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Review

Machine Learning for Advanced Additive Manufacturing

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SUMMARY

Increasing demand for the fabrication of components with complex designs has spurred a revolution in manufacturing methods. Additive manufacturing stands out as a promising technology when it comes to prototyping multi-functional and multi-material designs. However, challenges still exist in the additive manufacturing process, such as mismatched material properties, lack of build consistency, and pervasive imperfections in the printed part. These inherent challenges can be avoided by implementing algorithms to detect imperfections and modulate printing parameters in real time. In this paper, several algorithms, with a focus on machine learning methods, are reviewed and explored to systematically tackle the three main stages of the additive manufacturing process: geometrical design, process parameter configuration, and *in situ* anomaly detection. Current challenges and future opportunities for algorithmically driven additive manufacturing processes, as well as potential applications to other manufacturing methods, are also discussed.

Progress and Potential

Current additive manufacturing methods are capable of creating multi-scale, multi-material, and multi-functional products that are difficult to fabricate using traditional techniques. Challenges still lie in the mismatch between theoretical design expectations and practical manufacturing capabilities. Recent research efforts have been dedicated to solving these difficulties through traditional optimization or simulation methods. In this review, advanced algorithms for additive manufacturing are discussed and potential applications utilizing state-of-the-art artificial intelligence methods are proposed. This paper aims to provide insights into next-generation algorithm-driven additive manufacturing.

INTRODUCTION

Computers, one of the symbols of the third industrial revolution, have brought tremendous advances to traditional manufacturing methods. Automated systems such as computer numerical control (CNC) machining and robotic assembly lines greatly promote efficiency and consistency in fabrication.[1,2] Among these systems, additive manufacturing (AM), typically known as three-dimensional (3D) printing, stands out due to its capability of creating complex, multi-material, and multi-functional designs.[3–7] This capability is integral in bringing about the fourth industrial revolution, otherwise known as Industry 4.0, aimed at advancing manufacturing through data and machine intelligence.

A typical AM manufacturing workflow starts at the design stage wherein computer-aided design (CAD) software is used to create a CAD model of the part of interest. The design may impose constraints on the 3D-printing process, such as resolution limitations and the need for support structures for overhanging structures (discussed in the Geometrical Design section). The CAD model is then sliced to produce partial instructions defining the geometry and then fed into the 3D printer to make the part. In order to complete these instructions, a set of 3D-printing process parameters need to be specified. As such, process parameters are oftentimes manually adjusted and corrected based on the condition of the outputted product. However, this trial-and-error process largely depends on the experience of the operator to recognize anomalies and, subsequently, make corresponding corrections of process parameters, resulting in a tedious and inefficient procedure while various defects may be generated throughout the printing process. Additionally, the multitude of combinations of process parameters has a big impact on the final quality of the product.

To resolve the abovementioned issues, considerable studies have been conducted to optimize the manufacturing process using simulation, high-throughput experiments, and sensor technologies.[8–10] For example, topology optimization (TO) is used to create designs with given constraints and objective functions to maximize material performance in the continuum scale[11,12] and nanoscale.[13] Simulations are developed for various AM methods to understand the effects of different combinations of process parameters.[14,15] Additionally, machine learning (ML) and computer vision models are developed to study the relationships between process parameters and product quality.[16,17] These techniques have the potential to create the next generation of smart, low-cost, and efficient AM systems.

This review highlights recent studies of algorithmically driven AM processes with a focus on three central aspects: (1) geometrical design, (2) process parameter configuration, and (3) *in situ* anomaly detection. Considering the algorithms behind some of these AM systems, ML methods are of special interest for their advanced capability in discovering rules and learning principles behind data based on underlying patterns and features. Generally, there are three major types of ML algorithms: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning uses models based on labeled training data to predict the desired output. Typical methods, including support vector machine (SVM) and Gaussian processes (GP), can be applied for classification and regression problems.[18,19] Unsupervised learning methods, such as clustering and self-organizing map (SOM), are advantageous to be applied to problems that have no pre-existing labels on their dataset.[20,21] These methods aim to minimize human supervision during problem solving while maintaining satisfactory performance. Reinforcement learning (RL) focuses on learning from the consequence (reward or punishment) of actions in the state of an environment to achieve the maximum award. RL has shown its powerful capability in board games (e.g., Go) and the field of autonomous vehicles.[22,23] Besides the simple regression and SVM methods, there are other widely used models called neural networks (NNs). NNs imitate the idea of biological NNs and have learnable network parameters determined through iterative training processes. Due to the ability to construct complicated structures in the model, NNs have been actively adopted in image recognition, natural language processing, and many other different areas.[24,25]

An overview of this paper is shown in Figure 1 to highlight the details and connections between each stage of the AM process as well as various algorithms used in AM applications. This paper is divided into several subtopics of interest, which are organized as follows. In the geometrical design section, TO and ML methods are discussed and compared with one another. In the processing parameter configuration and *in situ* anomaly detection sections, conventional approaches such as genetic algorithm and image processing methods as well as ML methods are discussed with detailed literature examples. In the discussion section, an overview table is included to discuss the specialty of various ML algorithms in different AM applications. Finally, current challenges and future opportunities of ML algorithms are explored in terms of the above three stages in the AM process as well as potential applications to other manufacturing methods.

GEOMETRICAL DESIGN

As the first step in the manufacturing process, designing a high-performance part that meets the application's requirements is critical. AM enables the building of complex lattice structures with different material distributions. AM does come

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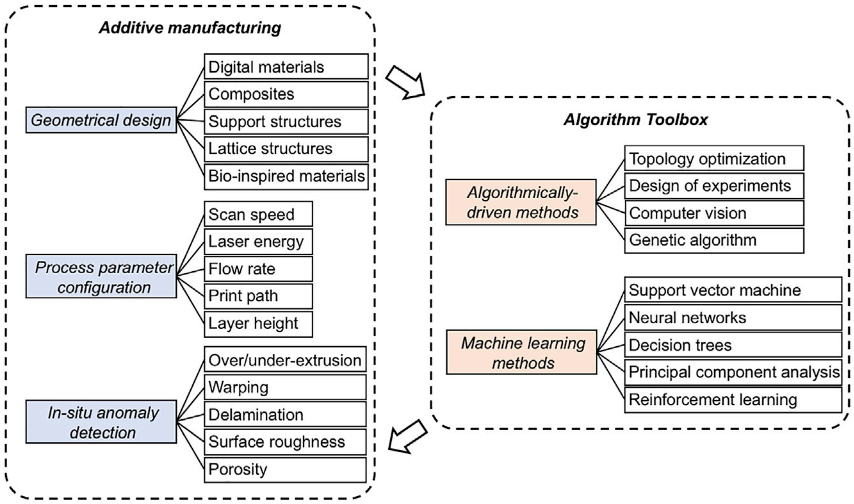

Figure 1. Schematic Showing the Connections between the Three Main Stages of Additive Manufacturing (Geometrical Design, Process Parameter Configuration, and *In Situ* Anomaly Detection) and Various Algorithms

with unique challenges of its own, such as overhang structures that require additional support, known as support structures. In this section, TO and ML methods for part design are discussed, examining recent studies, current challenges, and future perspectives.

TO for AM

TO has been attracting enormous attention since the late twentieth century for minimizing material requirements and boasting higher generality than conventional parametric design methods.[12] TO in conjunction with AM, however, faces many obstacles. Support structures are intrinsic to the AM process and need to be explicitly included as an extra constraint in TO. For most polymer and metal 3D printers, a support structure is needed for any overhangs that exceed a threshold angle from the vertical printing direction. Support structures are usually removed manually, which increases labor and time costs. One approach to tackle this issue is to force the optimized design to be self-supported by introducing the overhang angles as a penalty term, which has a large coefficient in the loss function or is regarded as domain constraints for the design space.[26–29] As illustrated in Figure 2A, an overhang detection method has been developed which applies linear regression at all solid-void interfaces. Thereafter, any downward-facing edge that has a slope larger than the threshold would heavily penalize the objective function.[11]

However, self-supporting constraints can often substantially limit the space of practical designs.[37] As a result, researchers have attempted to achieve a balance between unconstrained and self-supporting TO approaches by introducing the amount of support structure and removal effort as soft penalties to the objective with small tunable coefficients.[30,38,39] One proposed approach for constrained support TO starts by first solving it within the unconstrained design space. The solution is then iteratively updated to minimize the tradeoff between the objective and soft penalties. Unnecessary cavities are removed from the original model, which substantially reduces the required amount of support material,[30] as seen in Figure 2B.

TO also enables the fabrication of complex lattice structures with the same time efficiency as bulk structures in AM. In the solid isotropic material (SIM) approach, which

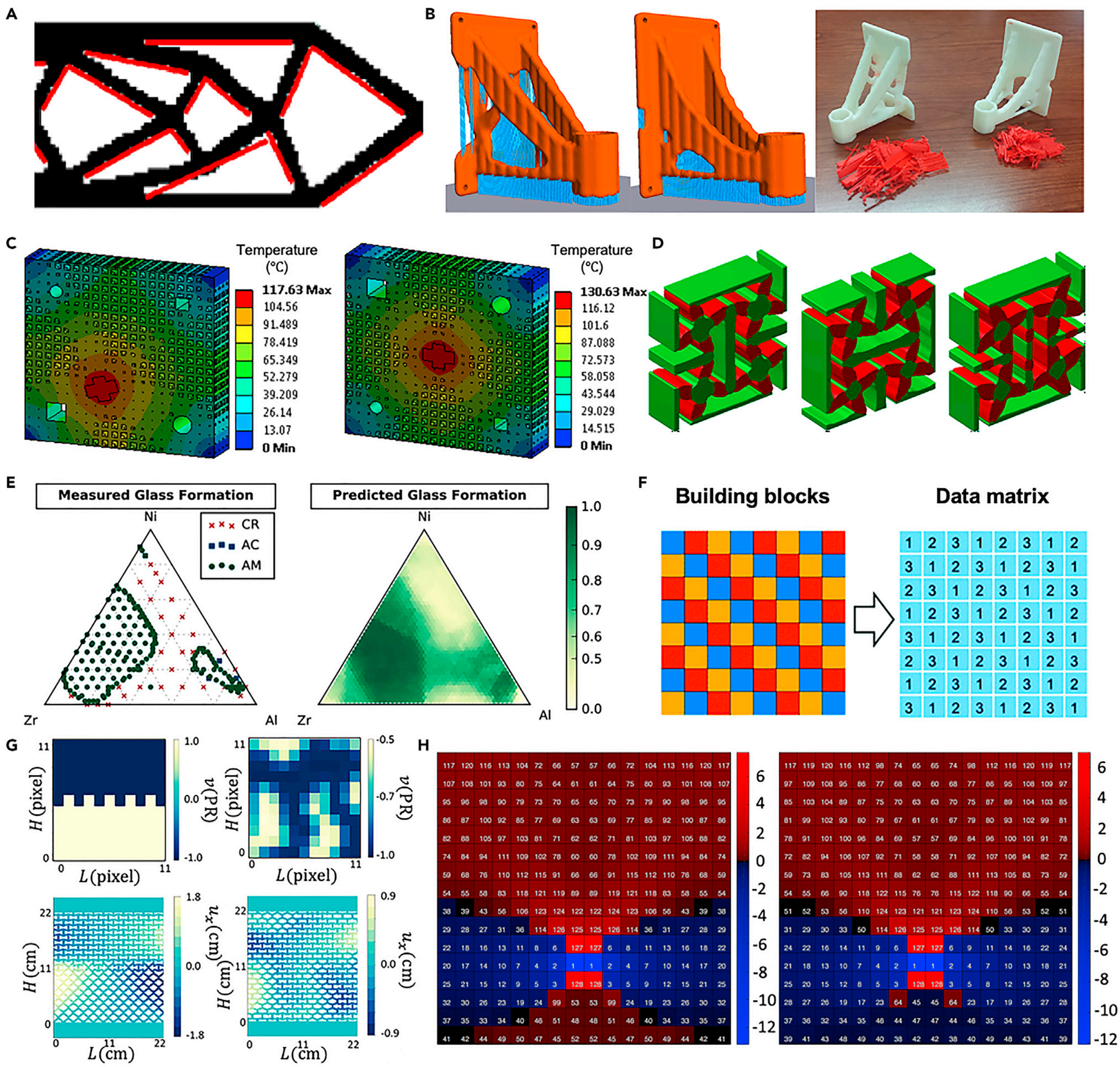

Figure 2. Topology Optimization and Machine Learning Design for 3D-Printed Materials

(A) Approximating the slope of the downward-facing edges through a linear fit for each iteration of TO. Adapted with permission from Brackett et al.[11] Copyright 2011, Solid Freeform Fabrication Symposium.

(B) The printed bracket requires much less support after adding a support penalty in the objective function. Adapted with permission from Mirzendehdel and Suresh.[30] Copyright 2016, Elsevier.

(C) AM allows for an optimized design to have a distribution of different lattice structures. Adapted with permission from Cheng et al.[31] Copyright 2018, Elsevier.

(D) AM allows for an optimized design to contain multiple materials, and thus, achieve better objective values. Adapted with permission from Vogiatzis et at.[32] Copyright 2017, Elsevier.

(E) The simulated and ML-predicted glass formation ability within the Ni-Al-Zr ternary. Adapted with permission from Ward et al.[33] Copyright 2016, Springer Nature.

(F) The design of a DM can be fed into an ML model by encoding different material voxels as different feature numbers. Adapted with permission from Gu et al.[34] Copyright 2018, Royal Society of Chemistry.

(G) A sample DM with each voxel representing different cell structures. Adapted with permission from Wilt et al.[35] Copyright 2019, Wiley-VCH.

(H) DM sensitivity analysis from linear models predicting toughness (left) and strength (right). Adapted with permission from Gu et al.[36] Copyright 2018, Elsevier.

takes the mass densities of material elements as design variables, optimized designs are sometimes screened to eliminate any intermediate-density regions, which are not physically existing materials. Using TO, these regions can now be represented as small-scale lattice structures with intermediate properties, greatly expanding the design space.[31,40–42] For example, Cheng et al.[31] considered intermediate-density regions as cubic lattice structures with a corresponding material volume fraction when optimizing the structure of a cooling channel. The material properties of such lattice structures are then computed through the homogenization of the representative volume elements.[31] As a result, the final design with optimized cooling functionality contains regions with graded lattice structures, as seen in Figure 2C. Moreover, this approach can be further extended to a multi-scale problem where the microstructures are optimized concurrently with the global geometry instead of selecting from a set of predetermined lattices.[43–45]

Additionally, with the help of advanced AM technologies (e.g., inkjet and polyjet), composites with intricate material distributions can be created and much success has been shown in the bioinspired materials community.[46,47] Taking advantage of this multi-material fabrication ability, researchers have modified the density-based approach so that the design parameter η describes the similarity of the representative volume element to the composite constituents or to void.[48–50] Similarly, the level-set method, which iteratively updates the design through a material phase velocity field, can also be upgraded to optimize composites. Instead of using one phase function to distinguish solid and void, the multi-material framework uses m level-set functions to represent at most 2^m material phases plus void.[32,51,52] Figure 2D demonstrates the results from Vogiatzis et al.[32] where composites are optimized to achieve negative Poisson's ratio under different constituent volume fractions.

ML-Driven Material Design

ML techniques have been attracting great attention for their ability to construct an analytical mapping from input features to output responses for different problems of interest. As a result, ML models are often considered as surrogate models that greatly accelerate the numerical simulation process at the expense of a small prediction bias.[53–57] Most ML models can be categorized into three groups in terms of their outputs: regression models, which give real number predictions; classification models, which give discrete class predictions; and unsupervised clustering models, which analyze the similarities of data points based on their features. Given the design information as input features, various ML techniques have been utilized to predict resultant mechanical and chemical properties, including strength, stiffness, deformation, toxicity, and stability.[33,58–62] For instance, Ward et al.[33] developed an ensemble of decision trees that can be developed to predict the bandgap energy, specific volume, and formation energy under different chemical compositions.[33] Their model produced Figure 2E, which shows a comparison between the simulated and predicted glass formation abilities within the Al-Ni-Zr ternary.[33]

The input features of an ML model can be extracted in various forms mechanically or chemically depending on the category of the material of interest. Specifically, for 3D printed materials, the concept of digital material (DM) was introduced to best represent complex composites or lattice structures produced by AM. A DM is an assembly of voxels where each voxel represents a lattice of a material element.[63] Thereafter, each voxel of the DM can be treated as an input feature of the ML model. Through this DM representation, Gu et al.[34] used a convolutional neural networks (CNN) to predict the toughness of the composite DM. As seen in Figure 2F, different material voxels are encoded as different input features to match the mathematical form of an

ML model.[34] A similar approach can be applied to predict the deformation of the entire material system under various unit cell distributions; for example, this can be used in the design of compliant actuators[35] (Figure 2G).

ML approaches utilize analytical forms that can greatly accelerate the prediction and optimization process in materials design compared with other computational methods.[64] For example, the sensitivity of all material voxels can be computed from a linear ML model[34] that is fitted to predict the composite strength, as seen in Figure 2H. An evolutionary algorithm is then used to generate top design candidates with the highest strength based on the sensitivities, which measure the importance of each material voxel.[36] Recently, studies have shown that ML can be used as a promising tool to accelerate the inverse-design process of materials. Inverse-design approaches generate suitable material designs with a given set of desired properties or functionality (from property to structure).[65–67] For instance, studies trained an NN with many hidden layers to predict the toughness of DM composites.[68] Then, gradient descent was performed on the NN to maximize the property of toughness using descent directions computed from backpropagation. Moreover, the ML model actively learns from training data generated around the current design point to reduce the bias within the local convex hull.[68] These studies show that ML can be used as a promising approach to accelerate the materials design process, which can be translated into a physical part with advances in AM.

PROCESS PARAMETER CONFIGURATION

After refining the geometrical designs, choosing appropriate process parameters becomes the next critical challenge in the printing process. Different AM methods have different sets of process parameters that govern the AM process. For example, in fused filament fabrication (FFF), where polymers are extruded layer by layer to create the structure, printing speed, flow rate of the material, and layer height settings are the key parameters in fabrication. Moreover, laser-assisted AM methods that share a similar layer-based manufacturing procedure, such as laser powder bed fusion (L-PBF) or sintering, have a different set of critical process parameters, such as laser power, laser speed, and scan strategy. This section deals with how genetic algorithms (GAs) and ML methods can be used to influence the quality of the final printing products through the selection of process parameters. Additionally, justifications for the application of ML are provided as well as related recent literature on the implementation of ML for optimizing and interpreting the analytical relationship between process parameters and product quality.

Optimization Through GA

As numerous process parameters are involved in the AM process and each parameter has a tunable range during fabrication, it is very time consuming to conduct experiments on every combination of the process parameters. Therefore, efficient methods are required to find the optimal set of process parameters. Here, GA is introduced for its wide application in solving optimization problems using biologically inspired operations to conduct evolutionary updates.[69,70] In a GA model, the first parent generation input set is initialized and then evaluated through a fitness function. If the target criterion (fitness function) is not fulfilled, operations such as mutation, crossover, and selection will be conducted to generate the second children generation. This iterative process will keep reproducing offspring until the objective is reached.

With the GA as a basis, multiple studies have been conducted on applying GA to optimize the process parameters in AM.[71–73] The first example that will be discussed is a GA model with the design of experiments (DOE) to find the optimal combination of process parameters that can minimize surface roughness and porosity characteristics of the printed part. In this study, the prints were created by FFF using acrylonitrile butadiene styrene (ABS) material and the process parameters of interest were slice thickness, road width, nozzle temperature, and air gap.[74] First, DOE was conducted to get the surface roughness and porosity results from different combinations of the four process parameters. Second, based on the experimental results, response surface methodology (RSM) was applied to get the fitness function, which was defined as a second-degree polynomial equation of the input variables (process parameters). Third, GA was applied to the problem to predict the optimal process parameter set. Conclusions were finally made that the minimum surface roughness occurs at the smallest value in the defined range of slice thickness, road width, and air gap with an intermediate nozzle temperature, which matched with the results of both the GA model and the experimental validation.

In the previous example, the objective of finding the best performance on surface roughness and porosity is reached independently. However, the multiple aims and evaluations of the final product are often coupled with each other. Another study used an advanced multi-objective genetic algorithm (MOGA) to optimize the combined goals in the L-PBF AM method (Figure 3B). The objectives include finding the optimal processing rate and energy efficiency as well as maximizing or minimizing the average grain size and the magnitude of columnar gains growth direction.[75] The MOGA model followed the same iterative procedure while extending the fitness function to a 3D coordinate space, where each dimension is a fitness function with its value determined by the process parameters. The input process parameters studied in this literature are laser power, scan velocity, hatch distance, and scan strategy. After convergence of the MOGA model, conclusions were made as follows. First, finer grain sizes and less influenced grain growth directions could be achieved if a scan strategy rotation of 67° is used; increasing laser energy density would lead to larger grain sizes. Second, a choice of medium-high scan velocity and medium hatch distance was ideal for creating an isotropic product. The MOGA method extends the capability of conventional GA models to tackle multi-objective tasks as well as investigate relationships between the process parameters and the quality of prints.

Machine Learns the Effects of Process Parameters

Although the GA method is able to provide some optimal solutions in the choice of process parameters, the range of each input variable is still highly limited. Besides, the fitness functions used in the algorithm are often developed through a second-order regression model and are accurate enough to determine the relationship of the target objective versus the process parameters. Before starting a print job, an operator will want to assess the validity of the process parameters associated with the job as print failures are costly. Traditional approaches to generate predictions of print quality come at a high cost associated with the necessary computational and experimental resources. Specifically, depending on the scale of the part being analyzed, computational studies can take excessively long times, even with the utilization of high-performance computing (HPC) resources. Experimental trial-and-error procedures are not cheap either due to the iteration of adjustments. Hence, data-driven approaches and ML have a big role to play in making quick, accurate, and analytical predictions for the reliability and quality of printed parts. Furthermore, there are still complex interdependencies between the process parameters that are not sufficiently understood; ML has the potential to unravel these complexities and provide a better understanding of the physics at play.

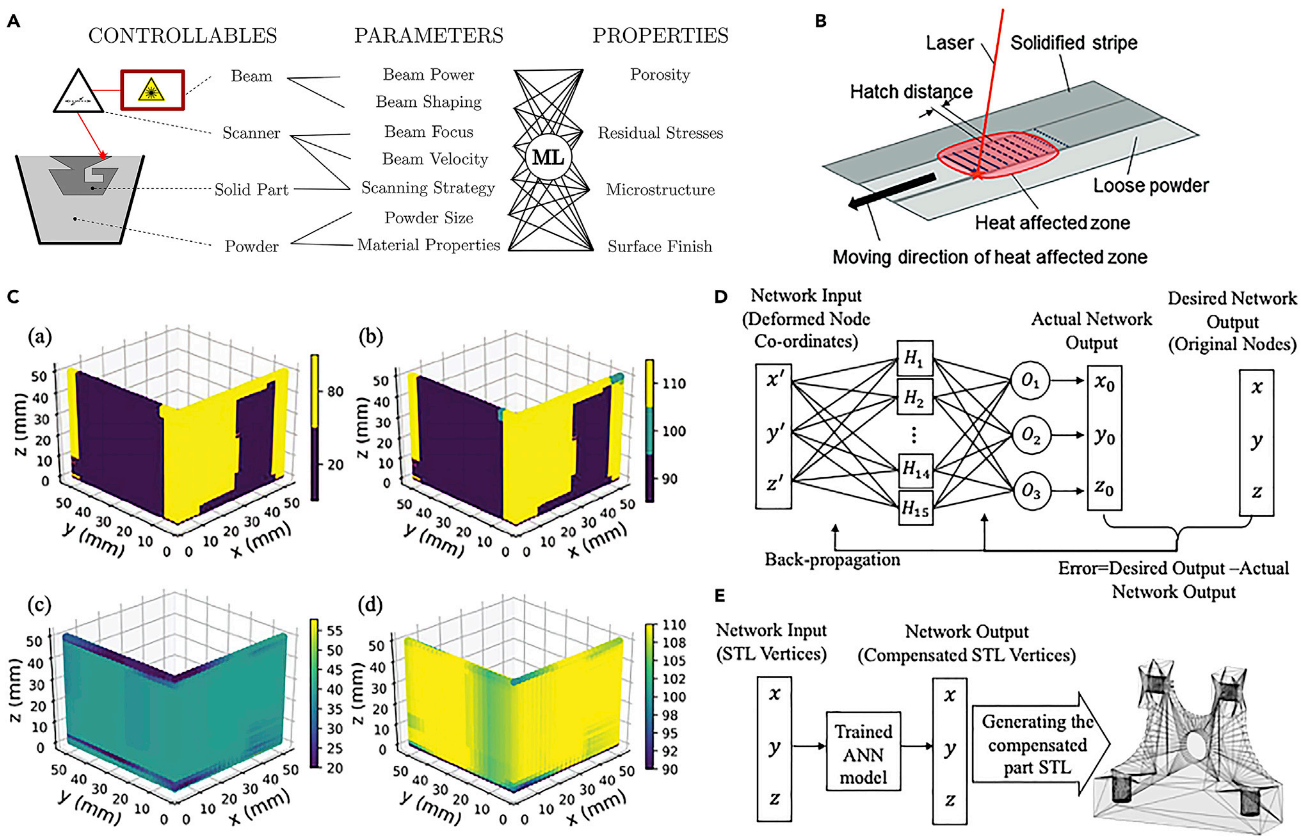

Figure 3. Applications of Optimizing and Understanding Process Parameter Configurations

(A) Schematic diagram of the L-PBF process including controllable parameters and properties.

(B) Strips with hatching created by laser in the L-PBF process. Adapted with permission from Krauss et al.[76] Copyright 2014, Elsevier.

(C) Processing parameters optimization for thin-wall structures: (a) original setting of print speed, (b) original setting of extrusion multiplier, (c) optimized setting of print speed, and (d) optimized setting of extrusion multiplier. Adapted with permission from Gardner et al.[16] Copyright 2019, Wiley-VCH.

(D) Schematic diagram of artificial neural network (ANN) model training based on geometric compensation. Adapted with permission from Chowdhury.[77] Copyright 2016, University of Cincinnati & OhioLINK.

(E) Schematic of compensated stereolithography (STL) generation using a trained ANN model. Adapted with permission from Chowdhury.[77] Copyright 2016, University of Cincinnati & OhioLINK.

In recent studies, ML approaches have been realized by many researchers who have implemented them in different aspects of AM jobs. For example, Gardner et al.[16] applied CNNs to predict print quality under various process parameter settings, including print speed, extrusion multiplier, and fan speed, in the FFF process. In the study, a CNN model was developed to distinguish the print condition (flaw or good quality) based on images captured under different combinations of process parameters. Part quality could be optimized by finding the parameter settings that are predicted to have the highest probability of no flaws. Examples of optimized print speed and extrusion multiplier for thin-wall structures are shown in Figure 3C. The work realized optimization of localized parameter settings for the FFF 3D-printing method using ML algorithms. Besides the applications in FFF, Kappes et al.[78] developed an ML model to predict part porosity based on print orientation and powder properties in L-PBF processes. A developmental ML technique was trained using a dataset consisting of 3,600 samples that correlate part porosity with print orientation. Through their investigations, they were able to provide insights on the effects of part position, print orientation, and the fraction of recycled powder on keyhole porosity development and lack of fusion defects. The study further showed that there is a weak correlation between the aforementioned process parameters and the porosity of a printed part. Additionally, Chowdhury[77] demonstrated the use of a feedforward NN for compensating for dimensional inaccuracies in printed parts caused by residual stresses. Given a part to be printed, the NN is first trained on the predicted post-print deformation of the part, which is obtained through thermomechanical simulations (Figure 3D). Next, a point cloud of the part geometry is input into the NN, which then outputs a compensated point cloud. The compensated point cloud is then post-processed to generate the new compensated geometry, which is used as the printing geometry (Figure 3E). Using this framework, significant improvements in dimensional tolerances were achieved as per the results reported.

IN SITU ANOMALY DETECTION

During the fabrication process, various anomalies commonly occur due to the improper settings of process parameters. Traditional anomaly detection during the fabrication process greatly depends on the experience of the operators, and hence the identification of defects can be prone to inaccuracy, inconsistency, and delays through *ex situ* examining methods. In order to assess the printing condition and product quality in an efficient and accurate manner, *in situ* monitoring systems for detecting defects are highly needed. Enhanced computer vision methods, improved experimental setups, and novel simulation approaches have been developed and are continuously being updated in the literature to address these issues. In this section, novel image processing methods and ML algorithms are analyzed to demonstrate the capability of *in situ* anomaly detection in the AM process.

Real-Time Anomaly Detection Using Novel Image-Processing Methods

Detection systems heavily rely on direct feedback, as shown by the numerous studies using *in situ* assessments of real-time image streams. In one such study, a 3D digital image correlation (DIC) camera, an advanced camera imaging reconstruction system, is used to monitor the surface geometry of a printed part during an FFF print process. The system is able to reconstruct the surface geometry through correlating stereoscopic images (Figure 4A).[79] During the data correlation process, a random sample consensus (RANSAC) algorithm was applied to eliminate outliers for the point cloud alignment task and comparisons were made between the 3D-DIC and CAD models (Figure 4B). The results further showed that this method is capable of detecting porosities inside the printed part to a resolution of 0.0202 mm in the point cloud. This work demonstrates the capability of the 3D-DIC system to detect *in situ* porosity and shows great potential for application to other AM methods, such as L-PBF, where *in situ* detection and diagnosis of porosity defects is also a big challenge.

Besides the novel methods applied in the FFF process, other image processing algorithms are also being developed in L-PBF to address various types of defects generated in the complicated fabrication process. In a recent study, image segmentation methods were developed with a high-resolution image system to determine the accuracy of *in situ* geometry identification of L-PBF layer-wise images.[80] Here, several active contour methods, such as active contours without edges (ACWE) and level-set methods with bias field estimation (LSM-BFE), have been applied to create an *in situ* closed curve (boundary) outlining the layer-wise printing geometry and were compared with *ex situ* ground truth optical microscopy images shown in Figure 4C. Tests were conducted under different laser scan directions, printing geometries, and lighting conditions, with results concluding that dark illumination

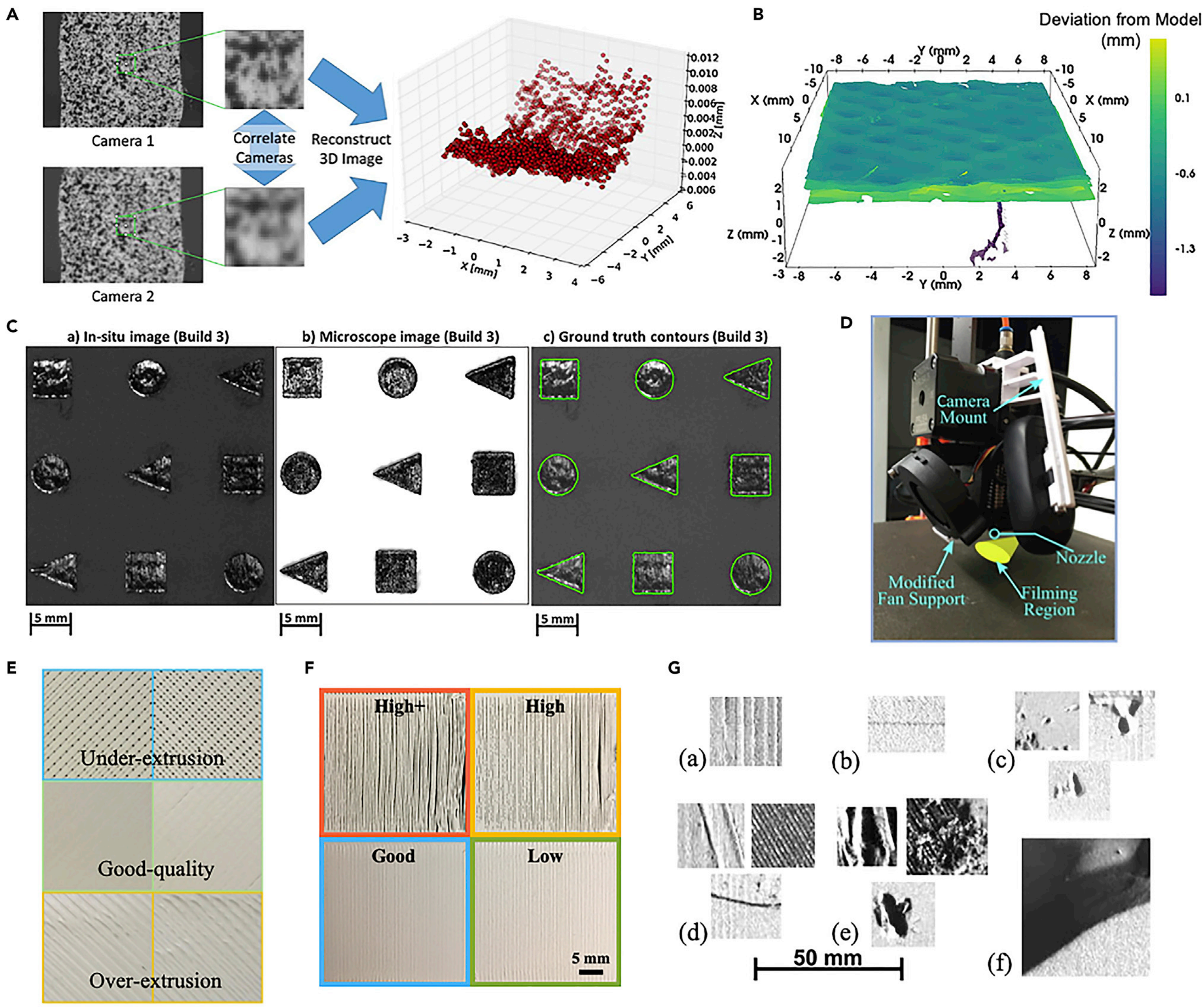

Figure 4. Applications of Anomaly Detection Using Image Processing Methods and ML Algorithms

(A) A surface geometry reconstruction system based on 3D-DIC methods. Adapted with permission from Holzmond and Li.[79] Copyright 2017, Elsevier.
(B) Deviation between the 3D-DIC and the CAD models. Adapted with permission from Holzmond and Li.[79] Copyright 2017, Elsevier.
(C) Examples of the *in situ* image, microscope image, and ground truth contours for different printing geometries. Adapted with permission from Caltanissetta et al.[80] Copyright 2018, Elsevier.
(D) Experimental setup for a real-time anomaly detection system, where a camera is mounted on the extruder through a 3D-printed cantilever structure. Adapted with permission from Jin et al.[17] Copyright 2019, Elsevier.
(E) Three printing qualities for the intra-plane condition: under-extrusion, good quality, and over-extrusion. Adapted with permission from Jin et al.[17] Copyright 2019, Elsevier.
(F) Four conditions of the nozzle height (high+, high, good, and low) that may cause delamination. Adapted with permission from Jin et al.[81] Copyright 2020, Wiley-VCH.
(G) Six categories of anomalies in L-PBF: (a) recoater hopping, (b) recoater streaking, (c) debris, (d) super-elevation, (e) part failure, and (f) incomplete spreading. Adapted with permission from Scime and Beuth.[10] Copyright 2018, Elsevier.

configurations leads to the best segmentation and measurement performance; the ACWE method was more computationally efficient and hence superior for *in situ* implementation; the total measurement variability was about 1.6%–3.2% of the normal dimension for squared and circular shapes. This work provided an effective imaging tool for layer-wise *in situ* assessments on geometry accuracy during the L-PBF process.

In Situ Anomaly Detection Using ML

Studies using novel image processing methods demonstrate significant progress of *in situ* anomaly detection tasks. However, these approaches largely depend on the specific problems and are unable to detect multiple and different types of defects simultaneously. For these reasons, ML methods hold great promise in overcoming these problems as they are able to analyze underlying patterns and features within datasets. New ML approaches are developed to address these problems using more universal methods with high efficiency and accuracy.

By establishing imaging systems to monitor the fabrication process, computer vision and ML algorithms can be applied for recognizing and classifying various defects in real time during the FFF process.[17,81] In the following study, a universal serial bus (USB) camera was attached to the print nozzle providing a fixed filming view of the printing area around the nozzle (Figure 4D). In-plane printing conditions, including over- and under-extrusion (Figure 4E), were analyzed by training CNN models based on real-time images. Classification results were predicted to determine *in situ* printing status. Similar methodologies were also applied to recognize inter-planar defects such as delamination, where nozzle height was the primary process parameter to be monitored and the model was trained based on input images with four different types of nozzle height (Figure 4F). The accuracy of the two models reached 98% for intra-planar defects and 91% for delamination problems. Additionally, an automated closed-loop correction system was set up, modifying printing parameters based on the prediction results of the ML model. The overall response rate for anomaly detection was verified to be faster than the speed of an experienced operator. The results demonstrate the remarkable performance of *in situ* anomaly detection using ML models.

Unsupervised learning techniques are also developed and used with AM processes other than FFF, such as L-PBF and inkjet printing.[10,82] In one study, six representative anomalies, including recoater hopping, recoater streaking, debris, super-elevation, part failure, and incomplete spreading, were examined for the L-PBF process, with the image of each case[10] shown in Figure 4G. The model applied a filter bank to the input images and obtained a dictionary based on the clustering of the filter response. After that, images were analyzed based on the similar match of the dictionary into histograms (fingerprints). During detection, the new image would follow the same procedure and obtain a fingerprint. By comparing the similarity of the fingerprints in the database, corresponding defects could be traced. The model was reported to have an overall 98% accuracy in detecting seven cases (six defects plus anomaly free) and 95% accuracy classifying the six anomalies. This method provided a general and invaluable approach for solving the multiple anomaly detection problems with high accuracy during the L-PBF manufacturing process without a complicated data preparation procedure. This technique can also be adaptively applied to other general defect detection tasks in various manufacturing systems.

DISCUSSION

The integration of ML algorithms in the three main stages of AM processes has shown the feasibility and efficiency of the explored methods. Among these innovative state-of-the-art algorithms, it is also meaningful to discuss the advantage of each algorithm with respect to their applicable problems. Besides the general NN model discussed in the introduction, there are other special networks that have specific advantages. In particular, CNNs are widely applied in image recognition problems for their ability in extracting patterns and feature information embedded in the

Table 1. Overview of ML Algorithms Used in Additive Manufacturing Applications

AM Applications	ML Algorithms
Structural optimization	clustering,[20] SVM,[83] NNs,[84]
Material design	decision trees,[33] CNNs[34]
Process parameter determination	PCA,[85] NNs[77,86]
Defects detection	clustering,[10] SVM,[18] CNNs[17]
Quality assessment	SOM,[21] GP,[19] CNNs[81]

images; recurrent neural networks (RNNs) are usually applied to sequential input data as the internal hidden state (memory) of the network can store extra temporal information. In AM processes, there are problems that are reminiscent of typical problems (such as image recognition) that are applicable to CNNs. For example, in defect detection problems, images are directly monitored and fed into an ML model to diagnose the printing condition. In addition, for DM design, a DM is an assembly of voxels that can be regarded as a matrix conserving both material and spatial information for the input of the CNN model. However, not all problems in the AM process can be easily broken down into a labeled dataset. Hence, other unsupervised approaches are considered; for instance, clustering can be used in the pre-processing of structural optimization, where density distribution is optimally classified in the literature.[20] Additionally, principal component analysis (PCA) can be applied to determine and optimize the dominant process parameters involved in certain AM applications. Table 1 shows an overview of ML algorithms used in AM applications.

From the examples shown in Table 1, various NN approaches are actively and effectively adopted to tackle AM applications. However, it is not a trivial process to properly determine the number of hidden layers and nodes needed for an NN model. A common approach involves a trial-and-error process that tunes the number of layers and nodes needed to obtain optimal performance of the model structure. However, this method can be inefficient and time consuming. To expedite the determination of the NN architecture, various rules are adopted. Firstly, a proper combination of layers and nodes should be selected based on the size of the dataset. Although a deeper NN may achieve better performance, insufficient data could lead to overfitting problems, which leads to an inferior trained model. In other words, the size of the training data should always be greater than the number of learnable parameters in the model. Secondly, considering a smaller number of hidden layers at the trial of model constructions and then building up the architecture based on the training results could be an effective strategy. Sometimes, several hidden layers could be sufficient to obtain a high-performance model in many practical problems.[87] Thirdly, taking advantage of pre-trained models can be used, as some ML algorithms (e.g., residual NNs, densely connected convolutional networks) are so impactful that pre-trained models are available from online databases. During the training process, the main body of the architecture as well as pre-trained parameters can be kept while modifying the last several layers to fit the problem settings. The computational time and resources are significantly improved using this method. Following these general steps can be helpful in achieving an efficient NN architecture.

CHALLENGES AND PERSPECTIVE

Algorithm-based methods, especially ML, provide several benefits and advantages in different types of AM processes as so far discussed. However, there remain challenges, giving rise to future opportunities in the development of the three AM stages. The outlook for enhanced algorithms as well as the development direction of the introduced methods and potential applications are as follows:

(1) Refined interface settings for TO: TO of multi-scale or multi-material frameworks in general does not take into consideration practical limitations at phase transition boundaries. Namely, the interfaces are assumed to be strong and have an abrupt material change, which is not the case for many AM technologies. Researchers have observed various interface characteristics, including porosity, material indent, lack of fusion, and serrated surfaces, which can generate lower (sometimes higher) shear and tensile strengths, gradient properties, and heterogeneity at the material intersections.[70–73] These interfacial effects heavily depend on the choice of material, printing mechanism, and process parameters. Therefore, studying these constraints from experiments and adding them to the design phase is a crucial step to reach practical solutions.
(2) Further exploration of ML-based 3D printed material design: the prediction objective can be extended to nonlinear material behaviors including deformation, crack evolution, and damage accumulation where complex mapping functions may be required. A more general design space can be constructed so that the geometry, distribution, and material constituents are all considered within a single model. At the same time, the ML models can be incorporated with well-developed physical principles of materials. It has been shown to be possible to optimize and generalize an NN using the governing partial differential equations, which greatly reduces the required number of labels obtained from simulations. For instance, researchers have predicted fluid mechanics using NNs trained with the Navier-Stokes equations.[74,75] A similar method can potentially be adopted to save the computational cost of material behavior simulations. Lastly, most researchers focus on forward models, leading to a lack of studies on generative models, named so for their ability to generate possible material designs given a set of desired properties.
(3) Training data collection and computational cost saving: the effectiveness of ML models is entirely dependent on the availability and quality of training data. Training data in the context of AM process parameters and anomaly detection are obtained from either numerical or empirical methods. Numerical methods provide the ability to obtain data based on simulating physical models, while empirical data are acquired through experiments. However, simulations can be highly complicated and sometimes prone to inaccuracy due to the complexity of the problem. Additionally, conducting numerous repeatable experiments to collect data can be also time consuming and tedious. Hence, autonomous high-throughput experiments can be established to conduct training data collection processes. Studies have shown promising results on acquiring a satisfying amount of training data using high-throughput methods in AM.[78,88] Additionally, the computational cost for training will also increase dramatically when the setting variables are augmented. Here, feature extraction methods that reduce the problem domain (e.g., PCA) and advanced learning strategies (e.g., Bayesian optimization) can be used to save the computational cost and time needed for ML.[85,88]
(4) Spillover to other manufacturing methods: the summarized and proposed algorithm-based methods discussed above are not limited to AM techniques. Indeed, they are applicable to many other types of AM technologies, such as binder jetting, as well as traditional manufacturing processes, including CNC machining and even bridge construction. For example, a random forest

algorithm, which is a typical decision tree ML structure, was applied to a CNC milling process to successfully detect cyber-physical attacks with 91.1% accuracy.[89] Another study developed a bridge crack detection system with an active contour model and SVM to recognize and evaluate material failures.[90]

State-of-the-art algorithms explored in this review have shown their capability in solving critical problems in different types of manufacturing methods, and it is believed that algorithmically driven methods hold huge potential and great promise in the development of Industry 4.0 as the next generation of the industrial revolution.

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AUTHOR CONTRIBUTIONS

All authors contributed to the preparation of the manuscript.

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