Progress in Additive Manufacturing (2021) 6:181–197
https://doi.org/10.1007/s40964-021-00172-8

REVIEW ARTICLE

Additive manufacturing embraces big data

Kaiming Bi[1] · Dong Lin[1] · Yiliang Liao[2] · Chih-Hang Wu[1] · Pedram Parandoush[1]

Received: 2 April 2020 / Accepted: 3 March 2021 / Published online: 16 March 2021

Abstract
Additive manufacturing (AM) is a relatively novel method to fabricate 3D objects by adding layer-upon-layer materials. As one of the most anticipated techniques in recent years, AM already made advances in design, production, and supply chain process of the manufacturing industry. AM is a digital manufacturing technology in which a massive amount of data is generated during the process. Accordingly, obtaining useful information from these data to improve current AM technology becomes a challenge. Meanwhile, Big Data research provides an ideal solution for dealing with the massive data obtained from AM processes. Besides the contributions in the AM research and production, Big Data analysis methods can also be used to help designers and engineers by collecting valuable information from clients and customers. From a business perspective, the manufacturing sector will benefit from the established Big Data sharing platform to promote and popularize new products. On the other hand, customers will obtain desired commodities with the help of a new-type 3D printing service system. The goal of this article is to summarize the contributions from the existing literature in the AM and Big Data field and prospect how Big Data methods can offer a better future for AM technology. It also introduces recent developments in AM technology combined with the internet of things (IoT), cloud, and cybersecurity. Future directions in AM and Big Data, which include AM data unification, completed AM data-sharing platform, and smart AM production process is pointed out as well.

Keywords Additive manufacturing · Big Data · Internet of things · Cybersecurity · Data analysis

1 Introduction

Additive manufacturing (AM), which is also known as three-dimensional (3D) printing, is defined as a process of adding materials layer-by-layer into a 3D product. Unlike the traditional manufacturing processes, which remove the materials from the object, AM can transform the digital files or computer-aided design (CAD) models into 3D objects, directly. Therefore, AM considerably reduces the waste materials during the manufacturing process. The additive nature of this process also makes it significantly more efficient in producing complex and custom geometries over traditional subtractive manufacturing methods. The early concepts of AM were introduced in the 1980s [1]. Hull developed stereolithography (SLA) fabrication system in 1986 [2]. After that, many AM process categories such as material extrusion, powder bed fusion (PBF), and sheet lamination were proposed [3–5]. Nowadays, AM is widely used in the manufacturing and medical industries, as well as sociocultural sectors. The ever increasing demand for AM technology, owing to its potential in fabricating low-cost and customizable objects, provides a broad development prospect for AM [6].

However, uncertainty in meeting engineering quality standards hinders the widespread adoption of this technology in various engineering applications, such as construction, aerospace, automotive and electronic industries. The uncertain quality was the main barrier for the broad adaptation of AM for 47% of surveyed manufacturers [7]. Specifically, since the material extrusion process is highly dependent on the accuracy of the nozzle to extrude the melted materials, it is difficult to 3D print the finely detailed items with high quality [8, 9]. Since the grain size of powder may not be constant during the fusion process, the PBF method also suffers from poor surface quality [10]. In addition, in

✉ Chih-Hang Wu
chw@ksu.edu

✉ Pedram Parandoush
pedramp@ksu.edu

1 Department of Industrial Engineering, Kansas State University, Manhattan, KS 66506, USA

2 Department of Mechanical Engineering, University of Nevada, Reno, NV 89557, USA

PBF-based methods, it is relatively difficult to set up appropriate control parameters for PBF due to its elaborate process [11]. For other AM methods, VAT photopolymerization has the problem in brittle components, and sheet lamination exhibits curvatures and inaccuracies [12, 13]. In addition to the quality, the aesthetics condition is another problem in many AM methods [14]. These limitations severely restrict the commercialization of AM technology. To further refine the existing AM methods, many Big Data technologies and machine learning, deep learning and artificial intelligence are expected to address many of these challenges associated with AM.

As with other emerging technologies like Cloud Computing and the internet of things (IoT), Big Data offers the opportunity for AM to replace the traditional manufacturing process for various applications. As an emerging topic, Big Data has been developing rapidly in recent years. Big Data was defined as "an all-encompassing term for any collection of data sets so large and complex that it becomes difficult to process using traditional data processing applications" [15, 16]. The generalized challenges of Big Data include data collection, data storage, data analysis, data sharing, data visualization, and data security. Recently, an exceeding number of research efforts in Big Data focused on the Big Data analysis. Finance, healthcare, and engineering Industries have extensively applied Big Data analysis methods to their experimental database. Plenty of innovative contributions were accomplished at the intersection of Big Data with traditional research fields.

Among the subcategories of data analytic, AM and Big Data are some of the most noteworthy and anticipated research fields. As two of the most valuable technological advancements in Industry 4.0, both Big Data and AM technologies have the potential to trigger a new industrial revolution [17]. Big Data analysis methods, such as machine learning, deep learning, and heuristic algorithm can be utilized to classify data and predict the output of the AM process. The refined information from data analysis of AM processes can also support designing better and more efficient AM products [23]. Moreover, data sharing is another promising research direction in Big Data and AM. A developed data-sharing platform can improve research efficiency and enhance the cooperation in the AM industry [18]. Furthermore, the attractive combination of the IoT and AM could further grow the commercial value of AM technology.

In addition, since Big Data and AM technology are both selected as nine pillars of technological advancement in Industry 4.0 [16], the combination of AM and Big Data is expected to have a border impact in the future. Hence, this paper analyzes the future of the AM industry in the context of the Industry 4.0 evolution and discusses the potential development direction of AM and Big Data in the era of the internet.

To discuss the benefits from AM and Big Data with more details, this paper searched 272 recent articles from AM product diagnosis, prediction, and design area using Big Data technics. A major portion of this literature is found from academic search engines like Google Scholar, Microsoft Academic, and Researchgate using AM and several methods of data analytics as keywords. Through reviewing the 272 selected articles, 133 of them were excluded in final screening due to the less relevance and repetition. The reset 139 articles from the original search strategy were used in the final analysis. The rest of this paper is organized into the following sections: we review recent interdisciplinary contributions between Big Data analysis and AM in Sect. 2. The latest improvements in AM information and communications technologies are discussed including the IoT sharing concepts, Cloud AM platform, and AM cybersecurity in Sect. 3. The prospects of future AM and Big Data are analyzed in Sect. 4. Finally, Sect. 5 concludes the discussion of the review.

2 Data analysis methods and additive manufacturing research

With the development of Big Data analysis, computer-based machine learning has been greatly used in classification, prediction, and numerical optimization. By applying machine learning methods, such as Bayesian, Neural Network, and Clustering methods, the collected experimental data in the AM process can be analyzed and generalized into models or general rules. Beyond machine learning and deep learning, geometrical analysis, sensitive analysis, signal analysis, and optimization are used as supplementary methods to manipulate data from AM processes. Both of these analysis methods can significantly improve AM research, manufacturing, and design.

2.1 Big data analytics methods for AM products identification and diagnosis

As a fundamental method of machine learning, classification and identification can utilize the existing labeled data as a training set to differentiate the unlabeled data set. However, the identification for AM products is difficult, since the standard statistic, cloud deviations, and conventional measurement methods cannot detect a significant difference between similar 3D-printed components [19]. Moreover, current 3D printing users always implement their fresh ideas by designing unconventional and peculiar products [20]. High geometric complexity in shapes also brings technological difficulties in classifying AM products [21]. Furthermore, dimensional accuracy for various 3D printers is not currently uniform [22, 23]. Meaning, AM identification technology is expected to classify products with different accuracy standards [24].

To realize real-time monitoring process conditions using sensor signals for the mater extrusion method, Bastani et al proposed an online sparse estimation-based classification method to build a framework to classify and identify AM components [25]. They considered the data from sensor signals as a linear system and solved the underdetermined linear system by machine learning methods. Several algorithms, such as neural networks, support vector machines, greedy Bayesian estimation, and quadratic discriminant methods were used for the mater extrusion process. The greedy Bayesian estimation had the best accuracy rate (about 90%) in their implementation [25]. Tootooni et al. extended the previous research to differentiate and classify the dimensional variation of mater extrusion AM products. They employed a laser-scanning technique and consider 2 million data points for each unclassified component [26]. They utilized spectral graph theory to manage the scanned data. The implemented sparse representation technique provided a higher classification accuracy (about 95%). Scime and Beuth implemented AM product classification methods for the PBF process and developed a monitoring system that can detect and classify the unsuccessful components from the acceptable PBF products [27]. This trained automatic system utilized unsupervised heuristic-based learning algorithms to analyze the images of the AM process. This system was already tested to predict the location of defects in the final product. It also showed the potential to become a feedback control system that can detect the anomalies during the AM process. For the selective laser melting (SLM) AM process, researchers developed a feedback control system with optical sensors [28, 29]. This control system could analyze the process parameters and feedback signals and identify the current AM process stage. Then, the AM process will be corrected by the feedback control system with the updated process parameters.

Another well-known application of data analysis methods in AM is the diagnosis of 3D-printed products. Machine learning was first introduced to diagnose the malicious infill defects in mater extrusion AM products by analyzing the image data. By extracting the features of AM products from the layer-by-layer 3D printing process images, machine learning algorithms such as decision trees and naïve Bayes were utilized to analyze the data. The analysis results can be used to inspect the existing defects in the 3D printing process [30]. The accuracy rate of the successful detection was around 90% in the validation examples. This method was further improved to detect the real-time error for PBF products based on sensor signals. The images for each building layer of powder bed fusion were collected using a high resolution digital single-lens reflex camera [31]. Multiple visual features were extracted from the images and classified using supervised machine learning. Computed tomography (CT) scan was applied to validate the classification results. After the cross-validation, more than 80% of the defects in the 3D-printed products could be successfully detected. Using an infrared camera, features in electron beam melting (EBM) components could be extracted from thermal images [32–35]. The thermal images included detailed surface temperature profiles which can be analyzed to provide information to update the setting for the next layer. To further improve the quality and repeatability of PBF parts, Yao et al introduced a novel multifractal analysis technique for the detection of defects during the direct metal laser sintering (DMLS) process [36]. This method can characterize the image data of AM components using the multifractal spectrum, then locate the defects by analyzing the image data. In addition, other research groups considered different supervised learning methods for detection in PBF to better control the material thickness, geometry errors, cooling rate, microstructure, and composition during PBF and mater extrusion AM process [37, 38]. Mazumder considered an innovative smart optical-monitoring system that could observe spectral intensity during the AM process [39]. The relation between the spectral and defects was obtained by supervised learning. The smart optical-monitoring system could locate the defects by analyzing the spectral intensity and interrupt the manufacturing process to cease the propagation of the defects. Rather than a supervised learning method, unsupervised learning technique is another method to detect defects of AM parts. To improve the geometric accuracy, researchers used self-organizing map method to analyze the AM data from sheet lamination and mater extrusion AM parts [40]. This method could effectively remove 97% of extraneous and irrelevant AM data by unsupervised learning, then established the relationship between process conditions and geometric accuracy in AM parts. Therefore, this relationship could be utilized to improve geometric accuracy using appropriate process conditions. In addition to the above contributions, related researches also promoted the development in AM components diagnosis [38, 41–47], and the sustainability of the AM components [48–50].

Instead of using the image and signal AM data, Wu et al collected the acoustic emission data from the mater extrusion process as feature information [51]. With the help of support vector machines (SVMs) method, acoustic emission data could be utilized to detect if the extrusion nozzle is blocked. Validation results showed that this new method can effectively serve as a non-intrusive diagnostic method for the extrusion nozzle process.

In Table 1, the advantages and deficiencies of existing methods in identification and diagnosis are summarized by different AM types. Instead of the deficiencies listed on the table, two common problems existed in the most current AM methods. First, the above analysis methods are highly

Table 1 Summary of current contributions in the identification and diagnosis of AM products

AM types	Data source	Big Data analytics methods	Advantages	Deficiencies
Material extrusion	Sensor signal data [25] Laser-scanning data [26] Acoustic emission data [47]	Machine learning algorithms: neural networks, support vector machines, Bayesian estimation, decision trees [25] Spectral graph theory [26]	High accuracy rate in identification and diagnosis High implement ability	Receiving excessive amounts of irrelevant data Non-uniform approach to process data
Powder bed fusion	Image data [27, 30, 36] Thermal images data [32] Process control parameters: material thickness, cooling rate, geometry errors [37]	Supervised learning: regression, support vector machines [39] Unsupervised learning: clustering, anomaly detection [36] Heuristic algorithm [27]	Ability to locate the exact position of defects Automatically setup the feedback control to correct the process	The training process takes time Low accuracy in the diagnosis and corresponding feedback control
Sheet lamination	Layer-by-layer image [40]	Neural networks, self-organized map [40]	Improve the overall geometric accuracy	Takes time to analysis the image data by each layer

dependent on the accuracy of the data. Since most of the data are collected during the AM process, high-quality data acquisition equipment is required to guarantee the accuracy of the collected data. Second, in most of the current methods, the AM process is separated from the data analysis process. Meaning, AM process has to be slow down to obtain the result of data analysis. To save time and corresponding cost, the data analysis process should be combined as a part of the AM process in the future.

Currently, the contributions mainly focus on the mater extrusion and power bed-related AM methods. Data-based diagnosis methods still lack in the rest of AM types, such as light polymerized, binder jetting, and directed energy deposition. Since these methods are less popular than the widely used AM method like extrusion nozzle and PBF, only a few research attempts to improve these non-mainstream AM methods using data. The future research in data-based AM diagnosis is expected to cover more AM methods.

2.2 Big data analytics methods for AM process prediction

Setting control parameters for the AM process is extremely challenging for many 3D printing methods. To find a suitable parameter setting before the AM process, data analysis, and machine learning methods were largely applied for parameter prediction based on the historical process data. Machine learning was first used in the prediction of the main processing parameters of laser cladding. To better evaluate the effect of the laser processing parameters, Davim et al collected plentiful geometric data of cladding (deposit height, width, and depth penetration) using different combinations of processing parameters (laser power, scanning velocity, and powder mass flow rate) [52]. With this experimental data set, multiple regression analyses determined the mathematical relationship between the processing parameters and geometric data of laser cladding. Based on this predictive model, laser cladding could find new applications (for example: the repairs of metal components) owing to the convenience of this mathematical model. This research was extended by considering processed variables (for example: the powder feeding rate divided by laser scanning speed) in the regression analysis [53]. Neuro-fuzzy is an alternative method of regression to predict the clad height in terms of laser pulse frequency, laser pulse energy, and traverse speed [54]. With the cross-validation based on the experiment data, the absolute error rate of clad height prediction was only around 0.07%. To further improve the geometry effects on the layer thickness, surface quality, and dimensional accuracy in the layered deposition process, Xiong et al. utilized a neural network to analyze the experimental data from gas metal arc welding based rapid manufacturing (as shown in Fig. 1) [55]. They used wire feed rate, welding speed, arc voltage, and the distance between the nozzle to plate as input variables to predict the width and height of their products. The predicted error rates of their final products varied from 1.5 to 5.5%, which was better than the error rates from regression-based methods (1.8–6.7%). To quantify the ultimate tensile strength and nominal strain of polylactic acid with low-cost material extrusion 3D printers, Lanzotti et al. utilized a supervised learning method to differentiate the important processing parameters with insignificant parameters [56]. By analyzing the experimental data with a regression-based learning method, they found out that layer thickness, infill orientation, and the value of shell perimeter have a decisive impact on the product failure mechanism, i.e., ductile and brittle failure. To reduce human intervention during the material extrusion AM process, Vijayaraghavan et al compared several different supervised learning methods to characterize the process parameters of 3D-printed components

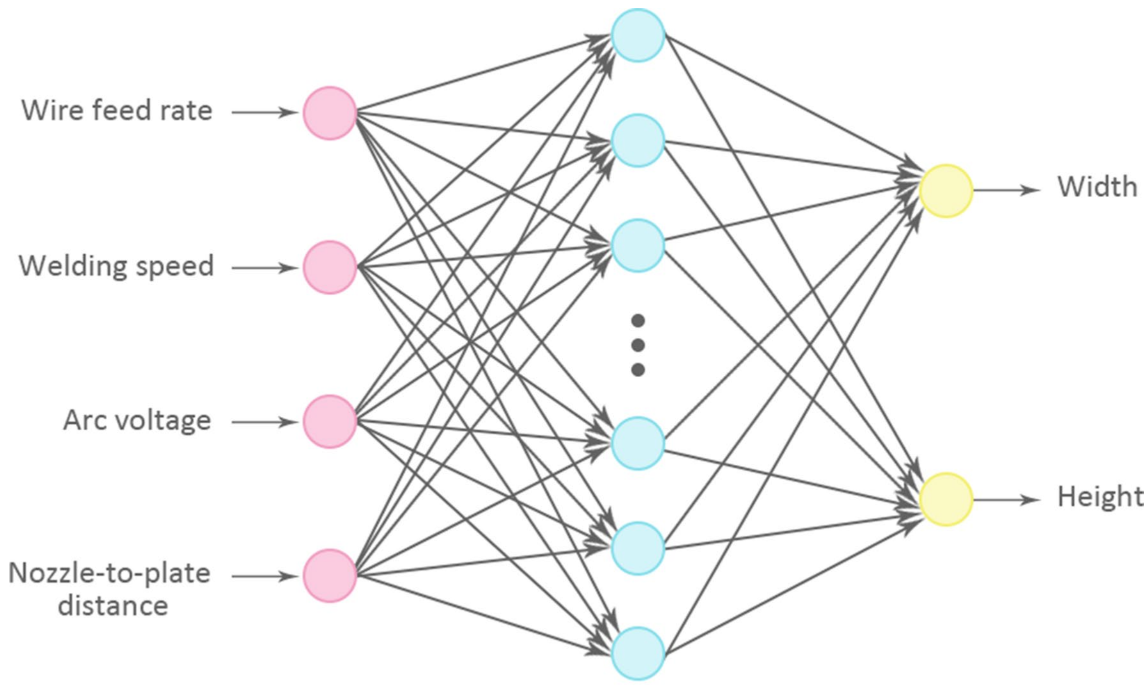

Fig. 1 Multilayer neural network using input parameters to predict the system output [55]

[57]. They employed computational comparisons and sensitivity analysis for different machine learning methods (genetic programming; support vector regression; artificial neural network). Based on the accuracy of the prediction results, the artificial neural network received the best performance in building a functional relationship between input and output data from the material extrusion AM process. Recently, to address the shape deviation of CAD models in the material extrusion process, Zhu et al analyzed the tolerance of material extrusion with a guess-process multi-task supervised learning algorithm [58]. They mapped in-plane geometric deviations into an established deviation space, then they used statistic learning to estimate the geometric deviation in multiple geometries. In addition to the material extrusion AM method, the influence of process parameters for the powder bed fusion were researched by other groups [59, 60]. Using supervised regression and ANOVA, it was determined that printing direction can significantly affect the dimensional error and surface roughness. Beyond that, AM parameter setting could also be predicted by finite element methods and analysis of the geometric data [61–64].

In addition to geometric characteristics, machine learning was also utilized to analyze the porosity and bending elasticity of AM products. To improve the density, surface quality, and mechanical properties of AM components, Gaussian process-based predictive model was utilized to predict the porosity of metallic products produced by power bed fusion [65, 66]. Bayesian inference framework was used to estimate the statistical model parameters for spatial prediction based on the previous experimental data. The validation was completed by calculating the standard error between observed porosity and the fitted porosity from the model. Lam and Savalani further studied the porosity of AM products in selective laser sintering (SLS) by genetic programming based heuristic algorithm [67]. In their research, genetic programming was utilized to discover the hidden non-linear relationship between open porosity data and the corresponding dominant input process parameters. The analysis reflected that laser power, laser scan speed, and layer thickness contributed to the open porosity with different percentages (53%, 32.09%, and 14.81%, respectively). Zhang et al. discussed the factors that can influence the bending elasticity of 3D-printed objects [68]. They trained an echo state network using an experimental dataset that stored the relationship between multi-dimension shell thickness and bending elasticity. The experimental results verified that the bending behavior is controllable using a reasonable setting for shell thickness.

In Table 2, the advantages and deficiencies of existed contributions in AM process prediction are summarized. The common advantage is that most of the current contributions can predict the outcome of AM components with the processing parameters. Therefore, the predicted model can help us to adjust the parameters for receiving better 3D-printed results. The common problem reflected in prediction accuracy, difficulty in data measurement, and feasibility in

Table 2 Summary of current contributions in AM process prediction

AM types	Data source	Big Data analytics methods	Advantages	Deficiencies
Material extrusion	AM processing parameters: layer thinness, infill orientation, the value of shell perimeter [56]	Supervised learning: regression, support vector machines, neural networks [55, 57] Genetic programming [57]	Reduce the ductile and brittle failure Reduce the shape deviation Reduce human intervention during the mater extrusion process	Numerous preplanned experiments are required to train the prediction model The prediction model may not be accurate due to bias from the collected data
Powder bed fusion	Geometric data, surface data, printing directions [59, 64, 67]	Supervised learning: regression, echo state network, naïve Bayes [59, 64] Heuristic algorithm [67]	Reduce dimensional error and surface roughness Improve the density and mechanical properties	Some characteristics of AM components are hard to quantitate and measure, such as surface roughness, porosity, and elasticity
Directed energy deposition	Heat treatments data, chemistries and microstructures data, yield and tensile strength data [62]	Neural network [62] Genetic algorithm [64]	Obtain appropriate yield and tensile strength of the AM components	High requirements on the accuracy of the measurement

parameter selection. In most cases, the prediction model can not consider the uncertain condition and accidents during the AM process. Meaning, the most prediction model work for the ideal conditions. In addition, some process and characteristic parameters are hard to measure or exist the non-negligible measuring errors. Moreover, the predicted model cannot cover all of the relative control parameters. Therefore, to guarantee the accuracy of the prediction, significant AM process parameters have to be included in the model.

2.3 Big data analytics methods for AM design

Although quality, material, and construction characteristics are very important for AM products, designers and engineers still need to consider other factors to obtain a valuable AM product. A good visual artifact has to be guaranteed to maintain the utility value of the 3D-printed products [69]. For the majority of 3D printing techniques, the support material is necessary to keep the balance during the manufacturing process [23]. Even though the balance of AM products can be maintained by adding support, removing the added supports may result in unsightly surface artifacts and a rough surface finish. Especially, when the supports are attached to small features, it is hard to distinguish the details of AM products with removable support. Although using support material is unavoidable in most cases, the negative influence of support can be reduced by avoiding using the supports in visually significant regions. Zhang et al. utilized a machine learning-based perceptual model to analyze the collected human preference data [70]. The learning results could provide suggestions for some known metrics, including the area of support, visual saliency, preferred viewpoints, and smoothness preservation. The neural network-based learning algorithm also provided an F-score, which represented the goodness of the printing direction on account of human aesthetic perception. The experimental result with the highest F-score achieved a better performance compared to existing state-of-the-art softwares (as shown in Fig. 2). Adapting mimic modification to reduce support is another way to keep the beauty of the AM products [71, 72]. Using K-means clustering learning algorithm to process the data of joint point between support and part, the shape of mater extrusion products were revised based on the computation. Historical experimental data were used to minimize the volume of support material (as shown in Fig. 3). The validation examples showed a good balance between beauty and stability of these mater extrusion AM products.

Support material is not the only factor to restrict the visual artifact of the AM products. Color, material choice, geometry, and aesthetics also greatly affect the AM design [73]. Topology optimization is a typical geometrical method to reduce material waste [74–76]. To verify the optimization result, a well-known topological optimization problem Messerschmidt-Bölkow-Blohm (MBB) beam was used as a validation example. AM researchers implemented their optimization algorithms into a mater extrusion-based MBB problem [77–79]. The topology optimization algorithm could reduce material utilization and improve relative compliance for the given AM example (as shown in Fig. 4). In addition to the topological optimization of AM, the material of AM components could also be adjusted to improve the performance of the AM process. AM technology is compatible with a large range of materials such as polymers, metals, ceramic, and even biological materials [80]. Thus, Gu et al. utilized a database including thousands of structured data for mater extrusion AM products. They utilized finite element analysis to calculate the mechanical properties of mater

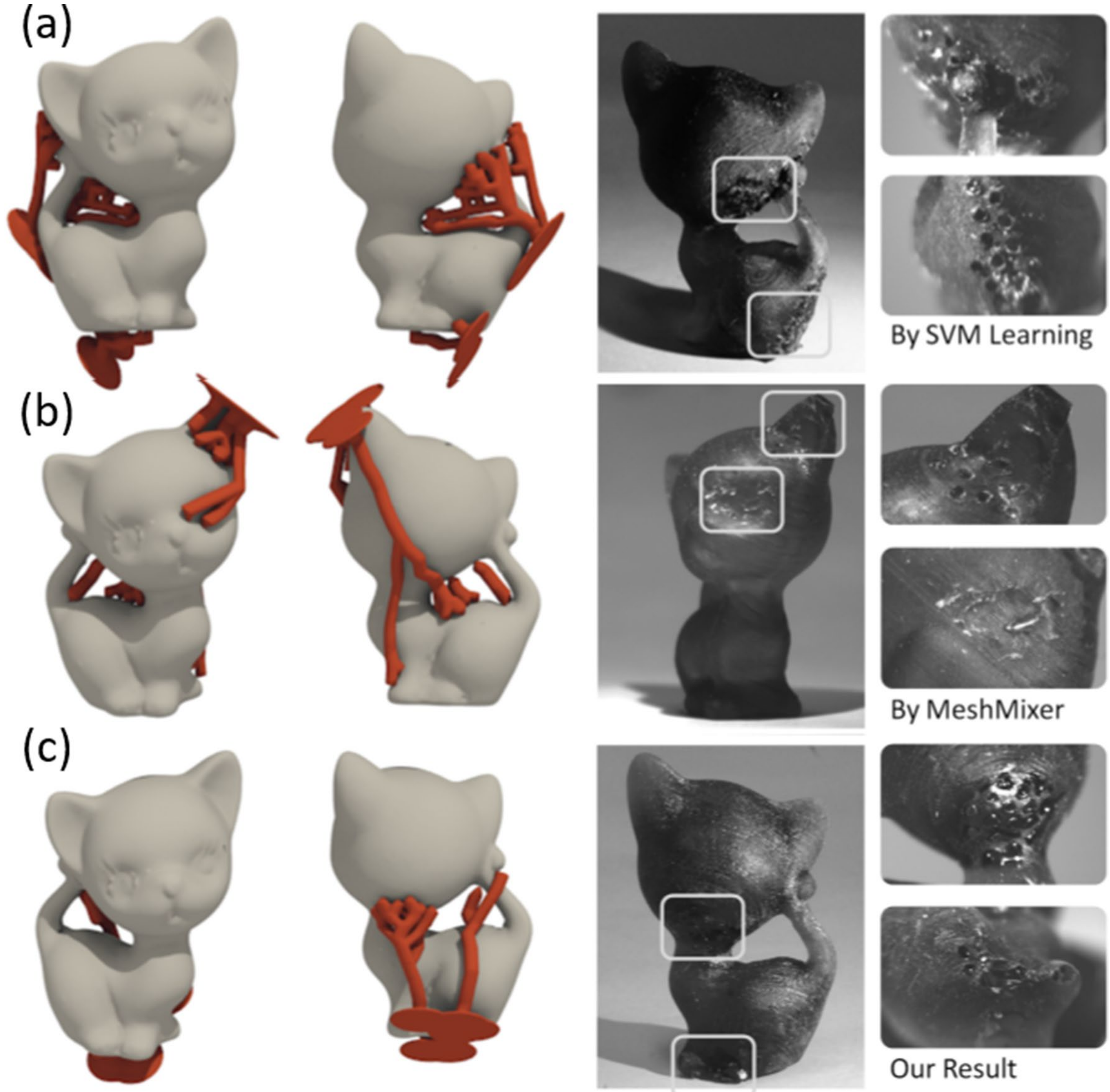

Fig. 2 Comparison of the 'best' printing directions determined by a linear SVM learning (**a**), Autodesk MeshMixer (**b**) and learning model (**c**). Zhang et al. nonlinear model results in less material cost and better feature preservation [70]

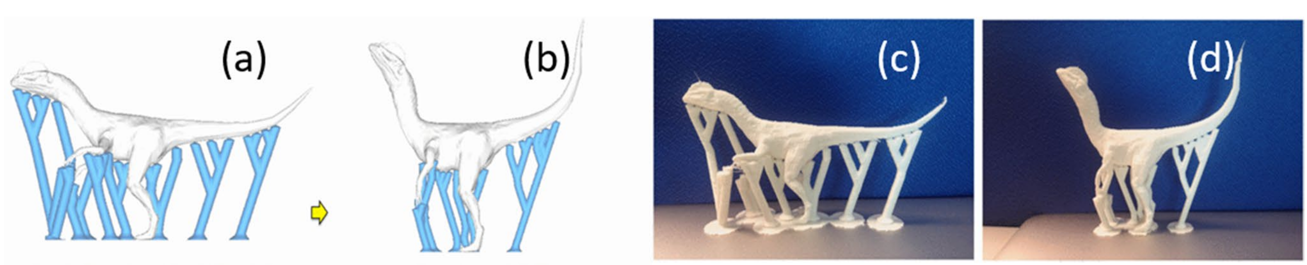

Fig. 3 Result of shape optimization on the dinosaur's model: (left) the input model needs to add supports with 29 APs and (right) the optimized model and its supporting structure with 19 APs—that is 34.5% reduction [71]

extrusion AM components and trained the unsupervised learning algorithm with processed data [81]. This algorithm was then used to design hierarchical materials with better stiffness and roughness properties. Beyond the geometry and

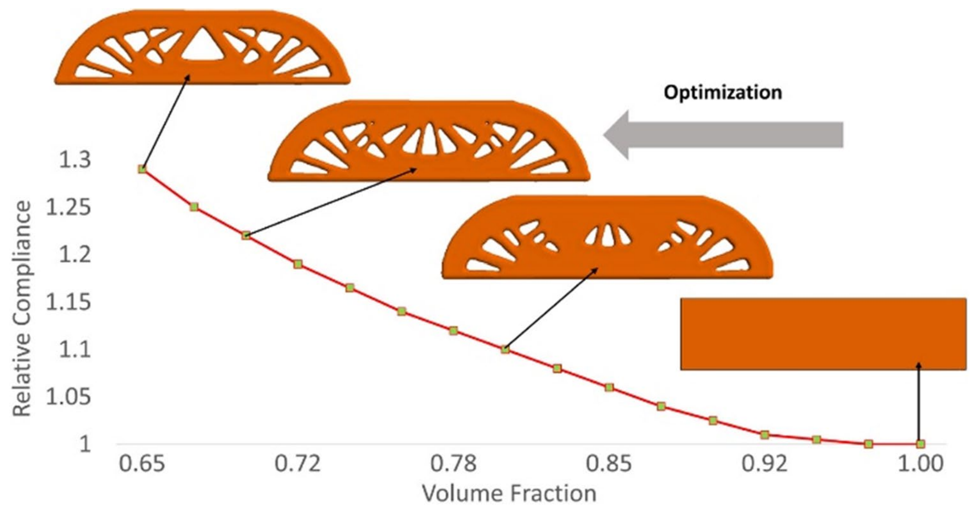

Fig. 4 Compliance Pareto curve for the MBB beam under topology optimization [78]

material, some AM processes can create products in full color to improve the commercial value of AM products [82]. Specifically, the colored 3D printing methods are applied in photonic crystals and bio-compatible materials [83, 84].

The existed contributions using the data analysis method to improve AM design are summarized in Table 3. In general, these methods are effective to reduce material waste, enhance visual aesthetics, and improve the commercial value of AM products. Currently, most contributions are limited at the research stage. Future work should focus on how to apply these methods to benefit the AM design in the commercial AM industry. For the research part in AM design and data analysis, the future works are expected on other different types of contributions, such as prolong the life of AM products, simplify the AM design to save the processing time, and increase the robustness of 3D printing process.

3 Information and communications technology of additive manufacturing

In 2015, the Boston Consulting Group defined nine pillars of technological advancement in Industry 4.0: Big Data and Analytics, Autonomous Robots, Simulation, Horizontal and Vertical System Integration, the Industrial internet of things (IoT), cybersecurity, the cloud, additive manufacturing, augmented reality [16, 85]. Most of them are already applied to the industry, but in the Industry 4.0 era, these techniques have the potential to cause a new industrial revolution. In this section, we will review the contributions of IoT, Cloud, and cybersecurity in AM.

Table 3 Summary of current contributions in AM design

Contributions	Methods	Advantages	Deficiencies
Enhance the aesthetics and commercial value of AM products	Change the printing direction and the area of support [70]	Avoid using supports in visually significant regions	Highly depends on the shape of the components May require more supports
	Create full-color AM products [83, 84]	Broad application prospects	Limitations in combined with other AM methods
Reduce the materials	Minor adjust the body shape of the AM products by algorithm [71, 72]	Reduce the support and the potential damage due to removing the support	Change the original design of the AM products
	Topology optimize the geometrical characteristic of mater extrusion AM components [74-79]	Reduce the material volume fraction and improve the relative compliance	Increase the possibility of failure due to the more sophisticated design
	Experimental design and regression analysis [73]	Optimize both energy consumption and material waste during the AM process	Only could be applied for mater extrusion with a standard shape

3.1 Digital manufacturing technologies for AM products

IoT is a new concept, which is interpreted as the worldwide network of interconnected objects that are allowed to connect, interact, and exchange data based on standard communication protocols [86]. Overall, IoT has two kinds of general advantages. First, IoT can build an object-system that connect specific objects in the system constantly. Second, IoT can provide virtual reachability for the object-system through the internet. With the help of the internet and the Big Data environment, the sensors from the IoT system can follow the object through the whole life cycle [87]. IoT can improve the manufacturing process to become "smart". Since IoT provides not only the object-system environment with data but also the possibility of digital automation and control equipment, IoT has been one of the main factors to lead the rapidly changing manufacturing industry in the last decade [88].

AM requires virtual design and digital control during the 3D printing process [89]. In general, the rapid development of the Internet and Big Data environment benefits the AM through sharing the manufacturing data. Caputo et al developed a conceptual framework to explain the AM benefits from IoT in four stages [90]. First, 3D printing products can be embedded in 3D readable codes, meaning the 3D printing data is shareable through the Internet. Second, 3D printers are always connected to the Internet and therefore the shared data can be transmitted between 3D printers through the environment of IoT. Third, the 3D printing process is considered as the connection between AM products and 3D printers. This printing process can be remotely controlled and monitored, which accords with the general concept of "smart manufacturing". Fourth, AM products can be modified during the printing process with help from the data provided by current or previous 3D printing processes. The successful implementation of all four stages could promote AM technology to a high level of "smart manufacturing". Qin et al introduced an IoT framework to reduce the energy consumption of AM processes [91]. This framework could discover the energy consumption knowledge of the AM system using a material attribute parameter and design information. Mourtzis et al. discussed a massive volume of data collected from the IoT adoption in AM [92]. Lu and Cecil proposed an IoT collaborative framework [93], which used the engineering Enterprise Modeling Language to exchange AM data between the various software and physical components.

Beyond IoT applications in AM processes, the combination of AM and IoT may launch a revolution in the supply chain of the manufacturing industry. As shown in Fig. 5, the IoT can improve the existing design, manufacturing, and distribution process in the 3D printing industry. Kaur applied the concept of "Machine to Machine" to AM in which AM

Fig. 5 The 3D printing service provider supply chain on the internet

products can be delivered as tangible goods to our computer through the internet [94]. Kaur also anticipated that 3D printing will participate in wider application fields and receiving goods in a digital form will become mainstream. Kaur's anticipation was partially proved by research of 3D Printing Services in Europe from Rogers et al. [94, 95]. Their research showed that there are 558 companies currently working on 3D Printing Services and fringe works in six selected European countries of Germany, Austria, Switzerland, Luxembourg, Belgium, and the Netherlands. Among all of these 558 companies, 105 of them work on Consumer 3D Printing Services, meaning that the revolution of digital-based delivery is currently ongoing. In the future, it is expected that the AM industry (include designers, factories, and franchisers) will be distributed to various separate locations [96]. Moreover, the current restrictions on the location of production will be removed with personal and customized fabrication associated with AM.

The word "The Cloud" derived from the concept of cloud computing, which is a model for enabling ubiquitous, convenient, and on-demand network access to a shared pool of configurable computing resources [97]. Xu considered cloud manufacturing (CMfg) as a manufacturing version of cloud computing [98]. In CMfg, distributed manufacturing resources are centralized at cloud services and managed uniformly. Therefore, CMfg resources can be utilized by clients according to their requirements without any waste. Wu et al. discussed the key commercial implementations of CMfg, which include automation, industrial control systems, service composition, flexibility, business models, and proposed implementation models and architectures [99]. Tao et al. introduced four typical CMfg service platforms, i.e., public, private, community, and hybrid CMfg service platforms [100]. They also analyzed main advantages of CMfg: (1) reduce resource idle capacity and increase utilization; (2) reduce the up-front investments and lower the cost to benefit from high-value manufacturing resources; (3) reduce infrastructure and administrative cost, energy-saving, and maintenance cost; (4) generate new types and classes of manufacturing/business model; and (5) optimize industrial distribution and speed up the transformation.

As one of the digital manufacturing techniques, 3D Printing Services could massively benefit from sharing AM resources into the cloud system. As shown in Fig. 6,

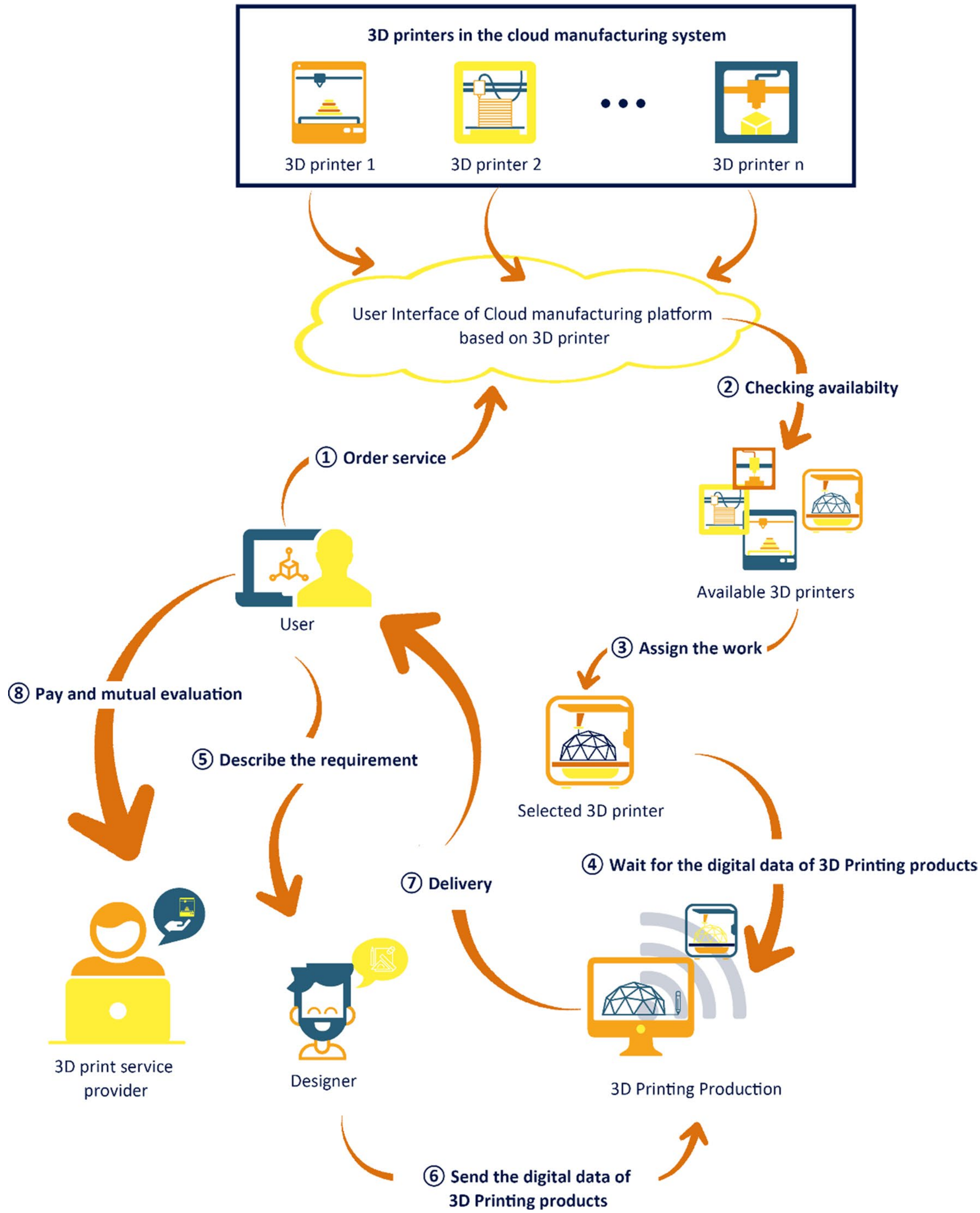

Fig. 6 Various services in cloud manufacturing

Cloud service greatly reduces the production and inventory cost for 3D printing manufacturers. In the meantime, the Cloud-based 3D printing process saves a lot of efforts from customers and designers. Liu et al discussed the benefits of an established Cloud-based 3D printing platform with data [101]. Their research showed that the key to profitability from a Cloud-based 3D printing platform is to keep the platform sustainable and healthy. Mai et al proposed a framework for a 3D printing service platform [102]. This research integrated the distributed data from different 3D Printing Services by establishing and analyzing a 3D Model library. However, due to the limitation of funds and data from collaborating institutions, currently, this sharing platform remains in the local area network testing stage. Guo and Qiu further discussed the prospect of cloud-based AM [103]. They summarized the emphasis and the future research direction of 3D printing cloud manufacturing, namely 3D printer access technology, 3D printing service control and scheduling technology, and 3D printing service evaluation technology. Baumann and Roller reviewed recent researches in AM and cloud manufacturing [104]. They suggested that AM resources should adopt a strict principle of transparency and service composition in adherence to the Cloud computing paradigm. However, the Cloud-based 3D printing platform is still a concept and in an ongoing stage due to two general reasons: (a) the lack of profit opportunities and investment motive; (b) the difficulty in managing and exhibiting the data from distributed 3D printing services [105].

3.2 Cybersecurity considerations for AM products

Cybersecurity is the protection of cyberspace and assets that can be reached *via* cyberspace [106]. Since AM is a digital thread, which allows rapid communication, iteration, and sharing of a design model through the internet, hackers have the opportunity for cyber-attacks aimed at the AM products [107]. Sturm et al classified cyber-attacks in the AM process in four main steps: the CAD model, the STL file, the toolpath file, and the physical machine itself [108]. Hackers can steal and corrupt CAD files in the first step by worms. The example is the Crypto Locker malware, which can encrypt CAD files and then ask ransom from users to unlock these files [109]. Hackers can also design an attack to cause fatal damage for AM products. They can imagine malware to build AM products that have almost no difference in appearance with normal products. However, the hacked AM products may contain critical defects at the interior of the structure.

To reduce harmful effects from cyber-attacks, researchers obtained achievements to secure the 3D printing process. Al Faruque et al simulated the cyber-attacks using emitted cyber-data via physical side-channels, which included acoustic, power thermal, and electromagnetic emissions [110]. To mimic the cyber-attackers, researchers adopted thermal emission data collected by the thermal camera to reconstruct the 3D objects. They can extract the nozzle/plate movement track data from thermal video, then obtain the speed of 3D printer actuators at each direction (as shown in Fig. 7). Reconstructed code can be obtained by recoding the actuator's speed data, therefore this research proved the serious vulnerability of AM systems. Al Faruque et al extended their previous research to simulate acoustic side-channel attacks on AM systems [111]. They built a learning model to analyze the relationship between moving direction, moving speed, nozzle coordinates, and extrusion amount using training acoustics data. Utilizing this trained learning model, researchers could predict the manipulation of information with the hacked acoustic data. They used the mater extrusion AM system as a validation example and the average accuracy of their prediction was 78.35%. Chhetri et al proposed a kinetic cyber-attack detection method to prevent the cyber-attack through side-channels [112]. Their method set up a fictitious adversary, manipulated by the learning model. By analyzing the analog emission with the adversary model, researchers could detect the vulnerable information points that are useful to hackers. The security level of AM processes is enhanced by improving the design of these vulnerable information points. More recently, another new side-channel attacking method against cloud-based AM systems was proposed using the smart-phone as the attack carrier [113]. In this research, both acoustic and magnetic side-channel attacks were formulated using the smartphone built-in sensors (as shown in Fig. 8). In this experiment, the side-channel signals could reconstruct the G-code of the ongoing AM process with the mean tendency error of 6–10%. The potential defense mechanisms are also discussed in this work. Using dummy task injections, hardware shielding, or side-channel interfaces, the threats of side-channel attacks could be reduced.

4 Prospect of the future AM and big data

Nowadays, AM is moving from an initial research stage to a mature technology [114]. Many of AM practitioners believe that AM technology has a significant commercial value [21, 115, 116]. Huang et al. considered that education and training will replace research to become mainstream in AM, and the wide University-Industry Collaboration and technology transfer will further promote the development of AM technology [24]. AM technology is expected to have a significant impact on multiple industries, including aerospace, logistic, healthcare, automotive, and electronics [23, 117–120].

In the meantime, the future of Big Data area is also extensively favored due to the updates in both software and

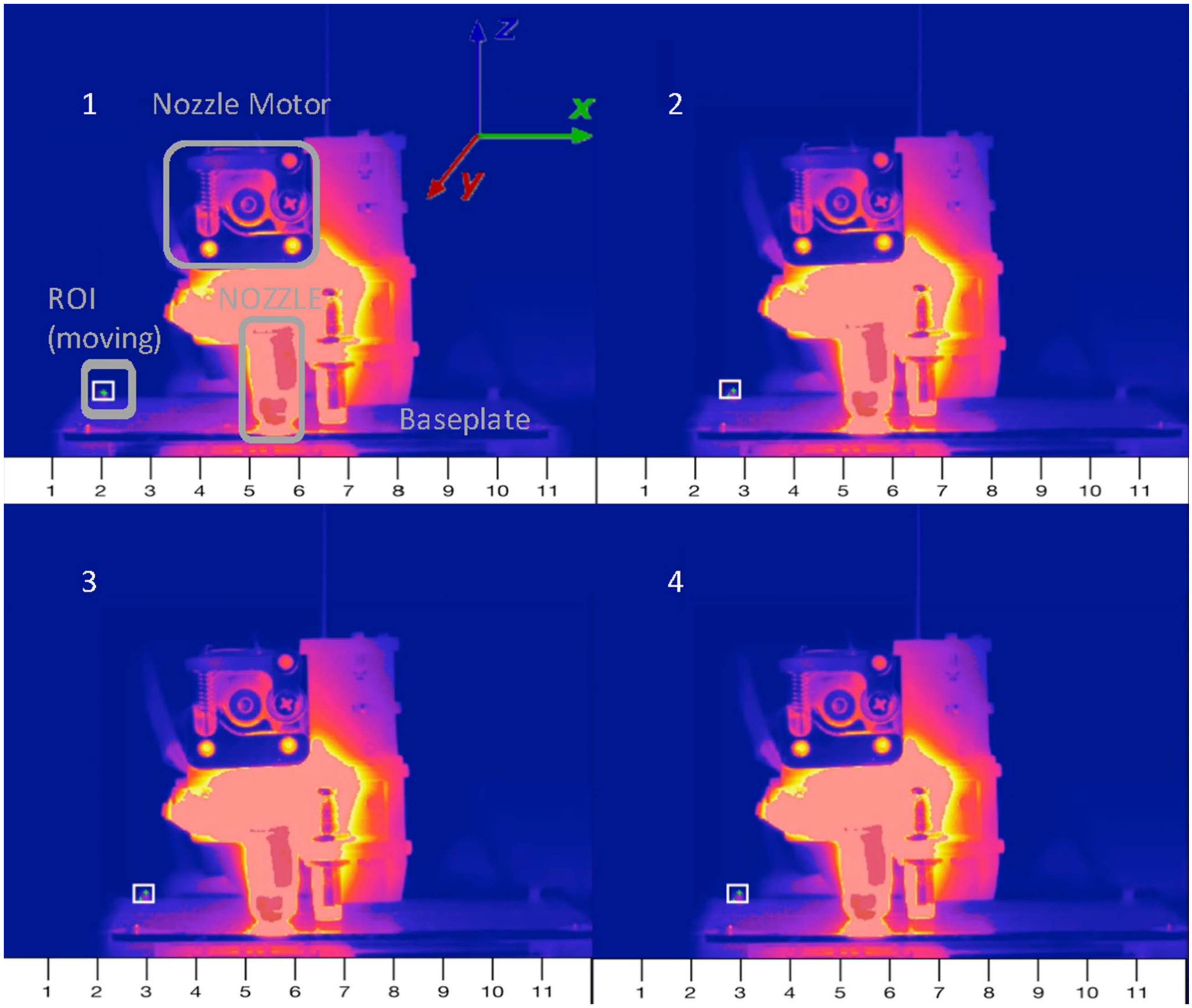

Fig. 7 Tracking a pin installed on the baseplate moving from right to left by a thermal camera [110]

hardware. With the steady improvement at the hardware level, Big Data technology will be benefited in various areas, such as data variety and velocity, data storage, data integration solutions, and data processing and analysis [121]. Fan and Bifet's forecast for the future of Big Data suggest that it will greatly improve in analytics architecture, distributed mining, time-evolving data, data visualization, and hidden big data [122]. These technological innovations will also bring the development of cloud technology [15, 123].

In view of the bright prospects for both AM and Big data, the AM and Big data interdisciplinary field will reflect a growing role in the future of manufacturing research. In the coming years, modeling, sensing, control, and process innovation with data will still be the crucial technical research goals of AM [24]. Cloud-based and internet-based platforms will benefit the AM research in the near future [124–129]. Under the influence of the big data technology, several innovative concepts are proposed for manufacturing systems: predictive manufacturing [130–132], smart manufacturing [133–135], and cyber-physical manufacturing [136–138]. The goal of these new concepts is to enable the AM process with "self-aware" capabilities and intelligence. The future development of these concepts can be utilized in AM systems. Additionally, new technologies, such as predictive AM and smart AM will further benefit the research on AM systems.

Compare to the AM in research, the commercial prospect of this interdisciplinary technology has a brighter anticipated future. Jiang et al. made a prediction for the economic and societal implications of AM in 2030 [139]: (1) more than 50% of the AM industry capacity will be in-house production capacity; (2) small and medium enterprises will share

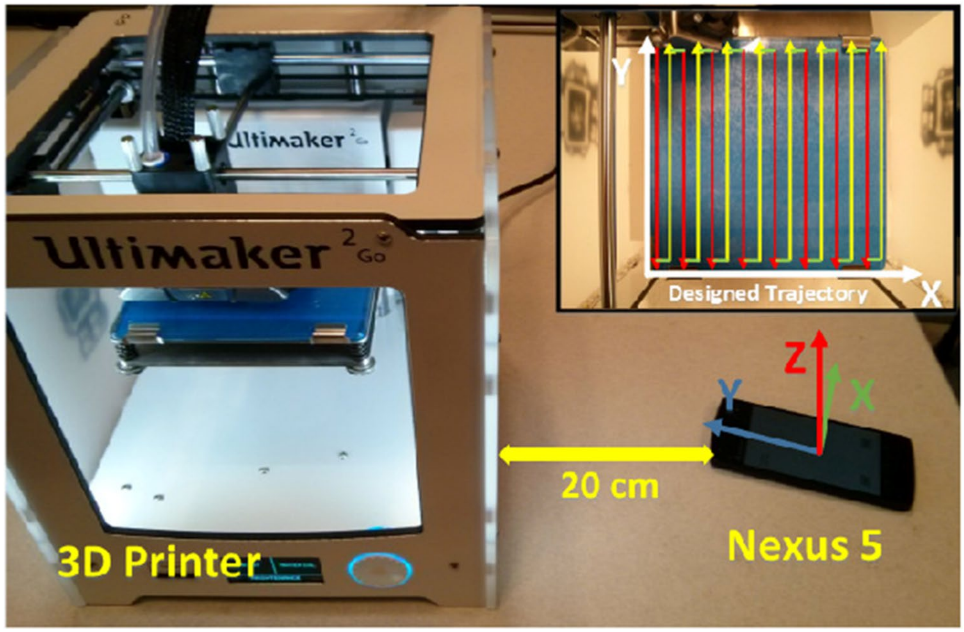

Fig. 8 A specific trajectory is designed to investigate the relationship between the directional movement and the magnetic side-channel [113]

their AM production resources to achieve higher assessments; (3) local AM production near customers will result in a de-globalization of supply chains; (4) more than 25% of final products will be sold as digital files instead of physical products (similar to digital format selling); (5) more consumers will utilize online databases to purchase product designs and have private 3D printers at home; (6) normal forms of intellectual property will be largely used in the AM industry. To reach these expectations by 2030, a uniform AM information sharing platform with a corresponding database will be required. Standard AM data format will be recognized and unified at a worldwide level. Well-established AM intellectual property will be necessary to protect the benefit of designers and manufacturers in the AM field.

5 Conclusion

As an emerging technology, AM promotes a new digital transformation of the manufacturing industry. It built a connection between manufacturing and multiple new technologies born in the information era. These new technologies provide fresh ideas to develop and improve 3D printing crafts. Meanwhile, AM also offers an environment for new technologies to practice and grow. In this chapter, we summarize the past contributions, current situation, and future potential development in the AM and Big Data area. The corresponding time shift is shown in Fig. 9.

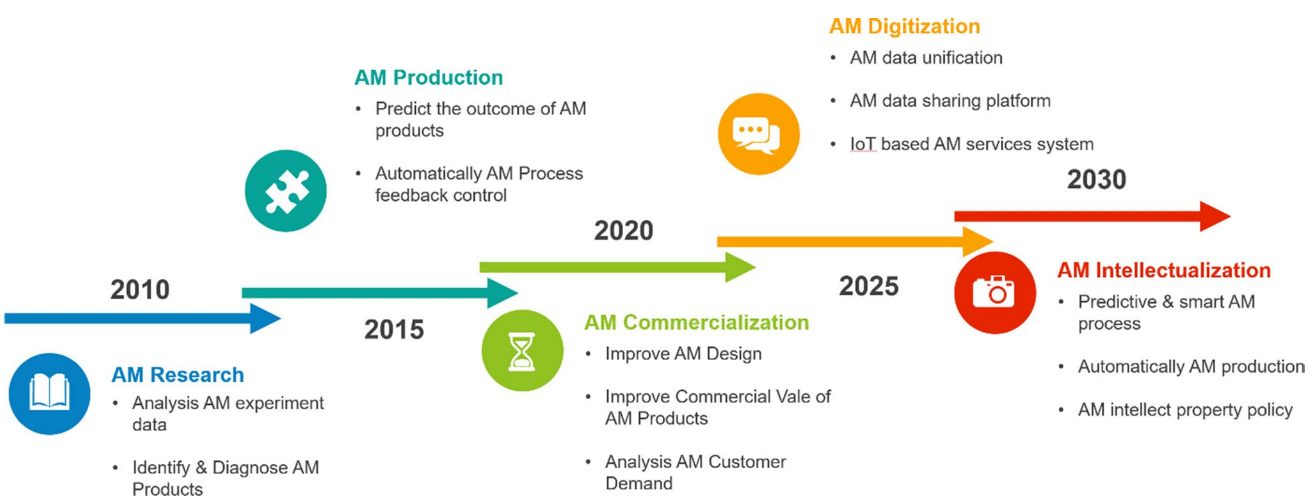

Fig. 9 Past, current, and future of AM and Big Data analysis

Big Data is one of the most famous new technologies in the information era. The prevalence of Big Data technology can be an opportunity for AM to become a viable fabrication technique in the manufacturing industry. This opportunity benefits AM in both research and commercial popularizing. For AM research, massive amounts of data from the 3D printing process can be processed by Big Data analysis to obtain various types of useful information. A variety of Big Data analysis methods can be used to classify or diagnose the AM products and predict the outcome of the AM process before the production. Specifically, Big Data technology can facilitate the AM process in detecting product defects, reducing geometry errors, analyzing feedback signals, and updating process parameters. Big Data techniques could help to control the cooling rate, microstructure, composition and, other mechanical properties for various AM systems, such as PBF, mater extrusion, and sheet lamination. In addition, a portion of the AM product design may be processed by Big Data methods according to the client requirements.

Utilization of Big Data data and transfer technology has a great effect on commercial AM systems. IoT technology enhances the marketization ability of AM technology. Customers can order 3D printing services through the Internet on demand. Meanwhile, IoT technology speeds up the AM service processes in both production and delivery. In addition, Cloud-based AM brings benefits to AM service providers by improving the profit model. AM service companies can offer their idle 3D printing equipment to be used on the Cloud and reduce the waste of resources. Similarly, AM companies can borrow 3D printers from the Cloud when their equipment is occupied. Therefore, the AM industry will receive better prospects with the development and integration of Big Data technology.

The next step in the AM and Big Data integration is data unification and generalization in the AM process. At the current stage, the main barrier of data sharing for both AM research and AM commerce is the unstandardized database existed in different institutions. Data transmission efficiency will be substantially increased if a common database format is adopted in the AM industry. Cybersecurity is another potential problem that may exist in the future of AM research. Even though only seldom cases reported the attack to the AM systems, complete information safety mechanism should be established to provide a reliable environment for the mainstream adoption of Big Data in the AM industry.

References

1. Kodama H (1981) A scheme for three-dimensional display by automatic fabrication of three-dimensional model. J IEICE 64:1981–1984
2. Hull CW (1986) Apparatus for production of three-dimensional objects by stereolithography. Google Patents
3. Frazier WE (2014) Metal additive manufacturing: a review. J Mater Eng Perform 23(6):1917–1928
4. Ahn S-H et al (2002) Anisotropic material properties of fused deposition modeling ABS. Rapid Prototyp J 8(4):248–257
5. Mueller B, Kochan D (1999) Laminated object manufacturing for rapid tooling and patternmaking in foundry industry. Comput Ind 39(1):47–53
6. Esmaeilian B, Behdad S, Wang B (2016) The evolution and future of manufacturing: a review. J Manuf Syst 39:79–100
7. Coopers PW (2014) 3D printing and the new shape of industrial manufacturing. Pricewaterhouse Coopers LLP, London
8. Carneiro OS, Silva A, Gomes R (2015) Fused deposition modeling with polypropylene. Mater Des 83:768–776
9. Ning F et al (2015) Additive manufacturing of carbon fiber reinforced thermoplastic composites using fused deposition modeling. Compos B Eng 80:369–378
10. Sutton AT et al (2017) Powder characterisation techniques and effects of powder characteristics on part properties in powder-bed fusion processes. Virtual Phys Prototyp 12(1):3–29
11. King WE et al (2014) Observation of keyhole-mode laser melting in laser powder-bed fusion additive manufacturing. J Mater Process Technol 214(12):2915–2925
12. Paul BK, Voorakarnam V (2001) Effect of layer thickness and orientation angle on surface roughness in laminated object manufacturing. J Manuf Process 3(2):94
13. Steinmann B (2006) Stereolithographic resins with high temperature and high impact resistance. Google Patents
14. Conner BP et al (2014) Making sense of 3-D printing: creating a map of additive manufacturing products and services. Addit Manuf 1:64–76
15. Hashem IAT et al (2015) The rise of "big data" on cloud computing: review and open research issues. Inf Syst 47:98–115
16. Rüßmann M et al (2015) Industry 4.0: The future of productivity and growth in manufacturing industries. Boston Consult Group 9(1):54–89
17. Wang L, Alexander CA (2016) Additive manufacturing and big data. Int J Math Eng Manag Sci 1(3):107–121
18. Guha S, Kumar S (2018) Emergence of big data research in operations management, information systems, and healthcare: past contributions and future roadmap. Prod Oper Manag 27(9):1724–1735
19. Rao PK et al (2016) Assessment of dimensional integrity and spatial defect localization in additive manufacturing using spectral graph theory. J Manuf Sci Eng Trans Asme 138(5)
20. Lipson H, Kurman M (2013) Fabricated: the new world of 3D printing. Wiley, Hoboken
21. Gao W et al (2015) The status, challenges, and future of additive manufacturing in engineering. Comput Aided Des 69:65–89
22. Ollison T, Berisso K (2010) Three-dimensional printing build variables that impact cylindricity. J Ind Technol 26(1)
23. Huang SH et al (2013) Additive manufacturing and its societal impact: a literature review. Int J Adv Manuf Technol 67(5–8):1191–1203
24. Huang Y et al (2015) Additive manufacturing: current state, future potential, gaps and needs, and recommendations. J Manuf Sci Eng 137(1):014001
25. Bastani K, Rao PK, Kong Z (2016) An online sparse estimation-based classification approach for real-time monitoring in advanced manufacturing processes from heterogeneous sensor data. IIE Trans 48(7):579–598
26. Tootooni MS et al (2017) Classifying the dimensional variation in additive manufactured parts from laser-scanned three-dimensional point cloud data using machine learning approaches. J Manuf Sci Eng 139(9):091005

27. Scime L, Beuth J (2018) Anomaly detection and classification in a laser powder bed additive manufacturing process using a trained computer vision algorithm. Addit Manuf 19:114–126
28. Craeghs T et al (2010) Feedback control of layerwise laser melting using optical sensors. Phys Proc 5:505–514
29. Craeghs T et al (2012) Detection of process failures in layerwise laser melting with optical process monitoring. Phys Proc 39:753–759
30. Wu M et al (2016) Detecting malicious defects in 3d printing process using machine learning and image classification. In: ASME 2016 international mechanical engineering congress and exposition. American Society of Mechanical Engineers
31. Gobert C et al (2018) Application of supervised machine learning for defect detection during metallic powder bed fusion additive manufacturing using high resolution imaging. Addit Manuf 21:517–528
32. Rodriguez E et al (2012) Integration of a thermal imaging feedback control system in electron beam melting. In: Proceedings of the solid freeform fabrication symposium
33. Wegner A, Witt G (2011) Process monitoring in laser sintering using thermal imaging. In: SFF symposium, Austin
34. Krauss H, Eschey C, Zaeh M (2012) Thermography for monitoring the selective laser melting process. In: Proceedings of the solid freeform fabrication symposium
35. Price S, Cooper K, Chou K (2012) Evaluations of temperature measurements by near-infrared thermography in powder-based electron-beam additive manufacturing. In: Proceedings of the solid freeform fabrication symposium. University of Texas, Austin
36. Yao B et al (2018) Multifractal analysis of image profiles for the characterization and detection of defects in additive manufacturing. J Manuf Sci Eng 140(3):031014
37. Gobert C et al (2018) Application of supervised machine learning for defect detection during metallic powder bed fusion additive manufacturing using high resolution imaging. Addit Manuf 21:517–528
38. Gobert C (2017) Online discontinuity detection in metallic powder bed fusion additive manufacturing processes using visual inspection sensors and supervised machine learning. Pennsylvania State University
39. Mazumder J (2015) Design for metallic additive manufacturing machine with capability for "Certify as You Build." Proc CIRP 36:187–192
40. Khanzadeh M et al (2018) Quantifying geometric accuracy with unsupervised machine learning: using self-organizing map on fused filament fabrication additive manufacturing parts. J Manuf Sci Eng 140(3):031011
41. Albakri MI et al (2017) Impedance-based non-destructive evaluation of additively manufactured parts. Rapid Prototyp J 23(3):589–601
42. Yan W et al (2018) Data-driven multi-scale multi-physics models to derive process–structure–property relationships for additive manufacturing. Comput Mech 61(5):521–541
43. Malekipour E, El-Mounayri H (2018) Defects, process parameters and signatures for online monitoring and control in powder-based additive manufacturing. Mechanics of additive and advanced manufacturing, vol 9. Springer, pp 83–90
44. Spierings AB, Herres N, Levy G (2011) Influence of the particle size distribution on surface quality and mechanical properties in AM steel parts. Rapid Prototyp J 17(3):195–202
45. Craeghs T et al (2011) Online quality control of selective laser melting. In: Proceedings of the solid freeform fabrication symposium, Austin
46. Berumen S et al (2010) Quality control of laser-and powder bed-based additive manufacturing (AM) technologies. Phys Proc 5:617–622
47. Kleszczynski S et al (2012) Error detection in laser beam melting systems by high resolution imaging. In: Proceedings of the twenty third annual international solid freeform fabrication symposium
48. Shemelya C et al (2015) Multi-functional 3D printed and embedded sensors for satellite qualification structures. In: 2015 IEEE sensors. IEEE
49. Akmal JS et al (2018) Implementation of industrial additive manufacturing: intelligent implants and drug delivery systems. J Funct Biomater 9(3):41
50. Wasserfall F (2015) Embedding of SMD populated circuits into FDM printed objects. In: Solid freeform fabrication symposium
51. Wu H, Wang Y, Yu Z (2016) In situ monitoring of FDM machine condition via acoustic emission. Int J Adv Manuf Technol 84(5–8):1483–1495
52. Davim JP, Oliveira C, Cardoso A (2008) Predicting the geometric form of clad in laser cladding by powder using multiple regression analysis (MRA). Mater Des 29(2):554–557
53. Nenadl O et al (2014) The prediction of coating geometry from main processing parameters in laser cladding. Phys Proc 56:220–227
54. Alimardani M, Toyserkani E (2008) Prediction of laser solid freeform fabrication using neuro-fuzzy method. Appl Soft Comput 8(1):316–323
55. Xiong J et al (2014) Bead geometry prediction for robotic GMAW-based rapid manufacturing through a neural network and a second-order regression analysis. J Intell Manuf 25(1):157–163
56. Lanzotti A et al (2015) The impact of process parameters on mechanical properties of parts fabricated in PLA with an open-source 3-D printer. Rapid Prototyp J 21(5):604–617
57. Vijayaraghavan V et al (2015) Process characterisation of 3D-printed FDM components using improved evolutionary computational approach. Int J Adv Manuf Technol 78(5–8):781–793
58. Zhu Z et al (2018) Machine learning in tolerancing for additive manufacturing. CIRP Ann 67(1):157–160
59. Delgado J, Ciurana J, Rodríguez CA (2012) Influence of process parameters on part quality and mechanical properties for DMLS and SLM with iron-based materials. Int J Adv Manuf Technol 60(5–8):601–610
60. Verma A, Tyagi S, Yang K (2015) Modeling and optimization of direct metal laser sintering process. Int J Adv Manuf Technol 77(5–8):847–860
61. Paul R, Anand S (2012) Process energy analysis and optimization in selective laser sintering. J Manuf Syst 31(4):429–437
62. Tapia G, Elwany A (2014) A review on process monitoring and control in metal-based additive manufacturing. J Manuf Sci Eng 136(6):060801
63. Yasa E et al (2009) Investigation on occurrence of elevated edges in selective laser melting. In: International solid freeform fabrication symposium, Austin
64. Gong H et al (2014) Melt pool characterization for selective laser melting of Ti-6Al-4V pre-alloyed powder. In: Solid freeform fabrication symposium
65. Tapia G, Elwany A, Sang H (2016) Prediction of porosity in metal-based additive manufacturing using spatial Gaussian process models. Addit Manuf 12:282–290
66. Meier H, Haberland C (2008) Experimental studies on selective laser melting of metallic parts. Materialwiss Werkstofftech 39(9):665–670
67. Garg A, Lam JSL, Savalani M (2015) A new computational intelligence approach in formulation of functional relationship of open porosity of the additive manufacturing process. Int J Adv Manuf Technol 80(1–4):555–565
68. Zhang X et al (2016) Data-driven bending elasticity design by shell thickness. In: Computer graphics forum. Wiley Online Library

69. Desai DR, Magliocca GN (2013) Patents, meet Napster: 3D printing and the digitization of things. Geo LJ 102:1691
70. Zhang X et al (2015) Perceptual models of preference in 3D printing direction. Acm Trans Graph 34(6):1–12
71. Hu KL, Jin S, Wang CCL (2015) Support slimming for single material based additive manufacturing. Comput Aided Des 65:1–10
72. Hu K, Zhang X, Wang CC (2015) Direct computation of minimal rotation for support slimming. In: 2015 IEEE international conference on automation science and engineering (CASE). IEEE
73. Thompson MK et al (2016) Design for additive manufacturing: trends, opportunities, considerations, and constraints. CIRP Ann 65(2):737–760
74. Ponche R et al (2014) A novel methodology of design for additive manufacturing applied to additive laser manufacturing process. Robot Comput Integr Manuf 30(4):389–398
75. Langelaar M (2017) An additive manufacturing filter for topology optimization of print-ready designs. Struct Multidiscip Optim 55(3):871–883
76. Langelaar M (2016) Topology optimization of 3D self-supporting structures for additive manufacturing. Addit Manuf 12:60–70
77. Gaynor AT, Guest JK (2016) Topology optimization considering overhang constraints: eliminating sacrificial support material in additive manufacturing through design. Struct Multidiscip Optim 54(5):1157–1172
78. Mirzendehdel AM, Suresh K (2016) Support structure constrained topology optimization for additive manufacturing. Comput Aided Des 81:1–13
79. Rezaie R et al (2013) Topology optimization for fused deposition modeling process. Proc CIRP 6:521–526
80. Sing SL et al (2016) Laser and electron-beam powder-bed additive manufacturing of metallic implants: a review on processes, materials and designs. J Orthop Res 34(3):369–385
81. Gu GX et al (2018) Bioinspired hierarchical composite design using machine learning: simulation, additive manufacturing, and experiment. Mater Horizons 5(5):939–945
82. Ford S, Despeisse M (2016) Additive manufacturing and sustainability: an exploratory study of the advantages and challenges. J Clean Prod 137:1573–1587
83. Boyle BM et al (2017) Structural color for additive manufacturing: 3D-printed photonic crystals from block copolymers. ACS Nano 11(3):3052–3058
84. Mohammed M et al (2016) Applications of 3D topography scanning and multi-material additive manufacturing for facial prosthesis development and production. In: Proceedings of the 27th annual international solid freeform fabrication symposium
85. Chung M, Kim J (2016) The internet information and technology research directions based on the fourth industrial revolution. KSII Trans Internet Inf Syst 10(3):1311-1320
86. Gubbi J et al (2013) Internet of things (IoT): a vision, architectural elements, and future directions. Future Gener Comput Syst Int J Esci 29(7):1645–1660
87. Ashton K (2009) That 'internet of things' thing. RFID journal 22(7):97–114
88. Schwab K (2017) The fourth industrial revolution. Crown Business, New York, p 192
89. Lee C, Leem CS, Hwang I (2011) PDM and ERP integration methodology using digital manufacturing to support global manufacturing. Int J Adv Manuf Technol 53(1–4):399–409
90. Caputo A, Marzi G, Pellegrini MM (2016) The internet of things in manufacturing innovation processes: development and application of a conceptual framework. Bus Process Manag J 22(2):383–402
91. Qin J, Liu Y, Grosvenor R (2017) A framework of energy consumption modelling for additive manufacturing using internet of things. Proc CIRP 63:307–312
92. Mourtzis D, Vlachou E, Milas N (2016) Industrial big data as a result of IoT adoption in manufacturing. Proc CIRP 55:290–295
93. Lu Y, Cecil J (2016) An internet of things (IoT)-based collaborative framework for advanced manufacturing. Int J Adv Manuf Technol 84(5–8):1141–1152
94. Kaur S (2012) How is "Internet of the 3D Printed Products" going to affect our lives? Pushing frontiers with the first lady of emerging technologies. IETE Tech Rev 29(5):360–364
95. Rogers H, Baricz N, Pawar KS (2016) 3D printing services: classification, supply chain implications and research agenda. Int J Phys Distrib Logist Manag 46(10):886–907
96. Dilberoglu UM et al (2017) The role of additive manufacturing in the era of industry 4.0. Procedia Manufacturing 11:545–554
97. Mell P, Grance T (2011) The NIST definition of cloud computing
98. Xu X (2012) From cloud computing to cloud manufacturing. Robot Comput Integr Manuf 28(1):75–86
99. Wu D et al (2013) Cloud manufacturing: Strategic vision and state-of-the-art. J Manuf Syst 32(4):564–579
100. Tao F et al (2011) Cloud manufacturing: a computing and service-oriented manufacturing model. Proc Inst Mech Eng Part B J Eng Manuf 225(10):1969–1976
101. Liu XW et al (2014) Research on profit mechanism of 3D Printing Cloud Platform based on customized products. Appl Mech Mater 703: 318–322
102. Mai JG et al (2016) Customized production based on distributed 3D printing services in cloud manufacturing. Int J Adv Manuf Technol 84(1–4):71–83
103. Guo L, Qiu J (2018) Combination of cloud manufacturing and 3D printing: research progress and prospect. Int J Adv Manuf Technol 96(5):1929–1942
104. Baumann FW, Roller D (2017) Survey on additive manufacturing, cloud 3D printing and services. arXiv: 1708.04875
105. Lehmhus D et al (2015) Cloud-based automated design and additive manufacturing: a usage data-enabled paradigm shift. Sensors 15(12):32079–32122
106. von Solms R, van Niekerk J (2013) From information security to cyber security. Comput Secur 38:97–102
107. Chhetri SR, Canedo A, Faruque MAA (2018) Confidentiality breach through acoustic side-channel in cyber-physical additive manufacturing systems. ACM Trans Cyber-Phys Syst 2(1):3
108. Sturm L et al (2014) Cyber-physical vunerabilities in additive manufacturing systems. Context 7(8)
109. Mustaca S (2014) Are your IT professionals prepared for the challenges to come? Comput Fraud Secur 2014(3):18–20
110. Al Faruque MA et al (2016) Forensics of thermal side-channel in additive manufacturing systems. In: CECS Technical Report# 16-01. University of California Irvine
111. Faruque A et al (2016) Acoustic side-channel attacks on additive manufacturing systems. In: Proceedings of the 7th international conference on cyber-physical systems. IEEE Press
112. Chhetri SR, Canedo A, Al Faruque MA (2016) Kcad: kinetic cyber-attack detection method for cyber-physical additive manufacturing systems. In: 2016 IEEE/ACM international conference on computer-aided design (ICCAD). IEEE.
113. Song C et al (2016) My smartphone knows what you print: Exploring smartphone-based side-channel attacks against 3d printers. In: Proceedings of the 2016 ACM SIGSAC conference on computer and communications security. ACM
114. Bandyopadhyay A, Bose S (2015) Additive manufacturing. CRC Press, Boca Raton
115. Tanenbaum JG et al (2013) Democratizing technology: pleasure, utility and expressiveness in DIY and maker practice. In:

Proceedings of the SIGCHI conference on human factors in computing systems. ACM
116. Despeisse M et al (2017) Unlocking value for a circular economy through 3D printing: a research agenda. Technol Forecast Soc Chang 115:75–84
117. Uriondo A, Esperon-Miguez M, Perinpanayagam S (2015) The present and future of additive manufacturing in the aerospace sector: a review of important aspects. Proc Inst Mech Eng Part G J Aerosp Eng 229(11):2132–2147
118. Khajavi SH, Partanen J, Holmström J (2014) Additive manufacturing in the spare parts supply chain. Comput Ind 65(1):50–63
119. Silva JV, Rezende RA (2013) Additive Manufacturing and its future impact in logistics. IFAC Proceedings Volumes 46(24):277–282
120. Gausemeier J et al (2011) Thinking ahead the future of additive manufacturing. Future Appl
121. Assunção MD et al (2015) Big Data computing and clouds: trends and future directions. J Parallel Distrib Comput 79:3–15
122. Fan W, Bifet A (2013) Mining big data: current status, and forecast to the future. ACM SIGKDD Explor Newsl 14(2):1–5
123. Agrawal D, Das S, El Abbadi A (2011) Big data and cloud computing: current state and future opportunities. In: Proceedings of the 14th international conference on extending database technology. ACM
124. Chong L, Ramakrishna S, Singh S (2018) A review of digital manufacturing-based hybrid additive manufacturing processes. Int J Adv Manuf Technol 95(5–8):2281–2300
125. Weiss F, Roth D, Binz H (2018) Content and functions of an internet-based platform for supporting development of additively manufactured parts. In: DS92: proceedings of the design 2018 15th international design conference
126. Rudolph J-P, Emmelmann C (2017) A cloud-based platform for automated order processing in additive manufacturing. Proc CIRP 63:412–417
127. Lee J et al (2013) Recent advances and trends in predictive manufacturing systems in big data environment. Manuf Lett 1(1):38–41
128. Babiceanu RF, Seker R (2015) Manufacturing operations, internet of things, and big data: towards predictive manufacturing systems. Service orientation in holonic and multi-agent manufacturing. Springer, pp 157–164
129. Khan AR et al (2021) Predictive manufacturing: classification of categorical data. J Qual Technol
130. Chekurov S et al (2018) The perceived value of additively manufactured digital spare parts in industry: An empirical investigation. Int J Prod Econ 205:87–97
131. Holmström J et al (2010) Rapid manufacturing in the spare parts supply chain: alternative approaches to capacitydeployment. J Manuf Technol Manag
132. Kretzschmar N et al (2018) Evaluating the readiness level of additively manufactured digital spare parts: an industrial perspective. Appl Sci 8(10):1837
133. Davis J et al (2012) Smart manufacturing, manufacturing intelligence and demand-dynamic performance. Comput Chem Eng 47:145–156
134. Kang HS et al (2016) Smart manufacturing: past research, present findings, and future directions. Int J Precis Eng Manuf Green Technol 3(1):111–128
135. Lu Y, Morris KC, Frechette S (2016) Current standards landscape for smart manufacturing systems. Natl Inst Stand Technol NISTIR 8107:39
136. Lee J, Bagheri B, Kao H-A (2015) A cyber-physical systems architecture for industry 4.0-based manufacturing systems. Manuf Lett 3:18–23
137. Wang L, Törngren M, Onori M (2015) Current status and advancement of cyber-physical systems in manufacturing. J Manuf Syst 37:517–527
138. Monostori L et al (2016) Cyber-physical systems in manufacturing. CIRP Ann 65(2):621–641
139. Jiang R, Kleer R, Piller FT (2017) Predicting the future of additive manufacturing: a Delphi study on economic and societal implications of 3D printing for 2030. Technol Forecast Soc Chang 117:84–97