SCIENCE CHINA
Technological Sciences

Special Topic: Industrial Artificial Intelligence
•Review•

September 2020 Vol.63 No.9: 1600–1611
https://doi.org/10.1007/s11431-020-1581-2

Smart additive manufacturing: Current artificial intelligence-enabled methods and future perspectives

WANG YuanBin[1], ZHENG Pai[2], PENG Tao[1], YANG HuaYong[1] & ZOU Jun[1*]

[1] *State Key Laboratory of Fluid Power and Mechatronic Systems, Zhejiang University, Hangzhou 310027, China;*
[2] *Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Kowloon, Hong Kong 999077, China*

Received December 10, 2019; accepted March 25, 2020; published online May 15, 2020

Additive manufacturing (AM) has been increasingly used in production. Because of its rapid growth, the efficiency and robustness of AM-based product development processes should be improved. Artificial intelligence (AI) is a powerful tool that has outperformed humans in numerous complex tasks. AI-enabled intelligent agents can reduce the workforce required to scale up AM production and achieve higher resource utilization efficiency. This study provides an introduction of AI techniques. Then, the current development of AI-enabled AM product development is investigated. Existing intelligent agents are used for problems in product design, process design and production stages. Based on the review, current research gaps and future research directions are identified. To guide future development of more efficient and comprehensive intelligent agents, a smart AM framework based on cloud-edge computing is proposed. Global consideration can be realized in the cloud environment, and a fast response can be achieved at the edge nodes.

additive manufacturing, artificial intelligence, product development, cloud-edge computing

Citation: Wang Y B, Zheng P, Peng T, et al. Smart additive manufacturing: Current artificial intelligence-enabled methods and future perspectives. Sci China Tech Sci, 2020, 63: 1600–1611, https://doi.org/10.1007/s11431-020-1581-2

1 Introduction

The development of additive manufacturing (AM) technologies, also known as 3D printing, has increased in recent years [1,2]. Because 3D printing can produce geometrically complex parts without accessories (e.g., fixtures and molds) [3,4], it has been applied to a wide range of applications including aerospace, medicine, footwear, etc. [5]. AM can realize mass customization and personalization without cost penalties. The customization process requires knowledge and experience to implement suitable adjustments. Currently, the success of AM highly relies on the users' knowledge and experience to make the right decisions in the product development process [6,7]. As a complex process, product development involves multiple stages, including design, process planning, production planning, and process monitoring. These stages are highly interrelated, and the decision makers should have sufficient knowledge of the rules of each stage. Unsuitable decisions may dramatically influence the results of AM. With the rapid growth of the AM market, the accessibility of this knowledge should be increased to help people achieve more flexible, adaptive and intelligent AM operations.

Artificial intelligence (AI), in contrast to natural intelligence, is intelligence demonstrated by machines and software rather than living systems [8]. The purpose of AI is to develop intelligent agents that can perceive its environment and take actions that maximize its chance to successfully achieve predefined goals [9]. Empowered by the explosive growth of accessible data, AI, especially deep learning techniques, has experienced another large increase in recent years. The capability of AI has been similar to or

*Corresponding author (email: junzou@zju.edu.cn)

surpassed human performance in several areas, including image recognition [10] and game playing [11,12].

Because of the potential of AI, research interests in applying it to AM processes have increased to improve the product development process. AI has been referred to as a machine learning technique at some places [8,13], however, it is broader than that. It is a group of techniques that enables machines to interact with the environment and adaptively solve problems. These techniques enable the creation of intelligent agents to perceive the environment, infer based on a knowledge model, search answers from solution repositories, learn from historical data, communicate, take action, etc.

AM-based product development is a complex process that combines design, parameter selection, planning, manufacturing, control, and other aspects. There are numerous issues that have been dealt with using different AI techniques. In 2017, an initial survey was conducted on AI applications in AM, however, it focused on the manufacturing preparation process [14]. Other aspects have not been investigated. Numerous new trends have emerged, such as deep learning-based process monitoring and control. Considering the rapid development of AI-related areas, the research progress in recent years should be summarized to guide future development.

In this study, a survey was conducted to investigate the current status of AI-enabled AM. A global view of the product development process was considered, and the current knowledge gaps and system limitations were identified. Based on the survey, we provide a vision for future development to achieve a smarter AM production environment. The remainder of this paper is as follows. Section 2 introduces the basic methods and techniques related to AI. Section 3 reviews the current research activities on intelligent agent development for AM. A framework for future smart AM environment is proposed in Section 4. Section 5 provides the conclusions drawn from this research.

2 Overview of AI

The fundamental goal of AI research is to develop intelligent agents that can perform rational actions in a dynamic environment [15]. The basic structure of an intelligent agent is shown in Figure 1. The inputs come from its environment, and the outputs affect the environment. An intelligent agent could be software or hardware. For software, the human-machine interface (HMI) is used to provide inputs and deliver outputs in the form of commands, files, suggestions or other information. For hardware, sensors are used as input devices, including image sensors (e.g. charge coupled device (CCD)), global positioning system (GPS), sound sensors (e.g., microphone), etc. The layer between the inputs and outputs contains the core functions that form problems and generate solutions. These functions can be based on various structured and unstructured information and knowledge (e.g., the physical model, expert knowledge and historical data).

2.1 Types of intelligent agents

There are mainly three types of intelligent agents based on their methods of generating action: a reflex agent, goal-based agent and utility-based agent [15].

A reflex agent takes input signals and directly generates

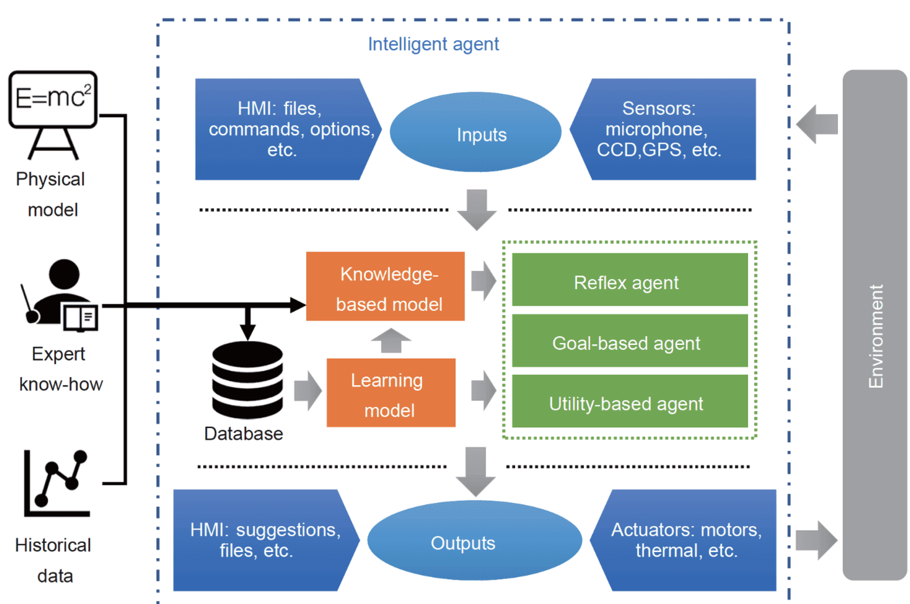

Figure 1 (Color online) The basic structure of intelligent agents.

reactions accordingly. It could be based on simple IF-THEN rules or more complex models (e.g., physical models, statistical models and knowledge models). The problems to be solved are often straightforward and do not involve extra optimization or complex trade-offs.

A goal-based agent predicts the future status of the environment and tries to achieve predefined goals. In this situation, there are usually multiple solutions. Criteria are used to measure their performances. The goal could be maximizing or minimizing the criteria. Various advanced methods have been proposed for this type of searching and planning problem, including genetic algorithms [16], particle swarm optimization [17], and simulated annealing algorithms [18], to find the optimal solutions. Most problems in practice are complex, thus this method requires large computational power and a long processing time.

A utility-based agent is used when there are multiple goals that may conflict [19]. Trade-offs are required to achieve the best utility. Using a goal state and non-goal state in the goal-based agents is not enough to measure the level of satisfaction of the users on each criterion. Therefore, the utility theory is applied to model the user preference [20]. When multiple agents are involved, the theory of game [21] could be applied to model the players' performance. These problems are typically knowledge-intensive and frequently interact with the users.

2.2 Typical AI models

All these agents rely on various models to project input signals to output actions. For AI, the models based on knowledge and learning have received increasing attention.

A knowledge-based model solves problems by imitating human expertise [22]. It consists of a knowledge model and an inference system. Certain knowledge can be represented by rule-based models [23], case-based models, and ontology [24]. Uncertain knowledge can be represented by Bayesian networks [25] and fuzzy logic [26].

A learning model discovers patterns from historical data and creates models for problem solving. This type of model has been disruptive in many areas recently, including illness diagnosis and self-driving. There are various types of learning models, such as supervised and unsupervised, discriminative and generative, deep learning and non-deep learning, etc. [8]. The learning model has been widely applied to the manufacturing environment for image recognition [27,28], equipment monitoring, diagnosis [29–31], etc.

3 AI-enabled AM

3.1 ICT-driven AM development

The development of AM has been driven by advanced information and communication technologies (ICT). It can be summarized into four stages, as shown in Figure 2. The first AM machine was developed by Hull in the 1980s [32] and is controlled by local computers. In the mid-1990s, researchers attempted to connect AM machines to a network to achieve remote monitoring and control [33,34]. Users could send 3D models to printers remotely and receive the status of the printing processes. In the early 2000s, researchers started to treat AM as a service and accept online orders from distributed customers [35–37]. These methods have developed a bridge between distributed service demanders and providers. The requirements of the service demanders could be matched to the capabilities of the solutions from the service providers.

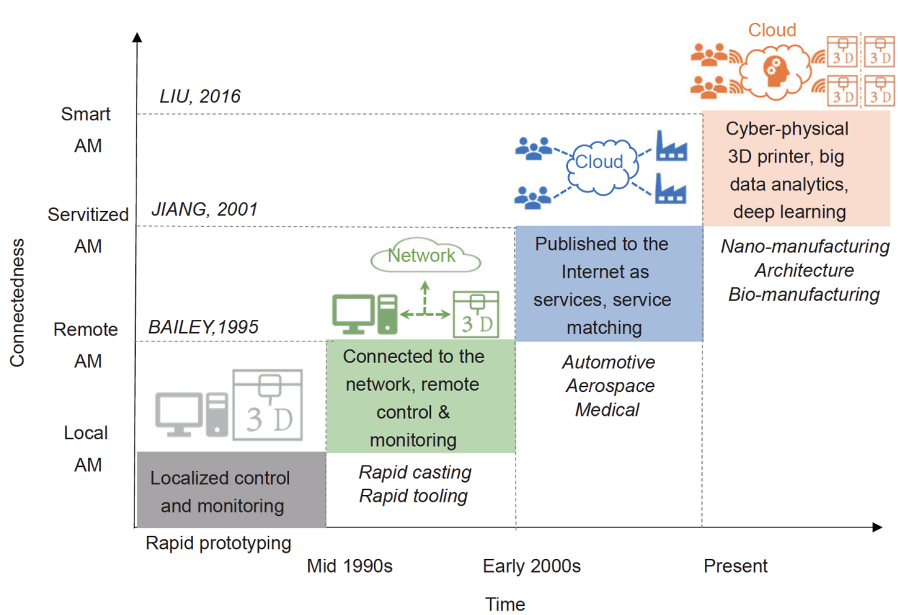

Figure 2 (Color online) Development of AM.

Recently, researchers started to integrate advanced ICTs, such as the cyber-physical system (CPS) [7,38] and deep learning [39], to automatically process complex information and help users make rational decisions in product development processes.

The demand to develop intelligent agents has increased, driven by the increase of connectedness and application areas [5], as shown in Figure 2.

At the market level, cloud-based AM platforms have been proposed [7,40] and companies (e.g. Shapeways and 3D Hubs) have started to sell 3D printing services online. Customers can directly use AM resources via the Internet. However, the customers should have enough knowledge to make the correct decisions and print the expected parts. To fulfill the growing needs for AM knowledge, AI tools are required to make them accessible via the Internet and help customers make rational decisions.

At the system level, the CPS has shown great potential recently [41]. Researchers have also developed CPS for 3D printers [7,38,42,43]. A digital twin of the physical 3D printer has to process a lot of data and optimize the printing process in real-time. In this situation, AI technologies become critical to generate solutions automatically when facing different printer statuses based on digitalized expert knowledge or patterns from historical data.

At the technology level, the booming ICTs, including cloud computing, edge computing, 5G, and Internet of things (IoT), enable large amounts of real-time data to be efficiently gathered and processed. Human experts cannot deal with the large amounts of data efficiently. Thus, learning-based agents have become a popular research area in recent years. These technologies have provided advanced solutions for various aspects of intelligent agents development for AM, including data acquisition, machine-to-machine communication, and efficient computation.

3.2 AM-based product development

There are four major stages in the development of 3D printed parts: product design, process design, production and service (Figure 3), not necessarily in the same order. Product design and process design are often conducted concurrently as the design features and process parameters are interrelated [25]. The information gathered at different stages can be used at other stages to optimize the products.

Various intelligent agents have been proposed to solve problems in these stages. In general, there are four types of problems. Knowledge-intensive problems rely on expert knowledge to quickly assess potential solutions and find suitable ones. For example, the design rules, such as a minimum feature size and heterogeneous properties, should be considered by designers in the design stage. Otherwise, the design model may not be printable. Attention-intensive problems require continuous attention on running equipment or other objects, and adjustments are made adaptively. Printing process monitoring is a typical example of an attention-intensive problem that requires continuous attention during the printing process to identify problems as early as possible. Computation-intensive problems include searching and planning problems that require a large amount of computational power to find optimal answers. For example, the design space for 3D printing products is large. A large amount of computational power is required to explore possible solutions and predict its properties to identify the optimal design model. Preference-intensive problems require modelling the users' preferences to help them make rational decisions. This type of problem usually occurs in the process design stage to match the preferences of the properties of the printed part to the process parameters. In this situation, there may be multiple properties that conflict. Therefore, the trade-offs become the central problem.

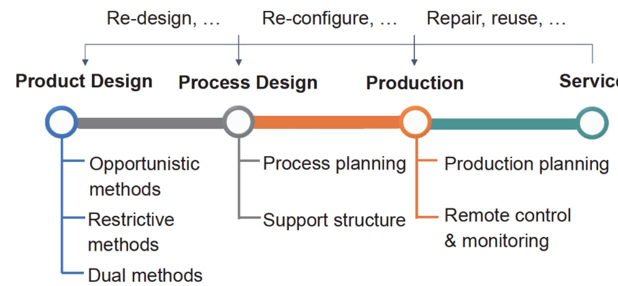

Figure 3 (Color online) AM product development process.

3.3 Intelligent agents for product design

There are three types of product design methods: opportunistic, restrictive, and dual methods [44]. Opportunistic methods are used to explore the geometric possibilities provided by AM. Topology optimization and elementary shapes are the most commonly applied methods. Restrictive methods are used to identify the boundaries of design spaces, in terms of the geometry and properties. These boundaries should be represented as rules to automatically check manufacturability. Dual methods combine both types of methods to generate more practical design proposals. Various intelligent agents have been proposed to solve these problems. The details are listed in Table 1.

Initially, a majority of the research focused on a single aspect, opportunistic or restrictive. For opportunistic methods, the optimal design solutions searched for specific tasks. These types of searching problems are computation-intensive and various goal-based agents have been proposed. Physical models are applied to simulate the properties of the printed parts. For restrictive methods, the purpose is to check if a design can be printed with the desired quality and properties. This is a knowledge-intensive problem, where the

Table 1 Intelligent agents for product design

Aspects	Proposed agents	Problem type	Agent type	Model type
Opportunistic methods	Design feature database [45]	Knowledge-intensive	Reflex	Knowledge-based
	Topology optimization [46–48]	Computation-intensive	Goal-based	Physical
	Elementary shapes [49–52]	Computation-intensive	Goal-based	Physical
Restrictive methods	Knowledge-based system [25,53]	Knowledge-intensive	Reflex	Knowledge-based
	Key feature recognition [54,55]	Knowledge-intensive	Reflex	Knowledge-based & physical
Dual methods	Part consolidation [56]	Computation-intensive	Goal-based	Knowledge-based & physical
	Topology optimization for manufacturability [57,58]	Computation-intensive	Goal-based	Knowledge-based & physical

relationships between the design features, process features, and properties of the printed parts should be understood. These rules need to be encoded as various knowledge-based models to form reflex agents. The manufacturability can then be determined for a given design model. More recently, researchers have merged both types of methods as dual methods to generate more manufacturable design models. In these scenarios, multiple models are involved, including knowledge-based and physical models, to consider manufacturability in the searching process.

In the product design stage, the integration of opportunistic and restrictive methods provides a promising solution to fulfil the complex design and manufacturing requirements and generate more reliable design proposals. However, current methods only consider simple design rules, such as thin features and size limitations [57,58]. In practice, the design rules are more complex [59]. How to engage these complex knowledge models in opportunistic methods is still not understood.

3.4 Intelligent agents for process design

In the process design stage, optimal process-related settings and parameters are chosen to achieve the desired properties. Process planning and support structure optimization are involved. In process planning, optimal printing strategies are chosen for specific tasks. These include material-related settings (e.g., material types and ingredients), machine-related settings (e.g., power energy and layer height) and design-related settings (e.g., build orientation and trajectory). As many AM processes require support structures to avoid failures, the least amount of support materials should be used to achieve the required quality. The design of the support structures also influences the printed properties [60]. Therefore, support structure optimization has become an important topic in recent years [61,62]. Various intelligent agents have been proposed to solve this problem. The details are listed in Table 2.

There are multiple parameters (e.g., layer thickness, printing speed, and base temperature) for the printing process, and they often have a different impact on various aspects of the printed parts. Therefore, multi-criteria decision making (MCDM) methods are widely adopted to help users make rational decisions for parameter selection. As the user preferences influence the decisions, modeling these preferences becomes crucial. Knowledge also plays a significant role in mapping the parameters with printed results. Therefore, these utility-based agents usually have a knowledge-based model for inference.

Path planning of AM processes is also complex. Two aspects are involved: horizontal trajectory optimization and adaptive layer slicing. The first aspect influences the efficiency of the printing process while the second is a trade-off between the printing efficiency and part quality, in terms of dimensional accuracy and surface roughness. As a planning problem, various goal-based agents have been proposed to determine optimal solutions within shorter computational times.

Build direction optimization is another important topic owing to the heterogeneous properties of the printed parts. These agents are also goal-based to search for the optimal direction for a given design and achieve the best quality.

Table 2 Intelligent agents for process design

Aspects	Proposed agents	Problem type	Agent type	Model type
Process planning	MCDM for parameter selection [63–66]	Preference-intensive & knowledge-intensive	Utility-based	Knowledge-based & physical
	Path planning [67–71]	Computation-intensive	Goal-based	Physical
	Build direction optimization [72–74]	Computation-intensive	Goal-based	Physical
Support structure optimization	Topology optimization [75,76]	Computation-intensive	Goal-based	Physical
	Elementary shapes [77,78]	Computation-intensive	Goal-based	Physical

They involve physical models to predict the surface roughness, accuracy, and other properties. Support structure optimization is similar to the opportunistic methods of product design, while targeting the support structures. The purpose is to reduce the mass of the materials and improve the ease of removal while ensuring functional performance.

In the process design stage, utility-based agents have been introduced to tackle different user preferences on the properties of the printed parts. However, the accuracy of the knowledge-based model is important for projecting user requirements to suitable printing parameters. Furthermore, the process parameters, build directions, and support structures are interrelated. More comprehensive models are required to find global optimal solutions.

3.5 Intelligent agents for production

In the production stage, there could be multiple printing tasks simultaneously, especially in cloud manufacturing. Considering the long pre-processing and post-processing times, it is more efficient to print as many parts as possible for each print [79,80]. In this situation, production planning becomes important to improve the overall production efficiency. The deadline of each task, design geometries, required parameters, etc. should be considered. The fabrication process typically requires hours or days to finish. During this period, defects may occur, and they may cause the part to fail. Therefore, real-time monitoring of the printing process is required to quickly identify these defects, fix the problem, and avoid unnecessary waste of time and money. Various intelligent agents have been proposed to solve these problems. The details are listed in Table 3.

Production planning starts from single-print scenarios, where the user attempts to place as many parts as possible into one printing space. Each part could rotate and move to any place in the printing space to provide infinite possible solutions. The genetic algorithm (GA) has been widely used to find a sub-optimal solution with reasonable computation time. The problem becomes more complex to plan for multiple prints. There are more printers available, which may have different statuses (idle or working). The parts may have different deadlines. If the task space is also dynamic (i.e., a new task could be added at any time), the computation speed will become crucial for a fast response. Here, the GA-based algorithms cannot meet the efficiency requirement. Therefore, various heuristic methods are proposed to use predefined rules to narrow the searching space.

Real-time control and monitoring have been evaluated in recent years owing to the rapid development of machine learning techniques. Image processing is one of the most popular areas in machine learning and has enabled various image-based monitoring agents for AM processes. These agents use learning models to extract complex features of targeted patterns from historical images and identify them in real-time images. AR-based methods have also become popular. Users can capture the 3D point cloud of the printing part and compare it to the design model to identify discrepancies. In addition, various sensors (e.g., temperature, vibration, and power sensors) and process parameters can be used to predict the quality of the printed parts. The learning models are required to find features from the time-series data.

In the production stage, attention-based problems have occurred, and learning models have advantages for solving these problems. These agents could release people from tedious process monitoring tasks. However, the image-based and AR-based methods can only identify visible defects. Sensor-based methods are able to identify invisible defects; however, the relationships of the printing parameters and part quality must be defined in advance. Furthermore, the available data for the AM processes are limited. How to use the limited data to generate more robust and general models is still a challenge.

3.6 Global methods

The intelligent agents mentioned previously are developed for solving single problems. However, these problems are not isolated. For example, the design of a product will influence the selection of the printing parameters and production plan. The process capability (e.g., minimum feature size and printing resolution) will influence the design of the product. Therefore, optimal AM solutions can only be achieved with global consideration. The first step is to define a uniform data format to carry the information from different stages. Lu et al. proposed an integrated data schema for AM [96]. A cloud-based automated design and AM platform was proposed to integrate the data in the service stage to optimize

Table 3 Intelligent agents for production

Aspects	Proposed agents	Problem type	Agent type	Model type
Production planning	Single print optimization [81–84]	Computation-intensive	Goal-based	Physical
	Multiple prints optimization [79,85–87]	Computation-intensive	Goal-based	Physical
Real-time control & monitoring	Image-based methods [39,88–91]	Attention-intensive	Reflex	Learning
	AR-based methods [42,92]	Attention-intensive	Reflex	Physical
	Sensor-based methods [93–95]	Attention-intensive	Reflex	Learning & physical

the product design, process setting, and production strategy [97]. The framework was the focus, and efficient utilization of big data has not been fully studied. A conceptual design and modelling framework were presented to integrate various simulation and prediction models for the product development process [98]. This framework focused on reflex agents and other types of agents were not considered. Majeed et al. proposed a big data-driven framework for AM process analysis and optimization [99]. Data acquisition, management, modelling, and utilization were discussed. A knowledge-based computer-aided production planning (CAPP) framework was proposed to integrate the product and process design stages [100]. Processing big data requires computational resources. How to efficiently process computation-intensive models and provide a fast response for distributed users has not been discussed.

3.7 Discussion

Current studies have shown that AM-based product development could benefit from AI techniques. Various intelligent agents have been developed to provide decision assistance in the product design, process design, and production stages.

In the first two stages, the main purpose is to determine the optimal design of the product and process. Therefore, the problems are knowledge and computation-intensive. Reflex and goal-based agents have been widely applied. The knowledge-based models in the reflex agents can gather expert knowledge and make it available to non-expert users. AM involves a large amount of knowledge from different disciplines, and there is a shortage of experts. Therefore, these agents can help more users take advantage of AM. The goal-based agents can find optimal solutions from a large design space. Physical models are usually involved in simulation and determine whether the goals and constraints are satisfied. This type of agent can use the computational power to maximize the efficiency of material utilization. The waste of materials, energy, and time could be minimized.

In the production stage, learning models have printing process control and monitoring advantages. Operators no longer need to sit beside the printer and continually check its status. From historical data, this model can identify the features of abnormal situations. These agents enlarge the production scale without dramatically expanding the operating team. Deep learning techniques have shown more potential to deal with complex problems as they can automatically extract the important features in multiple levels, as performed by the human brain [101].

Although successful applications of intelligent agents have been reported, there are still several knowledge gaps to be explored.

(1) Scattered and conflicting knowledge management is evaluated. AM knowledge is the central part of AM intelligence. As a multi-disciplinary area, the related information is widely scattered at different locations and in different formats (e.g., test data, text, physical models, statistical models, rules, ontologies, and graphical databases). They may be described with different standards and conflict with each other. Knowledge bases for small applications have been developed. However, the knowledge in different aspects is interrelated. Informed decisions can only be made with global consideration. Therefore, integrating these pieces of information to form a comprehensive and accurate knowledge base is a challenging task.

(2) A deeper understanding of AM processes is required. Physical models are also important to predict the performance of AM processes for goal-based agents. Current models may work well in specific circumstances, however, their accuracy and generality should be improved to generate more realistic results. This type of model can also be applied in the sensor-based method for remote control and monitoring. In this situation, the computational efficiency of these models becomes more important to achieve real-time feedback.

(3) For big data management and utilization, AI techniques are data-hungry, especially learning models. Currently, there are no standard databases that are similar to ImageNet in AM to gather all the data available along with the corresponding tags for researchers to test the generality of their models in a larger scale. Furthermore, the application of learning models in AM is not similar to other areas. Abnormal situations are not common in practice. Therefore, the data gathered for training are limited. Using the limited data to train robust models requires further study.

(4) For integration of different models, most of the current agents have single models, which may not be adequate for many applications. For example, the goal-based agents for product design require physical models to simulate the properties and knowledge-based models to examine the manufacturability of the proposed design. The reflex agents for real-time control and monitoring require combining learning and knowledge models for complex problems. To develop more effective and practical agents for complicated scenarios, efficiently combining different types of models for better performance should be studied.

(5) A wider application of the learning models is possible. Current learning models are mainly developed for real-time control and monitoring. The techniques could potentially tackle more complex problems. The emerging reinforcement learning methods can learn rules in strategical tasks. Advanced deep learning methods have been proposed for 3D models. These emerging techniques could develop useful agents for product and process design stages. The execution of trained models could be more efficient than the commonly used searching algorithms. The first challenge is standardizing the data model for the design process to prepare the

training data.

(6) For an efficient computational strategy, a trend of AM development is to develop online services. In this situation, the intelligent agents serve distributed users via the internet. The agents with searching and planning algorithms usually require a large computational power. In addition, some tasks require a fast response. Learning-based real-time control and monitoring is required for the training and execution stages, respectively. Although cloud-based design and simulation software have been developed, real-time tasks cannot be performed. Therefore, a new efficient computational framework should be studied to fulfil both requirements.

4 Framework of smart AM

From Section 3.7, one problem that hinders the development of AI for AM is the lack of high-quality and high-volume AM related information. This information includes the data from testing and monitoring, expert knowledge, standards, algorithms, physical models, and other types of information. From the rapid development of AI for image processing, the cloud platforms, such as ImageNet, can be used to gather distributed image data to a central location to allow anyone to access the data and develop innovative ideas. Furthermore, information processing efficiency is another important aspect, as there are numerous scenarios in AM that require a real-time response. Existing platforms discussed in Section 3.6 mainly focus on a specific aspect of AM, such as product design, fabrication or CAPP. The efficiency of data processing in the platform has not been fully considered. To realize more intelligent AM with a high efficiency, a cloud-edge computing-based framework for smart AM is proposed based on AI. The goal is to provide future development of intelligent agents for AM. Although the proposed framework is designed for AM, it could also be applied to other manufacturing processes with minor adjustments.

4.1 Definition of smart AM

Smart manufacturing can be defined as a fully integrated, collaborative manufacturing system that responds in real time to meet dynamic changing demands and conditions of the factory, supply network, and customer requirements [102]. Traditional manufacturing processes involve multiple operations (e.g., molding, heat treatment, milling, grinding, etc.). Therefore, this definition mainly applies to the manufacturing management aspect. The manufacturing process of AM is simpler, without extra tools and complex procedures [3]. The focus is changed from the manufacturing and assembly aspects to the products. A wider design space can be explored, and faster prototypes can be achieved. Therefore, AM from the product-centric perspective should be understood. Considering of the whole product lifecycle and integrating different stages to provide better global product solutions. Hence, Smart AM is defined in this study as "a fully integrated, collaborative additive manufacturing system that responds in real time to support ubiquitous and intelligent design, manufacturing and services of 3D printed products."

4.2 Cloud-edge computing

Cloud computing utilizes simple centralized architectures with dedicated data centers to offer several allowances, such as self-service provisioning, elasticity, pay per use, etc. [103]. Big data generated from distributed IoT devices cannot be properly handled by the remote cloud owing to the large consumption of time, energy, and bandwidth with a high response time [104]. Privacy concerns are another critical issue. Services providers may not want to expose their confidential data on the cloud.

Multi-access edge computing (MEC) was standardized by the European Telecommunications Standards Institute (ETSI) and Industry Specification Group (ISG) and defined as "MEC provides an IT service environment and cloud computing capabilities at the edge of the mobile network, within the radio access network (RAN) and in close proximity to mobile subscribers"[1)]. MEC offers cloud computing capabilities within the RAN and connects the users directly to the nearest cloud service-enabled edge network, by deploying edge nodes at the base stations to enhance computation efficiency and avoid bottlenecks and system failure [105]. A comparison of cloud and edge computing [106] is listed in Table 4. Combining the advantages of both methods, cloud-edge computing could handle more complex demands in the industrial environment [107,108].

4.3 Proposed framework

The proposed smart AM framework is shown in Figure 4. Because massive data are generated in the process, the cloud-

Table 4 Comparison of cloud and edge computing

Criterion	Edge computing	Cloud computing
Computing equipment location	On-premises	Remote
Computation power	Limited	Unlimited
Storage	Limited	Unlimited
Latency	Low	High
Accessibility	Local	Public

1) ETSI. Multi-access Edge Computing (MEC). https://www.etsi.org/technologies/multi-access-edge-computing, accessed 30 January 2020

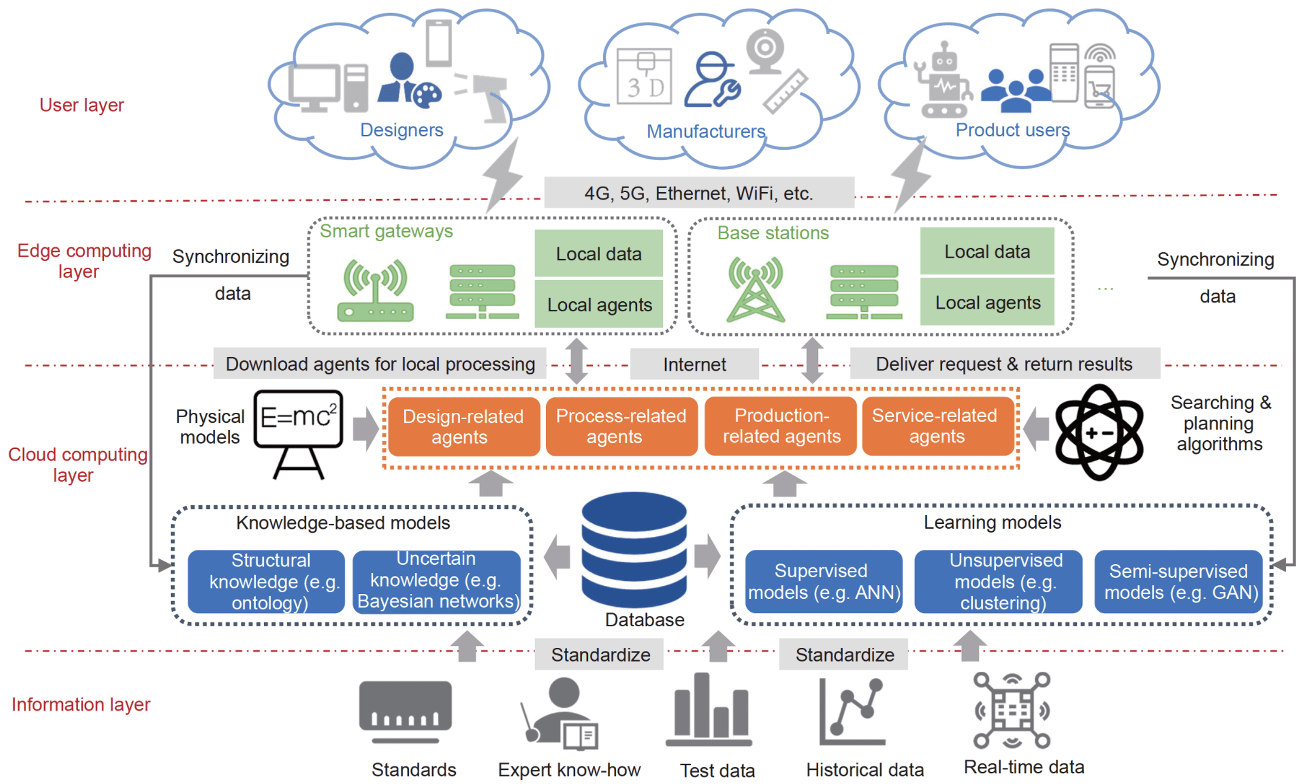

Figure 4 (Color online) Smart AM framework.

edge computing framework is applied to facilitate efficient information transmission and processing.

The information layer contains the source information for the platform to form basic knowledge and models. The information could come from the standards, expert know-how, test data, historical data, real-time data, etc. As in a different format, this information should be standardized before integrated processing.

The cloud computing layer is responsible for distributed information integration, forming intelligent agents for public access and processing computationally heavy tasks. For central information storage, the cloud environment can form more comprehensive knowledge-based and learning models to developing effective agents. Combining the physical models and searching and planning algorithms, various agents can be formed for different stages. Hybrid models can be developed as they are all available in the cloud environment.

The edge computing layer is used to process light agents for a fast response and to reduce the burden for the cloud. For example, the learning-based agents can put the training process in the cloud, while the execution process at the edge can achieve maximum efficiency and response time. The reflex agents can be deployed at the edge, as they do not require large computation. Conversely, the goal-based agents often require a large computational power, thus, it is better to deploy them in the cloud. The edge nodes can also synchronize useful local data to the cloud when the network is not busy for model improvement.

The users can access these agents and resources from the user layer using various devices.

5 Conclusion

Because of deep learning development, AI use has increased in many fields. The unique capabilities of AI have also increased the attention given to the improvement of AM-based product development. This study reviewed the current research activities on the application of AI in AM, including product design, process design, production and services. Several research gaps and future directions are summarized. To develop a more efficient and comprehensive environment for AI-enabled AM, a smart AM framework is proposed. Cloud-edge computing is applied to fulfil the computational requirements of different types of agents. The aim of this study is to better understand how AI techniques can help AM product development and provide our view of the future of smart AM.

This work was supported by the National Natural Science Foundation of China (Grant No. 51890885) and the Natural Science Foundation of Zhejiang Province (Grant No. LY19E050019).

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