review, J. Non-Cryst. Solids 557 (2021) 119419.
[471] J. Seo, R.K. Kapania, Development of deep convolutional neural network for structural topology optimization, AIAA J. 61 (3) (2023) 1366–1379.
[472] A. Prathyusha, G.R. Babu, A review on additive manufacturing and topology optimization process for weight reduction studies in various industrial applications, Mater. Today Proc. 62 (2022) 109–117.
[473] Y. Xing, L. Tong, An online autonomous learning and prediction scheme for machine learning assisted structural optimization, Thin-Walled Struct. 184 (2023) 110500.
[474] T. Yoo, S. Lee, K. Yoo, H. Kim, Reinforcement learning based topology control for UAV networks, Sensors 23 (2) (2023) 921.
[475] S.K. Patel, J. Surve, J. Parmar, A. Natesan, V. Katkar, Graphene-based metasurface refractive index biosensor for hemoglobin detection: machine learning assisted optimization, IEEE Trans. Nanobiosci. (2022).
[476] J.K. Wilt, C. Yang, G.X. Gu, Accelerating auxetic metamaterial design with deep learning, Adv. Eng. Mater. 22 (5) (2020) 1901266.
[477] S. Jafar-Zanjani, M.M. Salary, D. Huynh, E. Elhamifar, H. Mosallaei, Tco-based active dielectric metasurfaces design by conditional generative adversarial networks, Adv. Theory Simul. 4 (2) (2021) 2000196.
[478] C. Gurbuz, F. Kronowetter, C. Dietz, M. Eser, J. Schmid, S. Marburg, Generative adversarial networks for the design of acoustic metamaterials, J. Acoust. Soc. Am. 149 (2) (2021) 1162–1174.
[479] A. Challapalli, D. Patel, G. Li, Inverse machine learning framework for optimizing lightweight metamaterials, Mater. Des. 208 (2021) 109937.
[480] T. Gahlmann, P. Tassin, Deep neural networks for the prediction of the optical properties and the free-form inverse design of metamaterials, Phys. Rev. B 106 (8) (2022) 085408.
[481] O. Khatib, S. Ren, J. Malof, W.J. Padilla, Learning the physics of all-dielectric metamaterials with deep Lorentz neural networks, Adv. Opt. Mater. 10 (13) (2022) 2200097.
[482] J. Chen, W. Ding, X.-M. Li, X. Xi, K.-P. Ye, H.-B. Wu, R.-X. Wu, Absorption and diffusion enabled ultrathin broadband metamaterial absorber designed by deep neural network and pso, IEEE Antennas Wirel. Propag. Lett. 20 (10) (2021) 1993–1997.
[483] T. Shah, L. Zhuo, P. Lai, A. De La Rosa-Moreno, F. Amirkulova, P. Gerstoft, Reinforcement learning applied to metamaterial design, J. Acoust. Soc. Am. 150 (1) (2021) 321–338.
[484] L. Rosafalco, J.M. De Ponti, L. Iorio, R. Ardito, A. Corigliano, Optimised graded metamaterials for mechanical energy confinement and amplification via reinforcement learning, Eur. J. Mech. A, Solids 99 (2023) 104947.
[485] L. Rosafalco, J.M. De Ponti, L. Iorio, R. Ardito, A. Corigliano, Optimised graded metamaterials for energy harvesting via reinforcement learning, preprint, arXiv:2211.09528, 2022.
[486] S.B. Oliva, F.T. Bölle, A. Las, X. Xia, I. Castelli, Reinforcement Learning-Based Design of Shape-Changing Metamaterials, 2023.
[487] S. Kumar, S. Tan, L. Zheng, D.M. Kochmann, Inverse-designed spinodoid metamaterials, npj Comput. Mater. 6 (1) (2020) 73.
[488] Y. Wang, Q. Zeng, J. Wang, Y. Li, D. Fang, Inverse design of shell-based mechanical metamaterial with customized loading curves based on machine learning and genetic algorithm, Comput. Methods Appl. Mech. Eng. 401 (2022) 115571.
[489] A.P. Garland, B.C. White, S.C. Jensen, B.L. Boyce, Pragmatic generative optimization of novel structural lattice metamaterials with machine learning, Mater. Des. 203 (2021) 109632.
[490] Y. Chang, H. Wang, Q. Dong, Machine learning-based inverse design of auxetic metamaterial with zero poisson's ratio, Mater. Today Commun. 30 (2022) 103186.
[491] Y. Singh, J. Singh, S. Sharma, A. Sharma, J.S. Chohan, Process parameter optimization in laser cutting of coir fiber reinforced epoxy composite-a review, Mater. Today Proc. 48 (2022) 1021–1027.
[492] R. Chaudhari, H. Parmar, J. Vora, V.K. Patel, Parametric study and investigations of bead geometries of GMAW-based wire–arc additive manufacturing of 316L stainless steels, Metals 12 (7) (2022) 1232.
[493] Z. Chen, C. Han, M. Gao, S.Y. Kandukuri, K. Zhou, A review on qualification and certification for metal additive manufacturing, Virtual Phys. Prototyp. 17 (2) (2022) 382–405.
[494] N. Fountas, J. Kechagias, D. Manolakos, N. Vaxevanidis, Single and multi-objective optimization of FDM-based additive manufacturing using metaheuristic algorithms, Proc. Manuf. 51 (2020) 740–747.
[495] N. Padhye, K. Deb, Multi-objective optimisation and multi-criteria decision making in SLS using evolutionary approaches, Rapid Prototyping J. (2011).
[496] O.A. Mohamed, S.H. Masood, J.L. Bhowmik, Mathematical modeling and FDM process parameters optimization using response surface methodology based on Q-optimal design, Appl. Math. Model. 40 (23–24) (2016) 10052–10073.
[497] V. Wankhede, D. Jagetiya, A. Joshi, R. Chaudhari, Experimental investigation of FDM process parameters using Taguchi analysis, Mater. Today Proc. 27 (2020) 2117–2120.
[498] A. Peng, X. Xiao, R. Yue, Process parameter optimization for fused deposition modeling using response surface methodology combined with fuzzy inference system, Int. J. Adv. Manuf. Technol. 73 (1–4) (2014) 87–100.

[499] P.K. Gurrala, S.P. Regalla, Optimization of Support Material and Build Time in Fused Deposition Modeling (FDM), Applied Mechanics and Materials, vol. 110, Trans Tech Publ, 2012, pp. 2245–2251.
[500] M. Srivastava, S. Rathee, S. Maheshwari, T. Kundra, Multi-objective optimisation of fused deposition modelling process parameters using RSM and fuzzy logic for build time and support material, Int. J. Rapid Manuf. 7 (1) (2018) 25–42.
[501] A. Rinanto, A. Nugroho, H. Prasetyo, E. Pujiyanto, Simultaneous optimization of tensile strength, energy consumption, and processing time on FDM process using Taguchi and PCR-TOPSIS, in: 2018 4th International Conference on Science and Technology (ICST), IEEE, 2018, pp. 1–5.
[502] D. Coupek, J. Friedrich, D. Battran, O. Riedel, Reduction of support structures and building time by optimized path planning algorithms in multi-axis additive manufacturing, Proc. CIRP 67 (2018) 221–226.
[503] A. Pajonk, A. Prieto, U. Blum, U. Knaack, Multi-material additive manufacturing in architecture and construction: a review, J. Build. Eng. 45 (2022) 103603.
[504] E. Ulu, R. Huang, L.B. Kara, K.S. Whitefoot, Concurrent structure and process optimization for minimum cost metal additive manufacturing, J. Mech. Des. 141 (6) (2019).
[505] R. Huang, E. Ulu, L.B. Kara, K.S. Whitefoot, Cost minimization in metal additive manufacturing using concurrent structure and process optimization, in: International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, vol. 58127, American Society of Mechanical Engineers, 2017, V02AT03A030.
[506] S.H. Nikam, N.K. Jain, M.S. Sawant, Optimization of parameters of micro-plasma transferred arc additive manufacturing process using real coded genetic algorithm, Int. J. Adv. Manuf. Technol. 106 (2020) 1239–1252.
[507] W. Wu, J. Xue, W. Xu, H. Lin, H. Tang, P. Yao, Parameters optimization of auxiliary gas process for double-wire SS316L stainless steel arc additive manufacturing, Metals 11 (2) (2021) 190.
[508] A.M. Aboutaleb, L. Bian, A. Elwany, N. Shamsaei, S.M. Thompson, G. Tapia, Accelerated process optimization for laser-based additive manufacturing by leveraging similar prior studies, IISE Trans. 49 (1) (2017) 31–44.
[509] T. Peng, J. Lv, A. Majeed, X. Liang, An experimental investigation on energy-effective additive manufacturing of aluminum parts via process parameter selection, J. Clean. Prod. 279 (2021) 123609.
[510] M. Khalid, Q. Peng, Investigation of printing parameters of additive manufacturing process for sustainability using design of experiments, J. Mech. Des. 143 (3) (2021).
[511] J. Watson, K. Taminger, A decision-support model for selecting additive manufacturing versus subtractive manufacturing based on energy consumption, J. Clean. Prod. 176 (2018) 1316–1322.
[512] Z. Liu, C. Li, X. Fang, Y. Guo, Energy consumption in additive manufacturing of metal parts, Proc. Manuf. 26 (2018) 834–845.
[513] Z. Ma, M. Gao, Q. Wang, N. Wang, L. Li, C. Liu, Z. Liu, Energy consumption distribution and optimization of additive manufacturing, Int. J. Adv. Manuf. Technol. 116 (2021) 3377–3390.
[514] A. Verma, R. Rai, Energy efficient modeling and optimization of additive manufacturing process, in: 2013 International Solid Freeform Fabrication Symposium, University of Texas at Austin, 2013.
[515] S. Peng, T. Li, J. Zhao, S. Lv, G.Z. Tan, M. Dong, H. Zhang, Towards energy and material efficient laser cladding process: modeling and optimization using a hybrid TS-GEP algorithm and the NSGA-II, J. Clean. Prod. 227 (2019) 58–69.
[516] A.K. Singh, A. Sadhu, A.K. Das, D.K. Pratihar, A.R. Choudhury, An approach towards energy and material efficient additive manufacturing: multi-objective optimization of stellite-6 deposition on SS304, Opt. Laser Technol. 148 (2022) 107799.
[517] A.G. Dharmawan, Y. Xiong, S. Foong, G.S. Soh, A model-based reinforcement learning and correction framework for process control of robotic wire arc additive manufacturing, in: 2020 IEEE International Conference on Robotics and Automation (ICRA), IEEE, 2020, pp. 4030–4036.
[518] A. Alafaghani, A. Qattawi, B. Alrawi, A. Guzman, Experimental optimization of fused deposition modelling processing parameters: a design-for-manufacturing approach, Proc. Manuf. 10 (2017) 791–803.
[519] S. Mahmood, A. Qureshi, D. Talamona, Taguchi based process optimization for dimension and tolerance control for fused deposition modelling, Addit. Manuf. 21 (2018) 183–190.
[520] A.H. Maamoun, Y.F. Xue, M.A. Elbestawi, S.C. Veldhuis, Effect of selective laser melting process parameters on the quality of Al alloy parts: powder characterization, density, surface roughness, and dimensional accuracy, Materials 11 (12) (2018) 2343.
[521] C. Wacker, M. Köhler, M. David, F. Aschersleben, F. Gabriel, J. Hensel, K. Dilger, K. Dröder, Geometry and distortion prediction of multiple layers for wire arc additive manufacturing with artificial neural networks, Appl. Sci. 11 (10) (2021) 4694.
[522] M.A. Matos, A.M.A. Rocha, A.I. Pereira, Improving additive manufacturing performance by build orientation optimization, Int. J. Adv. Manuf. Technol. 107 (2020) 1993–2005.
[523] H. Chen, Y.F. Zhao, Process parameters optimization for improving surface quality and manufacturing accuracy of binder jetting additive manufacturing process, Rapid Prototyping J. 22 (3) (2016) 527–538.
[524] A.M. Aboutaleb, M.A. Tschopp, P.K. Rao, L. Bian, Multi-objective accelerated process optimization of part geometric accuracy in additive manufacturing, J. Manuf. Sci. Eng. 139 (10) (2017).
[525] N. Garg, V. Rastogi, P. Kumar, Process parameter optimization on the dimensional accuracy of additive manufacture Thermoplastic Polyurethane (TPU) using RSM, Mater. Today Proc. 62 (2022) 94–99.
[526] W. Mycroft, M. Katzman, S. Tammas-Williams, E. Hernandez-Nava, G. Panoutsos, I. Todd, V. Kadirkamanathan, A data-driven approach for predicting printability in metal additive manufacturing processes, J. Intell. Manuf. 31 (2020) 1769–1781.
[527] Q. Chen, E. Juste, M. Lasgorceix, F. Petit, A. Leriche, Binder jetting process with ceramic powders: influence of powder properties and printing parameters, Open Ceram. 9 (2022) 100218.
[528] M. Raju, M.K. Gupta, N. Bhanot, V.S. Sharma, A hybrid pso–bfo evolutionary algorithm for optimization of fused deposition modelling process parameters, J. Intell. Manuf. 30 (2019) 2743–2758.
[529] B. Yang, Y. Lai, X. Yue, D. Wang, Y. Zhao, Parametric optimization of laser additive manufacturing of Inconel 625 using Taguchi method and grey relational analysis, Scanning 2020 (2020).
[530] C. Lu, J. Shi, Relative density and surface roughness prediction for Inconel 718 by selective laser melting: central composite design and multi-objective optimization, Int. J. Adv. Manuf. Technol. (2022) 1–19.
[531] C. Xia, Z. Pan, J. Polden, H. Li, Y. Xu, S. Chen, Modelling and prediction of surface roughness in wire arc additive manufacturing using machine learning, J. Intell. Manuf. (2022) 1–16.
[532] A. Yaseer, H. Chen, Machine learning based layer roughness modeling in robotic additive manufacturing, J. Manuf. Process. 70 (2021) 543–552.
[533] A. Selvam, S. Mayilswamy, R. Whenish, K. Naresh, V. Shanmugam, O. Das, Multi-objective optimization and prediction of surface roughness and printing time in FFF printed ABS polymer, Sci. Rep. 12 (1) (2022) 16887.
[534] D. Dong, C. Chang, H. Wang, X. Yan, W. Ma, M. Liu, S. Deng, J. Gardan, R. Bolot, H. Liao, Selective laser melting (SLM) of CX stainless steel: theoretical calculation, process optimization and strengthening mechanism, J. Mater. Sci. Technol. 73 (2021) 151–164.
[535] M. Oyesola, K. Mpofu, N. Mathe, S. Fatoba, S. Hoosain, I. Daniyan, Optimization of selective laser melting process parameters for surface quality performance of the fabricated Ti6Al4V, Int. J. Adv. Manuf. Technol. 114 (2021) 1585–1599.
[536] J. Gockel, L. Sheridan, B. Koerper, B. Whip, The influence of additive manufacturing processing parameters on surface roughness and fatigue life, Int. J. Fatigue 124 (2019) 380–388.
[537] B. Whip, L. Sheridan, J. Gockel, The effect of primary processing parameters on surface roughness in laser powder bed additive manufacturing, Int. J. Adv. Manuf. Technol. 103 (2019) 4411–4422.
[538] J.C. Fox, S.P. Moylan, B.M. Lane, Effect of process parameters on the surface roughness of overhanging structures in laser powder bed fusion additive manufacturing, Proc. CIRP 45 (2016) 131–134.
[539] Z. Li, Z. Zhang, J. Shi, D. Wu, Prediction of surface roughness in extrusion-based additive manufacturing with machine learning, Robot. Comput.-Integr. Manuf. 57 (2019) 488–495.
[540] J. Sun, Y. Yang, D. Wang, Parametric optimization of selective laser melting for forming Ti6Al4V samples by Taguchi method, Opt. Laser Technol. 49 (2013) 118–124.
[541] M. Yakout, M. Elbestawi, S.C. Veldhuis, Density and mechanical properties in selective laser melting of Invar 36 and stainless steel 316L, J. Mater. Process. Technol. 266 (2019) 397–420.
[542] A.M. Aboutaleb, M.J. Mahtabi, M.A. Tschopp, L. Bian, Multi-objective accelerated process optimization of mechanical properties in laser-based additive manufacturing: case study on Selective Laser Melting (SLM) Ti-6Al-4V, J. Manuf. Process. 38 (2019) 432–444.
[543] D.-s. Shim, Effects of process parameters on additive manufacturing of aluminum porous materials and their optimization using response surface method, J. Mater. Res. Technol. 15 (2021) 119–134.
[544] G. Tapia, A.H. Elwany, H. Sang, Prediction of porosity in metal-based additive manufacturing using spatial gaussian process models, Addit. Manuf. 12 (2016) 282–290.
[545] J.A. Lee, M.J. Sagong, J. Jung, E.S. Kim, H.S. Kim, Explainable machine learning for understanding and predicting geometry and defect types in Fe-Ni alloys fabricated by laser metal deposition additive manufacturing, J. Mater. Res. Technol. 22 (2023) 413–423.
[546] S. Bland, N.T. Aboulkhair, Reducing porosity in additive manufacturing, Metal Powder Rep. 70 (2) (2015) 79–81.
[547] A. Sola, A. Nouri, Microstructural porosity in additive manufacturing: the formation and detection of pores in metal parts fabricated by powder bed fusion, J. Adv. Manuf. Process. 1 (3) (2019) e10021.
[548] G. Kasperovich, J. Haubrich, J. Gussone, G. Requena, Correlation between porosity and processing parameters in TiAl6V4 produced by selective laser melting, Mater. Des. 105 (2016) 160–170.
[549] H. Gong, K. Rafi, H. Gu, T. Starr, B. Stucker, Analysis of defect generation in Ti–6Al–4V parts made using powder bed fusion additive manufacturing processes, Addit. Manuf. 1 (2014) 87–98.
[550] A. Singh, D. Cooper, N. Blundell, G. Gibbons, D. Pratihar, Modelling of direct metal laser sintering of eos dm20 bronze using neural networks and genetic algorithms, in: Proceedings of the 37th International MATADOR Conference, Springer Science & Business Media, 2012, p. 395.

[551] B. Kappes, S. Moorthy, D. Drake, H. Geerlings, A. Stebner, Machine learning to optimize additive manufacturing parameters for laser powder bed fusion of Inconel 718, in: Proceedings of the 9th International Symposium on Superalloy 718 & Derivatives: Energy, Aerospace, and Industrial Applications, Springer, 2018, pp. 595–610.
[552] D. Svetlizky, B. Zheng, D.M. Steinberg, J.M. Schoenung, E.J. Lavernia, N. Eliaz, The influence of laser directed energy deposition (DED) processing parameters for Al5083 studied by central composite design, J. Mater. Res. Technol. 17 (2022) 3157–3171.
[553] M. Ackermann, C. Haase, Machine learning-based identification of interpretable process-structure linkages in metal additive manufacturing, Addit. Manuf. 71 (2023) 103585.
[554] Z. Yang, D. Eddy, S. Krishnamurty, I. Grosse, P. Denno, P.W. Witherell, F. Lopez, Dynamic metamodeling for predictive analytics in advanced manufacturing, Smart Sustain. Manuf. Syst. 2 (2018) 18–39.
[555] P. Akbari, F. Ogoke, N.-Y. Kao, K. Meidani, C.-Y. Yeh, W. Lee, A.B. Farimani, Meltpoolnet: melt pool characteristic prediction in metal additive manufacturing using machine learning, Addit. Manuf. 55 (2022) 102817.
[556] T. Moges, Z. Yang, K. Jones, S. Feng, P. Witherell, Y. Lu, Hybrid modeling approach for melt-pool prediction in laser powder bed fusion additive manufacturing, J. Comput. Inf. Sci. Eng. 21 (5) (2021).
[557] J.F. Rodrı´guez, J.P. Thomas, J.E. Renaud, Design of fused-deposition ABS components for stiffness and strength, J. Mech. Des. 125 (3) (2003) 545–551.
[558] O.S. Es-Said, J. Foyos, R. Noorani, M. Mendelson, R. Marloth, B.A. Pregger, Effect of layer orientation on mechanical properties of rapid prototyped samples, Mater. Manuf. Process. 15 (1) (2000) 107–122.
[559] S.K. Panda, S. Padhee, S. Anoop Kumar, S.S. Mahapatra, Optimization of fused deposition modelling (FDM) process parameters using bacterial foraging technique, Intell. Inf. Manag. 1 (02) (2009) 89.
[560] A.K. Sood, R.K. Ohdar, S.S. Mahapatra, Parametric appraisal of mechanical property of fused deposition modelling processed parts, Mater. Des. 31 (1) (2010) 287–295.
[561] A. Fatimatuzahraa, B. Farahaina, W. Yusoff, The effect of employing different raster orientations on the mechanical properties and microstructure of fused deposition modeling parts, in: 2011 IEEE Symposium on Business, Engineering and Industrial Applications (ISBEIA), IEEE, 2011, pp. 22–27.
[562] B. Tymrak, M. Kreiger, J.M. Pearce, Mechanical properties of components fabricated with open-source 3-D printers under realistic environmental conditions, Mater. Des. 58 (2014) 242–246.
[563] T. Letcher, B. Rankouhi, S. Javadpour, Experimental study of mechanical properties of additively manufactured ABS plastic as a function of layer parameters, in: ASME International Mechanical Engineering Congress and Exposition, vol. 57359, American Society of Mechanical Engineers, 2015, V02AT02A018.
[564] S. Ziemian, M. Okwara, C.W. Ziemian, Tensile and fatigue behavior of layered acrylonitrile butadiene styrene, Rapid Prototyping J. (2015).
[565] X. Liu, M. Zhang, S. Li, L. Si, J. Peng, Y. Hu, Mechanical property parametric appraisal of fused deposition modeling parts based on the gray Taguchi method, Int. J. Adv. Manuf. Technol. 89 (2017) 2387–2397.
[566] X. Deng, Z. Zeng, B. Peng, S. Yan, W. Ke, Mechanical properties optimization of poly-ether-ether-ketone via fused deposition modeling, Materials 11 (2) (2018) 216.
[567] J. Fernandes, A.M. Deus, L. Reis, M.F. Vaz, M. Leite, Study of the influence of 3D printing parameters on the mechanical properties of PLA, in: Proceedings of the 3rd International Conference on Progress in Additive Manufacturing (Pro-AM 2018), Singapore, 2018, pp. 14–17.
[568] G. Dong, G. Wijaya, Y. Tang, Y.F. Zhao, Optimizing process parameters of fused deposition modeling by Taguchi method for the fabrication of lattice structures, Addit. Manuf. 19 (2018) 62–72.
[569] K. Swarna Lakshmi, G. Arumaikkannu, Influence of process parameters on tensile strength of additive manufactured polymer parts using Taguchi method, Adv. 3D Print. Addit. Manuf. Technol. (2017) 1–7.
[570] N. Tagscherer, A.M. Bär, S. Zaremba, K. Drechsler, Mechanical analysis of parameter variations in large-scale extrusion additive manufacturing of thermoplastic composites, J. Manuf. Mater. Process. 6 (2) (2022) 36.
[571] K. Rashed, A. Kafi, R. Simons, S. Bateman, Fused filament fabrication of nylon 6/66 copolymer: parametric study comparing full factorial and Taguchi design of experiments, Rapid Prototyping J. (2022).
[572] M. Spoerk, F. Arbeiter, H. Cajner, J. Sapkota, C. Holzer, Parametric optimization of intra-and inter-layer strengths in parts produced by extrusion-based additive manufacturing of poly (lactic acid), J. Appl. Polym. Sci. 134 (41) (2017) 45401.
[573] N.A. Fountas, J.D. Kechagias, N.M. Vaxevanidis, Optimization of selective laser sintering/melting operations by using a virus-evolutionary genetic algorithm, Machines 11 (1) (2023) 95.
[574] A. Du Plessis, I. Yadroitsava, I. Yadroitsev, Effects of defects on mechanical properties in metal additive manufacturing: a review focusing on X-ray tomography insights, Mater. Des. 187 (2020) 108385.
[575] T.A. Rodrigues, V. Duarte, J.A. Avila, T.G. Santos, R. Miranda, J. Oliveira, Wire and arc additive manufacturing of HSLA steel: effect of thermal cycles on microstructure and mechanical properties, Addit. Manuf. 27 (2019) 440–450.
[576] C. Wang, X. Tan, E. Liu, S.B. Tor, Process parameter optimization and mechanical properties for additively manufactured stainless steel 316L parts by selective electron beam melting, Mater. Des. 147 (2018) 157–166.
[577] M. Elsayed, M. Ghazy, Y. Youssef, K. Essa, Optimization of SLM process parameters for Ti6Al4V medical implants, Rapid Prototyping J. 25 (3) (2018) 433–447.
[578] N. Diaz Vallejo, C. Lucas, N. Ayers, K. Graydon, H. Hyer, Y. Sohn, Process optimization and microstructure analysis to understand laser powder bed fusion of 316L stainless steel, Metals 11 (5) (2021) 832.
[579] M. Zhang, C.-N. Sun, X. Zhang, P.C. Goh, J. Wei, D. Hardacre, H. Li, High cycle fatigue life prediction of laser additive manufactured stainless steel: a machine learning approach, Int. J. Fatigue 128 (2019) 105194.
[580] G. Shi, L. Li, Z. Yu, R. Liu, P. Sha, Z. Xu, Y. Guo, R. Xi, J. Liu, R. Xin, L. Chen, X. Wang, Z. Zhang, The interaction effect of process parameters on the phase transformation behavior and tensile properties in additive manufacturing of Ni-rich NiTi alloy, J. Manuf. Process. 77 (2022) 539–550.
[581] J. Torres, J. Cotelo, J. Karl, A.P. Gordon, Mechanical property optimization of FDM PLA in shear with multiple objectives, JOM 67 (2015) 1183–1193.
[582] X. Yang, R.A. Barrett, N.M. Harrison, S.B. Leen, A physically-based structure-property model for additively manufactured Ti-6Al-4V, Mater. Des. 205 (2021) 109709.
[583] S. Shrestha, G. Manogharan, Optimization of binder jetting using Taguchi method, JOM 69 (2017) 491–497.
[584] H. Xiao, W. Han, Y. Ming, Z. Ding, Y. Duan, A sensitivity analysis-based parameter optimization framework for 3D printing of continuous carbon fiber/epoxy composites, Materials 12 (23) (2019) 3961.
[585] A.D. Tura, H.B. Mamo, Characterization and parametric optimization of additive manufacturing process for enhancing mechanical properties, Heliyon 8 (7) (2022) e09832.
[586] F. Górski, W. Kuczko, R. Wichniarek, Impact strength of ABS parts manufactured using Fused Deposition Modeling technology, Arch. Mech. Technol. Automat. 34 (1) (2014) 3–12.
[587] M. Moradi, A. Hasani, Z. Pourmand, J. Lawrence, Direct laser metal deposition additive manufacturing of Inconel 718 superalloy: statistical modelling and optimization by design of experiments, Opt. Laser Technol. 144 (2021) 107380.
[588] M. Dada, P. Popoola, N. Mathe, S. Pityana, S. Adeosun, Parametric optimization of laser deposited high entropy alloys using response surface methodology (RSM), Int. J. Adv. Manuf. Technol. 109 (2020) 2719–2732.
[589] B.B. Ravichander, A. Rahimzadeh, B. Farhang, N. Shayesteh Moghaddam, A. Amerinatanzi, M. Mehrpouya, A prediction model for additive manufacturing of Inconel 718 superalloy, Appl. Sci. 11 (17) (2021) 8010.
[590] Z. Zhan, H. Li, Machine learning based fatigue life prediction with effects of additive manufacturing process parameters for printed SS 316L, Int. J. Fatigue 142 (2021) 105941.
[591] B.H. Lee, J. Abdullah, Z.A. Khan, Optimization of rapid prototyping parameters for production of flexible ABS object, J. Mater. Process. Technol. 169 (1) (2005) 54–61.
[592] J. Laeng, Z.A. Khan, S. Khu, Optimizing flexible behaviour of bow prototype using Taguchi approach, J. Appl. Sci. 6 (3) (2006) 622–630.
[593] A. Arivazhagan, S. Masood, Dynamic mechanical properties of ABS material processed by fused deposition modelling, Int. J. Eng. Res. Appl. 2 (3) (2012) 2009–2014.
[594] H. Jami, S.H. Masood, W. Song, Dynamic Response of FDM Made ABS Parts in Different Part Orientations, Advanced Materials Research, vol. 748, Trans Tech Publ, 2013, pp. 291–294.
[595] O.A. Mohamed, S.H. Masood, J.L. Bhowmik, M. Nikzad, J. Azadmanjiri, Effect of process parameters on dynamic mechanical performance of FDM PC/ABS printed parts through design of experiment, J. Mater. Eng. Perform. 25 (2016) 2922–2935.
[596] M. Srivastava, S. Rathee, Optimisation of FDM process parameters by Taguchi method for imparting customised properties to components, Virtual Phys. Prototyp. 13 (3) (2018) 203–210.
[597] Y. Zhang, K. Chou, A parametric study of part distortions in fused deposition modelling using three-dimensional finite element analysis, Proc. Inst. Mech. Eng., B J. Eng. Manuf. 222 (8) (2008) 959–968.
[598] A. Elkholy, R. Kempers, Investigation into the Influence of Fused Deposition Modeling (FDM) Process Parameters on the Thermal Properties of 3D-Printed Parts, 2018.
[599] L. Baich, G. Manogharan, H. Marie, Study of infill print design on production cost-time of 3D printed ABS parts, Int. J. Rapid Manuf. 5 (3–4) (2015) 308–319.
[600] Y.Y. Aw, C.K. Yeoh, M.A. Idris, P.L. Teh, K.A. Hamzah, S.A. Sazali, Effect of printing parameters on tensile, dynamic mechanical, and thermoelectric properties of FDM 3D printed CABS/ZnO composites, Materials 11 (4) (2018) 466.
[601] K. Chin Ang, K. Fai Leong, C. Kai Chua, M. Chandrasekaran, Investigation of the mechanical properties and porosity relationships in fused deposition modelling-fabricated porous structures, Rapid Prototyping J. 12 (2) (2006) 100–105.
[602] J.T. Cantrell, S. Rohde, D. Damiani, R. Gurnani, L. DiSandro, J. Anton, A. Young, A. Jerez, D. Steinbach, C. Kroese, P.G. Ifju, Experimental characterization of the mechanical properties of 3D-printed ABS and polycarbonate parts, Rapid Prototyping J. 23 (4) (2017) 811–824.
[603] G. Gao, F. Xu, J. Xu, Parametric optimization of FDM process for improving mechanical strengths using Taguchi method and response surface method: a comparative investigation, Machines 10 (9) (2022) 750.

[604] O.A. Mohamed, S.H. Masood, J.L. Bhowmik, Modeling, analysis, and optimization of dimensional accuracy of FDM-fabricated parts using definitive screening design and deep learning feedforward artificial neural network, Adv. Manuf. 9 (2021) 115–129.
[605] D. Gu, Y.-C. Hagedorn, W. Meiners, G. Meng, R.J.S. Batista, K. Wissenbach, R. Poprawe, Densification behavior, microstructure evolution, and wear performance of selective laser melting processed commercially pure titanium, Acta Mater. 60 (9) (2012) 3849–3860.
[606] T.-W. Na, W.R. Kim, S.-M. Yang, O. Kwon, J.M. Park, G.-H. Kim, K.-H. Jung, C.-W. Lee, H.-K. Park, H.G. Kim, Effect of laser power on oxygen and nitrogen concentration of commercially pure titanium manufactured by selective laser melting, Mater. Charact. 143 (2018) 110–117.
[607] B. Zhang, H. Liao, C. Coddet, Microstructure evolution and density behavior of CP Ti parts elaborated by self-developed vacuum selective laser melting system, Appl. Surf. Sci. 279 (2013) 310–316.
[608] H. Attar, S. Ehtemam-Haghighi, D. Kent, X. Wu, M.S. Dargusch, Comparative study of commercially pure titanium produced by laser engineered net shaping, selective laser melting and casting processes, Mater. Sci. Eng. A 705 (2017) 385–393.
[609] C. Qiu, N.J. Adkins, M.M. Attallah, Microstructure and tensile properties of selectively laser-melted and of HIPed laser-melted Ti–6Al–4V, Mater. Sci. Eng. A 578 (2013) 230–239.
[610] T.C. Dzogbewu, Laser powder bed fusion of Ti6Al4V-xCu: process parameters, J. Metals Mater. Miner. 31 (2) (2021) 62–70.
[611] B. AlMangour, D. Grzesiak, J.-M. Yang, In-situ formation of novel TiC-particle-reinforced 316L stainless steel bulk-form composites by selective laser melting, J. Alloys Compd. 706 (2017) 409–418.
[612] S. Dadbakhsh, M. Speirs, J.-P. Kruth, J. Schrooten, J. Luyten, J. Van Humbeeck, Effect of SLM parameters on transformation temperatures of shape memory nickel titanium parts, Adv. Eng. Mater. 16 (9) (2014) 1140–1146.
[613] S. Dadbakhsh, M. Speirs, J.-P. Kruth, J. Van Humbeeck, Influence of SLM on shape memory and compression behaviour of NiTi scaffolds, CIRP Ann. 64 (1) (2015) 209–212.
[614] T. Bormann, B. Müller, M. Schinhammer, A. Kessler, P. Thalmann, M. De Wild, Microstructure of selective laser melted nickel–titanium, Mater. Charact. 94 (2014) 189–202.
[615] W.M. Tucho, V.H. Lysne, H. Austbø, A. Sjolyst-Kverneland, V. Hansen, Investigation of effects of process parameters on microstructure and hardness of SLM manufactured SS316L, J. Alloys Compd. 740 (2018) 910–925.
[616] R. Li, J. Liu, Y. Shi, L. Wang, W. Jiang, Balling behavior of stainless steel and nickel powder during selective laser melting process, Int. J. Adv. Manuf. Technol. 59 (2012) 1025–1035.
[617] J.M. Walker, C. Haberland, M. Taheri Andani, H.E. Karaca, D. Dean, M. Elahinia, Process development and characterization of additively manufactured nickel–titanium shape memory parts, J. Intell. Mater. Syst. Struct. 27 (19) (2016) 2653–2660.
[618] K. Antony, T.R. Rakeshnath, Study on selective laser melting of commercially pure titanium powder, Proc. Inst. Mech. Eng., B J. Eng. Manuf. 233 (7) (2019) 1794–1807.
[619] C.Y. Yap, H.K. Tan, Z. Du, C.K. Chua, Z. Dong, Selective laser melting of nickel powder, Rapid Prototyping J. 23 (4) (2017) 750–757.
[620] M. Letenneur, A. Kreitcberg, V. Brailovski, Optimization of laser powder bed fusion processing using a combination of melt pool modeling and design of experiment approaches: density control, J. Manuf. Mater. Process. 3 (1) (2019) 21.
[621] M. Hiren, M. Gajera, K.G. Dave, V.P. Jani, Experimental investigation and analysis of dimensional accuracy of laser-based powder bed fusion made specimen by application of response surface methodology, Progr. Addit. Manuf. 4 (2019) 371–382.
[622] D. Ivanov, A. Travyanov, P. Petrovskiy, V. Cheverikin, E. Alekseeva, A. Khvan, I. Logachev, Evolution of structure and properties of the nickel-based alloy EP718 after the SLM growth and after different types of heat and mechanical treatment, Addit. Manuf. 18 (2017) 269–275.
[623] B. Vrancken, L. Thijs, J.-P. Kruth, J. Van Humbeeck, Heat treatment of Ti6Al4V produced by Selective Laser Melting: microstructure and mechanical properties, J. Alloys Compd. 541 (2012) 177–185.
[624] J. Wang, Y. Liu, P. Qin, S. Liang, T. Sercombe, L. Zhang, Selective laser melting of Ti–35Nb composite from elemental powder mixture: microstructure, mechanical behavior and corrosion behavior, Mater. Sci. Eng. A 760 (2019) 214–224.
[625] T. Riipinen, S. Metsä-Kortelainen, T. Lindroos, J.S. Keränen, A. Manninen, J. Pippuri-Mäkeläinen, Properties of soft magnetic Fe-Co-V alloy produced by laser powder bed fusion, Rapid Prototyping J. 25 (4) (2019) 699–707.
[626] F.C. Ewald, F. Brenne, T. Gustmann, M. Vollmer, P. Krooß, T. Niendorf, Laser powder bed fusion processing of Fe-Mn-Al-Ni shape memory alloy—on the effect of elevated platform temperatures, Metals 11 (2) (2021) 185.
[627] N.T. Aboulkhair, M. Simonelli, L. Parry, I. Ashcroft, C. Tuck, R. Hague, 3D printing of Aluminium alloys: additive Manufacturing of Aluminium alloys using selective laser melting, Prog. Mater. Sci. 106 (2019) 100578.
[628] J. Zhang, B. Song, Q. Wei, D. Bourell, Y. Shi, A review of selective laser melting of aluminum alloys: processing, microstructure, property and developing trends, J. Mater. Sci. Technol. 35 (2) (2019) 270–284.
[629] T.B. Sercombe, X. Li, Selective laser melting of aluminium and aluminium metal matrix composites, Mater. Technol. 31 (2) (2016) 77–85.
[630] K. Li, R. Ma, Y. Qin, N. Gong, J. Wu, P. Wen, S. Tan, D.Z. Zhang, L.E. Murr, J. Luo, A review of the multi-dimensional application of machine learning to improve the integrated intelligence of laser powder bed fusion, J. Mater. Process. Technol. (2023) 118032.
[631] Q. Liu, H. Wu, M.J. Paul, P. He, Z. Peng, B. Gludovatz, J.J. Kruzic, C.H. Wang, X. Li, Machine-learning assisted laser powder bed fusion process optimization for AlSi10Mg: new microstructure description indices and fracture mechanisms, Acta Mater. 201 (2020) 316–328.
[632] Z. Gu, S. Sharma, D.A. Riley, M.V. Pantawane, S.S. Joshi, S. Fu, N.B. Dahotre, A universal predictor-based machine learning model for optimal process maps in laser powder bed fusion process, J. Intell. Manuf. (2022) 1–23.
[633] W. Muhammad, J. Kang, O. Ibragimova, K. Inal, Experimental investigation and development of a deep learning framework to predict process-induced surface roughness in additively manufactured aluminum alloys, Weld. World 67 (4) (2023) 897–921.
[634] S. Lapointe, G. Guss, Z. Reese, M. Strantza, M. Matthews, C. Druzgalski, Photodiode-based machine learning for optimization of laser powder bed fusion parameters in complex geometries, Addit. Manuf. 53 (2022) 102687.
[635] C. Guo, S. He, H. Yue, Q. Li, G. Hao, Prediction modelling and process optimization for forming multi-layer cladding structures with laser directed energy deposition, Opt. Laser Technol. 134 (2021) 106607.
[636] B. Manjunath, A. Vinod, K. Abhinav, S. Verma, M.R. Sankar, Optimisation of process parameters for deposition of colmonoy using directed energy deposition process, Mater. Today Proc. 26 (2020) 1108–1112.
[637] P.-Y. Lin, F.-C. Shen, K.-T. Wu, S.-J. Hwang, H.-H. Lee, Process optimization for directed energy deposition of SS316L components, Int. J. Adv. Manuf. Technol. 111 (2020) 1387–1400.
[638] C. Félix-Martínez, J. Ibarra-Medina, D.A. Fernández-Benavides, L.A. Cáceres-Díaz, J.M. Alvarado-Orozco, Effect of the parametric optimization and heat-treatment on the 18Ni-300 maraging steel microstructural properties manufactured by directed energy deposition, Int. J. Adv. Manuf. Technol. 115 (11–12) (2021) 3999–4020.
[639] C. Wei, Z. Zhao, H. Ye, Y. Yang, J. Tang, X. Shen, G. Le, Two optimized post-heat treatments to achieve high-performance 90W–7Ni–3Fe alloys fabricated by laser-directed energy deposition, Mater. Sci. Eng. A 833 (2022) 142561.
[640] C. Li, P. Hodgson, M. Preuss, Y. Chen, X. Wu, Y. Zhu, Y. Tian, A. Huang, Rolling-assisted direct energy deposited Inconel 718: microstructural evolution and mechanical properties after optimized heat treatment, J. Mater. Sci. Technol. 144 (2023) 118–127.
[641] Y. Yao, Y. Huang, B. Chen, C. Tan, Y. Su, J. Feng, Influence of processing parameters and heat treatment on the mechanical properties of 18Ni300 manufactured by laser based directed energy deposition, Opt. Laser Technol. 105 (2018) 171–179.
[642] D. Kats, Z. Wang, Z. Gan, W.K. Liu, G.J. Wagner, Y. Lian, A physics-informed machine learning method for predicting grain structure characteristics in directed energy deposition, Comput. Mater. Sci. 202 (2022) 110958.
[643] T. Pham, T. Hoang, X. Tran, S. Fetni, L. Duchêne, H.S. Tran, A. Habraken, Characterization, propagation, and sensitivity analysis of uncertainties in the directed energy deposition process using a deep learning-based surrogate model, Probab. Eng. Mech. 69 (2022) 103297.
[644] J.-H. Kim, W.-J. Oh, C.-M. Lee, D.-H. Kim, Achieving optimal process design for minimizing porosity in additive manufacturing of Inconel 718 using a deep learning-based pore detection approach, Int. J. Adv. Manuf. Technol. 121 (3–4) (2022) 2115–2134.
[645] W.-J. Oh, C.-M. Lee, D.-H. Kim, Prediction of deposition bead geometry in wire arc additive manufacturing using machine learning, J. Mater. Res. Technol. 20 (2022) 4283–4296.
[646] I.Z. Era, M. Grandhi, Z. Liu, Prediction of mechanical behaviors of L-DED fabricated SS 316L parts via machine learning, Int. J. Adv. Manuf. Technol. 121 (3–4) (2022) 2445–2459.
[647] N.D. Jamnikar, S. Liu, C. Brice, X. Zhang, In-process comprehensive prediction of bead geometry for laser wire-feed DED system using molten pool sensing data and multi-modality CNN, Int. J. Adv. Manuf. Technol. 121 (1–2) (2022) 903–917.
[648] T.Q.D. Pham, T.V. Hoang, X. Van Tran, Q.T. Pham, S. Fetni, L. Duchêne, H.S. Tran, A.-M. Habraken, Fast and accurate prediction of temperature evolutions in additive manufacturing process using deep learning, J. Intell. Manuf. 34 (4) (2023) 1701–1719.
[649] S. Atre, J. Porter, T. Batchelor, K.K.M. Bulger, P. Gangopadhya, Process parameter optimization for binder jetting using 420 stainless steel, in: European Congress and Exhibition on Powder Metallurgy. European PM Conference Proceedings, The European Powder Metallurgy Association, 2016, pp. 1–6.
[650] S.-J. Huang, C.-S. Ye, H.-P. Zhao, Z.-a. Fan, Parameters optimization of binder jetting process using modified silicate as a binder, Mater. Manuf. Process. 35 (2) (2020) 214–220.
[651] K. Kreft, Z. Lavrič, j. Stanić, P. Perhavec, R. Dreu, Influence of the binder jetting process parameters and binder liquid composition on the relevant attributes of 3D-printed tablets, Pharmaceutics 14 (8) (2022) 1568.
[652] Y. Mao, J. Li, W. Li, D. Cai, Q. Wei, Binder jetting additive manufacturing of 316L stainless-steel green parts with high strength and low binder content: binder preparation and process optimization, J. Mater. Process. Technol. 291 (2021) 117020.
[653] N. Lecis, M. Mariani, R. Beltrami, L. Emanuelli, R. Casati, M. Vedani, A. Molinari, Effects of process parameters, debinding and sintering on the microstructure of

316L stainless steel produced by binder jetting, Mater. Sci. Eng. A 828 (2021) 142108.
[654] Z.-f. Zhang, L. Wang, L.-t. Zhang, P.-f. Ma, B.-h. Lu, C.-w. Du, Binder jetting 3D printing process optimization for rapid casting of green parts with high tensile strength, China Foundry 18 (2021) 335–343.
[655] H. Miyanaji, K.M. Rahman, M. Da, C.B. Williams, Effect of fine powder particles on quality of binder jetting parts, Addit. Manuf. 36 (2020) 101587.
[656] E.M. Jimenez, D. Ding, L. Su, A.R. Joshi, A. Singh, B. Reeja-Jayan, J. Beuth, Parametric analysis to quantify process input influence on the printed densities of binder jetted alumina ceramics, Addit. Manuf. 30 (2019) 100864.
[657] E. Aznarte Garcia, A.J. Qureshi, C. Ayranci, A study on material-process interaction and optimization for vat-photopolymerization processes, Rapid Prototyping J. 24 (9) (2018) 1479–1485.
[658] E.A. Garcia, C. Ayranci, A.J. Qureshi, Material property-manufacturing process optimization for form 2 vat-photo polymerization 3D Printers, J. Manuf. Mater. Process. 4 (1) (2020) 12.
[659] Y. Wang, Y. Wang, C. Mao, D. Mei, Printing depth modeling, printing process quantification and quick-decision of printing parameters in micro-vat polymerization, Mater. Des. 227 (2023) 111698.
[660] K. Ransikarbum, R. Pitakaso, N. Kim, A decision-support model for additive manufacturing scheduling using an integrative analytic hierarchy process and multi-objective optimization, Appl. Sci. 10 (15) (2020) 5159.
[661] S. Yacoubi, G. Manita, A. Chhabra, O. Korbaa, S. Mirjalili, A multi-objective chaos game optimization algorithm based on decomposition and random learning mechanisms for numerical optimization, Appl. Soft Comput. (2023) 110525.
[662] J.L.J. Pereira, G.A. Oliver, M.B. Francisco, S.S. Cunha, G.F. Gomes, A review of multi-objective optimization: methods and algorithms in mechanical engineering problems, Arch. Comput. Methods Eng. (2021) 1–24.
[663] A. Guo, D. Kong, X. Zhou, P. Qu, S. Wang, J. Li, F. Li, L. Wang, Y. Hu, Evaluation of material reuse degree in additive manufacturing by the improved resolution coefficient grey correlation method, Process Saf. Environ. Prot. 166 (2022) 451–460.
[664] M. Tamiz, D.F. Jones, E. El-Darzi, A review of goal programming and its applications, Ann. Oper. Res. 58 (1995) 39–53.
[665] B. Pérez-Cañedo, J.L. Verdegay, E.R. Concepción-Morales, A. Rosete, Lexicographic methods for fuzzy linear programming, Mathematics 8 (9) (2020) 1540.
[666] T.H.B. Huy, P. Nallagownden, K.H. Truong, R. Kannan, D.N. Vo, N. Ho, Multi-objective search group algorithm for engineering design problems, Appl. Soft Comput. 126 (2022) 109287.
[667] K. Deb, A. Pratap, S. Agarwal, T. Meyarivan, A fast and elitist multiobjective genetic algorithm: NSGA-II, IEEE Trans. Evol. Comput. 6 (2) (2002) 182–197.
[668] D. Lei, Pareto archive particle swarm optimization for multi-objective fuzzy job shop scheduling problems, Int. J. Adv. Manuf. Technol. 37 (2008) 157–165.
[669] Y.-J. Li, H.-N. Li, Interactive evolutionary multi-objective optimization and decision-making on life-cycle seismic design of bridge, Adv. Struct. Eng. 21 (15) (2018) 2227–2240.
[670] T. Murata, H. Ishibuchi, Moga: Multi-Objective Genetic Algorithms, IEEE International Conference on Evolutionary Computation, vol. 1, IEEE, Piscataway, NJ, USA, 1995, pp. 289–294.
[671] T.S. Leirmo, K. Martinsen, Evolutionary algorithms in additive manufacturing systems: discussion of future prospects, Proc. CIRP 81 (2019) 671–676.
[672] J. Zhang, X. Yao, Y. Li, Improved evolutionary algorithm for parallel batch processing machine scheduling in additive manufacturing, Int. J. Prod. Res. 58 (8) (2020) 2263–2282.
[673] A. Du Plessis, C. Broeckhoven, I. Yadroitsava, I. Yadroitsev, C.H. Hands, R. Kunju, D. Bhate, Beautiful and functional: a review of biomimetic design in additive manufacturing, Addit. Manuf. 27 (2019) 408–427.
[674] Y. Chen, X. Peng, L. Kong, G. Dong, A. Remani, R. Leach, Defect inspection technologies for additive manufacturing, Int. J. Extr. Manuf. 3 (2) (2021) 022002.
[675] S.K. Everton, M. Hirsch, P. Stravroulakis, R.K. Leach, A.T. Clare, Review of in-situ process monitoring and in-situ metrology for metal additive manufacturing, Mater. Des. 95 (2016) 431–445.
[676] I.S. Ramírez, F.P.G. Márquez, M. Papaelias, Review on additive manufacturing and non-destructive testing, J. Manuf. Syst. 66 (2023) 260–286.
[677] P. Sperling, G. Maeurer, N. Achilles, X-ray and Computed Tomography as a tool for quality assurance and process optimization in the field of additive manufacturing, in: International Symposium on Digital Industrial Radiology and Computed Tomography, 2019.
[678] Y. Fu, A.R. Downey, L. Yuan, T. Zhang, A. Pratt, Y. Balogun, Machine learning algorithms for defect detection in metal laser-based additive manufacturing: a review, J. Manuf. Process. 75 (2022) 693–710.
[679] P. Stavropoulos, P. Foteinopoulos, A. Papacharalampopoulos, G. Tsoukantas, Warping in SLM additive manufacturing processes: estimation through thermo-mechanical analysis, Int. J. Adv. Manuf. Technol. 104 (2019) 1571–1580.
[680] D. Xie, F. Lv, Y. Yang, L. Shen, Z. Tian, C. Shuai, B. Chen, J. Zhao, A review on distortion and residual stress in additive manufacturing, Chin. J. Mech. Eng., Addit. Manuf. Front. (2022) 100039.
[681] B. Cheng, K. Chou, Geometric consideration of support structures in part overhang fabrications by electron beam additive manufacturing, Comput. Aided Des. 69 (2015) 102–111.
[682] X. Qian, Undercut and overhang angle control in topology optimization: a density gradient based integral approach, Int. J. Numer. Methods Eng. 111 (3) (2017) 247–272.
[683] D. Obilanade, C. Dordlofva, P. Törlind, Surface roughness considerations in design for additive manufacturing-a literature review, Proc. Des. Soc. 1 (2021) 2841–2850.
[684] U.S. Kim, J.W. Park, High-quality surface finishing of industrial three-dimensional metal additive manufacturing using electrochemical polishing, Int. J. Precis. Eng. Manuf.-Green Technol. 6 (2019) 11–21.
[685] T. Voisin, R. Shi, Y. Zhu, Z. Qi, M. Wu, S. Sen-Britain, Y. Zhang, S. Qiu, Y. Wang, S. Thomas, et al., Pitting corrosion in 316L stainless steel fabricated by laser powder bed fusion additive manufacturing: a review and perspective, JOM 74 (4) (2022) 1668–1689.
[686] K. Tantratian, H. Yan, L. Chen, Predicting pitting corrosion behavior in additive manufacturing: electro-chemo-mechanical phase-field model, Comput. Mater. Sci. 213 (2022) 111640.
[687] B. Guo, Y. Zhang, Z. Yang, D. Cui, F. He, J. Li, Z. Wang, X. Lin, J. Wang, Cracking mechanism of hastelloy x superalloy during directed energy deposition additive manufacturing, Addit. Manuf. 55 (2022) 102792.
[688] S. Zhou, Y. Su, H. Wang, J. Enz, T. Ebel, M. Yan, Selective laser melting additive manufacturing of 7xxx series Al-Zn-Mg-Cu alloy: cracking elimination by co-incorporation of Si and TiB2, Addit. Manuf. 36 (2020) 101458.
[689] P. Jiang, M. Rifat, S. Basu, Impact of surface roughness and porosity on lattice structures fabricated by additive manufacturing-a computational study, Proc. Manuf. 48 (2020) 781–789.
[690] S. Mojumder, Z. Gan, Y. Li, A. Al Amin, W.K. Liu, Linking process parameters with lack-of-fusion porosity for laser powder bed fusion metal additive manufacturing, Addit. Manuf. 68 (2023) 103500.
[691] M. Atwya, G. Panoutsos, In-situ porosity prediction in metal powder bed fusion additive manufacturing using spectral emissions: a prior-guided machine learning approach, J. Intell. Manuf. (2023) 1–24.
[692] Y. Wei, F. Liu, F. Liu, D. Yu, Q. You, C. Huang, Z. Wang, W. Jiang, X. Lin, X. Hu, Effect of arc oscillation on porosity and mechanical properties of 2319 aluminum alloy fabricated by cmt-wire arc additive manufacturing, J. Mater. Res. Technol. 24 (2023) 3477–3490.
[693] Y. Cui, J. Cai, Z. Li, Z. Jiao, L. Hu, J. Hu, Effect of porosity on dynamic response of additive manufacturing Ti-6Al-4V alloys, Micromachines 13 (3) (2022) 408.
[694] P. Mondal, A. Das, A. Wazeer, A. Karmakar, Biomedical porous scaffold fabrication using additive manufacturing technique: porosity, surface roughness and process parameters optimization, Int. J. Lightweight Mater. Manuf. 5 (3) (2022) 384–396.
[695] N. Béraud, A. Chergui, M. Limousin, F. Villeneuve, F. Vignat, An indicator of porosity through simulation of melt pool volume in aluminum wire arc additive manufacturing, Mech. Ind. 23 (2022) 1.
[696] J. Yang, D. Gu, K. Lin, Y. Zhang, M. Guo, L. Yuan, H. Zhang, H. Zhang, Laser additive manufacturing of bio-inspired metallic structures, Chin. J. Mech. Eng., Addit. Manuf. Front. 1 (1) (2022) 100013.
[697] H. Liu, M. Ye, Z. Ye, L. Wang, G. Wang, X. Shen, P. Xu, C. Wang, High-quality surface smoothening of laser powder bed fusion additive manufacturing AlSi10Mg via intermittent electrochemical polishing, Surf. Coat. Technol. 443 (2022) 128608.
[698] L. Ladani, J. Razmi, M. Sadeghilaridjani, Fabrication of cu-cnt composite and cu using laser powder bed fusion additive manufacturing, Powders 1 (4) (2022) 207–220.
[699] E. Maleki, S. Bagherifard, M. Bandini, M. Guagliano, Surface post-treatments for metal additive manufacturing: progress, challenges, and opportunities, Addit. Manuf. 37 (2021) 101619.
[700] A.D. Brandão, R. Gerard, J. Gumpinger, S. Beretta, A. Makaya, L. Pambaguian, T. Ghidini, Challenges in additive manufacturing of space parts: powder feedstock cross-contamination and its impact on end products, Materials 10 (5) (2017) 522.
[701] E. Santecchia, P. Mengucci, A. Gatto, E. Bassoli, S. Defanti, G. Barucca, Cross-contamination quantification in powders for additive manufacturing: a study on Ti-6Al-4V and maraging steel, Materials 12 (15) (2019) 2342.
[702] A. du Plessis, S.G. le Roux, Standardized X-ray tomography testing of additively manufactured parts: a round robin test, Addit. Manuf. 24 (2018) 125–136.
[703] S. Xu, J. Liu, Y. Ma, Residual stress constrained self-support topology optimization for metal additive manufacturing, Comput. Methods Appl. Mech. Eng. 389 (2022) 114380.
[704] W. Huang, Q. Wang, N. Ma, H. Kitano, Distribution characteristics of residual stresses in typical wall and pipe components built by wire arc additive manufacturing, J. Manuf. Process. 82 (2022) 434–447.
[705] K.S. Ramani, C. He, Y.-L. Tsai, C.E. Okwudire, SmartScan: an intelligent scanning approach for uniform thermal distribution, reduced residual stresses and deformations in PBF additive manufacturing, Addit. Manuf. 52 (2022) 102643.
[706] Q. Wu, T. Mukherjee, A. De, T. DebRoy, Residual stresses in wire-arc additive manufacturing–hierarchy of influential variables, Addit. Manuf. 35 (2020) 101355.
[707] S. Islam, G.-J. Seo, M.R. Ahsan, H. Villarraga-Gómez, H.-J. Lee, D.B. Kim, Investigation of microstructures, defects, and mechanical properties of titanium-zirconium-molybdenum alloy manufactured by wire arc additive manufacturing, Int. J. Refract. Met. Hard Mater. 110 (2023) 106042.
[708] M. Caputo, C.V. Solomon, P.-K. Nguyen, A.E. Berkowitz, Electron microscopy investigation of binder saturation and microstructural defects in functional parts made by additive manufacturing, Microsc. Microanal. 22 (S3) (2016) 1770–1771.

[709] J. Bustillos, J. Kim, A. Moridi, Exploiting lack of fusion defects for microstructural engineering in additive manufacturing, Addit. Manuf. 48 (2021) 102399.
[710] J.L. Bartlett, A. Jarama, J. Jones, X. Li, Prediction of microstructural defects in additive manufacturing from powder bed quality using digital image correlation, Mater. Sci. Eng. A 794 (2020) 140002.
[711] X. Chen, F. Kong, Y. Fu, X. Zhao, R. Li, G. Wang, H. Zhang, A review on wire-arc additive manufacturing: typical defects, detection approaches, and multisensor data fusion-based model, Int. J. Adv. Manuf. Technol. 117 (2021) 707–727.
[712] C. Gobert, E.W. Reutzel, J. Petrich, A.R. Nassar, S. Phoha, Application of supervised machine learning for defect detection during metallic powder bed fusion additive manufacturing using high resolution imaging, Addit. Manuf. 21 (2018) 517–528.
[713] M.S. Hossain, H. Taheri, In situ process monitoring for additive manufacturing through acoustic techniques, J. Mater. Eng. Perform. 29 (10) (2020) 6249–6262.
[714] M. Borish, B.K. Post, A. Roschli, P.C. Chesser, L.J. Love, Real-time defect correction in large-scale polymer additive manufacturing via thermal imaging and laser profilometer, Proc. Manuf. 48 (2020) 625–633.
[715] J. Lewis, A.L. Moore, et al., In situ infrared temperature sensing for real-time defect detection in additive manufacturing, Addit. Manuf. 47 (2021) 102328.
[716] P. Charalampous, I. Kostavelis, D. Tzovaras, Non-destructive quality control methods in additive manufacturing: a survey, Rapid Prototyping J. 26 (4) (2020) 777–790.
[717] N.A. Surovi, S. Hussain, G.S. Soh, A study of machine learning framework for enabling early defect detection in wire arc additive manufacturing processes, in: International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, vol. 86229, American Society of Mechanical Engineers, 2022, V03AT03A002.
[718] S.A. Shevchik, C. Kenel, C. Leinenbach, K. Wasmer, Acoustic emission for in situ quality monitoring in additive manufacturing using spectral convolutional neural networks, Addit. Manuf. 21 (2018) 598–604.
[719] N.A. Surovi, G.S. Soh, Acoustic feature based geometric defect identification in wire arc additive manufacturing, Virtual Phys. Prototyp. 18 (1) (2023) e2210553.
[720] O.K. Bowoto, B.I. Oladapo, S. Zahedi, F.T. Omigbodun, O.P. Emenuvwe, Analytical modelling of in situ layer-wise defect detection in 3D-printed parts: additive manufacturing, Int. J. Adv. Manuf. Technol. 111 (2020) 2311–2321.
[721] J. Lesseur, B. Tranchand, T. Mancier, A. Montauzier, C. Larignon, S. Perusin, On the use of X-ray microtomography to control artificial defect geometries produced by metal additive manufacturing, Nondestruct. Test. Eval. 37 (5) (2022) 611–630.
[722] F.H. Kim, A.L. Pintar, S.P. Moylan, E.J. Garboczi, The influence of X-ray computed tomography acquisition parameters on image quality and probability of detection of additive manufacturing defects, J. Manuf. Sci. Eng. 141 (11) (2019) 111002.
[723] J.L. McNeil, K. Sisco, C. Frederick, M. Massey, K. Carver, F. List, C. Qiu, M. Mader, S. Sundarraj, S. Babu, In-situ monitoring for defect identification in nickel alloy complex geometries fabricated by L-PBF additive manufacturing, Metall. Mater. Trans. A 51 (2020) 6528–6545.
[724] A. Du Plessis, I. Yadroitsev, I. Yadroitsava, S.G. Le Roux, X-ray microcomputed tomography in additive manufacturing: a review of the current technology and applications, 3D Print. Addit. Manuf. 5 (3) (2018) 227–247.
[725] S. Bellens, P. Vandewalle, W. Dewulf, Deep learning based porosity segmentation in X-ray CT measurements of polymer additive manufacturing parts, Proc. CIRP 96 (2021) 336–341.
[726] V.R. Duarte, T.A. Rodrigues, M.A. Machado, J.P. Pragana, P. Pombinha, L. Coutinho, C.M. Silva, R.M. Miranda, C. Goodwin, D.E. Huber, et al., Benchmarking of nondestructive testing for additive manufacturing, 3D Print. Addit. Manuf. 8 (4) (2021) 263–270.
[727] A. Thompson, I. Maskery, R.K. Leach, X-ray computed tomography for additive manufacturing: a review, Meas. Sci. Technol. 27 (7) (2016) 072001.
[728] Z. Guo, P. Ni, Y. Dai, W. Zhang, K. Huang, Measurement of small defect testing accuracy in additive manufacturing alloy using industrial CT method, J. Phys. Conf. Ser. 1827 (2021) 012039, IOP Publishing.
[729] L. Chen, X. Yao, P. Xu, S.K. Moon, G. Bi, Rapid surface defect identification for additive manufacturing with in-situ point cloud processing and machine learning, Virtual Phys. Prototyp. 16 (1) (2021) 50–67.
[730] X. Li, X. Jia, Q. Yang, J. Lee, Quality analysis in metal additive manufacturing with deep learning, J. Intell. Manuf. 31 (2020) 2003–2017.
[731] C. Xia, Z. Pan, Y. Li, J. Chen, H. Li, Vision-based melt pool monitoring for wire-arc additive manufacturing using deep learning method, Int. J. Adv. Manuf. Technol. 120 (1–2) (2022) 551–562.
[732] R.M. Yazdi, F. Imani, H. Yang, A hybrid deep learning model of process-build interactions in additive manufacturing, J. Manuf. Syst. 57 (2020) 460–468.
[733] R. Li, M. Jin, Z. Pei, D. Wang, Geometrical defect detection on additive manufacturing parts with curvature feature and machine learning, Int. J. Adv. Manuf. Technol. 120 (5–6) (2022) 3719–3729.
[734] B. Zhang, S. Liu, Y.C. Shin, In-process monitoring of porosity during laser additive manufacturing process, Addit. Manuf. 28 (2019) 497–505.
[735] W.J. Wright, J. Darville, N. Celik, H. Koerner, E. Celik, In-situ optimization of thermoset composite additive manufacturing via deep learning and computer vision, Addit. Manuf. 58 (2022) 102985.
[736] Q. Tian, S. Guo, E. Melder, L. Bian, W. Guo, Deep learning-based data fusion method for in situ porosity detection in laser-based additive manufacturing, J. Manuf. Sci. Eng. 143 (4) (2021) 041011.
[737] S.M. Estalaki, C.S. Lough, R.G. Landers, E.C. Kinzel, T. Luo, Predicting defects in laser powder bed fusion using in-situ thermal imaging data and machine learning, Addit. Manuf. 58 (2022) 103008.
[738] D.Y. Kononenko, V. Nikonova, M. Seleznev, J. van den Brink, D. Chernyavsky, An in situ crack detection approach in additive manufacturing based on acoustic emission and machine learning, Addit. Manuf. Lett. 5 (2023) 100130.
[739] H. Wang, B. Li, F.-Z. Xuan, Acoustic emission for in situ process monitoring of selective laser melting additive manufacturing based on machine learning and improved variational modal decomposition, Int. J. Adv. Manuf. Technol. 122 (5–6) (2022) 2277–2292.
[740] K. Xu, J. Lyu, S. Manoochehri, In situ process monitoring using acoustic emission and laser scanning techniques based on machine learning models, J. Manuf. Process. 84 (2022) 357–374.
[741] W. Ren, J. Mazumder, In-situ porosity recognition for laser additive manufacturing of 7075-Al alloy using plasma emission spectroscopy, Sci. Rep. 10 (1) (2020) 19493.
[742] Y. Tan, F. Lin, M. Ali, Z. Su, H. Wong, Development of a novel beam profiling prototype with laser self-mixing via the knife-edge approach, Opt. Lasers Eng. 169 (2023) 107696.
[743] J. Petrich, Z. Snow, D. Corbin, E.W. Reutzel, Multi-modal sensor fusion with machine learning for data-driven process monitoring for additive manufacturing, Addit. Manuf. 48 (2021) 102364.
[744] K. Wang, J. Xu, S. Zhang, J. Tan, Economically evaluating energy efficiency performance in fused filament fabrication using a multi-scale hierarchical transformer, Int. J. Adv. Manuf. Technol. (2023) 1–15.
[745] M.R. Khosravani, T. Reinicke, On the environmental impacts of 3D printing technology, Appl. Mater. Today 20 (2020) 100689.
[746] W.E. Frazier, Metal additive manufacturing: a review, J. Mater. Eng. Perform. 23 (2014) 1917–1928.
[747] S. Ford, M. Despeisse, Additive manufacturing and sustainability: an exploratory study of the advantages and challenges, J. Clean. Prod. 137 (2016) 1573–1587.
[748] M. Khorram Niaki, F. Nonino, G. Palombi, S.A. Torabi, Economic sustainability of additive manufacturing: contextual factors driving its performance in rapid prototyping, Int. J. Manuf. Technol. Manag. 30 (2) (2019) 353–365.
[749] S.H. Huang, P. Liu, A. Mokasdar, L. Hou, Additive manufacturing and its societal impact: a literature review, Int. J. Adv. Manuf. Technol. 67 (2013) 1191–1203.
[750] K. Wang, Y. Song, Z. Huang, Y. Sun, J. Xu, S. Zhang, Additive manufacturing energy consumption measurement and prediction in fabricating lattice structure based on recallable multimodal fusion network, Measurement 196 (2022) 111215.
[751] K. Wang, Y. Song, H. Sheng, J. Xu, S. Zhang, J. Qin, Energy efficiency design for eco-friendly additive manufacturing based on multimodal attention fusion, J. Manuf. Process. 79 (2022) 720–730.
[752] A.H. Gutierrez-Osorio, L. Ruiz-Huerta, A. Caballero-Ruiz, H.R. Siller, V. Borja, Energy consumption analysis for additive manufacturing processes, Int. J. Adv. Manuf. Technol. 105 (1) (2019) 1735–1743.
[753] F.L. Garcia, A.O. Nunes, M.G. Martins, M.C. Belli, Y.M.B. Saavedra, D.A.L. Silva, V.A.d.S. Moris, Comparative LCA of conventional manufacturing vs. additive manufacturing: the case of injection moulding for recycled polymers, Int. J. Sustain. Eng. 14 (6) (2021) 1604–1622.
[754] L. Yi, B. Ravani, J.C. Aurich, Development and validation of an energy simulation for a desktop additive manufacturing system, Addit. Manuf. 32 (2020) 101021.
[755] P. Ramesh, S. Vinodh, Analysis of factors influencing energy consumption of material extrusion-based additive manufacturing using interpretive structural modelling, Rapid Prototyping J. 27 (7) (2021) 1363–1377.
[756] K. Wang, L. Yu, J. Xu, S. Zhang, J. Qin, Energy consumption intelligent modeling and prediction for additive manufacturing via multisource fusion and inter-layer consistency, Comput. Ind. Eng. (2022) 108720.
[757] G.O. Barrionuevo, P.M. Sequeira-Almeida, S. Ríos, J.A. Ramos-Grez, S.W. Williams, A machine learning approach for the prediction of melting efficiency in wire arc additive manufacturing, Int. J. Adv. Manuf. Technol. 120 (5) (2022) 3123–3133.
[758] K. Wang, J. Xu, S. Zhang, J. Tan, Antivibration and energy efficiency design for large stroke additive manufacturing based on dynamic trajectory adaption, Int. J. Adv. Manuf. Technol. 118 (9) (2022) 3015–3034.
[759] T. Li, J. Yeo, Strengthening the sustainability of additive manufacturing through data-driven approaches and workforce development, Adv. Intell. Syst. 3 (12) (2021) 2100069.
[760] J. Xu, K. Wang, H. Sheng, M. Gao, S. Zhang, J. Tan, Energy efficiency optimization for ecological 3D printing based on adaptive multi-layer customization, J. Clean. Prod. 245 (2020) 118826.
[761] X. Guo, J. Zhou, W. Zhang, Z. Du, C. Liu, Y. Liu, Self-supporting structure design in additive manufacturing through explicit topology optimization, Comput. Methods Appl. Mech. Eng. 323 (2017) 27–63.
[762] L. Wang, S. Tao, P. Zhu, W. Chen, Data-driven topology optimization with multiclass microstructures using latent variable gaussian process, J. Mech. Des. 143 (3) (2021) 031708.
[763] H. Ning, H. Wang, Y. Lin, W. Wang, S. Dhelim, F. Farha, J. Ding, M. Daneshmand, A survey on the metaverse: the state-of-the-art, technologies, applications, and challenges, IEEE Int. Things J. (2023).
[764] M.M. Queiroz, S. Fosso Wamba, S.C.F. Pereira, C.J. Chiappetta Jabbour, The metaverse as a breakthrough for operations and supply chain management: implications and call for action, Int. J. Oper. Prod. Manag. (2023).

[765] H. Xu, A. Berres, Y. Shao, C.R. Wang, J.R. New, O.A. Omitaomu, 13 toward a smart metaverse city, Adv. Scalable Intell. Geospat. Anal., Chall. Appl. (2023) 245.
[766] Y.K. Dwivedi, L. Hughes, Y. Wang, A.A. Alalwan, S.J. Ahn, J. Balakrishnan, S. Barta, R. Belk, D. Buhalis, V. Dutot, et al., Metaverse marketing: how the metaverse will shape the future of consumer research and practice, Psychol. Mark. 40 (4) (2023) 750–776.
[767] T. Huynh-The, T.R. Gadekallu, W. Wang, G. Yenduri, P. Ranaweera, Q.-V. Pham, D.B. da Costa, M. Liyanage, Blockchain for the metaverse: a review, Future Gener. Comput. Syst. (2023).
[768] X. Chen, D. Zou, H. Xie, F.L. Wang, Metaverse in education: contributors, cooperations, and research themes, IEEE Trans. Learn. Technol. (2023).
[769] F. Tao, B. Xiao, Q. Qi, J. Cheng, P. Ji, Digital twin modeling, J. Manuf. Syst. 64 (2022) 372–389.
[770] M. Singh, E. Fuenmayor, E.P. Hinchy, Y. Qiao, N. Murray, D. Devine, Digital twin: origin to future, Appl. Syst. Innov. 4 (2) (2021) 36.
[771] D. Jones, C. Snider, A. Nassehi, J. Yon, B. Hicks, Characterising the digital twin: a systematic literature review, CIRP J. Manuf. Sci. Technol. 29 (2020) 36–52.
[772] S. Haag, R. Anderl, Digital twin–proof of concept, Manuf. Lett. 15 (2018) 64–66.
[773] M. Liu, S. Fang, H. Dong, C. Xu, Review of digital twin about concepts, technologies, and industrial applications, J. Manuf. Syst. 58 (2021) 346–361.
[774] S. Boschert, R. Rosen, Digital twin—the simulation aspect, in: Mechatronic Futures: Challenges and Solutions for Mechatronic Systems and Their Designers, 2016, pp. 59–74.
[775] Q. Qi, F. Tao, T. Hu, N. Anwer, A. Liu, Y. Wei, L. Wang, A. Nee, Enabling technologies and tools for digital twin, J. Manuf. Syst. 58 (2021) 3–21.
[776] B. Schleich, N. Anwer, L. Mathieu, S. Wartzack, Shaping the digital twin for design and production engineering, CIRP Ann. 66 (1) (2017) 141–144.
[777] L. Wright, S. Davidson, How to tell the difference between a model and a digital twin, Adv. Model. Simul. Eng. Sci. 7 (1) (2020) 1–13.
[778] M. Attaran, B.G. Celik, Digital Twin: benefits, use cases, challenges, and opportunities, Dec. Anal. J. (2023) 100165.
[779] X. Liu, D. Jiang, B. Tao, F. Xiang, G. Jiang, Y. Sun, J. Kong, G. Li, A systematic review of digital twin about physical entities, virtual models, twin data, and applications, Adv. Eng. Inform. 55 (2023) 101876.
[780] S. Liu, J. Bao, P. Zheng, A review of digital twin-driven machining: from digitization to intellectualization, J. Manuf. Syst. 67 (2023) 361–378.
[781] C. Semeraro, A. Olabi, H. Aljaghoub, A.H. Alami, M. Al Radi, M. Dassisti, M.A. Abdelkareem, Digital twin application in energy storage: trends and challenges, J. Energy Storage 58 (2023) 106347.
[782] Y.-H. Kuo, F. Pilati, T. Qu, G.Q. Huang, Digital twin-enabled smart industrial systems: recent developments and future perspectives, Int. J. Comput. Integr. Manuf. 34 (7–8) (2021) 685–689.
[783] L. Xu, P. de Vrieze, X. Lu, W. Wang, Digital twins approach for sustainable industry, in: International Conference on Advanced Information Systems Engineering, Springer, 2022, pp. 126–134.
[784] K. Classens, W.M. Heemels, T. Oomen, Digital twins in mechatronics: from model-based control to predictive maintenance, in: 2021 IEEE 1st International Conference on Digital Twins and Parallel Intelligence (DTPI), IEEE, 2021, pp. 336–339.
[785] M. Braun, J. Krutzinna, Digital twins and the ethics of health decision-making concerning children, Patterns 3 (4) (2022).
[786] S. West, O. Stoll, J. Meierhofer, S. Züst, Digital twin providing new opportunities for value co-creation through supporting decision-making, Appl. Sci. 11 (9) (2021) 3750.
[787] A. Suvorova, Towards digital twins for the development of territories, in: Digital Transformation in Industry: Digital Twins and New Business Models, Springer, 2022, pp. 121–131.
[788] L. Scime, A. Singh, V. Paquit, A scalable digital platform for the use of digital twins in additive manufacturing, Manuf. Lett. 31 (2022) 28–32.
[789] C. Liu, L. Le Roux, C. Körner, O. Tabaste, F. Lacan, S. Bigot, Digital twin-enabled collaborative data management for metal additive manufacturing systems, J. Manuf. Syst. 62 (2022) 857–874.
[790] P. Nath, S. Mahadevan, Probabilistic digital twin for additive manufacturing process design and control, J. Mech. Des. 144 (9) (2022) 091704.
[791] M. Pantelidakis, K. Mykoniatis, J. Liu, G. Harris, A digital twin ecosystem for additive manufacturing using a real-time development platform, Int. J. Adv. Manuf. Technol. 120 (9–10) (2022) 6547–6563.
[792] F. Corradini, M. Silvestri, A digital twin-based self-calibration tool for fault prediction of FDM additive manufacturing systems, Ann. DAAAM Proc. 10 (2) (2021).
[793] A. Gaikwad, R. Yavari, M. Montazeri, K. Cole, L. Bian, P. Rao, Toward the digital twin of additive manufacturing: integrating thermal simulations, sensing, and analytics to detect process faults, IISE Trans. 52 (11) (2020) 1204–1217.
[794] R.S. Kenett, J. Bortman, The digital twin in Industry 4.0: a wide-angle perspective, Qual. Reliab. Eng. Int. 38 (3) (2022) 1357–1366.
[795] F. Pires, A. Cachada, J. Barbosa, A.P. Moreira, P. Leitão, Digital twin in industry 4.0: technologies, applications and challenges, in: 2019 IEEE 17th International Conference on Industrial Informatics (INDIN), vol. 1, IEEE, 2019, pp. 721–726.
[796] M. Jacoby, T. Usländer, Digital twin and internet of things—current standards landscape, Appl. Sci. 10 (18) (2020) 6519.
[797] Z. Zhang, F. Wen, Z. Sun, X. Guo, T. He, C. Lee, Artificial intelligence-enabled sensing technologies in the 5G/internet of things era: from virtual reality/augmented reality to the digital twin, Adv. Intell. Syst. 4 (7) (2022) 2100228.
[798] Y. Zheng, S. Yang, H. Cheng, An application framework of digital twin and its case study, J. Ambient Intell. Humaniz. Comput. 10 (2019) 1141–1153.
[799] C. Boje, A. Guerriero, S. Kubicki, Y. Rezgui, Towards a semantic construction digital twin: directions for future research, Autom. Constr. 114 (2020) 103179.
[800] R. Zhao, Z. Chen, F. Xue, A blockchain 3.0 paradigm for digital twins in construction project management, Autom. Constr. 145 (2023) 104645.
[801] M. Panarotto, O. Isaksson, V. Vial, Cost-efficient digital twins for design space exploration: a modular platform approach, Comput. Ind. 145 (2023) 103813.
[802] J. Argota Sánchez-Vaquerizo, Getting real: the challenge of building and validating a large-scale digital twin of barcelona's traffic with empirical data, ISPRS Int. J. Geo-Inf. 11 (1) (2021) 24.
[803] R. van Dinter, B. Tekinerdogan, C. Catal, Predictive maintenance using digital twins: a systematic literature review, Inf. Softw. Technol. (2022) 107008.
[804] M. Atalay, P. Angin, A digital twins approach to smart grid security testing and standardization, in: 2020 IEEE International Workshop on Metrology for Industry 4.0 & IoT, IEEE, 2020, pp. 435–440.
[805] M. Vuković, D. Mazzei, S. Chessa, G. Fantoni, Digital Twins in Industrial IoT: a survey of the state of the art and of relevant standards, in: 2021 IEEE International Conference on Communications Workshops (ICC Workshops), IEEE, 2021, pp. 1–6.
[806] O.J. Pinon Fischer, J.F. Matlik, W.D. Schindel, M.O. French, M.H. Kabir, J.S. Ganguli, M. Hardwick, S.M. Arnold, A.D. Byar, J.-H. Lewe, et al., Digital twin: reference model, realizations, and recommendations, Insight 25 (1) (2022) 50–55.
[807] K. Wang, Y. Wang, Y. Li, X. Fan, S. Xiao, L. Hu, A review of the technology standards for enabling digital twin, Digital Twin 2 (2022) 4.
[808] W. Yu, P. Patros, B. Young, E. Klinac, T.G. Walmsley, Energy digital twin technology for industrial energy management: classification, challenges and future, Renew. Sustain. Energy Rev. 161 (2022) 112407.
[809] X. Fang, H. Wang, G. Liu, X. Tian, G. Ding, H. Zhang, Industry application of digital twin: from concept to implementation, Int. J. Adv. Manuf. Technol. 121 (7–8) (2022) 4289–4312.
[810] D.-G.J. Opoku, S. Perera, R. Osei-Kyei, M. Rashidi, Digital twin application in the construction industry: a literature review, J. Build. Eng. 40 (2021) 102726.
[811] C. Mandolla, A.M. Petruzzelli, G. Percoco, A. Urbinati, Building a digital twin for additive manufacturing through the exploitation of blockchain: a case analysis of the aircraft industry, Comput. Ind. 109 (2019) 134–152.
[812] Y. Cai, Y. Wang, M. Burnett, Using augmented reality to build digital twin for reconfigurable additive manufacturing system, J. Manuf. Syst. 56 (2020) 598–604.
[813] G. Knapp, T. Mukherjee, J. Zuback, H. Wei, T. Palmer, A. De, T. DebRoy, Building blocks for a digital twin of additive manufacturing, Acta Mater. 135 (2017) 390–399.
[814] D.R. Gunasegaram, A. Murphy, A. Barnard, T. DebRoy, M. Matthews, L. Ladani, D. Gu, Towards developing multiscale-multiphysics models and their surrogates for digital twins of metal additive manufacturing, Addit. Manuf. 46 (2021) 102089.
[815] D. Gamdha, K. Saurabh, B. Ganapathysubramanian, A. Krishnamurthy, Geometric modeling and physics simulation framework for building a digital twin of extrusion-based additive manufacturing, preprint, arXiv:2305.07120, 2023.
[816] L. Fang, Q. Liu, D. Zhang, A digital twin-oriented lightweight approach for 3D assemblies, Machines 9 (10) (2021) 231.
[817] X. Lai, X. He, S. Wang, X. Wang, W. Sun, X. Song, Building a lightweight digital twin of a crane boom for structural safety monitoring based on a multifidelity surrogate model, J. Mech. Des. 144 (6) (2022) 064502.
[818] W. Sun, S. Lian, H. Zhang, Y. Zhang, Lightweight digital twin and federated learning with distributed incentive in air-ground 6g networks, IEEE Trans. Netw. Sci. Eng. 10 (3) (2022) 1214–1227.
[819] X. Zhang, B. Hu, G. Xiong, X. Liu, X. Dong, D. Li, Research and practice of lightweight digital twin speeding up the implementation of flexible manufacturing systems, in: 2021 IEEE 1st International Conference on Digital Twins and Parallel Intelligence (DTPI), IEEE, 2021, pp. 456–460.
[820] Z. Wang, Digital twin technology, in: Industry 4.0-Impact on Intelligent Logistics and Manufacturing, IntechOpen, 2020.
[821] G. Piao, J.G. Breslin, Factorization machines leveraging lightweight linked open data-enabled features for top-n recommendations, in: Web Information Systems Engineering–WISE 2017: 18th International Conference, Puschino, Russia, October 7-11, 2017, Proceedings, Part II 18, Springer, pp. 420–434, 2017.
[822] L. Tang, S. Ying, L. Li, F. Biljecki, H. Zhu, Y. Zhu, F. Yang, F. Su, An application-driven LOD modeling paradigm for 3D building models, ISPRS J. Photogramm. Remote Sens. 161 (2020) 194–207.
[823] J. Huo, J. Liu, G. Pei, T. Wang, Research on LOD lightweight method of railway four electric BIM model, in: Proceedings of the 2022 6th International Conference on Electronic Information Technology and Computer Engineering, 2022, pp. 492–497.
[824] J. Wang, X. Xia, Z. Zhang, Y. Zhang, Y. Shen, B. Ren, Class continuous lod algorithm for lightweight webgl rendering optimization, in: 2022 International Conference on Networking and Network Applications (NaNA), IEEE, 2022, pp. 489–494.
[825] V. Kamra, P. Kudeshia, S. ArabiNaree, D. Chen, Y. Akiyama, J. Peethambaran, Lightweight reconstruction of urban buildings: data structures, algorithms, and future directions, IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 16 (2022) 902–917.
[826] C. Zhang, B. He, R. Guo, D. Ma, When a tree model meets texture baking: an approach for quality-preserving lightweight visualization in virtual 3D scene construction, Int. J. Digit. Earth 16 (1) (2023) 645–670.

[827] A. Jagannath, J. Jagannath, Embedding-assisted attentional deep learning for real-world rf fingerprinting of bluetooth, IEEE Trans. Cogn. Commun. Netw. (2023).
[828] Y. Feng, J. Chen, Z. Huang, H. Wan, R. Xia, B. Wu, L. Sun, M. Xing, A lightweight position-enhanced anchor-free algorithm for sar ship detection, Remote Sens. 14 (8) (2022) 1908.
[829] X. Zhang, H. Wang, C. Xu, Y. Lv, C. Fu, H. Xiao, Y. He, A lightweight feature optimizing network for ship detection in sar image, IEEE Access 7 (2019) 141662–141678.
[830] W. Bao, X. Yang, D. Liang, G. Hu, X. Yang, Lightweight convolutional neural network model for field wheat ear disease identification, Comput. Electron. Agric. 189 (2021) 106367.
[831] T. Oberbichler, K. Bletzinger, Cad-integrated form-finding of structural membranes using extended catmull–clark subdivision surfaces, Comput. Aided Des. 151 (2022) 103360.
[832] S. Rosso, A. Curtarello, F. Basana, L. Grigolato, R. Meneghello, G. Concheri, G. Savio, Modeling symmetric minimal surfaces by mesh subdivision, in: Advances on Mechanics, Design Engineering and Manufacturing III: Proceedings of the International Joint Conference on Mechanics, Design Engineering & Advanced Manufacturing, JCM 2020, June 2-4, 2020, Springer, 2021, pp. 249–254.
[833] H. Shi, W. Ma, Z. Xu, P. Lin, A novel integrated strategy of easy pruning, parameter searching, and re-parameterization for lightweight intelligent lithology identification, Expert Syst. Appl. (2023) 120657.
[834] L. Duan, N.-c. Xiao, Z. Hu, G. Li, A. Cheng, An efficient lightweight design strategy for body-in-white based on implicit parameterization technique, Struct. Multidiscip. Optim. 55 (2017) 1927–1943.
[835] J. Xu, Y. Zhao, F. Xu, Rdpnet: a single-path lightweight cnn with re-parameterization for cpu-type edge devices, J. Cloud Comput. 11 (1) (2022) 54.
[836] A.M. Madni, C.C. Madni, S.D. Lucero, Leveraging digital twin technology in model-based systems engineering, Systems 7 (1) (2019) 7.
[837] P. Gope, P.K. Sharma, B. Sikdar, An ultra-lightweight data-aggregation scheme with deep learning security for smart grid, IEEE Wirel. Commun. 29 (2) (2022) 30–36.
[838] J. Qian, Z. Cao, X. Dong, J. Shen, Z. Liu, Y. Ye, Two secure and efficient lightweight data aggregation schemes for smart grid, IEEE Trans. Smart Grid 12 (3) (2020) 2625–2637.
[839] B.O. Soufiene, A.A. Bahattab, A. Trad, H. Youssef, LSDA: lightweight secure data aggregation scheme in healthcare using IoT, in: Proceedings of the 10th International Conference on Information Systems and Technologies, 2020, pp. 1–4.
[840] L. Chen, X. Yao, K. Liu, C. Tan, S.K. Moon, Multisensor fusion-based digital twin in additive manufacturing for in-situ quality monitoring and defect correction, Proc. Des. Soc. 3 (2023) 2755–2764.
[841] L. Chen, G. Bi, X. Yao, C. Tan, J. Su, N.P.H. Ng, Y. Chew, K. Liu, S.K. Moon, Multisensor fusion-based digital twin for localized quality prediction in robotic laser-directed energy deposition, Robot. Comput.-Integr. Manuf. 84 (2023) 102581.
[842] E.E.-D. Hemdan, W. El-Shafai, A. Sayed, Integrating digital twins with IoT-based blockchain: concept, architecture, challenges, and future scope, Wirel. Pers. Commun. (2023) 1–24.
[843] L. Chalal, A. Saadane, A. Rachid, Unified environment for real-time control of hybrid energy system using digital twin and IoT approach, Sensors 23 (12) (2023) 5646.
[844] N.H. Motlagh, M.A. Zaidan, L. Lovén, P.L. Fung, T. Hänninen, R. Morabito, P. Nurmi, S. Tarkoma, Digital twins for smart spaces: beyond IoT analytics, IEEE Int. Things J. (2023).
[845] R. Revetria, F. Tonelli, L. Damiani, M. Demartini, F. Bisio, N. Peruzzo, A real-time mechanical structures monitoring system based on digital twin, IoT and augmented reality, in: 2019 Spring Simulation Conference (SpringSim), IEEE, 2019, pp. 1–10.
[846] T. Moi, A. Cibicik, T. Rølvåg, Digital twin based condition monitoring of a knuckle boom crane: an experimental study, Eng. Fail. Anal. 112 (2020) 104517.
[847] M. Vlaeyen, H. Haitjema, W. Dewulf, Digital twin of an optical measurement system, Sensors 21 (19) (2021) 6638.
[848] M. Braglia, R. Gabbrielli, M. Frosolini, L. Marrazzini, L. Padellini, Using rfid technology and discrete-events, agent-based simulation tools to build digital-twins of large warehouses, in: 2019 IEEE International Conference on RFID Technology and Applications (RFID-TA), IEEE, 2019, pp. 464–469.
[849] M. Cai, S. Wang, X. Shen, Y. Jin, A scheme for anomalous rfid trajectory detection based on improved clustering algorithm under digital-twin-driven, in: Proceedings of the 16th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services, 2019, pp. 126–134.
[850] Y. Liu, Z. Wang, K. Han, Z. Shou, P. Tiwari, J.H. Hansen, Sensor fusion of camera and cloud digital twin information for intelligent vehicles, in: 2020 IEEE Intelligent Vehicles Symposium (IV), IEEE, 2020, pp. 182–187.
[851] X. Zhou, K. Sun, J. Wang, J. Zhao, C. Feng, Y. Yang, W. Zhou, Computer vision enabled building digital twin using building information model, IEEE Trans. Ind. Inform. 19 (3) (2022) 2684–2692.
[852] D.G. Broo, M. Bravo-Haro, J. Schooling, Design and implementation of a smart infrastructure digital twin, Autom. Constr. 136 (2022) 104171.
[853] C. Rausch, R. Lu, S. Talebi, C. Haas, Deploying 3D scanning based geometric digital twins during fabrication and assembly in offsite manufacturing, Int. J. Construct. Manag. 23 (3) (2023) 565–578.
[854] F. Jiang, L. Ma, T. Broyd, K. Chen, Digital twin and its implementations in the civil engineering sector, Autom. Constr. 130 (2021) 103838.
[855] H.H. Hosamo, M.H. Hosamo, Digital twin technology for bridge maintenance using 3D laser scanning: a review, Adv. Civ. Eng. (2022) 2022.
[856] H. Wang, L. Lv, X. Li, H. Li, J. Leng, Y. Zhang, V. Thomson, G. Liu, X. Wen, C. Sun, et al., A safety management approach for industry 5.0's human-centered manufacturing based on digital twin, J. Manuf. Syst. 66 (2023) 1–12.
[857] L. Arnemann, S. Winter, N. Quernheim, B. Schleich, Product life cycle management with digital twins for product generation development, Proc. Des. Soc. 3 (2023) 2955–2964.
[858] D. Kibira, G. Shao, R. Venketesh, Building a digital twin of an automated robot workcell, in: 2023 Annual Modeling and Simulation Conference (ANNSIM), IEEE, 2023, pp. 196–207.
[859] F. Hu, X. Qiu, G. Jing, J. Tang, Y. Zhu, Digital twin-based decision making paradigm of raise boring method, J. Intell. Manuf. 34 (5) (2023) 2387–2405.
[860] M. Rico, M.L. Taverna, M.R. Galli, M.L. Caliusco, Context-aware representation of digital twins' data: the ontology network role, Comput. Ind. 146 (2023) 103856.
[861] J. Vyskočil, P. Douda, P. Novák, B. Wally, A digital twin-based distributed manufacturing execution system for Industry 4.0 with AI-powered on-the-fly replanning capabilities, Sustainability 15 (7) (2023) 6251.
[862] G. Ke, Z. Dashun, M. Liqin, W. Jing, D. Juan, L. Shubo, Q. Huan, S. Lizhong, Intelligent machine plus production line digital twin model construction technology, J. Phys. Conf. Ser. 2478 (2023) 102011, IOP Publishing.
[863] G.N. Schroeder, C. Steinmetz, R.N. Rodrigues, R.V.B. Henriques, A. Rettberg, C.E. Pereira, A methodology for digital twin modeling and deployment for industry 4.0, Proc. IEEE 109 (4) (2020) 556–567.
[864] Q. Charrier, N. Hakam, K. Benfriha, V. Meyrueis, C. Liotard, A. Aoussat, A roadmap for monitoring cyber-physical systems through the digital twin using an IoT sensing architecture, Available at SSRN 4406361.
[865] A. Haghshenas, A. Hasan, O. Osen, E.T. Mikalsen, Predictive digital twin for offshore wind farms, Energy Inf. 6 (1) (2023) 1–26.
[866] S. Cavalieri, S. Gambadoro, Proposal of mapping digital twins definition language to open platform communications unified architecture, Sensors 23 (4) (2023) 2349.
[867] A.I. Khalyasmaa, A.I. Stepanova, S.A. Eroshenko, P.V. Matrenin, Review of the digital twin technology applications for electrical equipment lifecycle management, Mathematics 11 (6) (2023) 1315.
[868] J.V.A. Cabral, E.A.R. Gasca, A.J. Alvares, Digital twin implementation for machining center based on ISO 23247 standard, IEEE Latin Am. Trans. 21 (5) (2023) 628–635.
[869] Z. Huang, M. Fey, C. Liu, E. Beysel, X. Xu, C. Brecher, Hybrid learning-based digital twin for manufacturing process: modeling framework and implementation, Robot. Comput.-Integr. Manuf. 82 (2023) 102545.
[870] K. Abutalip, A. Al-Lahham, A. El Saddik, Digital twin of atmospheric environment: sensory data fusion for high-resolution PM 2.5 estimation and action policies recommendation, IEEE Access 11 (2023) 14448–14457.
[871] M. La Guardia, M. Koeva, Towards digital twinning on the web: heterogeneous 3D data fusion based on open-source structure, Remote Sens. 15 (3) (2023) 721.
[872] W. Zhao, C. Zhang, J. Wang, S. Wang, D. Lv, F. Qin, Research on digital twin driven rolling bearing model-data fusion life prediction method, IEEE Access (2023).
[873] K. de Koning, J. Broekhuijsen, I. Kühn, O. Ovaskainen, F. Taubert, D. Endresen, D. Schigel, V. Grimm, Digital twins: dynamic model-data fusion for ecology, Trends Ecol. Evol. (2023).
[874] M. Li, Y. Fu, Q. Chen, T. Qu, Blockchain-enabled digital twin collaboration platform for heterogeneous socialized manufacturing resource management, Int. J. Prod. Res. 61 (12) (2023) 3963–3983.
[875] A. Sasikumar, S. Vairavasundaram, K. Kotecha, V. Indragandhi, L. Ravi, G. Selvachandran, A. Abraham, Blockchain-based trust mechanism for digital twin empowered industrial internet of things, Future Gener. Comput. Syst. 141 (2023) 16–27.
[876] S. Liu, Y. Lu, J. Li, X. Shen, X. Sun, J. Bao, A blockchain-based interactive approach between digital twin-based manufacturing systems, Comput. Ind. Eng. 175 (2023) 108827.
[877] S. Huang, G. Wang, Y. Yan, X. Fang, Blockchain-based data management for digital twin of product, J. Manuf. Syst. 54 (2020) 361–371.
[878] I. Yaqoob, K. Salah, M. Uddin, R. Jayaraman, M. Omar, M. Imran, Blockchain for digital twins: recent advances and future research challenges, IEEE Netw. 34 (5) (2020) 290–298.
[879] B. Teisserenc, S. Sepasgozar, Adoption of blockchain technology through digital twins in the construction industry 4.0: a pestels approach, Buildings 11 (12) (2021) 670.
[880] J. Protner, M. Pipan, H. Zupan, M. Resman, M. Simic, N. Herakovic, Edge computing and digital twin based smart manufacturing, IFAC-PapersOnLine 54 (1) (2021) 831–836.
[881] F.P. Knebel, R. Trevisan, G.S. do Nascimento, M. Abel, J.A. Wickboldt, A study on cloud and edge computing for the implementation of digital twins in the oil & gas industries, Comput. Ind. Eng. 182 (2023) 109363.
[882] P. Durana, V. Krastev, K. Buckner, Digital twin modeling, multi-sensor fusion technology, and data mining algorithms in cloud and edge computing-based smart city environments, Geopolit. History Int. Relat. 14 (1) (2022) 91–106.
[883] J. Wang, Y. Liu, S. Ren, C. Wang, S. Ma, Edge computing-based real-time scheduling for digital twin flexible job shop with variable time window, Robot. Comput.-Integr. Manuf. 79 (2023) 102435.

[884] Z. Zhou, Z. Jia, H. Liao, W. Lu, S. Mumtaz, M. Guizani, M. Tariq, Secure and latency-aware digital twin assisted resource scheduling for 5G edge computing-empowered distribution grids, IEEE Trans. Ind. Inform. 18 (7) (2021) 4933–4943.
[885] Y. Xie, K. Lian, Q. Liu, C. Zhang, H. Liu, Digital twin for cutting tool: modeling, application and service strategy, J. Manuf. Syst. 58 (2021) 305–312.
[886] S.K. Pal, D. Mishra, A. Pal, S. Dutta, D. Chakravarty, S. Pal, S.K. Pal, D. Mishra, A. Pal, S. Dutta, et al., Signal processing for digital twin, in: Digital Twin–Fundamental Concepts to Applications in Advanced Manufacturing, 2022, pp. 117–187.
[887] P. Aivaliotis, K. Georgoulias, G. Chryssolouris, The use of digital twin for predictive maintenance in manufacturing, Int. J. Comput. Integr. Manuf. 32 (11) (2019) 1067–1080.
[888] Y. He, J. Guo, X. Zheng, From surveillance to digital twin: challenges and recent advances of signal processing for industrial internet of things, IEEE Signal Process. Mag. 35 (5) (2018) 120–129.
[889] S.H. Khajavi, N.H. Motlagh, A. Jaribion, L.C. Werner, J. Holmström, Digital twin: vision, benefits, boundaries, and creation for buildings, IEEE Access 7 (2019) 147406–147419.
[890] D. Burnett, J. Thorp, D. Richards, K. Gorkovenko, D. Murray-Rust, Digital twins as a resource for design research, in: Proceedings of the 8th ACM International Symposium on Pervasive Displays, 2019, pp. 1–2.
[891] R. Martinez-Velazquez, R. Gamez, A. El Saddik, Cardio twin: a digital twin of the human heart running on the edge, in: 2019 IEEE International Symposium on Medical Measurements and Applications (MeMeA), IEEE, 2019, pp. 1–6.
[892] Z. Lv, D. Chen, H. Feng, W. Wei, H. Lv, Artificial intelligence in underwater digital twins sensor networks, ACM Trans. Sens. Netw. 18 (3) (2022) 1–27.
[893] P. Angin, M.H. Anisi, F. Göksel, C. Gürsoy, A. Büyükgülcü, Agrilora: a digital twin framework for smart agriculture, J. Wirel. Mob. Networks Ubiquitous Comput. Dependable Appl. 11 (4) (2020) 77–96.
[894] W. Zhou, Research on wireless sensor network access control and load balancing in the industrial digital twin scenario, J. Sens. 2022 (2022) 1–12.
[895] R.-S. Balica, et al., Machine and deep learning technologies, wireless sensor networks, and virtual simulation algorithms in digital twin cities, Geopolit. History Int. Relat. 14 (1) (2022) 59–74.
[896] F. Pires, V. Melo, J. Almeida, P. Leitão, Digital twin experiments focusing virtualisation, connectivity and real-time monitoring, in: 2020 IEEE Conference on Industrial Cyberphysical Systems (ICPS), vol. 1, IEEE, 2020, pp. 309–314.
[897] Y. Yi, Y. Yan, X. Liu, Z. Ni, J. Feng, J. Liu, Digital twin-based smart assembly process design and application framework for complex products and its case study, J. Manuf. Syst. 58 (2021) 94–107.
[898] Q. Zhang, S. Shen, H. Li, W. Cao, W. Tang, J. Jiang, M. Deng, Y. Zhang, B. Gu, K. Wu, et al., Digital twin-driven intelligent production line for automotive mems pressure sensors, Adv. Eng. Inform. 54 (2022) 101779.
[899] J. Mertes, M. Glatt, C. Schellenberger, M. Klar, H.D. Schotten, J.C. Aurich, Development of a 5G-enabled digital twin of a machine tool, Proc. CIRP 107 (2022) 173–178.
[900] Y. Tai, L. Zhang, Q. Li, C. Zhu, V. Chang, J.J. Rodrigues, M. Guizani, Digital-twin-enabled IoMT system for surgical simulation using rAC-GAN, IEEE Int. Things J. 9 (21) (2022) 20918–20931.
[901] Z. Lv, D. Chen, H. Feng, R. Lou, H. Wang, Beyond 5G for digital twins of UAVs, Comput. Netw. 197 (2021) 108366.
[902] K. Bartsch, A. Pettke, A. Hübert, J. Lakämper, F. Lange, On the digital twin application and the role of artificial intelligence in additive manufacturing: a systematic review, J. Phys. Mater. 4 (3) (2021) 032005.
[903] D.R. Gunasegaram, A.B. Murphy, M. Matthews, T. DebRoy, The case for digital twins in metal additive manufacturing, J. Phys. Mater. 4 (4) (2021) 040401.
[904] J. Haw, S.L. Sing, Z.H. Liu, Digital twins in design for additive manufacturing, Mater. Today Proc. 70 (2022) 352–357.
[905] N. Jyeniskhan, A. Keutayeva, G. Kazbek, M.H. Ali, E. Shehab, Integrating machine learning model and digital twin system for additive manufacturing, IEEE Access (2023).
[906] D.B. Kim, G. Shao, G. Jo, A digital twin implementation architecture for wire+ arc additive manufacturing based on ISO 23247, Manuf. Lett. 34 (2022) 1–5.
[907] D. Guerra-Zubiaga, V. Kuts, K. Mahmood, A. Bondar, N. Nasajpour-Esfahani, T. Otto, An approach to develop a digital twin for industry 4.0 systems: manufacturing automation case studies, Int. J. Comput. Integr. Manuf. 34 (9) (2021) 933–949.