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Review article

3D printing in materials manufacturing industry: A realm of Industry 4.0

Tariku Sinshaw Tamir [a,b,c], Gang Xiong [b,d], Zhen Shen [b,e], Jiewu Leng [a,*], Qihang Fang [b], Yong Yang [f], Jingchao Jiang [g], Ehtisham Lodhi [b], Fei-Yue Wang [b,d]

[a] *State Key Laboratory of Precision Electronic Manufacturing Technology and Equipment, Guangdong University of Technology, Guangzhou, 510006, China*
[b] *Beijing Engineering Research Center of Intelligent Systems and Technology, Institute of Automation, Chinese Academy of Sciences, Beijing, 100190, China*
[c] *Institute of Technology, Debremarkos University, Debremarkos, 269, Ethiopia*
[d] *Guangdong Engineering Research Center of 3D Printing and Intelligent Manufacturing, Cloud Computing Center, Chinese Academy of Sciences, Dongguan, 523808, China*
[e] *Intelligent Manufacturing Center, Qingdao Academy of Intelligent Industries, Qingdao, 266109, China*
[f] *State Key Laboratory of High Performance Ceramics and Superfine Microstructure, Shanghai Institute of Ceramics, Chinese Academy of Sciences, Shanghai, 201899, China*
[g] *Department of Mechanical and Automation Engineering, The Chinese University of Hong Kong, Shatin, Hong Kong*

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ABSTRACT

Additive manufacturing (AM), also known as 3D printing, is a new manufacturing trend showing promising progress over time in the era of Industry 4.0. So far, various research has been done for increasing the reliability and productivity of a 3D printing process. In this regard, reviewing the existing concepts and forwarding novel research directions are important. This paper reviews and summarizes the process flow, technologies, configurations, and monitoring of AM. It started with the general AM process flow, followed by the definitions and the working principles of various AM technologies and the possible AM configurations, such as traditional and robot-assisted AM. Then, defect detection, fault diagnosis, and open-loop and closed-loop control systems in AM are discussed. It is noted that introducing robots into the assisting mechanism of AM increases the reliability and productivity of the manufacturing process. Moreover, integrating machine learning and conventional control algorithms ensures a closed-loop control in AM, a promising control strategy. Lastly, the paper addresses the challenges and future trends.

1. Introduction

Manufacturing evolves from concept development to procedures and tools for producing items for use or sale. It is defined as an industrial production process that transforms raw materials into completed items for sale on the market [1]. Generally, manufacturing methods are classified as forming, casting, subtracting, and additive, shown in Fig. 1(a), (b), (c), and (d), respectively. 1) Forming –

* Corresponding author.
E-mail addresses: tamir@ia.ac.cn (T.S. Tamir), gang.xiong@ia.ac.cn (G. Xiong), zhen.shen@ia.ac.cn (Z. Shen), jwleng@gdut.edu.cn (J. Leng), fangqihang2020@ia.ac.cn (Q. Fang), yangyong@mail.sic.ac.cn (Y. Yang), jjia547@aucklanduni.ac.nz (J. Jiang), lodhi2018@ia.ac.cn (E. Lodhi), feiyue.wang@ia.ac.cn (F.-Y. Wang).

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Nomenclature

3D	Three dimensional	LPD	Laser powder deposition
AM	Additive manufacturing	LR	Linear regression
BIS	Beam interference solidification	LTP	Liquid thermal polymerization
BJ	Binder jetting	MJ	Material jetting
BPM	Ballistic particle manufacturing	MJM	Multijet modelling
CAD	Computer-aided design	ML	Machine learning
CAM	Computer-aided manufacturing	NN	Neural network
CNC	Computer numerical control	PBF	Powder bed fusion
CNN	Convolutional neural network	RF	Random forest
DED	Directed energy deposition	SFP	Solid foil polymerization
DMD	Direct metal deposition	SGC	Solid ground curing
DMLS	Direct metal laser sintering	SL	Stereolithography
DOF	Degrees of freedom	SLC	Selective laser cladding
DT	Decision tree	SLM	Selective laser melting
EBM	Electron beam manufacturing	SLS	Selective laser sintering
FDM	Fused deposition modelling	SM	Social manufacturing
HIS	Holographic interference solidification	STL	Standard triangle language
IJP	Inkjet printing	SVM	Support vector machine
LENS	Laser engineered net shaping	VP	Vat photopolymerization
LOM	Laminated object manufacturing	WAAM	Wire arc additive manufacturing

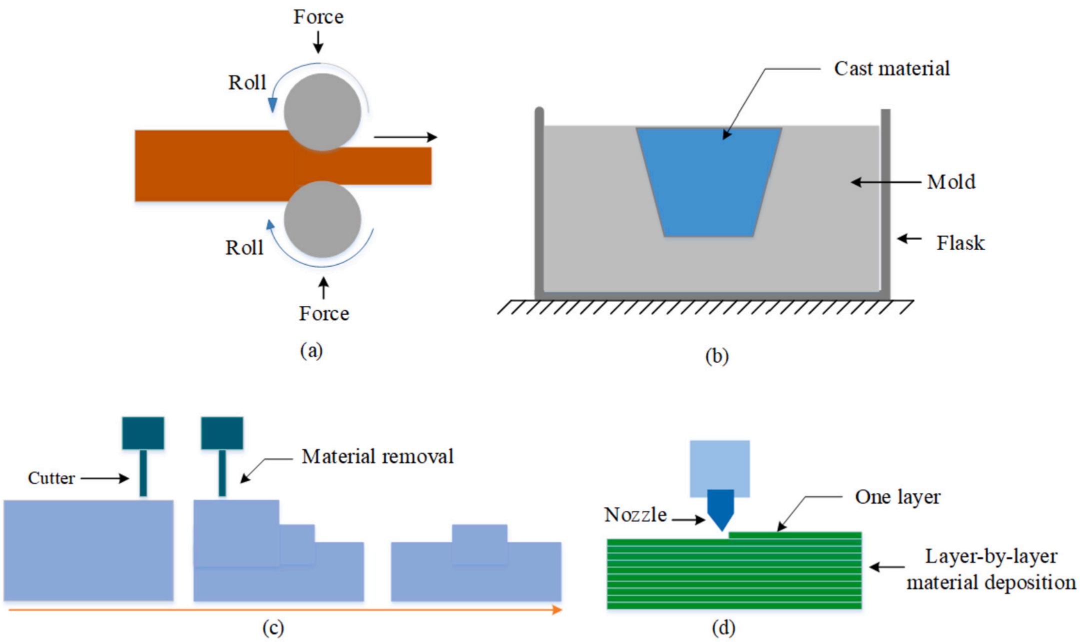

Fig. 1. Modes of manufacturing, (a) forming, (b) casting, (c) subtracting, and (d) additive.

applying force to a block of material to change its shape. 2) Casting – taking a row of solid material and turning it into liquid, then putting it in a shaping device or mold to make an object. 3) Subtracting – a material removal process to produce an object from large models. 4) Additive manufacturing (AM) – making parts through layer-by-layer material accumulation techniques.

Forming is a process of manufacturing wherein materials such as metals undergo plastic deformation and possess the required sizes and shapes through the application of appropriate stresses, including shear, tension, and compression [2,3]. During the forming, no material is removed: it is completely changed into the required shape using deformation techniques. The most common forming processes are forging, extrusion, thread rolling, rotary swagging, electromagnetic forming, and explosive forming.

Casting is a process of manufacturing that involves pouring molten material, such as metal and plastic, into a mold and allowing it to solidify to produce a manufactured part [4,5]. It can make complex shapes that might be expensive and difficult to produce using other manufacturing processes such as solid material cutting.

Subtractive manufacturing refers to the removal of materials from bars, solid blocks, metals, rods of plastic, or others through drilling, boring, cutting, and grinding. It can be done manually or via computer numerical control (CNC). The manufacturing tool in CNC receives input of computer-aided design (CAD) model. Then, computer simulation produces the toolpaths to facilitate the cutting mechanism across the part geometry. These instruct the machine on how to make cuts, holes, channels, and any other features that necessitate the removal of material. The CNC tools use this computer-aided manufacturing (CAM) data to manufacture items with little or no human intervention. The manufacturing processes, such as AM and advanced robotics, have been created and are progressively used by various industrial sectors in recent years, fundamentally altering how things are manufactured.

AM, or 3D printing, on the other hand, is a vital component of Industry 4.0 that uses digital 3D design data to build up a component in a layer-by-layer material accumulation method. AM initially emerged as rapid prototyping [6]. It was first used to create conceptual models to explore design concepts, as well as for form and fit applications for the creation of anatomical or architectural models [7]. Then, the technology progressed to rapid tooling that allows the production of thermoforming, injection molding, or blow molding tools, as well as the fabrication of electrodes for electrical discharge machining [8]. Finally, AM moved to rapid manufacturing, allowing the production of completely functional goods. Currently, AM is applied for producing parts in many fields, including aerospace, biomedical, and automotive industries [9–11].

3D printing allows manufacturers to choose a product's shape, texture, and toughness. These goods can also be produced using a variety of 3D printing materials [12–17]. Plastic is currently the most widely used raw material for 3D printing, making manufacturing toys and household items simple. Making plastic products involves melting thermoplastic filaments and deposition them layer-by-layer into the desired shape. The types of plastic can be made from polylactic acid (PLA), acrylonitrile butadiene styrene (ABS), polyvinyl alcohol plastic (PVA), or polycarbonate (PC). Plastic materials can be strengthened by adding a carbon fiber composite top coat. Carbon fiber materials are viable alternatives to building stronger items. Metals are the most often used materials after plastics in the 3D printing industry. Metals come in various forms, including titanium, bronze, gold, nickel, aluminum, and stainless steel. Powdered materials can also be used for 3D printing, which involves melting the powder and distributing it in layers to create the desired patterns, thickness, and texture. Alumide and polyamide (nylon) can be used to make powders. Powdered materials, such as copper, steel, and other metals, are easier to mold into desired shapes. Resin is one of the less popular 3D printing materials. High-detail, paintable, and transparent resin materials can all be put into these categories. Additionally considered 3D printing materials are graphene, nitinol, and paper.

A desirable 3D printer must have the following characteristics to advance AM technologies and accommodate various applications. First, a 3D printer must incorporate a reliable and productive AM process, after which a part's physical/mechanical quality and geometrical precision can be controlled. Based on this, the user-defined manufacturing specifications can then be met. Second, a 3D printer's productivity should increase or become efficient enough to process more manufacturing operations. Current 3D printers, on the other hand, have difficulty meeting these performance goals. One major issue with controllability is that most 3D printers use open-loop control. They use a trial-and-error method to determine their material and processing parameters. These parameters are then set before the start of an AM process, with no change at the time of 3D printing. When AM processes face unwanted physical reactions and are subject to disturbances from various sources, an open-loop control system may attempt to fail the control process and various defects are likely to occur [18].

Regarding product quality and production efficiency, the aforementioned issues severely impede the development of the AM industry. The importance of incorporating process monitoring, control, and optimization functions into AM for quality control has been recognized by both researchers and practitioners. In addition, closed-loop control and optimization methods can be designed to avoid interference and improve part quality.

The contribution of the paper includes a review and summary of technologies, configurations, and monitoring of AM that cover the following aspects:

- Discusses the definitions and working principles of various AM technologies.
- Details about various AM configurations, including traditional and robot-assisted AM.
- Discusses fault diagnosis and defect detection of AM and also intends to discuss various control systems, such as open-loop and closed-loop monitoring systems.
- Highlights research directions in hopes of filling the knowledge gap regarding fault diagnosis, control, monitoring, and optimization of AM.

The rest of the paper is organized as follows – Section 2 details various AM technologies with unique features of each. Section 3 elaborates on different AM configurations, including traditional AM and robot-assisted AM. Section 4 discusses fault diagnosis and defect detection of AM. Following that, control systems, including the open-loop and closed-loop AM, are reviewed in section 5. Challenges and future trends are discussed in Section 6, followed by conclusions and perspectives in Section 7.

2. AM process structure and technologies

This section discusses the general AM process flow, from the product idea to the end product. In addition, various AM technologies, along with their working principles, are also discussed.

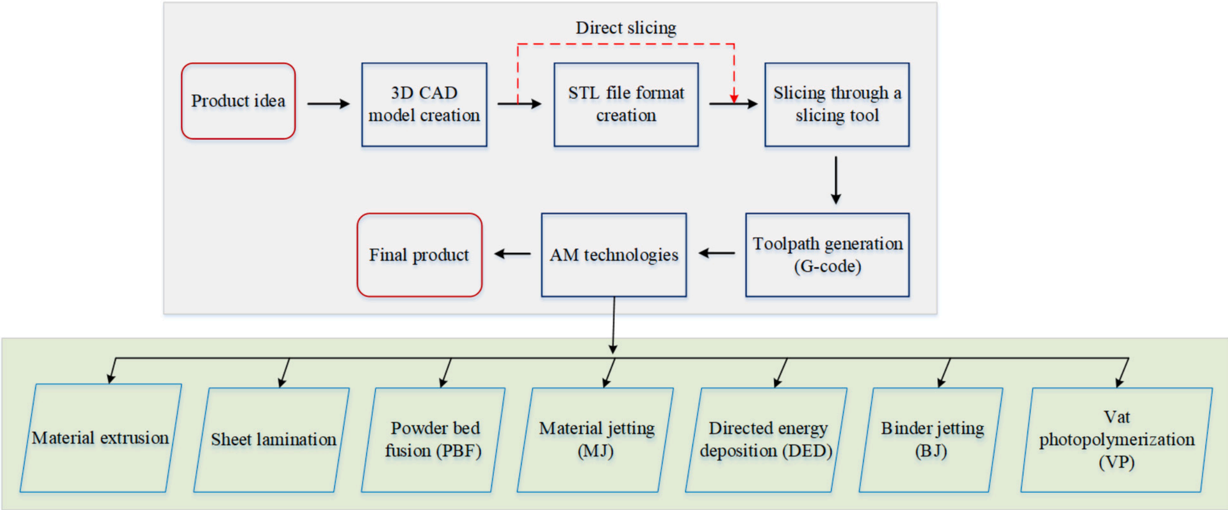

Fig. 2. AM process flow.

2.1. AM process structure

AM techniques begin from the creation of a CAD model. Then, the 3D CAD model is saved in the standard triangle language (STL) file format before being sliced into multiple cross-sections and sent to an AM system [19]. This format comprises a list of connected triangular planar facets representing an object's outer surface. Each facet is defined by its vertices and a unit surface normal vector pointing away from the part's interior [20]. Last, the STL model is sliced into cross-sections to generate toolpaths using planar or non-planar slicing techniques. The process of intersecting the STL file with a set of horizontal planes is called planar slicing [21,8]. Each horizontal plane produces a piecewise linear planar contour. Non-planar slicing, on the other hand, is the process of slicing parts by using curved layers that stretch across the X-, Y-, and Z-axes [22–25]. This slicing technique enables printing curved parts with a smoother external finish, regardless of factors such as hot end, filament type, and post-processing. If the slicing is done with the same layer thickness, it is known as uniform slicing; otherwise, adaptive slicing in which a variable layer thickness is employed based on model geometry changes along the build direction [26–28].

The general AM process flow from the product idea to the final product formation is illustrated in Fig. 2. The 3D CAD model is mostly sliced after converting into STL file format. However, to reduce file format conversion error, some research works proposed a direct slicing from the 3D CAD model [29–32], as shown in Fig. 2. One crucial component in AM process flow is post-processing. However, the availability of this component in the process flow chart depends on the type of slicing techniques, AM configuration, and the like. Therefore, it is missed in Fig. 2 and is discussed in detail in the next section.

2.2. AM technologies

Today, there are numerous AM technologies available [33]. Their differences come from the dimensions, such as how layers are formed to create parts, the materials used, and the operating principles. Some methods, such as fused deposition modeling (FDM) [34], selective laser melting (SLM) [35], and selective laser sintering (SLS) [36] melt or soften materials to create the layers. In contrast, others, such as stereolithography (SL) [37–39] cure liquid materials. Each method constitutes advantages and disadvantages. As a result, some companies give the option between polymer and powder material for making the object. The main factors considered when selecting a machine can be the machine speed, the cost of materials, the cost of the printed object, and its color capabilities [40,41]. It is noted that there is a growing trend toward AM of structural, load-bearing structures, which takes advantage of the inherent design freedom of such a process.

Generally, AM technologies are classified into seven categories, according to the American Society for Testing and Materials standard F2792 [42]. It includes material extrusion, binder jetting (BJ), powder bed fusion (PBF), directed energy deposition (DED), material jetting (MJ), sheet lamination, and vat photopolymerization (VP). Therefore, AM technologies can be summarized more intuitively in the following categories to make readers clear and easily understandable. The advantages, disadvantages, and application areas of each AM category are shown in Table 1.

2.2.1. Laser-based

Laser-based AM technologies employ a laser source to melt, solidify or cure the material. Laser-based processes are classified into laser polymerization and melting based on the phase change mechanism. Laser polymerization technologies include SL, solid ground curing (SGC), liquid thermal polymerization (LTP), beam interference solidification (BIS), and holographic interference solidification (HIS). In such cases, the material is usually a photosensitive resin that cures when exposed to UV radiation from a low-power laser source. In laser melting, such as SLS, SLM, direct metal laser sintering (DMLS), laser engineered net shaping (LENS), direct metal

Table 1
Comparisons of AM categories.

Categories	Advantages	Disadvantages	Application areas
Laser-based [44]	Weight savings of parts, the reduced process time, and opportunities for new material development.	High manufacturing time, the lasers are expensive and may harm the operators.	Applicable in the aerospace, biomedical, and automotive fields.
Extrusion [45]	Easy for controlling, operating, and managing the process and more economical process.	Low column strength, high melt viscosity, material nozzle blockage, and lack of standards.	Applicable for producing polymers, plastic products, food products, concrete houses, metals, ceramics, and reinforced parts with fibers.
Material jetting [46]	Can produce highly accurate and smooth parts, multi-color and multi-material capability, and low wastage due to the on-demand jetting of the material.	Poor mechanical properties, mostly support materials are needed, relatively expensive technology, and limited material availability.	Applicable in producing anatomical medical models for pre-surgical and education purposes.
Adhesive [47]	Less manufacturing time, inexpensive, good handling strength, and wide range of materials.	Part strength depends on adhesive strength, and the part may be distorted due to absorption of water and not suitable for producing complex parts with thin geometry.	Applicable for prototyping and creating architectural models used in design and education.
Electron beam [48]	Precise and distortion-free, no fracture issue, can machine highly reactive metals, and can be applied to cut slots and holes in ceramics, metals, plastic, etc.	Expensive, there is a thermal effect, relatively high manufacturing time, a skilled operator is needed, and the electron beams may harm the operators.	Applicable in aerospace, chemical, textile, food, and automobile industries.

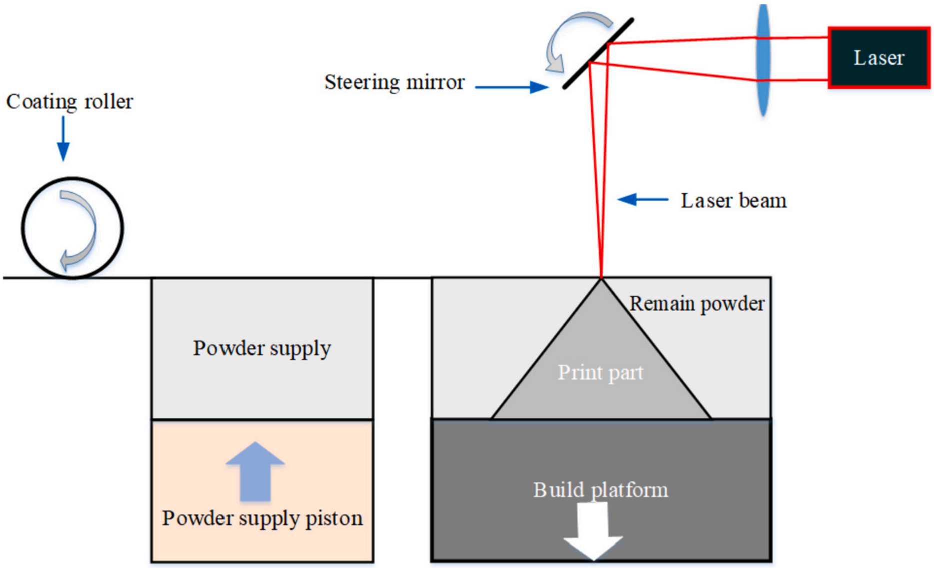

Fig. 3. Schematic of laser-based AM process.

deposition (DMD), laser powder deposition (LPD), and selective laser cladding (SLC), the material in the form of powder is supplied to the laser melting processes, either to a powder bed or to the processing head directly via nozzles. To melt the material, a laser beam is used, and then the material cools and solidifies to allow the part to get produced. The laser-based process is shown in Fig. 3 [43].

2.2.2. Extrusion

These technologies use a heated extrusion nozzle to melt or soften a material [49]. The most common material is plastic in the form of wire. After the material is melted, it is extruded through an extrusion nozzle and then cools to get solid and form the finished part geometry. In some applications, alloys, metals, polymers, bio-materials, composites, ceramics, and concrete can be utilized for such technology [21,50–52]. FDM and robocasting are the typical material extrusion processes. The extrusion process is illustrated in Fig. 4.

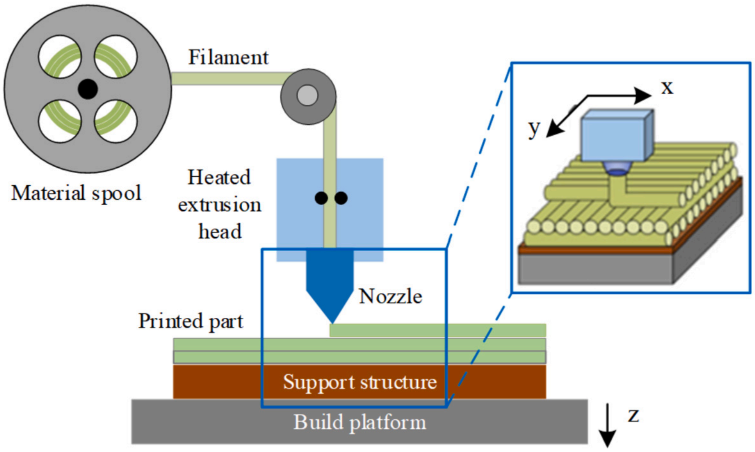

Fig. 4. Schematic of extrusion AM process.

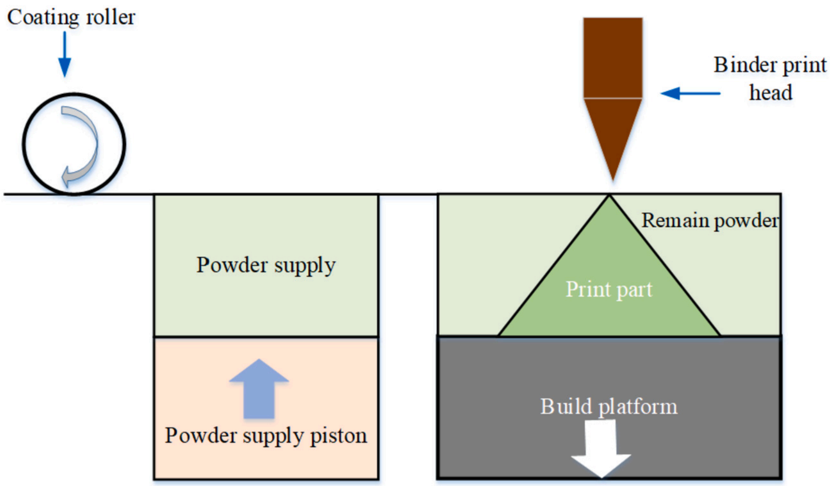

Fig. 5. Schematic of material jetting AM process.

2.2.3. Material jetting

Material jetting technologies employ thin nozzles to "spray" either molten material or, more commonly, a binder (adhesive) to bind the powder in a solid object in a controlled manner. The material jetting process onto a build platform can be either drop-on-demand (DOD) or continuous. Its operating principle of the process is similar to other laser-melting processes, with no occurrence of phase; instead, the binder continues to hold the powder particles together. Inkjet printing (IJP), three-dimensional printing (3DP), multijet modeling (MJM), ballistic particle manufacturing (BPM), and thermojet are examples of material jetting processes. The material jetting process is shown in Fig. 5 [43].

2.2.4. Adhesive

Adhesive-based technologies are not widely used. The operating principle encompasses a cutter (typically a laser), which cuts a plastic or a thin film of paper in the desired contours. The film is then pressed onto the previous one by a heated compactor, which can activate a heat-curing adhesive on the film's downward face to be bonded to the substrate. Laminated object manufacturing (LOM) and solid foil polymerization (SFP) are the typical adhesive processes. The adhesive process is illustrated in Fig. 6 [43].

2.2.5. Electron beam

Metal powder or wire as a raw material is placed in a vacuum and fused by an electron beam. Electron beam technologies are similar to laser-melting technologies, except that an electron beam is used as an energy source to melt or sinter the material. Electron beam manufacturing (EBM) is a typical electron beam technology. Fig. 7 illustrates the process [43].

Table 2 illustrates the part-building process of various types of AM technologies.

Far from the commonly known AM technologies, 3D bioprinting and 4D printing are emerging as new developments. As a type of 3D printing, 3D bioprinting can be applied in bio-applications [87–90], which uses biomaterials instead of metals and plastics to produce 3D objects. 4D printing, on the other hand, is similar to 3D printing in that it includes additional components known as

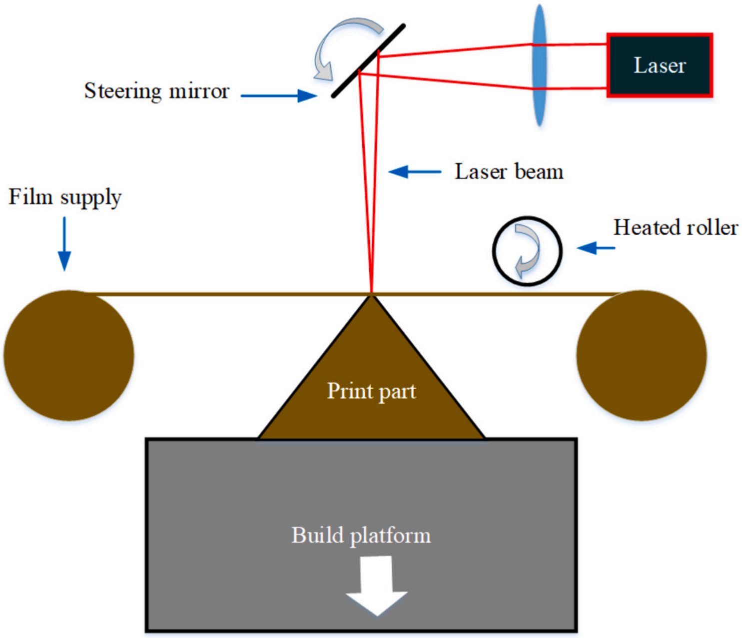

Fig. 6. Schematic of adhesive AM process.

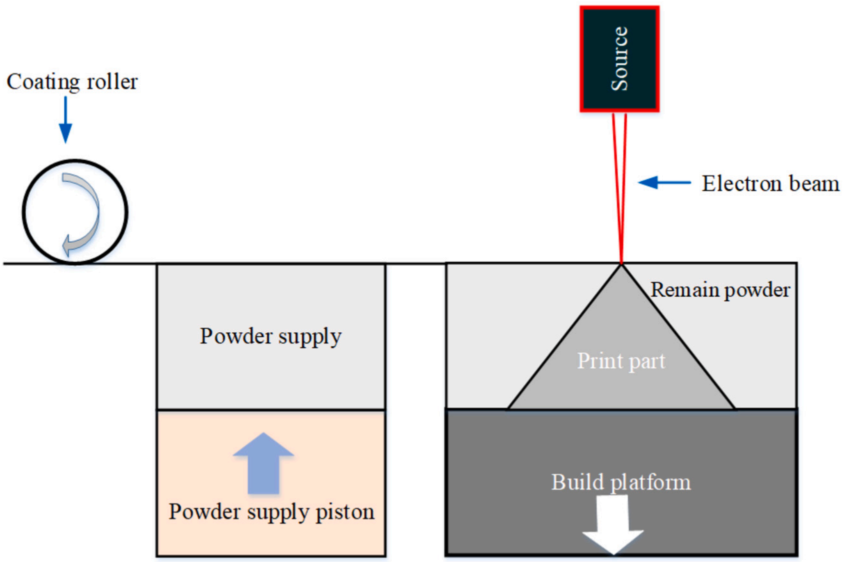

Fig. 7. Schematic of electron beam AM process.

stimulus-responsive materials [91] that are responsible for changing the structure of the 3D part when exposed to a stimulus. Stimuli can include light, temperature, and other environmental factors. Researchers are interested in 3D bioprinting and 4D printing because of their wide range of applications, and they intend to develop new methods and applications in these fields.

3. AM configurations

In this section, two AM configurations, i.e., traditional AM and robot-assisted AM, are discussed. In addition, the degree of freedom (DOF) associated with each AM configuration is briefed.

Table 2
Part building process of AM technologies.

Categories	Technologies	Part building process
Laser-based	SL	Based on the principle of photo-polymerization of photosensitive monomer resins by exposing to UV radiation [53–55].
	SGC	A photopolymer-based AM technology creates the layer geometry by passing a laser source [56,57].
	LTP	Similar to SL, this method builds the part using thermal energy to solidify successive layers of liquid thermosetting polymer [58,59].
	BIS	A point-by-point photosensitive polymer solidification at the intersection of two different wavelength laser beams [33,60].
	HIS	A projection of a holographic image onto a vat contained liquid photosensitive polymer, causing the polymer's entire surface to solidify rather than point-by-point [60,61].
	SLS	Heating of a fine powder using a laser beam (ranging from 7 W up to 200 W) to allow the grains to fuse together [62,63].
	SLM	Similar to SLS, but instead of sintering SLM possesses powder melting by using a higher laser beam (around 400 W) to form a part [64,65].
	DMLS	Similar to SLS/SLM, but DMLS uses metallic powder only with a laser power ranging from 200 W to 400 W [66,67].
	LENS	Metal powder stream is injected through a special powder delivery nozzle using a high-power laser beam to form a part [68,69].
	DMD	Similar to SLS/SLM with no powder bed, the powder is fed directly to the processing head using several nozzles similar to LENS [70,71].
	SLC	A Layer-by-layer generation of part by melting metal powder using a laser beam as heating source [72,73].
Extrusion	FDM	A movable head deposits a heated thermoplastic material onto a substrate and solidifies immediately. Then welds to the previous layers [74,75].
	Robocasting	A freeform fabrication method for depositing highly loaded colloidal slurries for composites and dense ceramics based on layer-by-layer fashion [76,77].
material jetting	IJP	A type of computer printing in which ink droplets are propelled onto plastic, paper, or other substrates to create a digital image [78,79].
	BPM	Involves injecting a stream of molten droplets of metals or thermoplastics from piezoelectric inkjet printing nozzles onto a target substrate [80,81].
Adhesive	LOM	Applying a heat-sensitive adhesive to one of the sides of a special type of paper so that the paper is supplied from a roll and bonded to the previous layer by using a heated roller [82,83].
	SFP	Based on the complete polymerization of a semi-polymerized plastic foil when exposed to a suitable light source, bonding occurs after complete polymerization [61,84].
Electron beam	EBM	A rapidly developing technology in which an electronic beam is used to melt metallic powder by an electron beam with a high voltage, typically 30–60 KV [85,86].

3.1. Traditional AM

This kind of AM configuration involves a conventional gantry system. It has mostly three DOF, including two horizontal (i.e., x-axis and y-axis) and one vertical (z-axis) motion. These motions are illustrated in Fig. 8. The traditional AM configuration process comprises the components as presented in Fig. 2. It includes 3D CAD model creation, STL file conversion, slicing, path planning, code generation, part building, and post-processing. Each stage contributes to the finally fabricated part's quality. The most commonly used slicing strategy is planar slicing. In such cases, support structures are required to build overhangs [92,93]. At the end of the part-building process, the so-called post-processing stage, the support structure materials must be removed. Various kinds of research are conducted using the concept of traditional AM configuration [94–97].

The commercially available traditional AM machines mostly have three DOF motions. This results in a limited part building freedom. The use of support structures in traditional AM is another issue, as it wastes material and time and creates part damage during the removal of the support material. In addition, such machines produce objects of small size, i.e., they are unable to fulfill customer satisfaction with large objects. Even though traditional AM has become an increasingly important part of developing new technologies and devices, using this technology on a larger scale remains difficult. For larger components, AM is typically time-consuming. It is possible to build parts quickly where surface quality and detail are not critical. For traditional AM processes, the machines must grow to a larger scale than the produced parts, which would limit the build volume in any case. Combining AM and robotics is one way to enable AM of large-scale products.

3.2. Robot-assisted AM

The assisting mechanism of robotic systems in the printing process enables multi-directional printing. As a result, various research teams are currently working on multi-directional slicing algorithms for reducing the use of support structures in the formation of complex shapes or overhangs. Besides, robot-assisted AM can produce large objects that traditional AM cannot.

Robot-assisted AM systems have a slightly different information flow than traditional three-axis AM systems. A unified strategy is difficult to implement because the information flow, in this case, depends on the type of robot and the operating language. The important feature of robot-assisted AM is converting the G-code into a desired robot language to control the robot joint trajectories

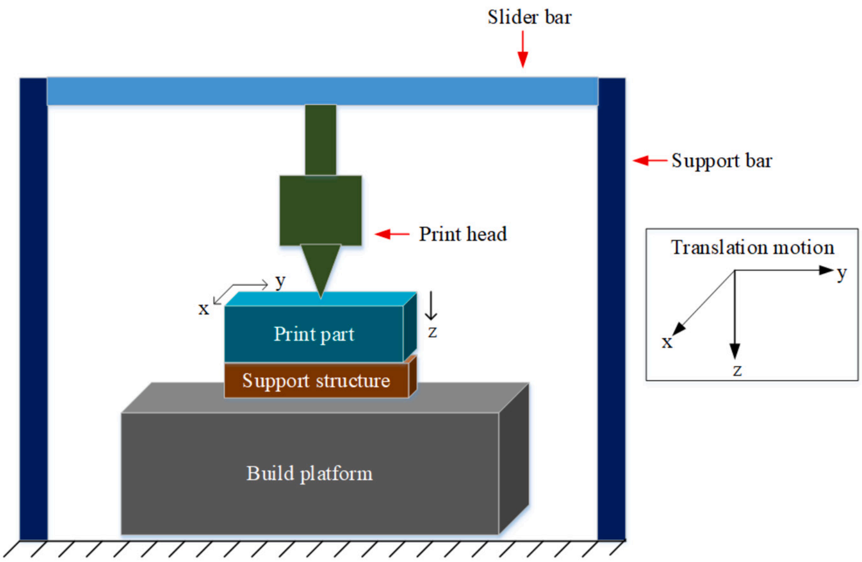

Fig. 8. Traditional AM configuration.

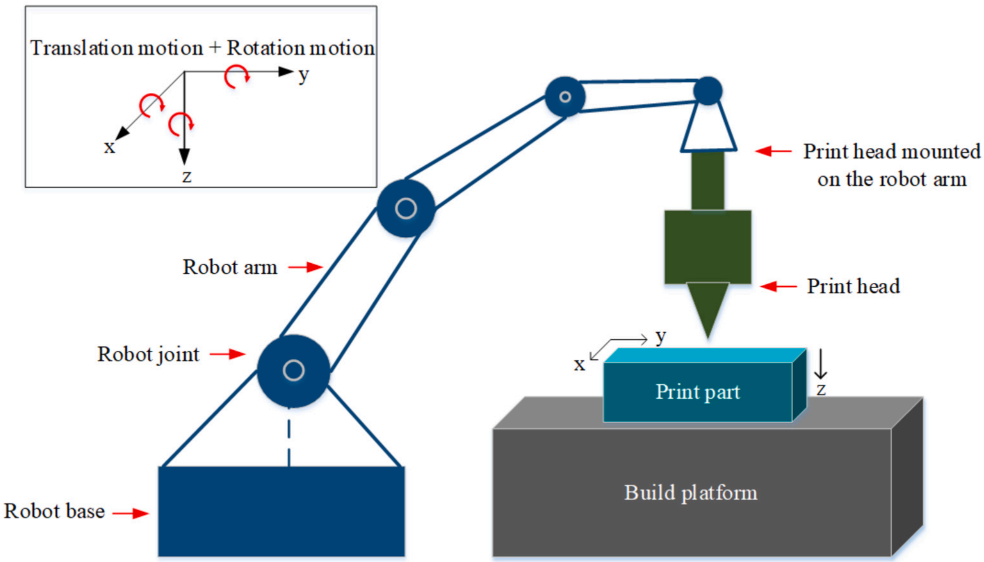

Fig. 9. Robot-assisted AM configuration.

during part building. The robot can be configured as five DOF, six DOF, or more than that. Thus, in such cases, a multi-axis robot-assisted AM can be ensured.

Robot-assisted AM is illustrated in Fig. 9.

With the advancement of multi-axis AM machines, complex motion control for the AM industry is possible. Various approaches are reported to reduce the number of layers and the use of support structures in the manufacturing process. Chakraborty et al. [98] proposed a parametric surface-based path generation technique called curved layer FDM, which uses curved accumulating layers instead of traditional flat layers in FDM. It has advantages in the manufacturing of thin and curved parts for increasing the strength, reducing the stair-step effect, and reducing the number of layers. Ding et al. [31] proposed a new strategy of decomposition-regrouping method of CAD models in STL format. The study first decomposes the CAD model into sub-volumes based on a simple curvature-based volume decomposition method. Then, a depth tree structure merges them into ordered groups for slicing. In [28,99], the curved layer parts of an object are identified for checking the mechanical performance. The experimental results indicated that curved layer parts outperformed planar layer parts in terms of mechanical properties. The toolpaths were created by intersecting the curved surface with vertical planes, then using the point offset algorithm. Zhao et al. [25] presented two nonplanar slicing approaches, including a decomposition-based curved surface slicing strategy and a transformation-based cylinder surface slicing technique. For the curved surface slicing strategy, the STEP model is decomposed into sub-volumes by concave loops. The toolpaths of the sub-volume are by curved surface slicing technique followed by five-axis toolpath generation. For the cylinder surface slicing technique, on the other hand, the mesh model is used to extract and analyze the cylinder surface for finding the axis and radius parameters. The cylinder surface-based mesh model is then transformed into a planar model. Following the transformation, slicing and toolpath generation are performed in the same way as traditional methods of planar slicing. Finally, the curved layer toolpaths are generated by the inverse transformation of toolpaths.

AM processes are prone to discretization effects. Stair-stepping artifacts degrade the surface quality of 3D printed objects in most technologies, especially when the surface slope is close to horizontal. In [100,101], the stair-stepping effects are reduced using multi-directional toolpaths in a single object. It is accomplished by first decomposing the model into different parts, slicing each part with a different orientation in a suitable manner, and finally merging the toolpaths of the parts of the entire object. Larger overhangs and improved surface quality are possible with the multi-directional object. Ding et al. [31] proposed a new decomposition-regrouping method for multi-directional slicing. Following the decomposition of the CAD model into sub-volumes, a depth-tree structure based on available topology information is used to regroup them into new orders for slicing.

Collisions within the toolpath are a significant issue when printing nonplanar layers. In [102], an algorithm for generating a 3D toolpath along a freeform surface is presented. The algorithm also has a collision-checking mechanism by generating an envelope surface with an approximated pointy nozzle. Yang et al. [103] proposed a novel FDM slicing method that combines nonplanar and planar layers, resulting in stronger and smoother surfaces. The proposed slicing algorithm has a mechanism to detect which parts of the object should be printed with nonplanar layers and generates collision-free toolpaths using a geometric model of the print head and extruder. Finally, yuan et al. [32] described a novel multi-directional wire arc additive manufacturing (WAAM) process. It can manufacture metal components additively in multiple directions, employing robotic gas metal arc welding. Several novel modules are highlighted, including positional bead modeling, multi-directional slicing, and deposition process optimization. The 3D model is decomposed into a set of optimal sub-volumes, and then sliced layers with the best deposition directions are generated.

Experts implemented a robot-assisted AM to build large objects. To aid in the construction of more affordable housing, the Total Kustom Company is working on large-scale 3D printing of houses. They have 3D printed large cement structures using their own 3D concrete printing technology, such as the concrete castle. Their initial design was printed piece by piece and then assembled by hand. Later, the project 3D printed an entire hotel suite in a single piece [104,105]. They are currently investing in an outstanding 3D concrete printing project. Similar 3D printing applications are found in [106–110]. Joris Laarman Lab's work combines AM and robotics. They progressed of using AM methods to build structures. Joris Laarman Lab's most exciting development is the MX3D metal printer. It was an extension of the Mataerial project launched in 2012 [111], in which a 6 DOF robot manipulator was used to extrude material along a pre-planned trajectory. The Joris Laarman laboratory and the Institute of Advanced Architecture of Catalonia (IAAC) had a collaboration to build the Mataerial project. The project team had received a patent of AM technique for multi-directional printing of fast-curing thermoplastic materials rather than just top-down or bottom-up. And it allowed almost any structure to be made without needing support or underlying layers. Evjemo et al. [112] presented the state-of-the-art large-scale AM looking into some applications such as buildings or sculptures. A proof of concept experiment for 3D printing using an industrial robotic manipulator is also presented. To realize such a system, trajectory planning algorithms and end effector translation control algorithms are conducted. Tamir et al. [113,114] proposed a novel robot-assisted AM of a 6 DOF Stewart platform manipulator, which possess multi-directional printing without support structures to substitute the printer build plate.

4. Defect detection and fault diagnosis in AM

This section presents the defect detection and fault diagnosis techniques in AM, which gives the knowledge to monitor, diagnose, and control the AM process.

4.1. Defect detection

Defects in AM are expressed as any abnormalities in the quality of the printed part due to some factors, such as the improper setting of printing parameters, machine mechanical problems, and post-processing problems. In-situ monitoring is used to capture defect-related process signatures. Various algorithms can be applied to analyze the defect detection process [115–118]. Typical defects in AM are listed as over-fill, under-fill, delamination, deformation, detachment, over-curing, over-melting, under-melting, balling, cracking, porosity, etc [119–121]. Macro- and micro-level defects are the possibilities of defects [122]. Most AM processes constitute part deformation as a common macro-level defects, whereas cracks can occur at either the macro- or micro-level. Thus, it is challenging for inspecting the possible anomalies occurred in the part formation. Moreover, defects may appear inside or on the surface of a part. For example, in FDM, the over/under-fill are the typical defects and can appear on the part's surface, whereas pores in PBF can be inside a part surface. It thus increases the need for monitoring techniques with a wide detection range.

Various systems are proposed for capturing defect-related process signatures for defect inspection. Optical monitoring techniques, such as high-speed cameras, high-resolution cameras, 3D reconstruction, interferometry, and x-ray imaging; thermal monitoring techniques, such as infrared cameras, pyrometers, and thermocouples; and acoustic monitoring techniques, such as acoustic emission and ultrasonics are used for defect detection. The defects can be detected either directly or indirectly. In the direct way, the detection system can collect the associated data about the quality of a part, which have the capability of identifying and measuring defect directly. For example, a high-resolution camera can capture part surface images, which can then be analyzed and segmented to identify defects such as over/under-fill. A 3D scanner can quantitatively characterize part surface quality by measuring layer height. The measurement resolution corresponds to the AM process signatures.

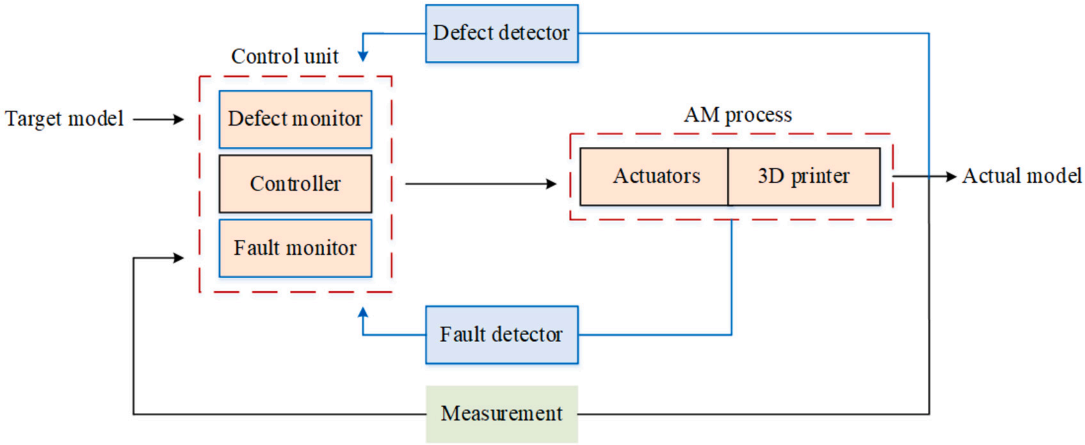

Fig. 10. Defect detection and fault diagnosis in AM control loop.

Indirect detection systems, on the other hand, possess the possible defects indirectly. The quality of the print part is associated with potential phenomenons, including melt pool morphology in PBF [123] and temperature differences of deposited material in FDM [124]. The mapping of process signatures into print part properties can be achieved using data-driven methods of classification and regression as common prediction tasks. There is an additional requirement for temporal resolution in such prediction systems. The typical process dynamics timescale and the data acquisition rate should be consistent for capturing process signatures effectively. Berumen et al. [125] demonstrated such relationships by considering the sampling rate of PBF monitoring as the quotient of scan speed and melt pool size. A 150 μm melt pool with a scan speed of 1 m/s necessitates a frame rate of 6666 frames per second. Readers can find more information on the time scales descriptions in PBF at [126,127], and in VP at [128,129].

Regardless of the above-mentioned requirements, monitoring methods in both direct and indirect detection systems must involve a compatible ground not to affect the original AM environment. It means that the additional system components such as sensors must not interfere with the AM process. However, the integration of sensors into the existing commercial 3D printers is difficult due to the compact structure and limited space of their building chambers, as well as a lack of open access to data communication protocols [130]. As a result, establishing their monitoring systems become challenging.

4.2. Fault diagnosis

The faults we discuss here are associated with AM actuators' operating and health conditions. The operating faults include the actuators' failure to execute the 3D printing task because of improper setting of the processing parameters and external disturbances. On the other hand, the faults associated with the health conditions may result from the mechanical damage of the AM actuators [131–133].

We consider an FDM 3D printer to discuss the possible faults that occur through the printing process. Three subsystems, including positioning [134–136], printing [137–139], and material feeding [136,140,141] are considered to analyze the faults. During the positioning systems, such as motor damage, motor out of step, and belt damage; printing systems, such as nozzle clogging; and material feeding systems, such as filament breakage and run-out, are typical faults. A 3D printer needs a proper positioning mechanism in order for the build platform and print head to move precisely. A faulty one impacts the geometrical accuracy of a part and causes defects. A 3D printer's printing system comprises actuators directly used for part forming. They differ depending on the AM process. The extruding materials of FDM, MJ, and BJ are molten filaments, resins, and binders respectively. Print head is responsible for material extrusion. Nozzle clogging is a common print head operation fault. This fault can be caused by the failure of control action of a fan and heater or feeding impure materials [142]. A clogged nozzle reduces the materials or binders' flow rate, affecting the quality of extruded lines.

The commonly used fault diagnosis methods are four: model-based, signal-based, knowledge-based, and hybrid one [143,144]. Model-based methods begin with the creation of a system model. The predicted output of the system model is then compared to real ones to detect faults. Signal-based methods make use of process measurements, and the faults can be identified from time or frequency based signals artificially. Knowledge-based fault diagnosis techniques work based on data-driven methods in which the fault indicator signals possess learning mechanisms using ML algorithms. Combining two of the three fault diagnosis techniques creates hybrid methods.

Most 3D printers have open-loop control systems to drive the actuator mechanism. However, such systems fail to ensure the part quality and health of a 3D printer in real-time. Thus, a closed-loop control approach comprising detection and diagnosis mechanisms is needed. Then, it improves the reliability and productivity of an AM process, which ensures product quality. The general closed-loop control block diagram of AM process is shown in Fig. 10.

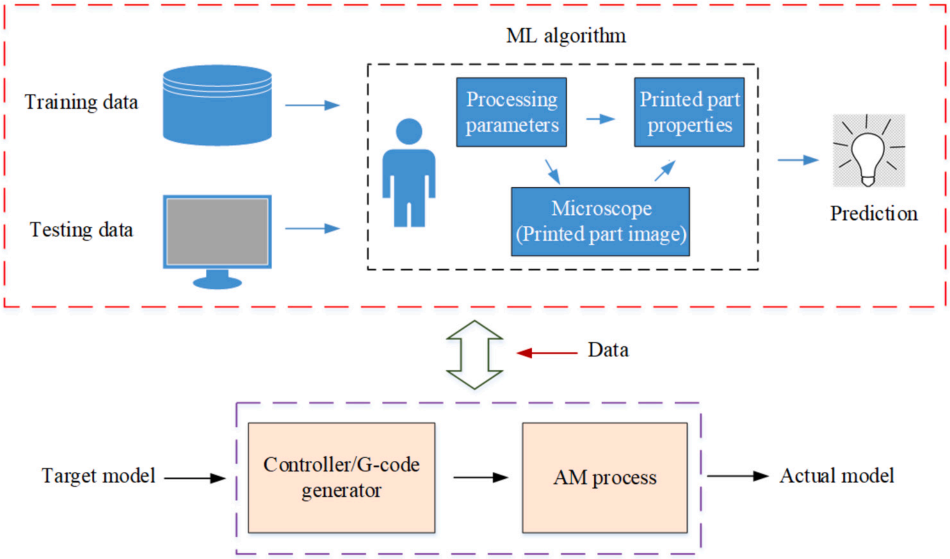

Fig. 11. Open-loop control of AM.

5. Control systems in AM

This section briefly discusses open-loop and closed-loop AM—ML-based prediction systems, as open-loop control systems and ML-based closed-loop control systems.

5.1. Open-loop AM

Various kinds of research that address open-loop AM control are conducted for ensuring the printed parts' quality and mechanical strength. The commonly applicable open-loop AM structures can be presented in two ways. The first approach uses various pre-printing design methods, including open-loop-based print path formation and support structure design. In such cases, different types of path generation approaches, including planar and non-planar slicing techniques by using either traditional AM or robot-assisted AM configurations, can be implemented. The second approach is ML-based pre-process parameter monitoring and optimization, an open-loop control method. In this way, various ML algorithms can be applied to predict some features of the printed part such that proper processing parameters setting can be achieved. A detailed review of the two approaches is discussed next. Fig. 11 illustrates the open-loop control scheme in AM.

Bin et al. [145] suggested a robot assisted 3D printing mechanism for generating multi-directional paths. This printing method improves the strength of the tensile specimen, elastic modulus, and ultimate tensile strength. Huang et al. [28] developed a curved surface slicing method, and the result demonstrates that the mechanical strength of a part increases as the curved layer gets thicker. Lim et al. [146] used planar and surface layer printing mechanism in a concrete 3D printing system, which concludes that surface layer printing produces greater strength of the part. The mechanical performance of a printed object was enhanced by Xia et al. [147] by building the toolpath in the direction of the maximum stress. Jin et al. [148] presented a curved layer slicing approach of printing path. The proposed system reduces the effects of the stair-step effect on the quality of the part. Furthermore, the B-spline is used to approximate curved surfaces accurately. Isa et al. [149] proposed a 5-axis path planning algorithm, which reduces the effects of staircases. Following that, their research examined the path and tool orientation conditions. Ding et al. [150] presented a path-planning method for WAAM to improve the part quality. Feng et al. [30] presented a slicing method for printing T-spline surfaces. Similarly, Xie et al. [151] presented a spline-based smoothing algorithm that is practically applicable, feasible, and effective for removing sharp corners around a printing path.

Li et al. [152] presented a data-driven system for surface roughness prediction in the AM industry. Sensors such as thermocouples, accelerometers, and infrared temperature sensors are used to collect vibration and temperature data. Then, these data are used to train the learning algorithm. Similarly, Wu et al. [153] developed an ML algorithm for predicting the surface roughness of the printed parts in FDM. The proposed system monitors the health condition of the printing process using multiple sensors. Khanzadeh et al. [154] proposed supervised ML algorithms for predicting porosity within printed parts based on melt pool boundary morphology. The melt pool signals are captured by a thermal monitoring system and labeled as normal or pore by x-ray tomography. Ko et al. [155] proposed a framework for constructing AM knowledge from the available AM data using ML algorithms. The proposed algorithm predicts printed part properties from the knowledge of processing parameters. Baumann et al. [156] also discussed the application of ML for solving problems in AM, such as process monitoring, process control, and quality enhancement of printed parts. Moreover, the applications of ML in AM are summarized in [157–163].

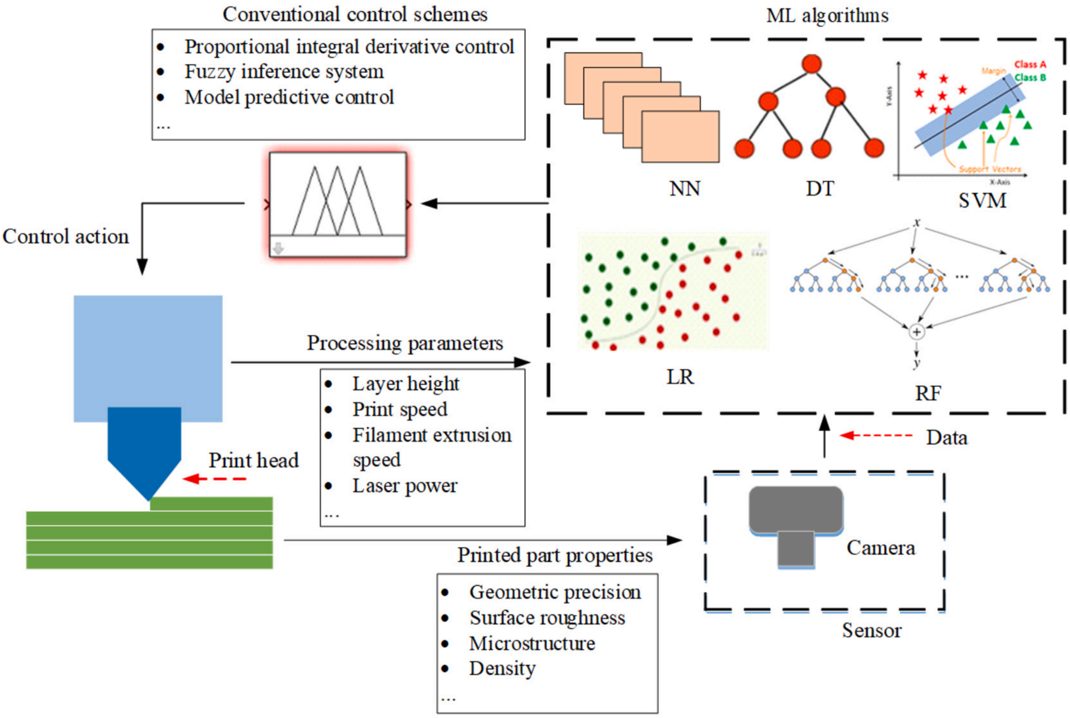

Fig. 12. Closed-loop control of AM.

5.2. Closed-loop AM

Important terms in AM, such as control, monitor, and optimize, have recently received much attention from the experts in the aspect of quality and mechanical strength of the printed parts [164]. The closed-loop control action can be done using either traditional control approaches or ML-based monitoring systems as illustrated in Fig. 12. The traditional control systems as presented in [137,165–171] use conventional control techniques, such as proportion-integration-derivation control, fuzzy inference system, and model predictive control. The ML-based ones [172–175], on the other hand, perform control tasks by combining ML algorithms, such as support vector machine (SVM), neural network (NN), linear regression (LR), decision tree (DT), and random forest (RF), with conventional ones. These are ML-based in-situ monitoring mechanisms. A detailed review of a closed-loop AM is discussed next.

Francis et al. [176] proposed a geometric compensation algorithm based on a convolutional neural network (CNN). The proposed compensation algorithm of a laser-based AM takes melt pool thermal history to predict the distortion. The geometric error is compensated by modifying the CAD model. Similarly, error compensation frameworks based on CNN are presented [177–179]. They use two networks: a prediction network and a compensation network. Wang et al. [180] proposed a layer time control and regression model for improving the quality of an AM product. The proposed system uses infrared camera data from a real-time print surface temperature. Wang et al. [181] also developed a closed-loop control system that combines an NN and vision-based techniques. The proposed system stabilizes the printing process in liquid metal jet printing. The study integrates a NN with a proportion-integration-derivation control and determine the drive voltage. Zhang et al. [182] proposed a feedback loop by using adaptive control in the ceramic AM process to improve print quality. A NN model is developed to create the relationship between the processing and control parameters, forming a closed-loop process. Tamir et al. [166] presented an error compensation strategy combining a feedback-based fuzzy inference system and a grey wolf optimization algorithm. This work discusses the possible errors in the 3D printing process and provides a monitoring framework to minimize the effect of errors on the printed object's quality. Moreover, the applications of closed-loop control systems in AM are summarized in [183–189].

6. Challenges and future trends

This section presents the existing challenges in the development of AM and then discusses the potential research directions related to parallel manufacturing, social manufacturing, and closed-loop ML.

6.1. Challenges in the development of AM

With the known benefits of AM in mind, the achievement of these technologies will be determined by how well the fabricated parts serve the market. It is critical that the one-of-a-kind ability to create such useful shapes and structures be changed into valuable products. Most importantly, costs must remain competitive throughout the entire product lifecycle. Although AM was initially used to create concept models, design prototypes, and visualization tools, the advances in material and printer technology allowed AM to produce spare parts, factory tooling, and end-use products. AM primarily produces low-volume parts, but eventually, it becomes vital to the overall production process. Despite this, a recent study discovered that most enterprise AM users use the technology for prototyping. In addition, some enterprises use AM to manufacture items that other manufacturing techniques cannot. This indicates that it is still challenging for manufacturers to incorporate AM technologies more broadly into their manufacturing processes [190–193]. The challenges arise from many dimensions, such as technological, software, quality assurance, workforce, financial, workflow, and integration. The challenges, such as slow production speed, materials development and inconsistencies in material properties, and manual post-processing, are categorized under technological challenges. In addition, limited capabilities in data preparation and design are software challenges. On the other hand, part-to-part variation and lack of industry-wide standards are quality assurance challenges. Workflow and integration challenges may also contain a disjointed AM ecosystem and lack of digital infrastructure. Substantial initial investment and lack of understanding and expertise in AM fall into financial and workforce challenges, respectively.

Since industrial robots have articulated structures, various sizes, cost advantages, and popularity in existing manufacturing automation, a robot-assisted AM has advantages in large-scale AM fabrication and curved surface printing. A robotic system adds an extra DOF to the current AM systems and manages the direction of material deposition of the part-forming process. It can form parts with curved structures without using supports. Unlike the traditional gantry system that characterizes the majority of the available AM machines, robotic arms reach large workspace area. Thus, robot-assisted AM can be used to produce large building construction components. However, it is still challenging to use robots in the assisting mechanism of AM. One major problem is controlling robot motions and AM systems simultaneously. Current slicing algorithms cannot directly generate robot language. In addition, a standard information flow is not available to link the CAD system to robot-assisted AM processes. The use of robots in an AM system may result in poor part quality due to the accuracy issue of the robotic systems [194]. As a result, a full-scale AM system by a robot manipulator must include some means of process monitoring, which then provides a feedback mechanism for controlling the part-building process. To build an efficient system, control and optimization algorithms must be designed for compensating the inaccuracies of the part-building process.

6.2. *Parallel manufacturing*

6.2.1. *Create digital twins and parallel systems for AM*

A parallel system consists of a real and virtual system that aids manufacturing experts in optimizing the control actions and manages the overall activities of the real system [195,196]. A digital twin represents the real system virtually, which aims for high-fidelity simulations and modeling [197,198]. Nowadays, the manufacturing process is becoming complex. Thus, it is wise to deal with a massive amount of manufacturing data for increasing the accuracy of models and simulations [199]. Parallel systems have three typical capabilities in the real scenario: monitoring, prediction, diagnosing [155,200–202]. Shen et al. [200] suggested a new concept called “space parallel additive manufacturing”. The proposed concept is a kind of intelligent manufacturing scheme based on cyber physical social system, knowledge automation, ACP method, and 3D printing technology. The application is mainly for space stations and satellites for supplying, repairing and production tasks by simply carrying 3D printers to space. A detailed review of the use of AM in space is given in [203].

Michael Grieves coined the term “digital twin” to describe product life cycle management [197,204]. Digital twins are similar to parallel systems in which seamless interactions between digital and physical systems are emerged to ensure virtual representations [205,206]. This theoretical concept is put into practice by creating a parallel system architecture with an emphasis on Industry 4.0. [207]. The enabling technologies for digital twins are also explained in healthcare, smart cities, and manufacturing [208]. In the manufacturing industry, digital twin technologies are increasingly used for designing, planning, and maintenance of production systems [209–211].

Incorporating digital twins and parallel systems into AM advances manufacturing technology that possesses real-time monitoring of the process. The development of virtual models improves smart manufacturing by simulating decisions and optimizations from design to operation [212,213]. As a result, this can positively impact the advancement of AM as a major component of Industry 4.0. Using real-time sensor data, the digital counterpart may access the instantaneous condition of its physical twin [214]. The physical system is subsequently provided with proper control commands. Digital twins and parallel system development are potential strategies for monitoring, diagnosing, and controlling manufacturing processes.

6.2.2. *Closed-loop machine learning in AM*

An ML is a data analysis technique that automates the creation of analytical models. It is a subfield of artificial intelligence based on the idea that systems can learn from data, identify patterns, and make decisions with little or no human intervention [215,216]. The aim of using ML in Engineering applications is mostly for prediction without any monitoring and feedback operation [217–222]. Meaning ML only predicts the value of certain system parameters aiming that the prediction may provide information for decision-making. A few closed-loop-based ML systems exist in some applications [172,223–226]. However, it is far from enough to say that closed-loop ML is widely applied across the engineering corner. It still needs further research to promote its application over performance enhancement.

In an AM system, controlling or monitoring action is a vital component to be yet given great attention by experts. However, most of the existing ML applications in AM are open-loop-like control structures. In such a way, the full-scale controlled and monitored

AM system cannot be guaranteed as it creates a print part quality issue. Thus, it is wise to extend the controlling mechanism into a closed-loop ML to ensure the print product's better quality and mechanical strength.

6.3. Social manufacturing

Professor Fei-Yue Wang coined the term "social manufacturing" (SM) in 2010 [227], and gave the formal definition in the article [228]: "The term social manufacturing refers to a customized, cost-effective, and real-time mode of production and consumption in which a consumer may actively contribute throughout the entire manufacturing process through the use of technologies like 3D printing, social media, and networks." Therefore, it is important to mention that SM is a ground-breaking social computing idea that has been hailed as a cutting-edge manufacturing solution for the upcoming era of customized and personalized products [228–230]. SM enables everyone in society to obtain innovation and manufacturing capacity, in the same way, social computing [231,232] enables everyone in society to obtain computing capacity. Furthermore, the SM era provides profitable and popular personalized products. Customer needs are inextricably linked to the SM industry's supply capacity. SM adheres to five trend characteristics proposed in Gartner's top ten strategic technology trends for 2020: hyper-automation, multi-experiences, democratization, human augmentation, transparency, and traceability. As a result, the evolution of SM is a possible future direction for intelligent manufacturing.

The SM system, supported by 3D printing, is applied for customizing products such as shoes, clothes, and dental crowns [233,234]. As a direct manufacturing technology, 3D printing has enormous potential. In addition, as software and internet services become more commonly available, customers can participate in the manufacturing process, enabling more manufacturing customization.

7. Conclusion

This paper presents a review and summary of various AM technologies and configurations. The two AM configurations, including robot-assisted AM and traditional AM, are discussed in detail. A robot-assisted AM provides multi-directional motion during a printing process, and this kind of AM configuration is a promising approach to enhance the quality of the printed objects. Defect detection and fault diagnosis in AM are also discussed. Moreover, two types of control systems in AM are discussed, including an open-loop and a closed-loop approach. Introducing machine learning into a conventional control system is a promising technique that achieves a closed-loop control approach in AM. Finally, different challenges in control, monitoring, and configurations of AM are discussed, and possible future trends are suggested.

CRediT authorship contribution statement

All authors listed have significantly contributed to the development and the writing of this article.

Declaration of competing interest

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

Data availability

No data was used for the research described in the article.

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