Additive Manufacturing 59 (2022) 103139

Contents lists available at ScienceDirect

Additive Manufacturing

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

Intelligent additive manufacturing and design state of the art and future perspectives

Yi Xiong [a,*], Yunlong Tang [b,c,**], Qi Zhou [d], Yongsheng Ma [e], David W. Rosen [f,g]

[a] School of System Design and Intelligent Manufacturing, Southern University of Science and Technology, Shenzhen 518055, China
[b] Mechanical and Aerospace Engineering Department, Monash University, Melbourne 3168, Australia
[c] Materials Science and Engineering Department, Monash University, Melbourne 3168, Australia
[d] School of Aerospace Engineering, Huazhong University of Science & Technology, Wuhan 430074, China
[e] Department of Mechanical and Energy Engineering, Southern University of Science and Technology, Shenzhen 518055, China
[f] Digital Manufacturing and Design (DManD) Centre, Singapore University of Technology and Design, 8 Somapah Road, 487372, Singapore
[g] The G. W. Woodruff School of Mechanical Engineering, Georgia Institute of Technology, Atlanta, GA 30332, USA

ARTICLE INFO

Keywords:
Additive manufacturing
Intelligent manufacturing
Cyber-physical system
Integrated design and manufacturing

ABSTRACT

In additive manufacturing (AM), intelligent technologies are proving to be a powerful tool for facilitating economic, efficient, and effective decision-making within the product and service development. Such capabilities hold great promise to significantly improve the producibility, repeatability, and reproducibility of the additive manufacturing process and unlock its complete design freedom for product innovation. This paper defines the concept of intelligent additive manufacturing and design (IAMD) while providing a triple-layer model for reference. Details about these three layers, i.e., digital thread layer, cyber-physical layer, and intelligent service layer, are presented. Moreover, both scientific and engineering challenges raised during the studies and implementations of IAMD are discussed together with potential solutions. The paper also outlines the future perspective on IAMD towards the directions of integrated design and manufacturing, cyber-physical AM, advanced artificial intelligence for AM, digital materials and products, as well as design for AM process chain.

1. Introduction

Additive manufacturing (AM) is an emerging technology that creates complex three-dimensional (3D) parts through a layer-wise addition of material. Contrary to current practices in subtractive and forming manufacturing, AM does not require specific jigs, fixtures, or tooling and thus has a simpler workflow and higher flexibility. Due to its outstanding ability to create parts with complex designs, multi-materials, and integrated functions, AM has been gradually adopted for applications in automotive, aerospace, and biomedical industries [1]. With fewer manufacturing constraints, AM enables the realization of advanced structures that otherwise would be unattainable. Examples of these structures include topological [2], cellular [3], and chain-mail [4] structures, which are lightweight, strong, and designable. Structural optimization based on computational methods is significantly advanced for leveraging design freedom brought by AM to improve the performance of these structures. Meanwhile, the advent of multi-material AM makes it possible to develop structures with tailored properties, e.g., functionally graded and heterogeneous materials. Additionally, AM also paves the road for developing all-in-one devices with embedded intelligence, e.g., sensing, control, and actuating, and with integrated functionalities [5], e.g., mechanical, electrical, and thermal functions. More importantly, AM also serves as the basis for developing other disruptive technologies, such as structural colors [6,7] and metamaterials [8].

However, decision-making for AM and its design is nontrivial due to **limited information**, **large uncertainties**, and **high-dimensional design spaces**. These challenges are inherent to AM and limit the broader adoption of AM for industrial applications. Firstly, due to the layer-wise nature of AM, the underpinning mechanism behind various phenomena in AM, crossing multi-scale and involving multi-physics, are still not well-understood and characterized. These highly coupled and nonlinear relationships make it extremely difficult for engineers to make optimal decisions resulting in printed builds with precise geometry and properties. Moreover, the current AM process is still challenged by

* Corresponding author.
** Corresponding author at: Mechanical and Aerospace Engineering Department, Monash University, Melbourne 3168, Australia.
E-mail addresses: xiongy3@sustech.edu.cn (Y. Xiong), yunlong.tang1@monash.edu (Y. Tang).

https://doi.org/10.1016/j.addma.2022.103139
Received 11 May 2022; Received in revised form 18 August 2022; Accepted 7 September 2022
Available online 9 September 2022

various uncertainties [9–11], e.g., the fluctuation of thermal boundary conditions during print. These high uncertainties greatly hinder the use of AM in high-performance applications, e.g., aerospace engineering. Meanwhile, exploring and exploiting such a high-dimensional design space with AM is highly challenging, even for experienced designers [12,13]. The lagging of design methods and tools behind the advent of manufacturing technology has jeopardized the full utilization of AM's unique capabilities for product innovation and production.

Relying on human intelligence solely is not sufficient to solve the above challenges in decision-making for AM. Thus, it is highly desired to introduce machine intelligence to complement human intelligence for facilitating the economy, efficiency, and effectiveness of decisions. This paradigm shift aims to automate and integrate design and manufacturing activities, supporting the concurrent design of materials, structures, and processes, ultimately boosting the capabilities of AM processes and facilitating related product innovation and production [14,15].

Also, AM is rooted in computer-aided technologies, i.e., computer-aided design, engineering, and manufacturing (CAD, CAE, and CAM), and is defined as the process of joining materials to make objects from 3D model data. Thus, AM has been known as a digital manufacturing process since its inception. In contrast to other manufacturing technologies, AM conducts more design and manufacturing tasks within a digital environment. These apparent advantages make AM an ideal candidate for realizing intelligent manufacturing, which is a broader concept of manufacturing that aims to optimize production and products by taking full advantage of advanced information and manufacturing technologies [16,17].

In the above context, the research on intelligent additive manufacturing and design (IAMD) has two primary tasks to improve the current decision-making process. The first goal is to improve the automation level of AM and design. Although computational design tools are becoming widely available, most design variables in AM are still determined using trial-and-error methods or rules of thumb. Meanwhile, the accumulated AM knowledge, particularly design knowledge, cannot be directly and easily transferred to novice engineers [18]. The second goal is to integrate the decision-making processes for AM design and manufacturing into one step. The current two-step approach causes a significant difference between the expectations of theoretical design and the real performance of as-fabricated parts. A material-structure-performance integrated design approach is desired.

Recent years have witnessed a surge of interest in this emerging research field ranging from intelligent AM design, equipment, product, and services. Considerable efforts have been made to explore the feasibility of utilizing emerging information technologies, such as cloud computing [19], data analytics [20],and artificial intelligence (AI) [21,22] to solve specific AM problems. Meanwhile, initiatives for intelligent AM, also known as smart AM, have been made in references [23–25]. The development of this fast-moving field calls for a formal concept of IAMD, and there is currently no clear roadmap for guiding its future development.

This paper aims to organize related knowledge surrounding IAMD, define this emerging concept with a triple-layer reference model, and present state-of-the-art and future perspectives to the researchers. However, it should be noted that this paper does not discuss specific applications and algorithms due to length constraints. Readers can refer to several excellent reviews on these topics for more details. In contrast to existing literature, the main contribution of this work is threefold. Firstly, a triple-layer reference model is proposed to extend the current study on the digital thread and cyber-physical system toward intelligent services, facilitating decision-making within AM. This model serves as the backbone to link existing and emerging topics in IAMD. Moreover, the study examines the use of several key technologies together for implementing the triple-layer reference model. Multidisciplinary design optimization, as a key technology to link design and manufacturing, is discussed for the first time. Lastly, the paper also points out the future direction of IAMD, such as the design for AM process chain, that have the potential to open up a new avenue for further exploration.

As shown in Fig. 1, integrating advanced intelligent technologies into the design-to-product workflow of AM encounters scientific and engineering challenges within each phase. The remainder of this paper is structured as follows. The definition of IAMD, and its triple-layer reference model, are presented in Section 2. Section 3 identifies key challenges and their potential solutions for IAMD. Future perspectives are outlined in Section 4. Finally, conclusions are drawn in Section 5.

2. Intelligent additive manufacturing and design system

Intelligent additive manufacturing and design can be broadly defined as a concept of manufacturing with the aim to maximize the value of AM by fully utilizing its design freedom in terms of materials, structures, and processes through interactions with cyber-physical systems based on both human and machine intelligence. With the use of such hybrid intelligence, AM technologies have undergone a tremendous change towards a more automated, integrated, service-oriented direction. This subsection discusses the details of this trend through a triple-layer reference model for intelligent AM and design systems, as shown in Fig. 2.

The reference model encompasses digital thread, cyber-physical, and intelligent service layers. The digital thread layer lies at the heart of the model and connects all AM stages, e.g., design, manufacturing, operation and service, with a backbone called a digital thread. The digital thread collects all types of design-to-product data. The digital thread layer is surrounded by a cyber-physical layer, an integration that comprises assets in both physical and virtual spaces. The cyber-physical system (CPS) reflects the process-structure-property relationships within the manufacturing process. Here, the CPS is not confined to a single subject but can be any AM equipment, product, and even material. The outermost layer of the model is the intelligent service layer, which includes intelligent AM design, equipment, product, and service. Some concepts within the outer loop are still under development. Thus, the intelligent AM service layer is less mature than the other two loops regarding the technology readiness level while still representing the future directions of IAMD.

The above three layers work together as follows: the information circulates within each loop and passes between different loops through interfaces. The intra-loop can be viewed as a fully automated end-to-end information workflow, which integrates different software design systems, manufacturing hardware, and manufacturing execution systems. Cyber-physical systems located in the middle layer consistently update their state values by reading both virtual and physical sensors through the digital thread. Meanwhile, the outer layer creates manufacturing and design services based on resources provided by the CPS to deliver intelligent AM products and related services.

2.1. Digital thread layer

AM is a data-intensive manufacturing process that generates considerable data across its lifecycle on part geometries, materials, processes, characterization, part qualification, and operation. The data carry valuable information and holds vast promise to enable data-driven applications to improve products' manufacturing process and performance. Thus, the concept of an AM-specific digital thread is proposed to collect all these design-to-product data and create a data ecosystem that enables the easy and secure generation, storage, analysis, and sharing of data, as shown in Fig. 3. Several prior works have studied the framework, data model, and implementation of digital thread [26–29]. Such a digital thread is the basis of the IAMD system for the following reasons. Firstly, the digital thread connects the design and manufacturing stages, allowing designers to make a more well-informed decision [30] at earlier design stages with post-design information, e.g., manufacturing uncertainties, available. Moreover, the digital thread provides

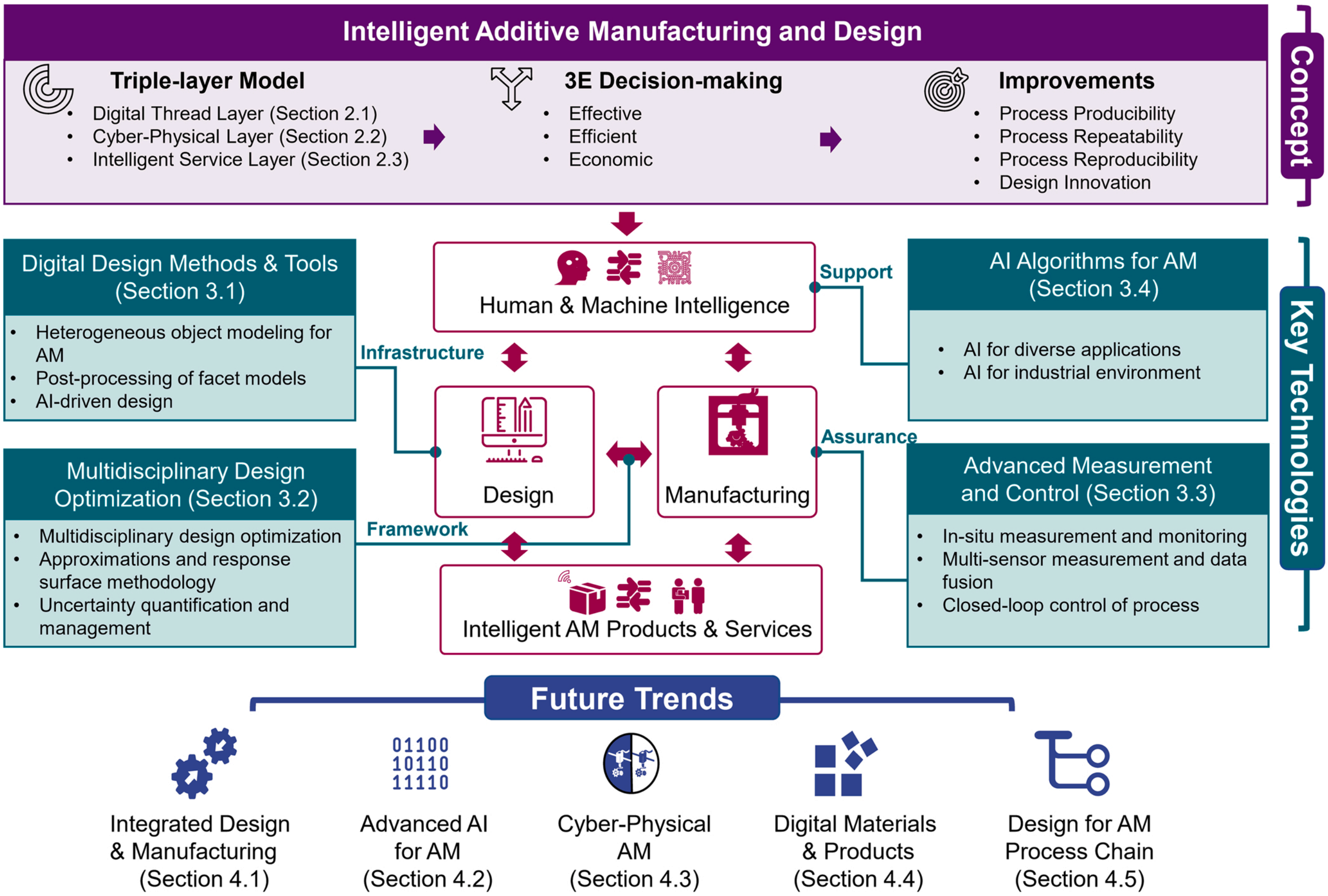

Fig. 1. Research framework for studies on intelligent additive manufacturing and design.

traceability to facilitate the producibility, repeatability, and reproducibility of AM builds, which is critical for part qualification. Additionally, the digital ecosystem improves data manageability, which eases further data management and analysis at any time.

Standardization of data representation greatly affects the efficiency of information exchange within the digital AM thread [31]. The data generated throughout different phases of AM is stored in various formats [32], e.g., 3D CAD models for part geometries, field and history outputs for CAE simulations, 2D slices for pre-processing, build files for machine executions, and images for in-process monitoring. Researchers from NIST (the national institute of standards and technology) developed a six-activity model [28] to classify these data sources. The lack of a uniform representation makes the communication between different activities unambiguous, inconsistent, and non-interoperable. There is an urgent need to develop a semantic environment [33] and common data model [34] that incorporate one part's design specification, geometrical description, process parameters, and measure properties within a single computer file. Motivated by this need, integrated data representations, including extended AMF [35], AMIDM [36] and STEP/STEP NC [37] for AM, have been proposed to support data collection, storage, and usage over the entire AM value chain. International standards, such as ASTM F3490–21, have also been developed for constructing data pedigree that is process agnostic and technology independent.

AM data within such a digital thread possess typical features of big data: volume, variety, and velocity (3 V). More specifically, the layer-wise nature results in the data model must store information across multiple scales, e.g., scan vector, layers, and solid parts, which results in a large volume of data. Meanwhile, as discussed above, various data are collected from cyber-physical systems [38]. Moreover, since AM is a highly dynamic manufacturing process, many critical phenomena need to be observed at a very high frequency. A minimum sampling rate of 200,000 frames per second is required for studying melt pool temperature and cooling rates in the metal powder bed fusion (PBF) process. Meanwhile, it can also be characterized by multi-source, multi--dimension, multi-noise (3 M), commonly found in manufacturing data [21].

2.2. *Cyber-physical system layer*

Efficiently maximizing the utilization of a large amount of data is one of the major challenges for the intelligent AM fabrication and design process. Cyber-physical technology is an ideal paradigm to address this challenge. This integration paradigm aims to provide different services for stakeholders in the value chains of AM by integrating different streams of data from the digital AM unit layer with physical or data-driven based models. Specifically, the virtual model can be considered a digital replica of AM process, machine, materials, designed products and even the entire manufacturing system. According to the type of data exchange between a physical object with its corresponding digital replica, the CPS for AM can be further categorized into a digital model, digital shadow, and digital twin, as shown in Fig. 4.

2.2.1. *Digital model*

The digital model is a category of CPS that is usually developed based on historical data collected from the cyber-physical layer. The service of the digital model usually is not related to the direct control of its corresponding physical objects or processes. However, it can indirectly affect its physical object or process. For example, a digital model can be established to optimize the printing orientation of parts with different geometries [39]. To build this model, only historical data that includes

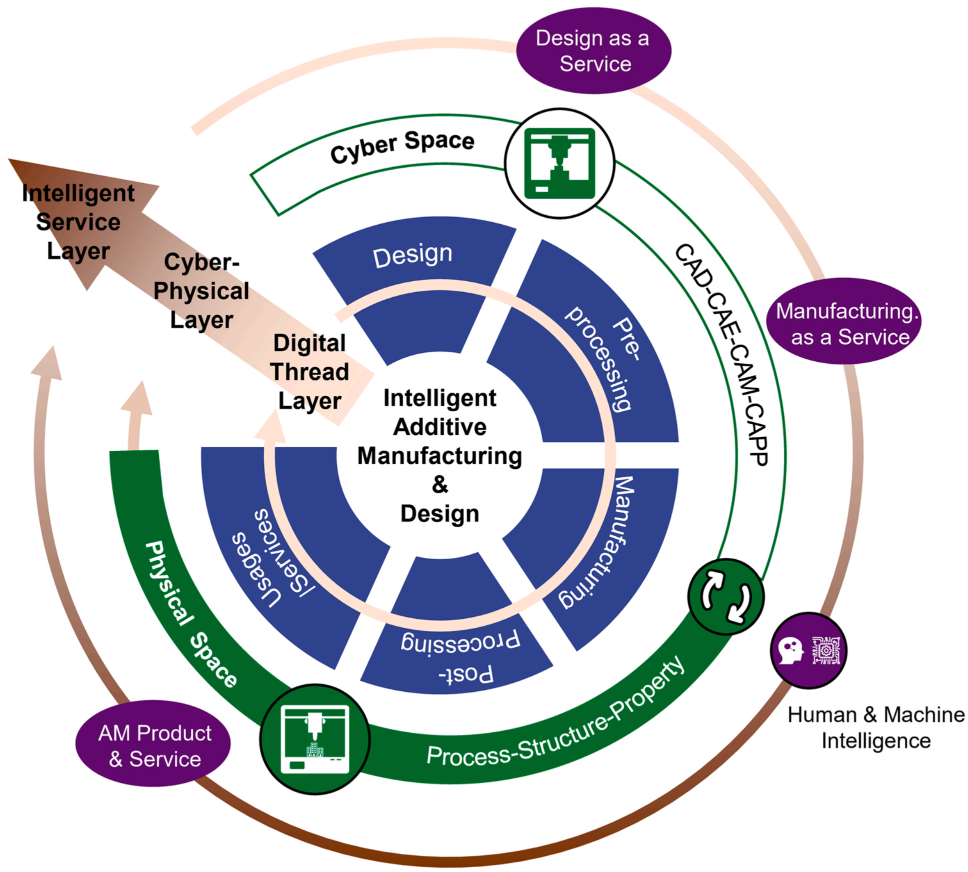

Fig. 2. A triple-layer model for intelligent additive manufacturing and design systems.

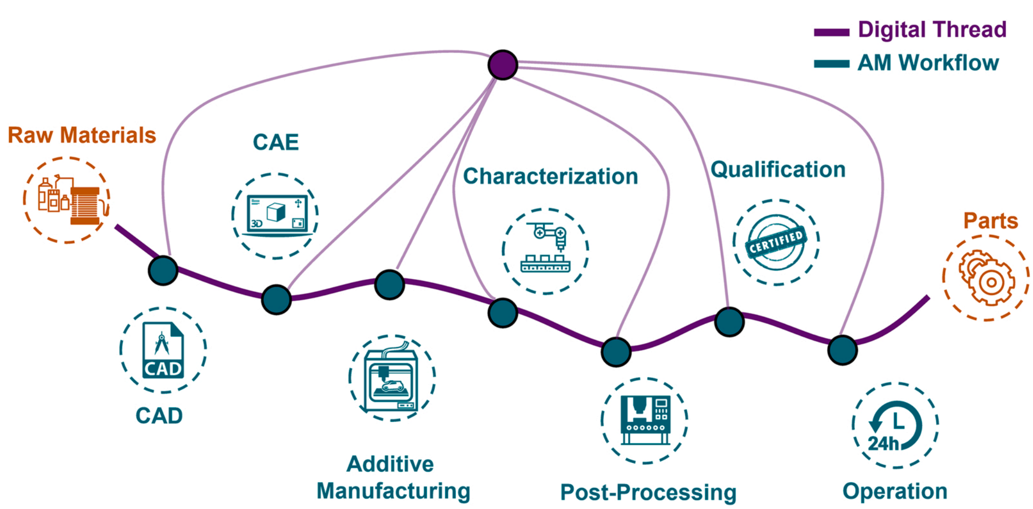

Fig. 3. The digital thread of additive manufacturing.

material properties and deformation of printed benchmark parts is used. The output of this model aims to predict the deformation of parts with different printing orientations and process parameters. Even though it cannot directly control the orientation of printed parts in the printing process, which it tries to digitally represent, the information it provides can help manufacturing engineers make the correct decision before the printing. Besides process planning [39,40], digital models can also be used for the prediction of AM fabricated part performance [41] or material properties [42], as well as the modeling of manufacturability of AM process [43]. The information obtained from the digital model of AM process can also be fed back to design stages and support better design optimization [41,43].

2.2.2. *Digital shadow*

The digital shadow is another category of CPS that is built based on the real-time data collected from its corresponding physical objects or processes. Similar to the digital model, digital shadows are also not used to directly control their corresponding physical objects or process. Usually, it provides a service that supports stakeholders to continuously improve the performance of its corresponding physical objects or

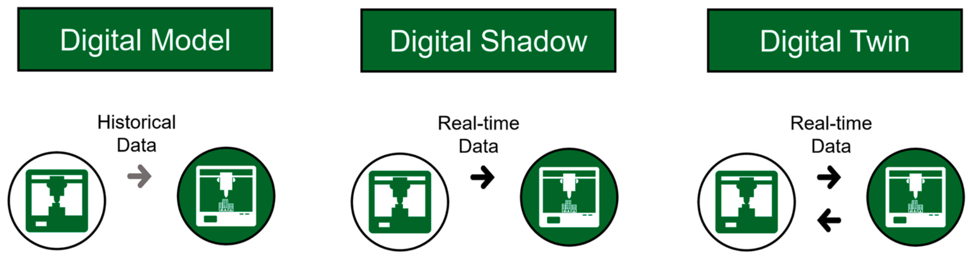

Fig. 4. Different models of cyber-physical systems for intelligent additive manufacturing and design.

process. The most common service in the field of AM that digital shadow is working on is for process monitoring and part qualification. For example, Scime et al. [44] has proposed an augmented intelligence relay framework to build a digital shadow for the qualification of parts fabricated by the PBF process; in this model, the real-time monitored process image data is used for process monitoring or qualification. Real-time data collected from different types of sensors can be integrated with multiple AI models to predict the localized tensile properties, which can be used for the qualification of fabricated parts. Compared to the digital model, the digital shadow is usually used for services that are more sensitive to real-time data during manufacturing or design. Thus, besides process monitoring or part qualification [45], the digital shadow of AM can also be directly used for failure detection [46] and predictive maintenance of machines.

2.2.3. *Digital twin*

Compared to the digital model and digital shadow, the unique feature of the digital twin is that this type of twin model enables the direct interaction between the physical and digital objects without human intervention. Compared to its two siblings, the service that the digital twin has played usually has a higher level of automation. It can be considered a nervous system added to the existing physical objects or processes. The most well-known service that the digital twin model involves is the adaptive process control of the AM process. This type of digital twin is usually built based on historical data, while real-time data will be used as its input. The twin model makes the correct action for the future fabrication process based on the real-time process conditions. In general, adaptive process planning is similar to conventional feedback loop control in the motion control system. However, the digital twin model provides more flexibility to the controller, which can even involve the entire manufacturing system. For example, the digital twin model can be used for virtual commissioning and dynamically scheduling different AM manufacturing resources. In the future, the digital twin of a product can be built that even supports the automated optimization and design of parts based on selected manufacturing machines without human intervention. Even though the digital twin model shows promising features and a high level of automation, it usually involves high implementation costs. Thus, stakeholders are still suggested to select the suitable types of digital twin models for the service they need.

2.3. *Intelligent AM service layer*

As discussed, the primary goal of developing the above digital twin-based cyber-physical AM system is to better support human-machine intelligence in making decisions that create products and associated services that satisfy customers' specific needs. In a broader sense, the stakeholder within the AM eco-system can be treated either as a service provider or a consumer. Herein, AM, same as other manufacturing technology, is undergoing a natural transformation of manufacturing as a service (MaaS) [47–51] to boost design and production capabilities. This subsection briefly discusses the impact of such a paradigm shift in the view of IAMD.

As shown in Fig. 5, services within the AM workflow include a) IAMD services and b) intelligent AM products and services. The first group of services can be viewed as resources used to create the second group of products and services. Both service types are controlled by human-machine intelligence. Such a service model of IAMD has several unique characteristics. Firstly, a hybrid intelligence is employed in decision-making to combine human and machine intelligence for obtaining better results than relying on each intelligence only. Moreover, more transparency and accessibility on design and manufacturing are provided to the decision-maker, including customers as well, to encourage value co-creation. Such characteristic is desired for all

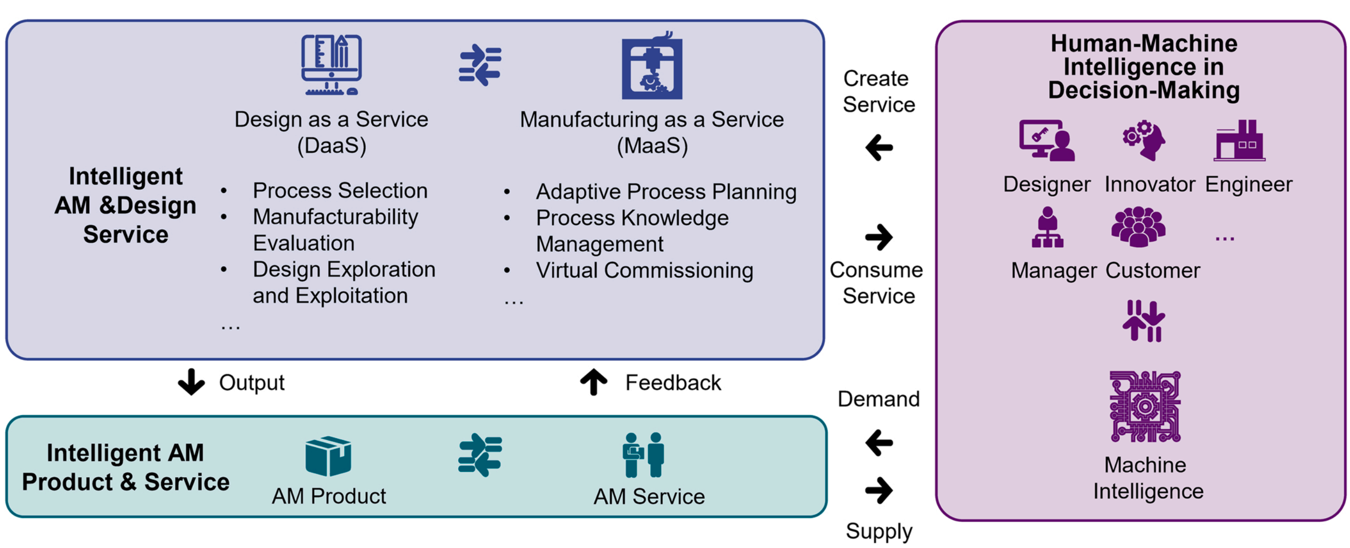

Fig. 5. The concept of intelligent additive manufacturing and design service.

manufacturing technologies but only can be easily implemented with AM due to its high process flexibility and agility. Additionally, bi-direction communications are allowed between services and decision-makers for timely feedback and response to dynamic environments. More details about the two types of services are detailed in the rest of the section.

2.4. Design as a service

Design for additive manufacturing (DfAM) is known as a design methodology with the aim to maximize product performance through the synthesis of shapes, sizes, hierarchical structures, and material compositions, subject to the capabilities of AM technologies[52]. Methods for DfAM include design heuristics, guidelines, computational design, and AI-assisted design. DfAM services include tasks for both redesigning of existing parts and designing from the ground up, which focus on design for opportunities and design to constraints [17,53], respectively. Hybrid intelligence has been applied in both tasks for creating design services. On the design to constraints side, services such as manufacturability evaluation [54,55] are desired given the limited ability of the human to understand the intricate relationships between design solutions and their manufacturing processes. Tools, e.g., automated decision support system (DSS) [56], and evaluation criteria [57–59] are developed to identify AM parts candidates. Meanwhile, previous research [60–62] also investigated decision support systems that match given product designs with processes, materials, and machines. Data-driven approaches are studied for instant cost-estimation [63,64]. Additionally, computational methods and tools for part consolidation [65] and decomposition [66,67] have been proposed to assist designers in decision-making.

On the opportunistic side, services, such as design space exploration and exploitation, are created for designers to gain insight into the design space of a specific problem and consequently make a well-informed decision. These tasks are nontrivial in DfAM because these design tasks, by nature, can be seen as multiscale, multidisciplinary, multi-objective, and high-dimensional problems. The existing design exploration and exploitation workflow is time-consuming and requires expertise since only a small set of variations can be tested in a reasonable amount of time. Meanwhile, there is an increasing need to further improve the efficiency and accuracy of DfAM methods for satisfying the diverse and rapidly changing market demands. Cost-efficient data-driven design space exploration methods based on surrogate modeling are proposed for mass customized products, such as ankle braces [12] and microbial fuel cell anodes [68]. Interactive design exploration and exploration methods [69] in DfAM are being explored to incorporate more human intelligence in decision-making.

2.5. Manufacturing as a service

The servitization of AM is carried out at several levels for different stakeholders with the assistance of hybrid intelligence. At the field level, the instrumentation of AM machines with sensors and monitoring systems supports services, including virtual commissioning for assisting field operations. These systems exist at different cost levels and for different AM processes, ranging from the low-cost OctoPi [70] for material extrusion to the expensive in-situ optical monitoring device for PBF. At the control level, knowledge-based computer aided systems that can capture, store, and reuse process knowledge are developed [71]. The use of data-knowledge-service structures allows the accumulated process know-how to benefit different stakeholders, e.g., product designers, operations engineers, and manufacturing bureaus through customized services. At the production planning level, software such as Materialise software tool Streamics [72] is developed as a manufacturing execution system with many embedded services, including end-to-end workflow control and machine planning for ensuring consistency in quality, traceability, and repeatability of AM parts.

2.6. Intelligent AM product & service

The direct outcomes of both design and manufacturing services are intelligent AM products and services. The advent of AM, particularly multi-material AM, enables the realization of intelligent and interconnected products with integrated functions [73], such as sensing [74], actuation, control, energy storage, and user interfaces [75]. These intelligent products make it viable to form a closed-loop design cycle with post-manufacturing data that improves product designs over time. This is critical to these products with design goals and constraints that change during the product service period or from one product generation to another according to the dynamic task environment. For instance, timely feedback about the interactions between assistive devices and their users can guide their AM and design processes. Additionally, highly customized products can be developed based on usage information collected from sensors. For maximizing information acquired for the design needs, previous studies [76] optimized the location of 3D printed sensors.

Additionally, several intelligent AM services based on digital infrastructures, such as cloud-based AM networks and product personalization, have emerged. These services are provided for all stakeholders within the AM ecosystem. For AM end-users, specific services can be AM workforce training etc. For machine manufacturers, AM machines and related services, such as online planning, are delivered together. Various business models with added-value services, such as the trade of data and transfer of accumulated AM knowledge, are expected to grow quickly. AM data possess polymorphic characteristics. For instance, Senvol [77] utilizes one dataset to provide diverse service types, e.g., Senovl database, Senovl API for automatic updates, and indexes for material characterization.

3. Key challenges and solutions

The implementation of the IAMD as represented by the triple-layer reference model is a non-trivial task. For digital thread and cyber-physical layers, the task is to have a seamless connection and systematic integration between design and manufacturing. Key challenges identified for realizing these two layers in the reference model are: 1. the digital design methods and tools, which serve as basic infrastructure for design; 2. advanced inspection and control, which provides assurance for manufacturing; 3. multidisciplinary design optimization, which offers a framework to link design and manufacturing. In addition, the realization of the intelligent service layer in the reference model is challenged by the lack of AI algorithms specific to AM. The rest of this section discusses these four key challenges with solutions in detail.

3.1. Digital design methods and tools

Digital design is the upper stream of AM fabrication process. The unique capabilities of AM processes bring both opportunities and challenges to further improve the performance of designed products. To address those opportunities and challenges, the role of digital design tools is becoming increasingly critical. They not only help designers to build geometry but also need to support the consideration of materials and process design which can be coupled with geometric design in AM. More importantly, the high degree of design freedom enabled by AM also requires the intelligence of digital design tools that can support designers to explore the design space. In this sub-section, the challenges that AM brings to digital design tools have been divided into three categories. Solutions for these challenges will be discussed respectively.

3.2. Heterogeneous object modeling for AM

Most existing CAD tools only support the modeling of a homogeneous object through B-Rep (boundary representation), implicit functions or polygon facet models, which seriously limits the multi-material and multi-scale design freedoms that AM has brought [78–80]. For a two-material part, designers need to build geometric models for two different materials and assemble them in the printing preparation software. Even though the techniques for multi-material or even heterogeneous objects with functional graded material compositions have been developed for more than two decades, they are still not widely adopted in existing design tools. The compatibility of these tools and existing CAD software is a major issue. Besides gradient material compositions, multi-scale micro- or mesoscale structures such as lattice or cellular materials brings another challenge to the convention design tool. These complex-shaped designs are manufactured with a single material but possess heterogeneous properties due to the rational design of micro- or mesoscale structures. Several methods, including implicit, F-Rep (function representation) and hybrid approaches, have been proposed to solve these issues, and some of them have been implemented in commercial CAD software. To further support the universal modeling and definition of meso- or microscale structures fabricated by AM, a universal material template has been defined [81]. Materials descriptors defined in the template provide a standard way to describe typical micro or mesoscale structures fabricated by AM, which provides a foundation for the next generation of CAD to support the modeling of both product's material and geometry.

3.3. Post-processing of facet models

For AM process, facet models with triangular or polygon mesh have been widely used. The geometry of some faceted models is easily controlled since they are converted from a native feature-based model, which is directly generated from a feature-based CAD tool. However, it should be noticed that there are still a great number of faceted models whose geometry is difficult to control. These models can be generated from Topology Optimization results or directly scanned from real physical objects. Due to the geometric complexities, these models usually contain some errors, such as non-manifold edges or small holes [82]. Albeit digital modeling tool such as Magics provides automated repairing of these model errors, manual operation is still needed, especially when the geometry is complex and automated repairing cannot generate the desired geometry. One step further to edit or control those facet models is even more difficult. To solve this challenge, there are two types of solutions. Firstly, remeshing [83] and mesh morphing [84] algorithms are developed, which enable the direct manipulation of the facet model. Some of those algorithms have been implemented into open-source tools such as MeshLab [85] to enable designers to edit facet models to achieve the desired post-processing like smoothness. However, those algorithms or tools are still difficult to parametrically control the shape of the model. The second approach is to reconstruct the feature-based model from the facet model. The reconstructed feature-based model can be easily modified. This approach can be further divided into three categories: skeleton-based, surface-based and volumetric-based [86]. Among them, skeleton-based approaches usually take advantage of different skeleton extraction algorithms to build the one-dimensional skeleton of input facet models. Then, this one-dimensional skeleton can be further thickened and converted into a feature-based model. Compared to skeleton-based reconstruction, surface-based approaches can be used for more complex geometries and achieve high accuracy of reconstruction. In surface-based approaches, the boundary of facet models will be fitted by different types of surfaces. For example, analytic surfaces such as fillets, arcs, lines and their extrusions can be used to fit the generated facet models from topology optimization [87]. However, this approach has certain limitations for the facet models whose geometry cannot be easily decomposed into those basic analytic shapes. Compared to analytic shape fitting, parametric surfaces such as NURBS surfaces [88] are more widely used. Even though surface-based approaches provide great flexibility to reconstruct the facet models with high complexities, the parametric control of reconstructed geometries is still a challenge. This issue can be well solved by volumetric-based approaches. For example, Du et al. [89] recently proposed an algorithm to reconstruct constructive solid geometry (CSG) tree. The shape of a reconstructed model can be easily controlled by directly manipulating the size of features on a CSG tree.

3.4. AI-driven design

The first two challenges mainly focus on the modeling of materials and geometry for AM-enabled design. Exploration of the design space of AM is another challenge that existing digital design tools are facing. Conventionally, designers can use CAD software to build several different designs with different geometries and materials. The performance of these designs can be evaluated manually using CAE software and then the best solution will be selected. This conventional design process is no longer valid for AM since both geometry and materials can be considered as the design variables, and numerous design variations can be generated. More importantly, mass customization brings an even higher requirement on the design tool itself. Thus, digital design tools themselves should have certain intelligence that assists designers to quickly combining geometry, materials and even process parameters to respond to the input design specifications and functional requirements. For example, on conceptual level design, a case-based reasoning system or ontology-based DfAM knowledge base can provide suggestions for designers on the potential parts in the product that can be beneficial to AM or can identify the potential parts that can be consolidated[90–92]. To further improve and enlarge the design space, GAN (Generative Adversarial Network) will be used to generate more design options. A conditional GAN model will be applied to automatically generate or modify the existing design concepts to meet specialized customer requirements[93]. In the detail design stage, AI algorithms such as Artificial Neural Networks and the Gaussian Process Regression (GPR) model can be applied to build the surrogate model that can describe the process-structure-properties relationship of AM process. This model will enable designers to optimize both geometries, process parameters and materials microstructures to further improve the performance of designed products. More importantly, the historical data from selected AM machines will be considered and fed into the Bayesian uncertainty analysis model. It will support the generation of parts geometry that can minimize the effects of uncertainty factors on the performance of designed AM fabricated parts. Besides part's performance, the environmental impacts, maintenance and other product key life cycle considerations will be predictable based on machine learning models established based on historical data or data obtained from physical-based simulation models as well as product life cycle analysis. More importantly, AI will enable the self-learning capabilities of design tools. A reinforcement learning algorithm can be applied to support designers iteratively improving the designed products fabricated by AM. In summary, AI techniques will fill the knowledge gap for the designers without expertise in AM technologies as advanced skills in geometric modeling. It will make the designed parts a good fit for each personalized customer's needs and shorten the lead time and cost during the design stage.

3.5. Advanced inspection and control

Sensing guarantees real-world information about AM is automatically and timely updated in the decision-making process. Meanwhile, control ensures these decisions on AM are executed as desired. However, sensing and control of AM processes remain challenging due to their high dynamics and complexities. In-situ sensing is needed to study the underlying physics, which happens at a fast speed (down to microsecond) in the temporal domain and at a small length scale (down to micro-meter) in the spatial domain. Advanced sensing methods, such as high spatiotemporal resolution sensing, multi-sensor data fusion, and real-time image processing, are critical. More and more closed-loop control AM systems are proposed to improve the manufacturing process.

3.5.1. In-situ inspection and monitoring

It is of great interest to gain insight into the AM process for part qualification and defect detection purposes. Thus, related technologies have been greatly advanced within the last decade. Commercial PBF machines with in-situ measurement systems have become the norm [94]. However, continuous efforts are being made to further improve the capability and quality of measurements. New sensing principles and devices have been adopted. For instance, advanced high spatiotemporal resolution sensing techniques, such as synchrotron x-ray tomography, have been used to capture the thermophysical phenomena within the melt pool of metal AM. In addition, due to the high sampling rate (up to 10 kHz) and resolution, signals captured from sensors are often locally processed before communications, only extracted features are then transferred and stored. Hardware, such as the field-programmable gate array (FPGA), is utilized [95]. Also, the in-situ data, e.g., melt pool images, can be used together with ex-situ measurement, e.g., bead geometries and porosity measurements, for training models to be later used for online monitoring [96,97]. Recent advances utilize deep transfer learning methods to inspect the quality of each layer based on visual images without manual feature extraction.

3.5.2. Multi-sensor measurement and data fusion

As discussed, since the AM process involves multiple length scales, combining different sensing principles to complement each other proves to be an efficient approach to overcome the limitations of a single sensor, e.g., conflicts between measurement resolution and range. Measurements conducted by different sensors are either spatial based, images from a camera, or temporal based, e.g., the melt pool temperature from an infrared thermometer. Correlating heterogeneous datasets, including both in-situ measurements and post-build characterizations for a component of interest and its AM processes into a single coordinate system, is an important research topic known as data registration [98,99]. Reference [100] reports a case study that combines sensing, monitoring data and scan path to facilitate anomaly detection. In addition, measurements are interpreted with the help of physics-based models to estimate process states, e.g., part wrappage [101].

3.5.3. Closed-loop control of process

The current open-loop controlled AM process suffers from quality issues, e.g., high failure rates and low repeatability. Many model-based feed-forward control schemes have been proposed based on empirical models from system identification, physics-based ordinary-differential-equation models [102] and finite-element analysis models [103]. However, modeling the complex AM process remains a challenge. Closed-loop controlled AM systems can analyze the printing process in real-time based on feedback from the online monitoring system and regulate the process variables to the desired state [104]. Both model-based and data-driven control strategies have been proposed for AM control. Due to the limitations inherent in manipulating the laser at high speeds, fine-grained closed-loop control may be difficult due to the lag time between the order to execute an action (i.e., changing the velocity or power) and the time at which the parameter is changed. Deep reinforcement learning-based control strategy is proposed for dynamic processes.

3.6. Multidisciplinary design optimization

Decision-making activities in AM often involve variables from several fields, including product design, material selection [105], and process planning [13]. However, the existing sequential design process does not sufficiently consider the couplings among these domains, such as shared variables, related constraints, and conflicting objectives, resulting in inefficient design workflows and suboptimal design solutions. To address the above issues, manufacturing constraints, e.g., support structures [106], and properties of as-fabricated parts, e.g., material anisotropy and geometric inaccuracy [107,108], are introduced into structural design. However, these methods still cannot fully consider the effects of couplings and realize a concurrent design of material-process-performance [109].

3.6.1. Multidisciplinary design optimization framework

Recently, the concept of multidisciplinary design optimization, a well-established design framework for complex systems [110], has been introduced into the DfAM field. As shown in Fig. 6, this concurrent optimization method supports a simultaneous design of AM products, materials, and manufacturing processes [111] under complex constraints. The workflow is based on the automated exchange of design information, and its main steps include problem decomposition, discipline analysis, solving strategy selection, and solution generation. Different multidisciplinary design optimization architectures, e.g., monolithic and distributed, should be carefully selected according to the nature of the problems.

3.6.2. Approximations and response surface methodology

Since various design evolution methods, e.g., experiments, measurements, and numerical simulations, are often used in discipline analysis, the time cost for different analyses is difficult to synchronize, and analyze information, e.g., gradients, are not accessible. To this end, surrogate modeling approaches such as GPR [12,112] are often used to approximate high-fidelity models and provide a rapid enough prediction to support design and optimization needs. Deep learning algorithms, e.g., conditional GAN [93], are applied to the manufacturing constraint-aware structural design applications in the early stage of design, where a large number of iterations are needed to satisfy the evolving design objectives. In addition, interactive visualization of the decision and trade spaces for the multi-objective design problems should also be studied further [13]. Another challenge to be addressed is the rational use of data with different fidelities and costs, including computer simulations and experiments, as well as analytical and numerical models. Various multi-fidelity metamodeling methods, e.g., co-Kriging, and scaling-function-based multi-fidelity surrogate modeling, for data assimilation have been proposed to ensure high accuracy and fast prediction while minimizing the cost [113,114]. Recently, reference [115] reported a deep learning-based method called multi-fidelity point-cloud neural network (MF-PointNN) for melt pool modeling.

3.6.3. Uncertainty quantification and management

One distinct feature of design optimization for AM in comparison to conventional manufacturing is the high process uncertainty[11,116]. AM products' variability results from multiple uncertainty sources, including raw materials, manufacturing processes, simulation models, and sensor measurements. Previous efforts are made in two directions: uncertainty quantification and process optimization under uncertainty. Both experiment- and simulation-based uncertainty quantification methods have been investigated. The experiment-based method mainly studies the effect of various process parameters on the as-built properties using physical experiments. Meanwhile, models at different time- and length scales have also been developed to represent the complexity involved within the multiscale nature, including the heat source, solidification, melt-pool, thermal distribution, and part distortion model. The convolution of all these scales of uncertainties calls for more sophisticated algorithms and analytical models. In addition, both the aleatory uncertainty, caused by the natural variability and epistemic uncertainty, due to the lack of knowledge, are found within the AM process. These uncertainties need to be identified and studied separately. Previous research utilizes reliability-based design optimization (RBDO) and robust design optimization (RDO) for determining process parameters to reduce uncertainties. However, due to the coupling nature among materials, processes, and structures, these uncertainties should also be simultaneously considered. Thus, incorporating these uncertainty quantification models within the multidisciplinary design optimization framework is desired for accounting for the propagation of

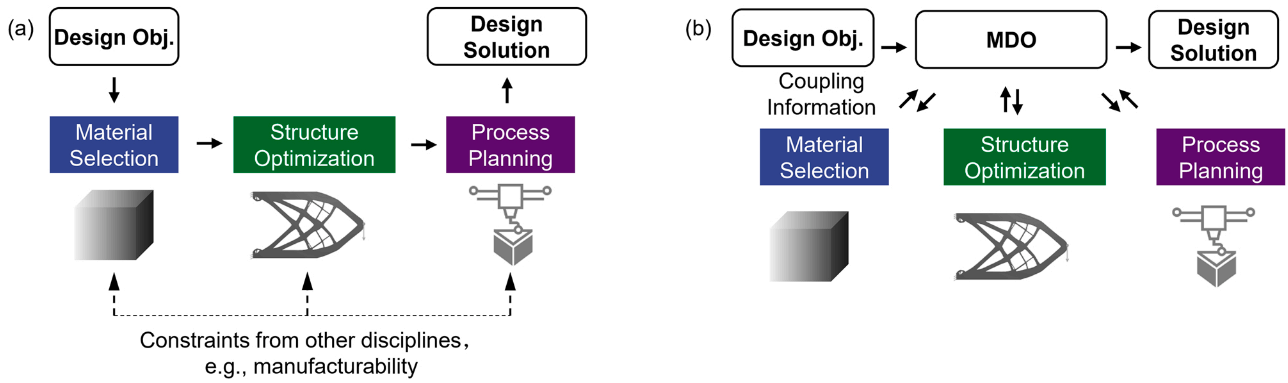

Fig. 6. (a) Sequential design for additive manufacturing process; (b)Concurrent design for additive manufacturing process based on multidisciplinary design optimization.

uncertainties among different disciplines or sequential steps and alleviating quality control issues.

3.7. AI for AM

AI is a powerful tool to automate decision-making and solve high-dimensional decision-making problems. Although AI has progressed rapidly, research on AI's application in AM remains a nascent field. Previous works [22,117–119] attempt to identify potential applications that can leverage AI as a powerful tool in solving AM problems. The next task is to extend the capability of current AI algorithms to solve problems in different AM scenarios and industrial environments.

3.7.1. AI for diverse applications

Current general AI cannot be applied directly in specialized AM applications as their requirements and resources are distinct. For instance, the task for predicting process-property relationships will be different for conceptual design with a low-cost fused deposition modeling process and for online monitoring with a high-end PBF process in terms of response time, fidelity level, and cost. Meanwhile, the implementation of AI also needs to consider existing resources within different AM scenarios, including data quality, data sources, and algorithm availability. As discussed above, AM data are often heterogeneous, limited, and unstructured. In addition, some applications, e.g., process planning, indeed accumulated a large amount of data, but these historical data are often not prepared for AI applications. Moreover, there is no suitable algorithm to cope with some widely used data representation within AM, e.g., CAD models and scan vectors. Specific AI algorithms, such as geometric deep learning, are still under development. For example, datasets based on the combination of geometry primitives have been created for training a 3D U-Net convolution neural network model that can predict residual stress distribution at a part-scale [120]. In summary, it is critical to clearly formulate the AM problem for developing AI solutions considering the requirements and resources.

3.7.2. AI for industrial environments

Applications of AI for solving AM problems in industrial settings are rarely reported. One main reason is data scarcity, as most commercial AM machines have a closed data environment in which files are encrypted. The size of available datasets is often small, facing the risk of overfitting. Advances methods, such as few-shot learning, have been proposed to use prior knowledge for tackling these issues from the aspects of data, model, and algorithm[121]. Moreover, industrial applications often have rigorous requirements regarding the speed, memory consumption, and computational cost of AI solutions. In such an environment, the AI agent should be capable of rapid decision-making to avoid any unplanned outages, such as machine breakdown. Algorithms based on edge, fog and cloud computing are promising solutions for addressing these concerns. Additionally, the less transparency of AI within the decision-making process creates barriers for safety-critical industries, e.g., aerospace engineering. The underlying rules and reasoning logics of AI models are poorly understood and remain "black boxes" to decision-makers. This greatly limits the broad adoption of AI for industry applications, e.g., quality assurance and part qualification, in which the process must have high interpretability, traceability and clarity. Fortunately, recent progress on explainable and mechanistic AI [122,123] shed light on these problems. Previous studies also demonstrate that models incorporated with physical process insights outperform purely data-driven black-box models [124].

4. Discussion and future trends

The section discusses future trends for each layer within reference model respectively, i.e., integrated design and manufacturing, cyber-physical AM, and advanced AI for AM. Also, digital materials and products as an outcome of the reference model is also elaborated. With the transition of AM towards a viable production option, the design for AM process chain is also identified as a future trend.

4.1. Integrated design and manufacturing

Design and manufacturing capabilities greatly affect the possibility to develop products that satisfy the customer's unique needs at a low cost. The development of design methodology for mass customization, such as product family design, and product platform, has been ahead of their manufacturing methods for a long period. Such a mismatch calls for flexible manufacturing processes. AM, as a flexible manufacturing process by default, can seamlessly integrate with these design methods to form a system for mass customization. Previously, the representation of design knowledge for customized DfAM was developed [125]. In the future, the use of a computational-based approach, e.g., generative design, supports the realization of personalization at affordable costs. Meanwhile, a data-driven framework that encompasses knowledge management and concurrent optimization of embodiment design and process parameters is also developed [126]. Additionally, the product platform and family design methodology for combined additive and subtractive manufacturing is being studied [127] to satisfy the conflicting objectives of product variation and manufacturing costs.

4.2. Cyber-physical AM

The current physics-based approach alone is inefficient in solving dynamic AM problems due to the large modeling error and high computational cost. Meanwhile, pure data-driven approaches cannot provide sufficient insight to support engineers in decision-making due to the lack of transparency and interpretability. To address these challenges, hybrid approaches relying on both physics-based and data-driven methods are therefore proposed as a new solution to provide timely response to in-situ changes and reduce data needs. In-situ process measurements can be used to calibrate the physics-based models. For instance, Bayesian calibration based on thermal imaging data is used to update the surrogate model constructed based on finite element analysis [128]. In-line feedback on additive print geometries is used to predict the performance of print builds without an expensive physics-based approach [129]. In addition, the concept of physics-informed data--driven method [129] and mechanistic artificial intelligence [123] are proposed, which integrate physics and domain knowledge into machine learning model inputs, outputs, architecture, and training. For instance, the spatiotemporal dependencies in AM processes, often modeled through physics-based simulation, are replaced with a graph neural network, which is faster to compute [130].

4.3. Advanced AI for AM

Current applications of machine intelligence in AM are still at a relatively low level. In corresponding to different types of human intelligence, machine intelligence can be divided into computational, perceptual, and cognitive intelligence. The applications of computational intelligence are reported for tackling AM design problems that require extensive computing, such as model-based design, structural design, and integrated computational material engineering (ICME). Meanwhile, perceptual intelligence in AM refers to the use of physical and cyber sensors to monitor the AM process. Such intelligence is critical to realizing a closed control loop for improving the producibility, repeatability, and reproducibility of the process. Cognitive intelligence in AM has received much attention due to its potential to manage AM-related knowledge. A machine learning-based approach is proposed in [131] to construct knowledge based on prior AM knowledge and data. Ontology methods and tools [90,132,133] have been adopted for management of AM knowledge that supports the structurization, storage, and reuse of design and process knowledge. Several studies [71,134] have demonstrated the use of knowledge engineering tools to support part design and process planning. Advanced machine learning algorithm such as reinforcement learning [135], and transfer learning supports knowledge reasoning that is geometry or even processed independently.

4.4. Digital materials and products

Digital material is a type of materials whose meso- or microscale structures can be directly controlled through digital manufacturing processes such as AM. Compared to conventional materials, the properties of digital materials can be fully customized, and it opens a new door to further push forward the boundary of the material properties space. Typical digital materials fabricated by AM include porous lattice [136], cellular materials, and continuous fiber composites whose orientations can also be digitally controlled through the optimized toolpath [137]. It also consists of those material jetting (e.g., Polyjet) printed digital composites with more than two types of polymers combined at the mesoscale. Existing research [81,138,139] has already proved that the performance of structures fabricated by digital materials can be further improved by spatially controlling the properties of digital materials fabricated by AM process. To further expand the applications of digital materials, a more advanced AM process should be developed which can combine multi-metals, metals-ceramics, or metal-fibers on micro- or mesoscale levels. This can further expand the design space of digital materials. Secondly, exploring multi-scale digital materials is a potential way to further push forward the boundary of the materials design space. Thirdly, a digital design tool should be developed which enables the design and modeling of digital materials in existing geometric-centered CAD tools.

4.5. Design for AM process chain

Considering the entire process chain instead of only the AM step within the decision-making process is indispensable for the development of high-quality industrial-grade parts. These parts, particularly metal ones, are often fabricated by multiple post-processing operations, e.g., heat treatment, support structure removal, and finished machining. The properties of the final part depend on the cumulative effects of each step in the process chain. Thus, the process exploration and planning must be carried out on both system and subsystem levels that consider each step's underlying mechanisms and interplays to achieve design requirements. For instance, the process chain can select a faster PBF process, e.g., using a large hatching distance and scanning speed, if subsequent heat treatment can provide the needed properties by reducing porosities of as-built parts. Research addressing this critical research issue is still in its infancy. Reference [140] outlines the problem formulation of product-process chain co-design for the first time, laying the foundation for further studies. Additionally, multidisciplinary design optimization tools, including the process chain map, are also proposed for problem-solving.

5. Conclusions

Utilizing intelligent technologies in AM and design for AM enables new opportunities to facilitate effective, efficient, and economic decision-making within the design-to-product workflow, boosting the capabilities of processes and product innovations. This paper presents the concept of IAMD from the perspective of its definition, key technologies, and future trends. The following points are emphasized within the paper.

(1) Within the path toward intelligent manufacturing, AM faces several challenges within AM's decision-making process, i.e., limited information, large uncertainties, and high-dimensional design spaces. These challenges are expected to be solved by the rational use of advanced machine and human intelligence.
(2) IAMD can be broadly defined as a concept of manufacturing with the aim to maximize the value of AM by fully utilizing its design freedom in terms of materials, structures, and processes through interactions with cyber-physical systems based on both human and machine intelligence. The reference model consists of three layers: digital thread, cyber-physical system, and intelligent service.
(3) Four key technologies within the development of IAMD are identified as follows: digital methods and tools provide the infrastructure for design; advanced sensing and control provide assurance for the manufacturing process; multidisciplinary design optimization creates a framework for co-design of products and process, and AI algorithms for AM support the decision-making by human and machine intelligence.
(4) Future trends of intelligent AM and design are recommended as follows: integrated design and manufacturing, advanced AI for AM, cyber-physical AM, digital materials and products, as well as design for AM process chain.

This review paper shed light on the concept of IAMD, which represents the advance of the intelligent manufacturing and cyber-physical system ideas to AM. However, the implementation of this concept still needs considerable efforts. Most case reported are still limited to proof-of-concept studies. Future works include implementations of several unrealized concepts, particularly these in intelligent services layers. Also, incorporating core values of industrial 5.0 [141], such as sustainability, human-centricity and resilience, into the IAMD is worth investigating.

CRediT authorship contribution statement

Xiong Yi: Writing – original draft, Visualization, Methodology, Investigation, Funding acquisition, Conceptualization. **Tang Yunlong:** Writing – original draft, Methodology, Investigation, Conceptualization. **Zhou Qi:** Writing – original draft, Investigation. **Ma Yongsheng:** Writing – review & editing, Supervision. **Rosen David W.:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:Yi Xiong reports financial support was provided by the National Key Research and Development Program of China. Yi Xiong reports financial support was provided by the National Natural Science Foundation of China. David Rosen reports financial support was provided by the Singapore National Research Foundation.

Data availability

Data will be made available on request.

Acknowledgments

X.Y. acknowledges the National Key Research and Development Program of China [Grant No. 2021YFB1715400] and National Natural Science Foundation of China [Grant No. 52105261]. D.R. acknowledges the Singapore National Research Foundation [Grant No. A19E10097].

References

[1] I. Gibson, D.W. Rosen, B. Stucker, Additive manufacturing technologies, Rapid Prototyp. Direct Digit. Manuf. vol. 54 (2009), https://doi.org/10.1007/978-1-4419-1120-9.

[2] N. Aage, E. Andreassen, B.S. Lazarov, O. Sigmund, Giga-voxel computational morphogenesis for structural design, Nature 550 (2017) 84–86, https://doi.org/10.1038/nature23911.

[3] X. Zheng, H. Lee, T.H. Weisgraber, M. Shusteff, J. DeOtte, E.B. Duoss, et al., Ultralight, ultrastiff mechanical metamaterials, Science 344 (1979) (2014) 1373–1377, https://doi.org/10.1126/science.1252291.

[4] Y. Wang, L. Li, D. Hofmann, J.E. Andrade, C. Daraio, Structured fabrics with tunable mechanical properties, Nature 596 (2021) 238–243, https://doi.org/10.1038/s41586-021-03698-7.

[5] G. Liu, Y. Xiong, L. Zhou, Additive manufacturing of continuous fiber reinforced polymer composites: Design opportunities and novel applications, Compos. Commun. 27 (2021), 100907, https://doi.org/10.1016/J.COCO.2021.100907.

[6] W. Zhang, H. Wang, H. Wang, J.Y.E. Chan, H. Liu, B. Zhang, et al., Structural multi-colour invisible inks with submicron 4D printing of shape memory polymers, Nat. Commun. (2021) 12, https://doi.org/10.1038/S41467-020-20300-2.

[7] J.Y.E. Chan, Q. Ruan, M. Jiang, H. Wang, H. Wang, W. Zhang, et al., High-resolution light field prints by nanoscale 3D printing, Nat. Commun. (2021) 12, https://doi.org/10.1038/S41467-021-23964-6.

[8] T. Chen, M. Pauly, P.M. Reis, A reprogrammable mechanical metamaterial with stable memory, Nature 589 (2021) 386–390, https://doi.org/10.1038/s41586-020-03123-5.

[9] S. Mahadevan, P. Nath, Z. Hu, Uncertainty Quantification for Additive Manufacturing Process Improvement: Recent Advances, ASCE-ASME J. Risk Uncert Engrg Sys Part B Mech. Eng. (2022) 8, https://doi.org/10.1115/1.4053184/1129174.

[10] 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. Trans. ASME (2019) 141, https://doi.org/10.1115/1.4043798/726777.

[11] Z. Wang, C. Jiang, P. Liu, W. Yang, Y. Zhao, M.F. Horstemeyer, et al., Uncertainty quantification and reduction in metal additive manufacturing, Npj Comput. Mater. (2020) 6, https://doi.org/10.1038/s41524-020-00444-x.

[12] Y. Xiong, P.L.T. Duong, D. Wang, S.I. Park, Q. Ge, N. Raghavan, et al., Data-driven design space exploration and exploitation for design for additive manufacturing, J. Mech. Des. 141 (2019) 101101–101101–12, https://doi.org/10.1115/1.4043587.

[13] Y. Xiong, Y. Tang, S. Park, D.W. Rosen, Harnessing process variables in additive manufacturing for design using manufacturing elements, J. Mech. Des., Trans. ASME (2020), https://doi.org/10.1115/1.4046069.

[14] Z. Jin, Z. Zhang, K. Demir, G.X. Gu, Machine learning for advanced additive manufacturing, Matter 3 (2020) 1541–1556, https://doi.org/10.1016/J.MATT.2020.08.023.

[15] J. Wang, Y. Ma, L. Zhang, R.X. Gao, D. Wu, Deep learning for smart manufacturing: Methods and applications, J. Manuf. Syst. 48 (2018) 144–156, https://doi.org/10.1016/j.jmsy.2018.01.003.

[16] R.Y. Zhong, X. Xu, E. Klotz, S.T. Newman, Intelligent Manufacturing in the Context of Industry 4.0: A Review, Engineering 3 (2017) 616–630, https://doi.org/10.1016/J.ENG.2017.05.015.

[17] D.W. Rosen, Thoughts on Design for Intelligent Manufacturing, Engineering 5 (2019) 609–614, https://doi.org/10.1016/J.ENG.2019.07.011.

[18] T.W. Simpson, C.B. Williams, M. Hripko, Preparing industry for additive manufacturing and its applications: Summary & recommendations from a National Science Foundation workshop, Addit. Manuf. 13 (2017) 166–178, https://doi.org/10.1016/J.ADDMA.2016.08.002.

[19] Y. Wang, Y. Lin, R.Y. Zhong, X. Xu, IoT-enabled cloud-Based Addit. Manuf. Platf. Support rapid Prod. Dev. vol. 57 (2019), https://doi.org/10.1080/00207543.2018.1516905.

[20] A. Majeed, Y. Zhang, S. Ren, J. Lv, T. Peng, S. Waqar, et al., A big data-driven framework for sustainable and smart additive manufacturing, Robot. Comput. -Integr. Manuf. 67 (2021), 102026, https://doi.org/10.1016/J.RCIM.2020.102026.

[21] C. Wang, X.P. Tan, S.B. Tor, C.S. Lim, Machine learning in additive manufacturing: State-of-the-art and perspectives, Addit. Manuf. 36 (2020), 101538, https://doi.org/10.1016/J.ADDMA.2020.101538.

[22] J. Qin, F. Hu, Y. Liu, P. Witherell, C.C.L. Wang, D.W. Rosen, et al., Research and application of machine learning for additive manufacturing, Addit. Manuf. 52 (2022), 102691, https://doi.org/10.1016/j.addma.2022.102691.

[23] Y. Qin, Q. Qi, P.J. Scott, X. Jiang, Status, comparison, and future of the representations of additive manufacturing data, Comput. -Aided Des. 111 (2019) 44–64, https://doi.org/10.1016/J.CAD.2019.02.004.

[24] H. Fuwen, C. Jiajian, H. Yunhua, Interactive design for additive manufacturing: a creative case of synchronous belt drive, Int. J. Interact. Des. Manuf. 12 (2018) 889–901, https://doi.org/10.1007/S12008-017-0453-5.

[25] L. Haghnegahdar, S.S. Joshi, N.B. Dahotre, From IoT-based cloud manufacturing approach to intelligent additive manufacturing: industrial Internet of Things—an overview, Int. J. Adv. Manuf. Technol. 119 (2022) 1461–1478, https://doi.org/10.1007/S00170-021-08436-X/FIGURES/10.

[26] D. Mies, W. Marsden, S. Warde, Overview of Additive Manufacturing Informatics: "A Digital Thread.", Integr. Mater. Manuf. Innov. 5 (2016) 114–142, https://doi.org/10.1186/S40192-016-0050-7/FIGURES/17.

[27] R. Bonnard, J.Y. Hascoët, P. Mognol, Data model for additive manufacturing digital thread: state of the art and perspectives 32 (2019) 1170–1191, https://doi.org/10.1080/0951192X.2019.1690681. ⟨Https://DoiOrg/101080/0951192×20191690681⟩.

[28] D.B. Kim, P. Witherell, Y. Lu, S. Feng, Toward a digital thread and data package for metals-additive manufacturing, Smart Sustain. Manuf. Syst. (2017) 1, https://doi.org/10.1520/SSMS20160003.

[29] R. Bonnard, J.Y. Hascoët, P. Mognol, E. Zancul, A.J. Alvares, Hierarchical object-oriented model (HOOM) for additive manufacturing digital thread, J. Manuf. Syst. 50 (2019) 36–52, https://doi.org/10.1016/j.jmsy.2018.11.003.

[30] V. Singh, K.E. Willcox, Decision-making under uncertainty for a digital thread-enabled design process, J. Mech. Des., Trans. ASME (2021) 143, https://doi.org/10.1115/1.4050108.

[31] D.B. Kim, P. Witherell, R. Lipman, S.C. Feng, Streamlining the additive manufacturing digital spectrum: A systems approach, Addit. Manuf. 5 (2015) 20–30, https://doi.org/10.1016/J.ADDMA.2014.10.004.

[32] Y. Qin, Q. Qi, P.J. Scott, X. Jiang, Status, comparison, and future of the representations of additive manufacturing data, Comput. -Aided Des. 111 (2019) 44–64, https://doi.org/10.1016/J.CAD.2019.02.004.

[33] Garanger K., Feron E., Garoche P.-L., Rimoli J.J., Berrigan J.D., Grover M., et al. Foundations of intelligent additive manufacturing. ArxivOrg n.d.

[34] G.P. Gujarathi, Y.S. Ma, Parametric CAD/CAE integration using a common data model, J. Manuf. Syst. 30 (2011) 118–132, https://doi.org/10.1016/j.jmsy.2011.01.002.

[35] Nassar A., Solid ER-2013 I., 2013 undefined, A proposed digital thread for additive manufacturing. RepositoriesLibUtexasEdu n.d.

[36] Lu Y., Choi S., Witherell P. Towards an integrated data schema design for additive manufacturing: Conceptual modeling. Proceedings of the ASME Design Engineering Technical Conference 2015;1A-2015. https://doi.org/10.1115/DETC2015–47802.

[37] R. Bonnard, J.Y. Hascoët, P. Mognol, I. Stroud, STEP-NC digital thread for additive manufacturing: data model, implementation and validation 31 (2018) 1141–1160, https://doi.org/10.1080/0951192X.2018.1509130. ⟨Https://DoiOrg/101080/0951192×20181509130⟩.

[38] L. Wang, M. Törngren, M. Onori, Current status and advancement of cyber-physical systems in manufacturing, J. Manuf. Syst. 37 (2015) 517–527, https://doi.org/10.1016/j.jmsy.2015.04.008.

[39] A.I. Borovkov, L.B. Maslov, K.S. Ivanov, E.N. Kovaleva, F.D. Tarasenko, M. A. Zhmaylo, Improving the printing process stability and the geometrical accuracy of the parts manufactured by the additive techniques, IOP Conf. Ser.: Mater. Sci. Eng. (2020) 986, https://doi.org/10.1088/1757-899X/986/1/012033.

[40] C.G. Klingaa, S. Mohanty, C. v Funch, A.B. Hjermitslev, L. Haahr-Lillevang, J. H. Hattel, Towards a digital twin of laser powder bed fusion with a focus on gas

flow variables, J. Manuf. Process. 65 (2021) 312–327, https://doi.org/10.1016/j.jmapro.2021.03.035.
[41] I. Sieber, R. Thelen, U. Gengenbach, Enhancement of high-resolution 3d inkjet-printing of optical freeform surfaces using digital twins, Micro (Basel) 12 (2021) 1–12, https://doi.org/10.3390/MI12010035.
[42] A. Özen, B.E. Abali, C. Völlmecke, J. Gerstel, D. Auhl, Exploring the Role of Manufacturing Parameters on Microstructure and Mechanical Properties in Fused Deposition Modeling (FDM) Using PETG, Appl. Compos. Mater. 28 (2021) 1799–1828, https://doi.org/10.1007/s10443-021-09940-9.
[43] Y. Tang, G. Dong, Q. Zhou, Y.F. Zhao, Lattice structure design and optimization with additive manufacturing constraints, IEEE Trans. Autom. Sci. Eng. 15 (2018) 1546–1562, https://doi.org/10.1109/TASE.2017.2685643.
[44] 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, https://doi.org/10.1016/J.MFGLET.2021.05.007.
[45] Chhetri S.R., Faezi S., Canedo A., Faruque M.A. al. QUILT: Quality inference from living digital twins in IoT-enabled manufacturing systems. IoTDI 2019 - Proceedings of the 2019 Internet of Things Design and Implementation 2019: 237–48. https://doi.org/10.1145/3302505.3310085.
[46] 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 52 (2020) 1204–1217, https://doi.org/10.1080/24725854.2019.1701753. ⟨Https://DoiOrg/101080/2472585420191701753⟩.
[47] Y. Liu, L. Wang, X.V. Wang, X. Xu, P. Jiang, Cloud manufacturing: key issues and future perspectives, Int. J. Comput. Integr. Manuf. 32 (2019) 858–874, https://doi.org/10.1080/0951192X.2019.1639217.
[48] D. Wu, D.W. Rosen, L. Wang, D. Schaefer, Cloud-based design and manufacturing: A new paradigm in digital manufacturing and design innovation, CAD Comput. Aided Des. 59 (2015) 1–14, https://doi.org/10.1016/j.cad.2014.07.006.
[49] D. Wu, J. Lane Thames, D.W. Rosen, D. Schaefer, Enhancing the product realization process with cloud-based design and manufacturing systems, J. Comput. Inf. Sci. Eng. (2013) 13, https://doi.org/10.1115/1.4025257.
[50] Tao F., Zhang L., Venkatesh V.C., Luo Y., Cheng Y. Cloud manufacturing: A computing and service-oriented manufacturing model. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 2011; 225: 1969–76. https://doi.org/10.1177/0954405411405575.
[51] A. Kusiak, Service manufacturing: Basic concepts and technologies, J. Manuf. Syst. 52 (2019) 198–204, https://doi.org/10.1016/j.jmsy.2019.07.002.
[52] D.W. Rosen, Research supporting principles for design for additive manufacturing, Virtual Phys. Prototyp. 9 (2014) 225–232, https://doi.org/10.1080/17452759.2014.951530.
[53] Y. Tang, Y.F. Zhao, A survey of the design methods for additive manufacturing to improve functional performance, Rapid Prototyp. J. 22 (2016) 569–590, https://doi.org/10.1108/RPJ-01-2015-0011.
[54] Y. Zhang, Y.F. Zhao, Hybrid sparse convolutional neural networks for predicting manufacturability of visual defects of laser powder bed fusion processes, J. Manuf. Syst. 62 (2022) 835–845, https://doi.org/10.1016/j.jmsy.2021.07.002.
[55] Y. Zhang, S. Yang, G. Dong, Y.F. Zhao, Predictive manufacturability assessment system for laser powder bed fusion based on a hybrid machine learning model, Addit. Manuf. 41 (2021), 101946, https://doi.org/10.1016/j.addma.2021.101946.
[56] S. Yang, T. Page, Y. Zhang, Y.F. Zhao, Towards an automated decision support system for the identification of additive manufacturing part candidates, J. Intell. Manuf. 31 (2020) 1917–1933, https://doi.org/10.1007/s10845-020-01545-6.
[57] L. Lawand, P. Andersson, M. Kokkolaras, Integrated design–manufacturing decision support for additively manufactured components, Int. J. Adv. Manuf. Technol. 119 (2022) 3917–3930, https://doi.org/10.1007/s00170-021-08590-2.
[58] E. Coatanéa, H.P.N. Nagarajan, S. Panicker, R. Prod'hon, H. Mokhtarian, A. Chakraborti, et al., Systematic manufacturability evaluation using dimensionless metrics and singular value decomposition: a case study for additive manufacturing, Int. J. Adv. Manuf. Technol. 115 (2021) 715–731, https://doi.org/10.1007/s00170-020-06158-0.
[59] C. Fuchs, T. Semm, M.F. Zaeh, Decision-based process planning for wire and arc additively manufactured and machined parts, J. Manuf. Syst. 59 (2021) 180–189, https://doi.org/10.1016/J.JMSY.2021.01.016.
[60] Y. Wang, R.Y. Zhong, X. Xu, A decision support system for additive manufacturing process selection using a hybrid multiple criteria decision-making method, Rapid Prototyp. J. 24 (2018) 1544–1553, https://doi.org/10.1108/RPJ-01-2018-0002.
[61] N. Kretzschmar, I.F. Ituarte, J. Partanen, A decision support system for the validation of metal powder bed-based additive manufacturing applications, Int. J. Adv. Manuf. Technol. 96 (2018) 3679–3690, https://doi.org/10.1007/s00170-018-1676-8.
[62] W. Liu, Z. Zhu, S. Ye, A decision-making methodology integrated in product design for additive manufacturing process selection, Rapid Prototyp. J. 26 (2020) 895–909, https://doi.org/10.1108/RPJ-06-2019-0174.
[63] S.L. Chan, Y. Lu, Y. Wang, Data-driven cost estimation for additive manufacturing in cybermanufacturing, J. Manuf. Syst. 46 (2018) 115–126, https://doi.org/10.1016/j.jmsy.2017.12.001.
[64] Y. Oh, M. Sharp, T. Sprock, S. Kwon, Neural network-based build time estimation for additive manufacturing: A performance comparison, J. Comput. Des. Eng. 8 (2021) 1243–1256, https://doi.org/10.1093/jcde/qwab044.
[65] Z. Nie, S. Jung, L.B. Kara, K.S. Whitefoot, Optimization of part consolidation for minimum production costs and time using additive manufacturing, J. Mech. Des., Trans. ASME 142 (2020) 1–14, https://doi.org/10.1115/1.4045106.
[66] W. Pan, S. Wang, X. Zhang, W.F. Lu, Y. Wang, H. Jiang, A kinematics-aware decomposition approach for complex CAD parts in additive manufacturing, Addit. Manuf. 50 (2022), 102493, https://doi.org/10.1016/j.addma.2021.102493.
[67] Y. Oh, H. Ko, T. Sprock, W.Z. Bernstein, S. Kwon, Part decomposition and evaluation based on standard design guidelines for additive manufacturability and assemblability, Addit. Manuf. 37 (2021), 101702, https://doi.org/10.1016/j.addma.2020.101702.
[68] S. Kang, X. Deng, R. Jin, A Cost-Efficient Data-Driven Approach to Design Space Exploration for Personalized Geometric Design in Additive Manufacturing, J. Comput. Inf. Sci. Eng. (2021) 21, https://doi.org/10.1115/1.4050984.
[69] Schulz A., Xu J., Zhu B.O. Interactive Design Space Exploration and Optimization for CAD Models, 2017. https://doi.org/10.1145/3072959.3073688.
[70] OctoPrint Documentation n.d. https://docs.octoprint.org/en/master/.
[71] Y. Xiong, A.G. Dharmawan, Y. Tang, S. Foong, G.S. Soh, D.W. Rosen, A knowledge-based process planning framework for wire arc additive manufacturing, Adv. Eng. Inform. (2020) 45, https://doi.org/10.1016/j.aei.2020.101135.
[72] Materialise Streamics n.d. https://www.materialise.com/en/software/streamics.
[73] N. Divakaran, J.P. Das, A.K. P V, S. Mohanty, A. Ramadoss, S.K. Nayak, Comprehensive review on various additive manufacturing techniques and its implementation in electronic devices, J. Manuf. Syst. 62 (2022) 477–502, https://doi.org/10.1016/J.JMSY.2022.01.002.
[74] I.D. Jung, M.S. Lee, J. Lee, H. Sung, J. Choe, H.J. Son, et al., Embedding sensors using selective laser melting for self-cognitive metal parts, Addit. Manuf. 33 (2020), 101151, https://doi.org/10.1016/J.ADDMA.2020.101151.
[75] R. Su, S.H. Park, X. Ouyang, S.I. Ahn, M.C. McAlpine, 3D-printed flexible organic light-emitting diode displays, Sci. Adv. 8 (2022) 8798, https://doi.org/10.1126/sciadv.abl8798.
[76] N. Munasinghe, T. Romeijn, G. Paul, Voxel-based sensor placement for additive manufacturing applications, J. Intell. Manuf. (2021) 1–13, https://doi.org/10.1007/S10845-021-01823-X/FIGURES/11.
[77] Senvol n.d. http://senvol.com/.
[78] B. Li, J. Fu, J. Feng, C. Shang, Z. Lin, Review of heterogeneous material objects modeling in additive manufacturing. Visual Computing for Industry, Biomed., Art. 3 (2020) 1–18.
[79] X.Y. Kou, S.T. Tan, Heterogeneous object modeling: A review, CAD Comput. Aided Des. 39 (2007) 284–301, https://doi.org/10.1016/j.cad.2006.12.007.
[80] Y. Tang, Y.F. Zhao, Multifunctional design of heterogeneous cellular structures, Struct. Multidiscip. Optim. 58 (2018) 1121–1138, https://doi.org/10.1007/s00158-018-1956-9.
[81] Y. Tang, Y. Xiong, S. Park, D.W. Rosen, Universal material template for heterogeneous objects with applications to additive manufacturing, Comput.-Aided Des. 129 (2020), 102929, https://doi.org/10.1016/j.cad.2020.102929.
[82] C. Feng, J. Liang, M. Ren, G. Qiao, W. Lu, S. Liu, A fast hole-filling method for triangular mesh in additive repair, Appl. Sci. (Switz.) (2020) 10, https://doi.org/10.3390/app10030969.
[83] Attene M., Falcidieno B. ReMESH: An interactive environment to edit and repair triangle meshes. Proceedings - IEEE International Conference on Shape Modeling and Applications 2006, SMI 2006, vol. 2006, 2006. https://doi.org/10.1109/SMI.2006.29.
[84] J. Hu, L. Liu, G. Wang, Dual Laplacian morphing for triangular meshes, Comput. Animat. Virtual Worlds vol. 18 (2007), https://doi.org/10.1002/cav.182.
[85] Cignoni P., Callieri M., Corsini M., Dellepiane M., Ganovelli F., Ranzuglia G. MeshLab: An open-source mesh processing tool. 6th Eurographics Italian Chapter Conference 2008 - Proceedings, 2008.
[86] S.C. Subedi, C.S. Verma, K. Suresh, A review of methods for the geometric post-processing of topology optimized models, J. Comput. Inf. Sci. Eng. (2020) 20, https://doi.org/10.1115/1.4047429.
[87] G. Yi, N.H. Kim, Identifying boundaries of topology optimization results using basic parametric features, Struct. Multidiscip. Optim. (2017) 55, https://doi.org/10.1007/s00158-016-1597-9.
[88] Hoppe H., Derose T., Duchamp T., Halstead M., Jin H., McDonald J., et al. Piecewise smooth surface reconstruction. Proceedings of the 21st Annual Conference on Computer Graphics and Interactive Techniques, SIGGRAPH 1994, 1994. https://doi.org/10.1145/192161.192233.
[89] T. Du, J.P. Inala, Y. Pu, A. Spielberg, A. Schulz, D. Rus, et al., InverseCSG: Automatic conversion of 3D models to CSG trees, SIGGRAPH Asia 2018 Tech. Pap., SIGGRAPH Asia (2018) 2018, https://doi.org/10.1145/3272127.3275006.
[90] T.J. Hagedorn, S. Krishnamurty, I.R. Grosse, A Knowledge-Based Method for Innovative Design for Additive Manufacturing Supported by Modular Ontologies, J. Comput. Inf. Sci. Eng. 18 (2018), 021009, https://doi.org/10.1115/1.4039455.
[91] Automated Knowledge-Based Design for Additive Manufacturing: A Case Study with Flow Manifolds n.d. https://onlinelibrary.wiley.com/doi/epdf/10.1002/cite.202100209?src=getftr (accessed August 18, 2022).
[92] M. Dinar, D.W. Rosen, A design for additive manufacturing ontology, J. Comput. Inf. Sci. Eng. 17 (2016), 021013, https://doi.org/10.1115/DETC2016-60196.
[93] 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, https://doi.org/10.1016/j.jmsy.2021.04.007.
[94] M. Grasso, A. Remani, A. Dickins, B.M. Colosimo, R.K. Leach, In-situ measurement and monitoring methods for metal powder bed fusion: An updated review, Meas. Sci. Technol. 32 (2021), 112001, https://doi.org/10.1088/1361-6501/ac0b6b.
[95] S. Clijsters, T. Craeghs, S. Buls, K. Kempen, J.P. Kruth, In situ quality control of the selective laser melting process using a high-speed, real-time melt pool

monitoring system, Int. J. Adv. Manuf. Technol. 5 (75) (2014) 1089–1101, https://doi.org/10.1007/S00170-014-6214-8.
[96] B. Yuan, G.M. Guss, A.C. Wilson, S.P. Hau-Riege, P.J. DePond, S. McMains, et al., Machine-Learning-Based Monitoring of Laser Powder Bed Fusion, Adv. Mater. Technol. (2018) 3, https://doi.org/10.1002/admt.201800136.
[97] J. Li, Q. Zhou, X. Huang, M. Li, L. Cao, In situ quality inspection with layer-wise visual images based on deep transfer learning during selective laser melting, J. Intell. Manuf. (2021), https://doi.org/10.1007/s10845-021-01829-5.
[98] S.P. Donegan, E.J. Schwalbach, M.A. Groeber, Multimodal registration and fusion of in situ and ex situ metal additive manufacturing data, Jom 73 (2021) 3250–3262, https://doi.org/10.1007/s11837-021-04883-9.
[99] S.C. Feng, Y. Lu, A.T. Jones, Z. Yang, Additive manufacturing in-situ and ex-situ geometric data registration, J. Comput. Inf. Sci. Eng. (2022) 1–13, https://doi.org/10.1115/1.4054202.
[100] A. Petsiuk, J.M. Pearce, Towards smart monitored AM: Open source in-situ layer-wise 3D printing image anomaly detection using histograms of oriented gradients and a physics-based rendering engine, Addit. Manuf. 52 (2022), 102690, https://doi.org/10.1016/J.ADDMA.2022.102690.
[101] M. Moretti, N. Senin, In-process monitoring of part warpage in fused filament fabrication through the analysis of the repulsive force acting on the extruder, Addit. Manuf. 49 (2022), 102505, https://doi.org/10.1016/J.ADDMA.2021.102505.
[102] Q. Wang, P. Michaleris, (Pan), A.R. Nassar, J.E. Irwin, Y. Ren, C.B. Stutzman, Model-based feedforward control of laser powder bed fusion additive manufacturing, Addit. Manuf. 31 (2020), 100985, https://doi.org/10.1016/J.ADDMA.2019.100985.
[103] J.E. Irwin, Q. Wang, P. Michaleris, (Pan), A.R. Nassar, Y. Ren, C.B. Stutzman, Iterative simulation-based techniques for control of laser powder bed fusion additive manufacturing, Addit. Manuf. 46 (2021), 102078, https://doi.org/10.1016/J.ADDMA.2021.102078.
[104] M. v Johnson, K. Garanger, J.O. Hardin, J.D. Berrigan, E. Feron, S.R. Kalidindi, A generalizable artificial intelligence tool for identification and correction of self-supporting structures in additive manufacturing processes, Addit. Manuf. 46 (2021), 102191, https://doi.org/10.1016/j.addma.2021.102191.
[105] S. Xu, J. Liu, B. Zou, Q. Li, Y. Ma, Stress constrained multi-material topology optimization with the ordered SIMP method, Comput. Methods Appl. Mech. Eng. 373 (2021), 113453, https://doi.org/10.1016/J.CMA.2020.113453.
[106] M. Zhou, Y. Lu, Y. Liu, Z. Lin, Concurrent topology optimization of shells with self-supporting infills for additive manufacturing, Comput. Methods Appl. Mech. Eng. 390 (2022), 114430, https://doi.org/10.1016/J.CMA.2021.114430.
[107] S. Li, S. Yuan, J. Zhu, C. Wang, J. Li, W. Zhang, Additive manufacturing-driven design optimization: Building direction and structural topology, Addit. Manuf. 36 (2020), 101406, https://doi.org/10.1016/J.ADDMA.2020.101406.
[108] S. Li, S. Yuan, J. Zhu, W. Zhang, H. Zhang, J. Li, Multidisciplinary topology optimization incorporating process-structure-property-performance relationship of additive manufacturing, Struct. Multidiscip. Optim. 63 (2021) 2141–2157, https://doi.org/10.1007/S00158-021-02856-9/FIGURES/16.
[109] D. Gu, X. Shi, R. Poprawe, D.L. Bourell, R. Setchi, J. Zhu, Material-structure-performance integrated laser-metal additive manufacturing, Science 2021 (1979) 372, https://doi.org/10.1126/SCIENCE.ABG1487/ASSET/A9D8D4AD-C761-4385-8477-1D5821D6F042/ASSETS/GRAPHIC/372_ABG1487_FA.JPEG.
[110] J.R.R.A. Martins, A.B. Lambe, Multidisciplinary Design Optimization: A Survey of Architectures, AIAA J. 51 (2013) 2049–2075, https://doi.org/10.2514/1.j051895.
[111] G. Liu, Y. Xiong, D.W. Rosen, Multidisciplinary design optimization in design for additive manufacturing, J. Comput. Des. Eng. 9 (2022) 128–143, https://doi.org/10.1093/jcde/qwab073.
[112] Y. Wang, P. Zheng, T. Peng, H.Y. Yang, J. Zou, Smart additive manufacturing: Current artificial intelligence-enabled methods and future perspectives, Sci. China Technol. Sci. 63 (2020), 1600–11.
[113] P. Pandita, S. Ghosh, V.K. Gupta, A. Meshkov, L. Wang, Application of Deep Transfer Learning and Uncertainty Quantification for Process Identification in Powder Bed Fusion, ASCE-ASME J. Risk Uncertain. Eng. Syst., Part B: Mech. Eng. (2022) 8, https://doi.org/10.1115/1.4051748.
[114] M. Cheng, P. Jiang, J. Hu, L. Shu, Q. Zhou, A multi-fidelity surrogate modeling method based on variance-weighted sum for the fusion of multiple non-hierarchical low-fidelity data, Struct. Multidiscip. Optim. (2021) 64, https://doi.org/10.1007/s00158-021-03055-2.
[115] X. Huang, T. Xie, Z. Wang, L. Chen, Q. Zhou, Z. Hu, A transfer learning-based multi-fidelity point-cloud neural network approach for melt pool modeling in additive manufacturing, ASCE-ASME J. Risk Uncertain. Eng. Syst., Part B: Mech. Eng. (2022) 8, https://doi.org/10.1115/1.4051749.
[116] Z. Hu, S. Mahadevan, Uncertainty quantification and management in additive manufacturing: current status, needs, and opportunities, Int. J. Adv. Manuf. Technol. 93 (2017) 2855–2874, https://doi.org/10.1007/s00170-017-0703-5.
[117] L. Meng, B. McWilliams, W. Jarosinski, H.Y. Park, Y.G. Jung, J. Lee, et al., Machine learning in additive manufacturing: a review, Jom 72 (2020) 2363–2377, https://doi.org/10.1007/s11837-020-04155-y.
[118] G.D. Goh, S.L. Sing, W.Y. Yeong, A review on machine learning in 3D printing: applications, potential, and challenges, Artif. Intell. Rev. 54 (2021) 63–94, https://doi.org/10.1007/s10462-020-09876-9.
[119] C. Wang, X.P. Tan, S.B. Tor, C.S. Lim, Machine learning in additive manufacturing: State-of-the-art and perspectives, Addit. Manuf. (2020) 36, https://doi.org/10.1016/j.addma.2020.101538.
[120] G. Dong, J.C. Wong, L. Lestandi, J. Mikula, G. Vastola, M.H. Jhon, et al., A part-scale, feature-based surrogate model for residual stresses in the laser powder bed fusion process, J. Mater. Process. Technol. 304 (2022), 117541, https://doi.org/10.1016/j.jmatprotec.2022.117541.
[121] Y. Wang, Q. Yao, J.T. Kwok, L.M. Ni, Generalizing from a Few Examples: A Survey on Few-shot Learning, ACM Comput. Surv. (2020) 53, https://doi.org/10.1145/3386252.
[122] A. Barredo Arrieta, N. Díaz-Rodríguez, J. del Ser, A. Bennetot, S. Tabik, A. Barbado, et al., Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI, Inf. Fusion (2020) 58, https://doi.org/10.1016/j.inffus.2019.12.012.
[123] M. Mozaffar, S. Liao, X. Xie, S. Saha, C. Park, J. Cao, et al., Mechanistic artificial intelligence (mechanistic-AI) for modeling, design, and control of advanced manufacturing processes: Current state and perspectives, J. Mater. Process. Technol. 302 (2022), 117485, https://doi.org/10.1016/J.JMATPROTEC.2021.117485.
[124] 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. (2020) 36, https://doi.org/10.1016/j.addma.2020.101659.
[125] H. Ko, S.K. Moon, J. Hwang, Design for additive manufacturing in customized products, Int. J. Precis. Eng. Manuf. 16 (2015) 2369–2375, https://doi.org/10.1007/s12541-015-0305-9.
[126] Y. Zhang, S.K. Moon, Data-driven design strategy in fused filament fabrication: Status and opportunities, J. Comput. Des. Eng. 8 (2021) 489–509, https://doi.org/10.1093/jcde/qwaa094.
[127] M. Moussa, H. ElMaraghy, Multiple platforms design and product family process planning for combined additive and subtractive manufacturing, J. Manuf. Syst. 61 (2021) 509–529, https://doi.org/10.1016/J.JMSY.2021.09.019.
[128] J. Li, R. Jin, H.Z. Yu, Integration of physically-based and data-driven approaches for thermal field prediction in additive manufacturing, Mater. Des. 139 (2018) 473–485, https://doi.org/10.1016/j.matdes.2017.11.028.
[129] S. Guo, M. Agarwal, C. Cooper, Q. Tian, R.X. Gao, W.G. Guo, et al., Machine learning for metal additive manufacturing: Towards a physics-informed data-driven paradigm, J. Manuf. Syst. 62 (2022) 145–163, https://doi.org/10.1016/J.JMSY.2021.11.003.
[130] M. Mozaffar, S. Liao, H. Lin, K. Ehmann, J. Cao, Geometry-agnostic data-driven thermal modeling of additive manufacturing processes using graph neural networks, Addit. Manuf. 48 (2021), 102449, https://doi.org/10.1016/J.ADDMA.2021.102449.
[131] 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, https://doi.org/10.1016/J.ADDMA.2020.101620.
[132] S. Kim, D.W. Rosen, P. Witherell, H. Ko, A Design for Additive Manufacturing Ontology to Support Manufacturability Analysis, J. Comput. Inf. Sci. Eng. 19 (2019) 1–10, https://doi.org/10.1115/1.4043531.
[133] E.M. Sanfilippo, F. Belkadi, A. Bernard, Ontology-based knowledge representation for additive manufacturing, Comput. Ind. 109 (2019) 182–194, https://doi.org/10.1016/j.compind.2019.03.006.
[134] 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, https://doi.org/10.1016/J.JII.2021.100218.
[135] Dharmawan A.G., Xiong Y., Foong S., Song Soh G. A Model-Based Reinforcement Learning and Correction Framework for Process Control of Robotic Wire Arc Additive Manufacturing. Proceedings - IEEE International Conference on Robotics and Automation, 2020, p. 4030–6. https://doi.org/10.1109/ICRA40945.2020.9197222.
[136] S. Xu, J. Liu, J. Huang, B. Zou, Y. Ma, Multi-scale topology optimization with shell and interface layers for additive manufacturing, Addit. Manuf. (2021) 37, https://doi.org/10.1016/j.addma.2020.101698.
[137] Y. Wang, G. Zhang, H. Ren, G. Liu, Y. Xiong, Fabrication strategy for joints in 3D printed continuous fiber reinforced composite lattice structures, Compos. Commun. 30 (2022), 101080, https://doi.org/10.1016/j.coco.2022.101080.
[138] N. Boddeti, Y. Tang, K. Maute, D.W. Rosen, M.L. Dunn, Optimal design and manufacture of variable stiffness laminated continuous fiber reinforced composites, Sci. Rep. 10 (2020) 1–15, https://doi.org/10.1038/s41598-020-73333-4.
[139] I.F. Ituarte, N. Boddeti, V. Hassani, M.L. Dunn, D.W. Rosen, Design and additive manufacture of functionally graded structures based on digital materials, Addit. Manuf. 30 (2019), 100839, https://doi.org/10.1016/J.ADDMA.2019.100839.
[140] Rosen D.W. Design for the Additive Manufacturing Process Chain. Proceedings of the 32nd Annual International Solid Freeform Fabrication Symposium, Austin, TX: 2021, p. 53–61.
[141] X. Xu, Y. Lu, B. Vogel-Heuser, L. Wang, Industry 4.0 and Industry 5.0—Inception, conception and perception, J. Manuf. Syst. 61 (2021) 530–535, https://doi.org/10.1016/J.JMSY.2021.10.006.